A19: UNDERWATER ACOUSTICS
Phase-coherent underwater acoustic communications in the presence of impulsive snapping shrimp noise

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ABSTRACT
Snapping shrimp are the dominant source of high-frequency (>1 kHz) biological noise in warm coastal waters. During an acoustic experiment conducted in the northeastern East China Sea (SAXEX15), highly impulsive, strong signals produced by shrimp snaps were observed continually in 100-m deep shallow water, affecting the performance of phase-coherent underwater acoustic communications in a rapidly time-varying environment. Two adaptive algorithms are applied to process high-frequency (11-32 kHz) communication sequences with various constellations from BPSK to 32-QAM: (1) traditional multichannel decision-feedback equalizer (M-DFE) and (2) time-reversal based DFE (TR-DFE). The preliminary analysis of the data leads to the following conclusions. First, both algorithms (M-DFE and TR-DFE) can provide a similar performance for low-order constellations such as BPSK and QPSK. For high-order constellations (16-QAM and 32-QAM), however, only TR-DFE has been successful for decoding with a data rate of up to 60 kb/s using a 16-element, 56-m aperture vertical array over a 3-km range. Second, high-order QAM constellations appear more resilient to the impulsive nature of the snaps, apparently treating the impulsive noise as one of the outer constellations, albeit with a burst of errors.

Keywords: Multichannel decision-feedback equalizer (M-DFE), Time-reversal-based DFE (TR-DFE), Snapping shrimp noise, SAXEX15

1. INTRODUCTION
A shallow-water acoustic variability experiment (SAXEX15) was conducted in the northeastern East China Sea in May 2015. The goal of SAXEX15 was to collect acoustic and environmental data appropriate for studying the coupling of oceanography, acoustics, and underwater communications in the dynamic region. The experimental site had a nearly flat sandy bottom with a water depth of approximately 100 m. Both fixed and towed transmissions were carried out to two moored arrays over ranges of 1-10 km. The acoustic transmissions were in various frequency bands (0.5-32 kHz) [1].

Snapping shrimp dominate the high frequency soundscape (>1 kHz) in warm shallow waters [2]. Surprisingly, the highly impulsive, strong signals were observed continually during SAXEX15 [3-5], affecting the performance of phase-coherent acoustic communications in this rapidly time-varying environment. In this paper, we analyze the communications data between a moored source (at 20 m depth) and a 16-element vertical receiver array separated by 2.8 km, which were collected over an extended period of 22 hours using the wide frequency band (11-22 kHz) with various constellations (e.g., QPSK, 16-QAM, and 32-QAM).

2. ADAPTIVE ALGORITHM
We consider two adaptive algorithms to decode the communication packets: (i) standard multichannel decision-feedback equalizer (M-DFE) with the least mean square (LMS) adaptive algorithm [6] and (ii) multichannel time-reversal combining followed by a single-channel DFE (TR-DFE) with frequent channel updates for time-varying environments [7]. In both cases, a second-order phase-locked loop (PLL) is applied for phase tracking.

3. PERFORMANCE
The highly impulsive nature of snapping shrimp noise had a significant impact on phase-coherent communications either by disrupting the phase tracking or causing burst errors. Nevertheless, both M-DFE
and TR-DFE provided a similar performance for low-order constellations such as BPSK and QPSK in terms of output signal-to-noise ratio (SNR), suggesting that either algorithm can be used.

However, M-DFE completely failed as the constellation increases to 16- or 32-QAM. On the other hand, TR-DFE continued to perform very well, as illustrated in a scatter plot of 32-QAM with a data rate of 30 kb/s [Fig. 1(a)]. What is really interesting is that TR-DFE with high-order constellations (16- or 32-QAM) showed a much better chance to overcome the phase disruption due to the impulsive shrimp noise than TR-DFE with low-order constellations. It appears that the strong shrimp noise was treated as one of the outer constellations, albeit with a burst of errors. To see the impact of fluctuating ocean environments, Fig. 1(b) shows the TR-DFE performance of various constellations (QPSK, 16-QAM and 32-QAM) over a 22-h period, indicating the performance can change as much as 8 dB.

Fig. 1. (a) An example of scatter plot for 32-QAM at 2.8-km range using the wide frequency band (11-22 kHz) with a symbol rate of 6 kHz. (b) Performance of TR-DFE communications for various modulations (QPSK, 16-QAM, and 32-QAM) over a period of 22 hours during SAVEX15.

REFERENCES
Effect of dolphin impulse signals on long-range underwater communication

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ABSTRACT
The biomimetic long-range acoustic communications experiment 2018 (BLAC18) was conducted in the east of Pohang, South Korea, to verify the feasibility of long-range underwater communication in the East Sea. During BLAC18, unwanted signals generated by dolphins were recorded. Dolphins generate two types of signals: whistle sounds, similar to the frequency modulation signal, and click sounds, similar to the impulsive signal. Whistle sounds were easily eliminated from the communication signal because they were separated in the frequency domain, whereas all frequency bands of the communication signal were contaminated by click sounds. In this paper, we’ll show the effect of click sounds and the cancellation technique.

Keywords: Dolphin, impulse signal, BLAC18, Communication

1. INTRODUCTION
A biomimetic long-range acoustic communication experiment 2018 (BLAC18), was conducted in the East Sea. The goal of BLAC18 was twofold: 1) to obtain the acoustic and environmental data for studying the long-range underwater communications and 2) to verify the feasibility of long-range underwater communication in the East Sea. During BLAC18, however, unwanted dolphin signals were recorded. About tens of thousands of dolphins are known to inhabit in the East Sea (1).

Dolphins generate two types of signals: whistle sound and click sound (2-4). The whistle sound, which is similar to the frequency modulation signal, is used to communicate with other dolphins. The click sound used to find prey has the characteristic of the impulse signal. If these marine animal signals overlap with the communication signal, the phase of the communication signal is distorted and needs to be eliminated. Whistle sounds recorded in the East Sea are outside the frequency band (< 4 kHz) of our designed signal and can be eliminated by bandpass filter. However, because the click sound is an impulse signal that occupies all frequency bands, cancellation in either the time or frequency domain is difficult.

In this paper, we will show how the click sound affects the communication signal and how to cancel the click sounds.

2. BLAC18
BLAC18 was conducted in deep water, about 20 km off the east of Pohang, South Korea, in October 2018. The depth of the operation area is between 1,000m ~ 1,500m. The experiment utilized a vertical line array (VLA) of 16 elements spanning to 42 m of a 1,000 m water column. The design frequency was about 268Hz. The depths of the source and the center of the VLA were about 200 m. The range between the source and VLA was 30 km.

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During BLAC18, we transmitted the signal packet consisting of a 3-s LFM signal as a channel probe, followed by a 2.47-s long communication signal. The carrier frequency and bandwidth of the channel probe signal and communication signal were set to 2,560 Hz and 640 Hz, respectively. Figure 1 (a) shows the received signals obtained from the VLA. The received signals included a number of impulse signals, which could also be seen clearly in the spectrogram [Figure 1 (b)]. In Figure 1, the red arrows indicate clearly visible impulse signals with large amplitudes, whereas the blue arrows show indistinguishable impulse signals in the time domain. Impulse signals act as interferers and distort the phase of the communication signal. However, because the cancellation in the time and frequency domains is difficult, this paper shows the cancellation approach in the spatial domain.

3. CANCELLATION OF DOLPHIN CLICKS

To spatially eliminate the click sounds, we use a time reversal processing approach. In general, the conventional time reversal processing (CTRP) is employed to recover the communication signal. CTRP approach is calculated by correlating the received signal with the channel impulse response (CIR) estimated from the probe signal (5):

\[ \hat{S}(\omega) = \mathbf{H}^\dagger(\omega) \mathbf{R}(\omega) \]  

where \( \hat{S}(\omega) \), \( \mathbf{R}(\omega) \) and \( \mathbf{H}(\omega) \) denote the estimated source signal, the received signal and the CIR, respectively. The superscript \( \dagger \) denotes the complex transpose.

Despite the presence of interferers, the influences of the interferer can be mitigated if the CIR of the interferers differs from the CIR of the desired signal. Figure 2 (a) depicts a scatter plot obtained by applying CTRP to the received signal depicted in Figure 1 (a). The majority of the symbols (red circles) are distributed around the information symbols (yellow circles), implying that their phase was not distorted. On the other hand, certain symbols (green circles) appear to diverge from the information symbols. These outliers are symbols in time that are influenced by strong click sounds. In other words, while CTRP can mitigate weak click sounds, strong click sounds continue to have an effect.
The communication signal including impulse signals can be considered as a multiple-input-multiple-output scenario. Adaptive time reversal processing (ATRP) approach is beneficial when there are interferers. ATRP spatially eliminates interferers without distorting the phase of the communication signal because it employs the weight vector based on minimum variance distortionless response (MVDR) (6). For ATRP, the CIR in Equation 1 is substituted the MVDR-based weight vector (7-8),

$$\mathbf{w}(\omega) = \frac{\mathbf{K}^{-1}(\omega)\mathbf{H}(\omega)}{\mathbf{H}^H(\omega)\mathbf{K}^{-1}(\omega)\mathbf{H}(\omega)}.$$  \hspace{1cm} (2)

Here, $\mathbf{K}(\omega)$ is the cross-spectral density matrix (CSDM) required to design the weight vector and is expressed as the sum CSDMs yielded by the CIRs of the communication and the click sounds.

Figure 2 (b) is a scatter plot using ATRP. Compared to CTRP, the positions of the green circles are gathered around the information symbol. The performance enhancement due to click cancellation is clearly evident in scatter plots with the migration of the distorted symbols.

4. SUMMARY

During the sea-going experiment, unwanted impulse signals generated by dolphin were recorded. The impulse signals distorted the phase of the communication signal. Two TRP approaches, which utilize the spatial domain, are employed to mitigate the impulse signals that overlap in the time and frequency domains. CTRP mitigated the weak impulse signal but not the strong impulse signal. In contrast, when ATRP was applied, outliers in the scatter plot migrated to information symbols as a result of the elimination of strong impulse signals.

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Cross-pattern coherence spatial filtering with hydrophone arrays for passive-sonar applications

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ABSTRACT
This paper presents a spatial post-filtering algorithm for passive-sonar systems deploying linear hydrophone arrays. The algorithm provides an attenuation parameter in the time-frequency domain based on the normalised cross-spectral density between two signals, which originate from two coincidentally steered conventional beamformers. The computed parameter can be applied as a single-channel spectral post-filter to the output of another beamformer to suppress background noise and interference. The technique is evaluated with simulated data of two 96-channel flank arrays, as well as with real-world data derived from smaller towed linear arrays. The evaluation includes two array configurations: a) a single-line configuration using two non-overlapping subdivisions of a linear array for the computation of the parameter, and b) a dual-line configuration using two parallel linear arrays. In all studied cases, the post-filter is shown to improve the resolution and background-noise suppression capabilities of the baseline beamformers. It is further shown that, in the dual-line configuration, the post-filter may improve the beamforming performance near the end-fire direction as well as further resolve the port-starboard ambiguity, which is a known drawback of towed linear arrays. Lastly, it is worth noting the relatively low computational complexity of the proposed technique compared to the more demanding adaptive beamformers.

Keywords: Array processing, Post filtering, Passive sonar

1 INTRODUCTION
Passive-sonar systems utilise hydrophone arrays to provide real-time imaging of the surrounding underwater soundfield. This task is typically performed by means of beamforming, i.e., combining the multichannel-array signals appropriately so that the captured acoustic energy originates from a specific focusing direction (1, 2). This process is repeated over a dense grid of directions on the horizontal plane and over time, resulting in a bearing-time record (BTR), a two-dimensional image of the soundfield energy, which is presented to the sonar operator.

The most common beamforming technique in the domain of underwater acoustics is the delay-and-sum (DaS) algorithm, also commonly called conventional beamforming (3, 4). Its popularity may be attributed to its simple implementation, low computational load, and robustness to noise. However, the number of available sensors in the array imposes limitations to the spatial selectivity of the DaS algorithm. Higher resolution may be achieved, under certain conditions, by employing adaptive beamforming techniques, such as the linearly-constrained minimum variance (LCMV) (5) and, a special case of LCMV, the minimum variance distortionless response (MVDR) (6, 7). These techniques operate by tracking the noise-field variation and adaptively searching for the weights that minimise the beamformer energy while keeping the signal in the desired direction undistorted. LCMV differs from MVDR in that it can also impose additional constraints in specific directions, such as nulls in the directions of interferers. There are, however, several downsides of these adaptive techniques. Their resolution is shown to drop in low signal-to-noise ratio (SNR) levels, often reducing to that of DaS (8). They are also known to be susceptible to steering vector errors and coherent reflections (9, 10). Last but not least, their computational complexity increases non-linearly with increasing number of sensors, a property that often makes them an undesirable option for contemporary sonar systems, which may employ arrays with hundreds or even thousands of hydrophones (11).

While beamformers are capable of capturing the acoustic energy from one specific direction while rejecting contributions from other directions, a further SNR improvement may be achieved by employing spatial
post-filters (12, 13). These filters typically measure the coherence between sensors and compute attenuation parameters in the time-frequency domain, which are then used to modulate the output of a beamformer. Although post-filters have been originally developed for speech enhancement applications, they have been recently deployed successfully for underwater soundfield visualisation demonstrating good noise suppression capabilities (14).

This paper presents a novel algorithm based on the cross-pattern coherence (CroPaC) post-filter (15). The proposed algorithm is specifically designed to operate with linear arrays, which are the most common type of hydrophone arrays found in passive-sonar systems. The arrays can either be mounted onto the sides of a submarine hull, in which case they are called flank arrays, or they can be towed on a cable behind a submarine or a surface ship. More recent applications where linear arrays can be encountered include autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) (16, 17). The proposed post-filter computes a coherence value between two signals captured by two non-overlapping linear arrays using conventional beamforming over a grid of steering directions. The resulting value is used to attenuate the output of another beamformer at the time-frequency points where the received energy corresponds to noise or interference; thus, improving its spatial selectivity with a relatively low increase on the computational load.

The remainder of the paper is organised as follows. Section 2 provides a brief discussion of related works, while the proposed algorithm is presented in Section 3. The performance evaluation on simulated and real experimental data is then conducted in Section 4. Section 5 discusses the computational advantages of the proposed algorithm and, finally, Section 6 provides conclusions and suggestions for future research directions.

2 RELATED WORK

The proposed technique belongs to a well-established class of signal enhancement techniques known as post-filters. Notable examples of such filters include the Zelinski (18), the McCowan (19) and the Leukimmiatis (20) post-filters, which compute coherence values based on the auto- and cross-spectral densities of signals captured by omnidirectional microphones. The differences between these implementations involve mainly the assumptions made for the characterisation of the noise field. The noise suppression capabilities of such filters in reverberant environments are investigated in more detail in (21).

An alternative approach is followed by the CroPaC post-filter (15), which utilises directional microphones derived through beamforming in order to compute the required auto- and cross-spectral densities. More specifically, the beam patterns used in the derivation of the CroPaC post-filter correspond to circular or spherical harmonic functions of different orders. The desired properties of these patterns are that a) they have maximum sensitivity and equal phase only in the look direction, and b) both diffuse and sensor noise are orthogonal between the patterns. As a result, the cross-spectral density between the beamformed signals provides a good estimation of the target signal energy, while noise, which is captured incoherently, is suppressed. CroPaC has demonstrated improved performance in diffuse-noise conditions compared to other post-filters, especially at low frequencies (22, 23, 24). Moreover, since it makes no assumptions on the properties of the noise field, it is more suitable for complex acoustic environments. A reformulated version of CroPaC for large circular arrays (14) has shown the potential of the CroPaC method for application in underwater environments with hydrophone arrays. However, none of the known versions of the CroPaC algorithm is suited for linear arrays, since the required patterns can be obtained optimally only by specific geometries, such as circular or spherical arrays. This motivated the development of the new version of the algorithm proposed here, which utilises different type of patterns that can be obtained by linear arrays.

The patterns involved in the computation of the proposed post-filter are generated by dividing a linear array to two non-overlapping sub-arrays and by applying conventional beamforming to each one of them. This idea draws its inspiration from a class or techniques known in the literature as split-beam processing (25, 26, 27). These techniques are widely used in underwater acoustics for bearing estimation of broadband signals with passive linear towed arrays. They operate by steering coincident beams from each sub-array and estimating the cross-correlations between the received signals. These cross-correlations provide the time delays through which the target bearings can be estimated. This method owes its popularity in the field to its reduced computational load compared to the full-aperture beamforming. However, its ability to detect weak signals in real-world passive-sonar scenarios is debated (26). Nevertheless, a recent study (27) proposed a split-beam processing algorithm that includes an essential prewhitening step, which is argued to improve the detection of broadband weak targets.

Another topic explored in this work, which may be of particular interest to the underwater community, concerns the potential benefits of the proposed method in resolving the port-starboard ambiguity of linear arrays. This problem is caused by the symmetry of the linear array patterns around their main axis, which results in identical beamformer outputs for targets located at symmetrical bearing angles. For flank arrays, the ambiguity may be sufficiently resolved through the acoustical shadowing offered by the submarine hull. Therefore, the
problem mainly concerns towed linear arrays where no such shadowing occurs. In this case, the methods proposed to resolve the ambiguity concern special arrangements of the hydrophones, such as linear arrays of triplets (28, 29, 30) or twin-line planar arrays (31, 32, 33). The proposed post-filter is tested on a dual-line towed array configuration and is shown to offer additional resolution of the port-starboard ambiguity when compared to employing beamforming without the post-filter applied.

3 PROPOSED METHOD

Contrary to the original CroPaC algorithm which is defined in the circular or spherical harmonic domains, the proposed post-filter operates directly in the space (sensor) domain. Thus, it is henceforth referred to as the space-domain CroPaC (SD-CroPaC) algorithm. The two linear array geometries examined in the work, namely the single- and dual-line configurations, are shown in Figure 1a. Since the working principle is the same for both configurations, the post-filter is derived here for the single-line configuration.

\[
\mathbf{x}(k,i) = s(k,i)\mathbf{v}(k) + \mathbf{n}(k,i),
\]

where \(s\) denotes the desired signal of the target source, \(\mathbf{v} \in \mathbb{C}^{Q \times 1}\) is the array transfer vector which describes the propagation from the target source to the array, and \(\mathbf{n} \in \mathbb{C}^{Q \times 1}\) is an additive noise component. It is assumed that the target source signal is captured by the array as a sum of plane waves (far-field approximation).

The proposed method provides a heuristic formula for a single-channel Wiener post-filter applied to the output of a beamformer. The post-filter’s general expression is

\[
h_{opt} = \frac{\Phi_{ss}}{\Phi_{ss} + \Phi_{nn}},
\]

where \(\Phi_{ss}\) and \(\Phi_{nn}\) are the signal and noise power spectral densities at the beamformer output. Note that the frequency and angle indices are omitted for brevity. Since \(\Phi_{ss}\) and \(\Phi_{nn}\) are not known a priori, they need to be estimated in order to derive the post-filter’s expression.

The signal processing flow of the SD-CroPaC post-filter is shown in Figure 1b. The linear array is first divided into two adjacent non-overlapping sub-arrays U and V, comprising \(M\) and \(Q - M\) sensors respectively.
The time-domain signals of the sub-arrays $x_U(t) \in \mathbb{R}^{M \times 1}$ and $x_V(t) \in \mathbb{R}^{(Q-M) \times 1}$ are first transformed into the time-frequency domain, typically with a short-time Fourier transform (STFT). The resulting signals $x_U(k,i) \in \mathbb{C}^{M \times 1}$ and $x_V(k,i) \in \mathbb{C}^{(Q-M) \times 1}$ produce respectively the signals $S_U$ and $S_V$ through DaS beamforming at an angle $\theta$. The post-filtering parameter is then computed as

$$G(k,i,\theta) = \max \left(0, \frac{2\Re[\Phi_U(k,i,\theta)]}{\Phi_U(k,i,\theta) + \Phi_V(k,i,\theta)} \right),$$

where $\Phi_U(k,i,\theta) = \mathbb{E}\{S_U^\ast(k,i,\theta)S_V(k,i,\theta)\}$ is the cross-spectral density between the beamformed signals $S_U$ and $S_V$, $\Phi_U(k,i,\theta) = \mathbb{E}\{|S_V(k,i,\theta)|^2\}$ and $\Phi_V(k,i,\theta) = \mathbb{E}\{|S_V(k,i,\theta)|^2\}$ are their auto-power spectral densities, $\Re$ denotes the real part, and $\mathbb{E}$ denotes an expectation operator. Note that the SD-CroPaC beam patterns are frequency dependent as opposed to the frequency invariant patterns of the original CroPaC algorithm.

The cross-spectral density between the two beamformed signals $\Phi_{UV}$ provides an approximation of the target signal’s energy $\Phi_t$ due to the fact that the two beamformers capture signals coherently in the look direction while rejecting diffuse noise and interferers. The real operator is applied to $\Phi_{UV}$ because the numerator of the post-filter transfer function (Eq. 2) expresses an energy quantity. The denominator is approximately two times the total energy at the output of the baseline beamformer; therefore, the numerator is multiplied by 2 to bound the value of the normalised cross-spectral density between -1 and 1. Finally, the half-wave rectification with the max operator discards all the negative values - by setting them to 0 - since they correspond to phases mismatches between the two beamformers. The resulting parameter $G$ can then be used to modulate the output of the baseline beamformer $b$ steered in the same direction

$$y(k,i,\theta) = G(k,i,\theta) \cdot b(k,i,\theta).$$

The baseline beamformer can be, for example, a DaS or MVDR beamformer that uses all the available sensors in the array. The filtered spatial spectrum of the soundfield is obtained by plotting the energy of the signal $y$ over a grid of angles $\theta$ that scan the horizontal plane. As is shown in the following experiments, the method is also directly applicable to baffled linear arrays, such as the flank arrays mounted onto the submarine hull, where the DaS beamformer may be optionally replaced by a spatial matched filter (SMF) to take into account scattering effects.

Fig. 2 shows two examples of the $G$ patterns obtained with a simulated 12-sensor uniform linear array (ULA), which is divided into sub-arrays of 7 and 5 sensors for the application of SD-CroPaC. The frequency range extends up to the aliasing limit $f = c/(2d)$. In Fig. 2a, the soundfield consists of a single plane-wave with incident angle $\theta = 90^\circ$. It can be seen that with increasing frequency the post-filter’s pattern becomes more directive, while more low-level side-lobes appear. The corresponding response of the filter when the array captures a diffuse noise field is depicted in Fig. 2b. The diffuse field was simulated as the sum of 5012 incoherent plane waves arriving from a uniform distribution of angles around the array. In this case, it is demonstrated that, above a certain frequency ($f \approx f_{al}/8$), the diffuse-field is captured incoherently between the two beamformers, resulting in sufficiently low $G$ values.

![Figure 2](image-url)
4 EXPERIMENTAL EVALUATION

4.1 Evaluation with simulated data of flank arrays

In this section, the proposed method is tested on simulated data of two uniform linear flank arrays mounted onto both sides (port-starboard) of a submarine. For the simulation, a Boundary Element Method (BEM) model of a submarine with flank arrays was created in the COMSOL Multiphysics® software. A view of the model geometry along with the adopted orientation of the coordinate system is shown in Fig. 3a. Each array comprises 96 hydrophones with inter-sensor distance \( d = 0.284 \) m, resulting in a total length of about 27 m and the distance between the arrays is 6.87 m. The hydrophones of the flank arrays were modelled as omnidirectional pressure sensors and their responses were simulated for incident plane waves on the horizontal plane from 360 angles uniformly distributed around the submarine. These responses correspond to the sum of the incident and scattered fields received by the sensors. Due to computational time limitations, the simulated frequencies were restricted in the range 300-800 Hz with a step of 10 Hz. The submarine hull was modelled as a perfectly rigid sound boundary and the acoustic environment as an infinitely large homogeneous water domain with \( c = 1480 \) m/s.

![Submarine model with flank arrays](image)

Figure 3. BEM model of submarine with two uniform linear flank arrays.

For these experiments, the targets were modelled as static white-noise sources in the far-field captured by the hydrophones as plane waves arriving from different angles \( \theta \). Accordingly, the ambient noise was simulated as a sum of incoherent plane waves arriving from all directions along the horizontal plane, representing a diffuse field. The noise level is described by the direct-to-diffuse ratio (DDR) expressed in dB, which is the ratio of the target’s energy over the total energy of the diffuse field.

In typical passive-sonar applications, each array is assigned a dedicated half-space area: the port array scans the horizontal plane over the angles \([-180^\circ, 0^\circ]\), while the starboard array steers the beams in the range \([0^\circ, 180^\circ]\). Sound waves arriving from the non-visible area of each array - the half-space area covered by the other array - are highly attenuated, especially at higher frequencies, through acoustic shadowing caused by the submarine hull. Therefore, the port-starboard ambiguity that linear arrays naturally suffer from is largely resolved. It is noted, however, that part of the acoustic power is still received from the non-visible area of each array, especially near the end-fire direction where the acoustic shadowing is less effective. Besides, it is known that linear arrays exhibit decreased performance near the end-fire due to lower resolution. These considerations motivated the study of a dual-line configuration in this model, as shown for example in Fig. 3b, where the information from both arrays is combined in order to improve performance near the end-fire. Hence, in the following experiments, the single-line configuration (using each flank array separately) is employed when the target is near the broadside, while the dual-line configuration when it is near the end-fire.

To assess the performance of SD-CroPaC in the single-line configuration, the starboard array is divided into two sub-arrays of 60 and 36 hydrophones, as described in Section 3. Fig. 4a shows the obtained spatial spectrum using DaS for a target at \( \theta = 80^\circ \) with DDR=0 dB, along with the corresponding spectrum when SD-CroPaC is applied to the DaS output. It can be seen that the post-filter offers additional background noise suppression as well as a better resolution of the target.
For the dual-line configuration, a static target was placed at $\theta = -5^\circ$ and the noise level was set to DDR $= -10$ dB. The corresponding sub-arrays U and V were selected to be the ones shown in Fig. 3b. It was observed in simulations that a number of sensors may be omitted, thus saving resources, without degrading the performance. Nonetheless, the optimal selection of sub-arrays is beyond the scope of the present study. The results of this experiment are shown in Fig. 4b. Note that, in this case, the DaS algorithm is replaced by a spatial matched filter (SMF), which is a more general beamforming approach that also accounts for the level differences between the sensor signals apart from the phase shifts. This choice was based on the observation that the beamforming performance improves when the level differences between the two arrays caused by the acoustical shadowing are taken into account. For comparison, the plot also includes the DaS output of the port array used in isolation as well as its filtered counterpart using SD-CroPaC. Note that, for the single-line configuration, the SMF approach does not offer any advantage compared to DaS; therefore, only the DaS spectrum is shown here. It is evident that the near end-fire performance is improved with the dual-line configuration compared to using the port array separately in terms of spatial resolution, bearing estimation accuracy, and background noise suppression. Moreover, even though the SD-CroPaC filter improves the spatial accuracy of the DaS beamformer in the single-line configuration, there is a more notable advantage demonstrated when using the proposed filter in the dual-line configuration.

### 4.2 Evaluation with real experimental data of a towed dual-line array

The method is also evaluated on real measurement data obtained through the use of a towed dual-line planar hydrophone array. The array comprises two parallel linear arrays of different dimensions separated by a distance $h = 0.135$ m. A sketch of the array geometry is shown in Fig. 5. The larger array (array A) consists of 8 non-uniformly distributed sensors and has a total length of $l_A = 2.08$ m. The $x$ coordinates of the sensor positions (in metres) are

$$x_A = [0.00, 0.08, 0.37, 0.75, 0.94, 1.07, 1.50, 2.08].$$

The smaller array (array B) is a uniform linear array of 6 sensors with inter-sensor distance $d = 0.07$ m, resulting in a total length of $l_B = 0.35$ m. The $x$ coordinates of its sensor positions (in metres) are

$$x_B = [0.79, 0.86, 0.93, 1.00, 1.07, 1.14].$$

The studied scenario involves a single target in shallow water moving around the array, whose position remains fixed throughout the recording. The target’s bearing changes from approximately $\theta = -105^\circ$ to $\theta = 75^\circ$ at a relatively constant speed. The duration of the recording is 300 s and the sampling frequency is 32 kHz.
First, the evaluation considers only the data of the non-uniform array A for the application of SD-CroPaC in single-line configuration. The array is divided into sub-arrays U and V, which consist of the first 4 ($q = 0, \ldots, 3$) and the remaining 4 hydrophones ($q = 4, \ldots, 7$) respectively. Due to axial symmetry (unbaffled linear array), the target is equally visible from both sides of the array (port-starboard ambiguity). Therefore, it is sufficient to steer the beams in the half-space $[0^\circ, 180^\circ]$. The obtained spatial spectra are averaged in the frequency range 2 kHz to 10 kHz. Note that, due to the non-uniform distribution of the hydrophones, it is less likely for grating lobes to appear; therefore, the aliasing limit can be set higher than the theoretical limit of the array ($f_{al}^A \approx 1280$ Hz). The BTR plots using DaS alongside its filtered version with SD-CroPaC are shown in Fig. 6. It can be observed that the post-filtering operation results in a BTR image of higher contrast in Fig. 6b, where the background noise is suppressed and the target is depicted with higher resolution. These observations are in agreement with those arising from the simulated data in Sec. 4.1. Note that, during the first 170 seconds where the true bearing of the target is negative, the BTR plots display the mirrored image of the target with a positive bearing.

Two slices of the BTR plots taken at different time instants are shown in Fig. 7. For comparison, the plots also include the MVDR output, along with its filtered version with SD-CroPaC. It is observed that SD-CroPaC offers an additional background level suppression of approximately 4-6 dB for both baseline beamformers. Moreover, the peak associated with the target is depicted with higher resolution, following the application of the proposed post-filter. It is interesting to note that, in this experiment, MVDR demonstrates a below-standard performance where its theoretical advantages are not evident: it only achieves a better resolution than DaS when the target is near the broadside, while it appears to be inferior to DaS in terms of background noise suppression. This may be explained by the noisy nature of the real-world data (sensor positioning errors, phase

![Figure 5. Geometry of the dual-line hydrophone array.](image)

![Figure 6. BTRs for the single-line configuration (Array A)](image)
mismatches, sensor noise), as well as by the acoustic conditions of the underwater environment; it is known that MVDR is susceptible to low-SNR conditions and to coherent interferers, such as reflections from the water surface. On the other hand, DaS is known to be more robust under non-ideal conditions. Overall, from this experiment, it may be concluded that the proposed method is valid despite the presence of noisy data under real-world conditions. A further conclusion is that the application scope of the method may be extended to non-uniform linear arrays consisting of as few as 8 sensors.

Figure 7. Spatial spectra at two different instants for the single-line configuration (Array A).

For the next experiment, the hydrophone signals from both linear arrays - forming a dual-line planar array - are used. The beams are steered over the whole horizontal space from \( \theta = -180^\circ \) to \( \theta = 180^\circ \), as there is no symmetry in this case. The beamformer outputs are averaged in the same range (2 kHz to 10 kHz) as in the previous case of the single array. Note that since the smaller array B is uniform, grating lobes are expected to appear above its aliasing frequency \( f_{B, \text{al}} \approx 10.5 \text{ kHz} \); therefore, the upper limit of 10 kHz guarantees that these will not appear. Regarding the implementation of SD-CroPaC, the sub-arrays U and V in the dual-line configuration as defined in Section 3, correspond to the arrays A and B, respectively. The BTR plots for this experiment are given in Fig. 8. It can be seen in Fig. 8b that, apart from the advantages observed previously in the single-line case regarding spatial resolution and noise suppression, this case presents the additional advantage of resolving the port-starboard ambiguity to a certain degree; the mirrored peaks which do not correspond to true targets are attenuated, compared to the real target peaks. The slices of the BTR plots (Fig. 9) taken at two time instants show that by applying DaS to the dual-line array, the level difference between the real and the mirrored peaks is 4-5 dB. By also applying the proposed post-filter, the corresponding level difference is extended to 8 dB for the target near broadside and to more than 10 dB for the target near endfire, in which case the port-starboard ambiguity appears to be almost fully resolved. Lastly, the performance of MVDR appears to degrade even more in this case, compared to the single-line configuration. This may be attributed to the accumulation of errors as more sensors are used.

5 COMPUTATIONAL CONSIDERATIONS

Despite the recent advances in beamforming techniques, conventional beamforming is still a favoured choice nowadays among sonar system designers, at least partly due to its low computational requirements. Adaptive beamformers may offer higher resolution of closely spaced targets under certain conditions, but this advantage is often offset by an increase in computational complexity. This issue becomes particularly important for sonar arrays that include hundreds or even thousands of hydrophones, because the CPU and memory requirements of adaptive techniques scale up considerably with increasing array size (11, 34). The implementation problems relate mainly to the inversion of the sample covariance matrix, which in practice has an algorithmic growth rate of \( O(Q^3) \) with brute-force computation or at best \( O(Q^2 \text{ Strassen}) \) using the Strassen algorithm (35), where \( Q \) denotes the number of sensors. By comparison, conventional beamformers have a linear time complexity \( O(Q) \), which makes them more suitable for real-time systems employing large hydrophone arrays. The computation of the proposed SD-CroPaC post-filter is based on a set of conventional beamformers utilising sub-arrays; therefore, its algorithmic growth rate is also linear with respect to the number of input signals \( O(Q) \). Note also that the SD-CroPaC steering weights may be calculated offline and stored, as opposed to the MVDR signal-dependent weights, which are calculated for every iteration. These cost-effective implementation characteristics of the pro-
posed method suggest its potential for incorporating it into modern sonar systems, where keeping computational costs low is highly prioritised.

6 CONCLUSIONS

This paper presents a post-filtering algorithm for applications requiring underwater soundfield visualisation with linear hydrophone arrays. The proposed method represents a space-domain reformulation of the Cross-Pattern Coherence (CroPaC) algorithm. In this sense, its applicability is not necessarily limited to linear arrays. Nevertheless, this study focused on two common linear array configurations, namely single-line and dual-line arrays, owing to their practical importance in passive sonar applications. The evaluation is performed on simulated data of large flank arrays using a BEM model of a typical submarine as well as on real hydrophone-array data of smaller towed arrays. The results suggest an analogous performance to the original algorithm, which consists in suppressing background noise and improving the spatial resolution of the baseline beamformers. A novel concept introduced in this paper is to use the two flank linear arrays found in many submarines - ordinarily deployed each separately for beamforming - in a dual-line array configuration, which, along with the proposed post-filter, may improve the beamformer performance at angles near end-fire. Moreover, it is shown that when the proposed method is applied to a towed dual-line array configuration, it may offer additional resolution of the port-starboard ambiguity. Finally, the computational requirements of the proposed method are argued to be low when compared to those of adaptive algorithms, which typically become quite demanding for a large number of sensors. Therefore, the post-filtering method, when paired with a signal-independent baseline beamformer, may represent a promising option for real-time passive-sonar applications.
ACKNOWLEDGEMENTS
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Implementation of a real-time time-varying channel simulator for verification tests of underwater acoustic communication systems

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ABSTRACT

Generally, sea trials for performance tests of underwater acoustic communication modems and network algorithms are time- and cost-consuming process, because the performance should be verified for various underwater channels and operating conditions. The Doppler shift channel environment due to the relative modem movement, the time-varying channel with time-varying environment, and various types of channels according to depth and locations are some examples. For this reason, we developed a real-time channel simulator that can simulate time-varying channels including Doppler shift in various marine environments and test conditions. In the simulator the Doppler shift was implemented using the change of the impulse response function according to the movement of the modem. Similarly, the time-varying channel is simulated by random change of each impulse in magnitude and time delay according to a given probability distribution function over time. The simultaneous sampling frequency of the eight-channel input and output module is 1 MHz, which covers operating frequency of eight modems up to several hundred kHz. It also has the simulation capability of delay time more than 20 s which corresponds to 30 km distance. For the system verification performance test was conducted and verified the key performances.

Keywords: Real-time channel simulator, Underwater acoustic communication, Time-varying channel

1. INTRODUCTION

Sound waves are mainly used for wireless underwater data transmission due to their lower attenuation rate than electromagnetic waves or light in water. Since the successful demonstration of the coherent modulation technique at sea numerous studies on underwater acoustic communication have been performed \cite{1,2}. Currently, commercial underwater acoustic modems are also available. However, due to the complexity of underwater acoustic communication channels, development of underwater acoustic modems still remains challenging work. KRISO, Korea Research Institute of Ships and Ocean Engineering, is developing a wireless underwater network, which comprises two heterogeneous network systems. One is a long-distance network with a transmission distance of 30 km and a transmission rate of 100 bps, and the other is a short-range high-speed network with a transmission distance of 200 m and a transmission rate of 100 kbps. For these networks the Doppler effect to be overcome is the frequency shift caused by platform movement speed of 10 m/s and 5 m/s, respectively. In addition as with other modems stable communication performance should be verified in a time-varying multi-path environment. Such an underwater communication channel environment varies greatly depending on location and time, and it takes a lot of time and cost for the verification of communication systems. For this reason, a system that simulates underwater communication channels in real time is absolutely necessary. Due to the complicated characteristics of underwater acoustic channels, it is still difficult to simulate them in real time, despite the recent improvement in computational ability. Computationally efficient algorithm was proposed and compared with real data \cite{3} and a fully integrated simulator was introduced for AUVs networking at various underwater environments \cite{4}. In this paper, a channel simulator that simulates stochastic underwater channels including Doppler shift in real time and that can verify key performance of the long-range/short-range

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networks under development is described.

2. SYSTEM DESCRIPTION

Figure 1 shows the developed real-time channel simulator. It is composed of two parts: a processing unit and an AD/DA module. AD/DA sampling frequency is 1 MHz with 16-bit resolution. The number of channels is eight for each AI and AO module. It has sufficient memory to store over 25-second 8-ch data to simulate node-to-node delay over 37.5 km distance. It also supports Doppler shift by platform movement with moving speed over 20 m/s. The number of multi-paths can be set arbitrarily up-to 9.

![Image of the real-time channel simulator](image-url)

Table 1 – Specifications of the channel simulator

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Remark</th>
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<tbody>
<tr>
<td>Sampling frequency</td>
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<td></td>
</tr>
<tr>
<td>Max number of nodes</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>Max number of multi-paths</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>Max delay of impulse response</td>
<td>&gt; 25 s</td>
<td>&gt; 37.5 km</td>
</tr>
<tr>
<td>Max velocity of moving node</td>
<td>&gt; 20 m/s</td>
<td></td>
</tr>
</tbody>
</table>

![Figure 1 - The front view of the real-time channel simulator](image-url)

3. PERFORMANCE TEST

A several tests were performed for the verification of key performances of the channel simulator. Another data acquisition system for generating arbitrary signals and saving output signals from the simulator. During the delay check test a rectangular pulse was used for the transmitting signal. The multi-path delays coincide with the theoretical values and the maximal delay was 25 s, which corresponds to 37.5 km distance for c=1500 m/s. For checking Doppler shift performance 6 kHz and 128 kHz tones were used. The platform moving velocity was set up-to 20 m/s. The frequency shift errors were within the spectral resolution for the both low and high tone signals. For checking time-varying characteristics of simulated channels, BPSK modulated PN sequence data was used. Channel fluctuation is observed in the spectrogram and the measured Doppler spread was within 10% error relative to the theoretical value.

ACKNOWLEDGEMENTS

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ABS-0991

**Study For Cavitation Inception Speed Of The Model Propeller Using Accelerometers Installed On The Model Ship**

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**ABSTRACT**

Naval vessels detect and identify the enemy under the water using sonar system. Therefore, it is necessary to reduce the noise of the own ship to detect the enemy and not to be detected from the enemy’s sonar system. In order to reduce the noise of the ship, cavitation of the propeller should be controlled and the ship must sail below the cavitation inception speed when engaged in anti-submarine warfare operations. Therefore, the cavitation inception speed should be monitored in real time. In this research, the monitoring algorithm for the cavitation inception speed of the model propeller using accelerometers installed on the model ship is described when it is operating in the cavitation tunnel.

Keywords: CIS(Cavitation Inception speed), Kurtosis, DEMON spectrum

1. **INTRODUCTION**

The importance of the conditions based monitoring for the sound and vibration in a ship is being emphasized since the noise and vibration for the propulsion system and large capacity onboard equipment such as the main generator are necessary to be controlled at the anti-submarine warfare operation. When the cavitation is initiated, the radiated sound of propeller increases rapidly and the sound is modulated in accordance with the number of blade. Since the submarine can identify the surface ship with its radiated sound occurred at the blade passing frequency of the propeller, surface ship should be operated under the cavitation inception speed at anti-submarine warfare operation.

Recently, many researchers are studying about sound monitoring of propeller cavitation using accelerometers attached on the hull\(^(1-2)\). In this research, the estimating method to define cavitation inception speed is investigated with the model scale ship using accelerometers attached on the hull perpendicularly above the propeller.

2. **Model Scale Test for Detection CIS**

2.1 **CIS Monitoring Algorithm**

In this research, the monitoring technic for the cavitation inception speed of the ship propeller is investigated using accelerometers installed on the hull above propeller.

The monitoring algorithm of cavitation inception speed developed in this research is as shown in Fig. 1. Considering the characteristics of the sonar sensor and background noise, the minimum sound pressure level that the sonar system is able to detect (Lp_min) can be estimated. If the transfer function can be defined between sound pressure level of the propeller and the acceleration of the hull above the propeller, the minimum hull acceleration caused by the sound pressure that the sonar system can detect (La_min) can be defined. If the cavitation is sufficiently developed, the sound pressure level as well as hull acceleration increases rapidly. In this research, the minimum hull acceleration level when
the cavitation is sufficiently developed is defined to $L_{a_{cav}}$. In Fig. 1, when the measured acceleration on the hull above the propeller is over than $L_{a_{cav}}$, this algorithm defines that the cavitation occurs already.

In this research, parameters to evaluate the cavitation inception are defined as below. Since the test is not full scale test but model scale one, the level of these parameters are different to the full scale test. These values are defined experimentally base on the various experience.

1. The minimum acceleration level that can found the cavitation inception speed ($L_{a_{min}}$): 100dB
2. The minimum DEMON spectrum level at the harmonics of shaft rate and blade passing frequency that can found the cavitation inception speed: 0.07m/s$^2$
3. The minimum DEMON spectrum kurtosis level that can found the cavitation inception speed: 3.0
4. The minimum acceleration level that can found the cavitation develops sufficiently: 107dB

Fig. 1 Estimation algorithm of the cavitation inception speed of the propeller

2.2 Monitoring Results

Using the algorithm to define cavitation inception speed as shown in Fig. 1, model scale test was performed with the test setup in Fig. 2. Fig. 3 is the monitoring results for 101~107 conditions as described in Table 1. In Fig. 3, the monitoring of Kurtosis, minimum acceleration of the hull that can be detect by sonar($L_{a_{min}}$), DEMON spectrum level at shaft rate and blade passing frequency, minimum acceleration when the cavitation is sufficiently developed($L_{a_{cav}}$) are denoted using blue color. In addition, the final decision that the cavitation occur is denoted using red color. In Fig. 3, it can be found that the cavitation is inceptioned at 104 condition for starboard side.

Considering Fig. 3, cavitation inception speed can be estimated form 104 conditions(24knots).

![Fig. 2 Model test setup](image)
The cavitation bubble could be detected at the propeller root in 105 condition when the cavitation was started to inspect visually at the cavitation monitoring window of the cavitation tunnel as shown in Fig. 4. Therefore, based on the visual inspection, the cavitation might occur between 104 and 105 condition, where the ship speed is 24~26 knots. Comparing the visual inspection to the inspection from accelerometers, cavitation inception speed from visual inspection is slightly higher than that from acceleration on the hull. Considering that the sound signal of the cavity can be detected before the cavity is detected visually, it can be conclude that the cavitation inception speed difference between acceleration and visual inspection in this test is allowable.

3. CONCLUSIONS

In this research, the cavitation inception speed of the model scale propeller is estimated with acceleration on the hull above the propeller. As a test result, it can be found that the cavitation is incepted about 24 knots.
When comparing the cavitation inception speed estimated by acceleration and visual inspection, they are similar considering the general delay time that cavitation sound occurs before the cavitation is visually inspected.

It can be expected that the results of this research can be used effectively with respect to the development of cavitation inception monitoring system for the ship propeller.

ACKNOWLEDGEMENTS

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Some issues on long-range propagation of acoustic waves related to environmental factors in the East Sea of Korea

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ABSTRACT

For acoustic waves propagating long-range, they may be dependent on environmental factors. The East Sea of Korea has several environmental factors to be considered for propagation including several water masses and big bathymetry variations. This paper deals with these environmental issues taking effects on the propagation of acoustic waves. Considering the water mass effects, we employ the concept of ‘Robustness of Detection (ROD)’ and a model based on the Gaussian beam tracing scheme to measure their effects on sensor detection range (DR). In the coastal area, we find that the two parameters, DR and ROD, show reverse patterns in general. We can see that the performances are highly dependent on the sensor receiving depths. For simulating the bathymetry effects, we use a 3-dimensional model based on the parabolic equation. The bathymetry effects include horizontal refractions of acoustic waves and data sources used in the simulation. The model results, propagation losses, give clear horizontal refractions responding to bathymetry distributions. Also, the propagation losses are sensitive to data sources employed in the simulations.

Keywords: Long-range propagation, Robustness of detection, Detection performance, Water mass, Bathymetry variation, Horizontal refraction

1. INTRODUCTION

For long-range propagation of acoustic waves, many environmental factors may take effects on their loss and direction which are main issues to surveillance systems with acoustic sensors. The East Sea of Korea has many water masses which are identified by their temperature, salinity and other physio-chemical properties. The East Sea also has complicated bathymetry distributions like sea mounts, banks, and canyons. This paper manages the issues of water mass and bathymetry effects on the propagation of acoustic waves.

Concerning the water mass issue, we focus on the relations between its variations (temporal, spatial) and detection performance assuming mid-frequency passive sensor. We use a model based on the Gaussian beam tracing scheme and mean temperature data in a coastal area of the East Sea. Concerning the bathymetry issue, we consider horizontal refractions of acoustic waves of low frequency in the selected regions of shallow and deep. For simulating horizontal refractions, we use a 3-dimensional model and bathymetry data of high resolution.

2. Water Masses and Detection Performances

2.1 Some Concepts

We can compute the maximum detection range (DR) at each grid point for each sensor as following (1).

\[ DR = \sum_i D_i / N \] (1)

Here, \( D_i \) and \( N \) represent the maximum DR at \( i \)-th bearing and number of bearings equally divided in 360\(^\circ\), respectively. In general, we can use some other concepts to measure sensor performance like \( \text{ynna}@add.re.kr \)
‘Effective Range (ER)’, ‘Near-continuous Range (NR)’ and ‘Maximum Detection Range (DR)’ (1). Among these, we borrow the concept ‘Maximum DR’ to measure long range detection including shadow and convergence zones. However, it is not complete definition to measure the performance of a sensor, specially in deep water, because it may not guarantee consistent detection when there exist shadow zones in horizontal and vertical directions. To complete the performance of a sensor, we adopt another definition ‘ROD’ as following (2).

\[ \text{ROD} = \frac{D_A - D_B}{D_B} \times 100\% \] (2)

Here, \( D_A \) and \( D_B \) denote shadow range and maximum DR, respectively.

In waters of less than, for example 500 m depth, sound speed is usually decided by temperature. The temperature variation may be analyzed using the Empirical Orthogonal Function (EOF) method. Spatio-temporal variations of temperature \( T \) can be decomposed into modal structure \( A_n \) and corresponding time coefficients \( B_n \) for each mode \( n \) as following (3).

\[ T(x, y, z, t) = \sum_n A_n(x, y, z)B_n(t) \] (3)

Solving the eigen-value problems, we get

\[ \frac{1}{N} TT^T \hat{e}_i = \lambda_i \hat{e}_i \] (4)

where \( T, \hat{e}_i, \lambda_i, N \) denote temperature matrix, eigen-vector, eigenvalue and number of spatial points, respectively. The modal structure \( A_n \) is normalized to magnitude of standard deviation of \( B_n \) to have a physical unit °C, while \( B_n \) has not any physical unit. Using historical data in the study area of the East Sea of Korea, we estimate that the 1-st EOF mode accounts for 78 % of total variance and 2-nd mode does 14 %.

2.2 Detection Performances

We select an area of Korean Peninsula which has about 80 grid points. Figure 1 presents bathymetry and examples of horizontal slices of 60m depth. The slices are temperature, DR (ratios relative to the maximum) and ROD (%) based on the re-analyzed environment at 28 October, 2007. The maximum DR is selected from the DRs at all grid points. We employ a model of Gaussian beam tracing scheme (4).

![Figure 1](image_url)

Figure 1 – The bathymetry and horizontal slices of 60 m depth in the study area. (a) bathymetry, (b) temperature, (c) relative DR and (d) ROD

The DR (Fig. 1c) shows high values in the northwest direction, where North Korean Cold Water develops along the bathymetry (5). Extremely low DR in lower part is due to relatively shallow flat bathymetry (Fig. 1a) where sound energy quickly decays by frequent interactions with the sea surface.
and bottom. When we look into the ROD (Fig. 1d), we can see that it shows reverse patterns to the DR variation. The ROD gives low values in the northwest region, where DR does high values. Meanwhile, in the region along the coastline and upper right (Fig. 1d), the ROD shows high values when DR does low values (Fig. 1c). In this example, DR and ROD variations show exactly negative phases, and this fact suggests we should consider the DR and ROD at the same time for complete description of sensor performance in deep water of complicated environment.

Figure 2 - Yearly variations of the EOF modes (top) and relative DR (bottom)

Figure 2 gives yearly variations of the principal components of the first two EOF modes (top) and DR (bottom) in the study area. We assume one source at 100 m depth and two kinds of receivers, surface (5 m) and underwater (100 m) with different sensor systems. And then, we calculate the DR at each point by averaging over all horizontal bearings. Once again, the maximum DR is selected from the DRs at all grid points of horizontal slice 5 m or 100 m, and relative DR is the ratio to the maximum. We get the relative DR every 10 days by taking average over 80 grid points. We can see that the 1-st mode follows seasonal variation but the 2-nd mode does not. The 2-nd mode is regarded to be related with some meso-scale phenomena like eddies and currents. When we get yearly variations of the DR for some passive sensor, we can see that the 1-st and 2-nd EOF modes have very high correlations (almost 0.9) with the relative DR variations against the surface (5 m) and the underwater (100 m) receivers, respectively.

Figure 3 shows typical sensor performances in winter and summer. We assume the DR (relative ratio) for a conventional passive sensor against a source of 100 m for larger area of the East Sea. When we keep the receiver depth to be 20 m (left two figures), we can see that the DR shows big differences between winter and summer. However, when we keep the receiver depth to be 100 m (right two figures), we can see very little differences between the two distributions. This fact implies that when we keep the receiver to be deep enough, we can expect very consistent detection performances in the study area regardless of the season.

Receiver depth: 20 m
Winter (Feb.) Summer (Aug.)
Receiver depth: 100 m
Winter (Feb.) Summer (Aug.)

Figure 3 – The relative DR distributions in winter (Feb.) and summer (Aug.) for receiving depth 20 m (left) and 100 m (right)
4. Bathymetry and Horizontal Refractions

4.1 Acoustic Model

We employ a model based on the parabolic equation with higher-order terms (5). Applying Padé and Taylor approximations to non-cross terms and cross terms respectively, we have the final expression to simulate 3-dimensional effects of environment with cross terms as following (6)

\[ u(x + \Delta x) = \prod_{i=1}^{m} \left( \frac{1 + a_i Y}{1 + b_i Y} \right) \prod_{j=1}^{n} \left( \frac{1 + a_i Z}{1 + b_i Z} \right) \left\{ 1 + \sum_{i=1}^{m} \sum_{j=1}^{n} c_{ij} Y^i Z^j \right\} u(x) \]  

Here, \( a_i \) and \( b_i \) are Taylor approximation coefficients. The Taylor approximation terms in \( \{ \} \) represent cross-terms with the coefficient \( c_{ij} \). By giving some modifications to the 1-st two terms, we can induce the form of summations which makes parallel processing possible and give the final expression as following (7)

\[ u(x + \Delta x) = \left\{ 1 + \sum_{i=1}^{n} \frac{a_i Y}{1 + b_i Y} \right\} \left\{ 1 + \sum_{i=1}^{n} \frac{a_i Z}{1 + b_i Z} \right\} \left\{ 1 + \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} Y^i Z^j \right\} u(x) \]  

Here, \( a_i \) and \( b_i \) are also approximation coefficients. The coefficient \( c_{ij} \) represents the cross-terms.

4.2 Bathymetry and Input

In simulating the horizontal refractions of acoustic waves, we employ a typical sound speed profile in winter and sandy bottom (density 1.99 g/cm\(^3\), attenuation 0.5 dB/wavelength) in the East Sea of Korea (6). We consider two kinds of bathymetry distributions in shallow (depth 50–400 m) and deep (depth 900–2,000 m) regions as shown in Figure 4. The source is located at \((X, Y, Z \text{ in km}) = (0, 5, 0.1)\), where the simulations area is \(X\) (propagating, latitude) = 25 km, \(Y\) (crossing, longitude) = 10 km. We assume the frequency to be 75 Hz.

![Figure 4 - Bathymetry distributions of shallow(left) and deep(right) regions](image)

4.3 Horizontal Refractions

We consider two kinds of data sources, KTOPO (Korean Topography) and ETOPO1 (Earth and Bathymetry) (6). The KTOPO has 30 m \(\times\) 30 m resolution but the ETOPO1 does 1’ \(\times\) 1’. With the KTOPO data, we get various grid resolutions 300 m, 600 m, and 1,800 m. With the grid resolution of 1,800 m, we compare the results with those with the ETOPO1 data.

Figure 5 shows propagation losses at shallow region (upper) and deep region (lower) with bathymetry data resolutions, 30 m (left), 300 m (middle), and 600 m (right). All figures are sliced at the receiver depth 100 m, while the source is located at 100 m. With varying resolutions of bathymetry at shallow region (upper), we can see the three results give similar major patterns throughout the maximum propagating range, 25 km. Propagation losses are little sensitive to bathymetry resolution and this pattern can be expected from the fact that the acoustic model employs bilinear interpolation over the bathymetry data before simulations (6). Horizontal refractions of acoustic fields are very
clear specially in the region $X = 10$–$25$ km, $Y = 5$–$10$ km, where the bathymetry increase with the cross range ($Y$) as shown in Figure 5. Horizontal refractions happen toward shallower region in the bathymetry distribution.

With varying resolutions of bathymetry at deep region (lower), we can see the three results also give similar major patterns and are little sensitive to bathymetry resolution. Horizontal refractions of acoustic fields are very clear specially in the region $X = 0$–$20$ km, $Y = 0$–$4$ km, where the bathymetry increase with the cross range ($Y$).

For the comparisons with data sources, we select the grid resolution of 1,800 m from the KTOPO which is similar to that of the ETOPO1. Figure 6 shows propagation losses of receiver depth 100 m at shallow region (upper) and deep region (lower) with bathymetry data sources, KTOPO (left) and ETOPO1 (right). In the short propagating range, $X = 0$–$7$ km, major patterns are similar between the two data sources but very different after the range. The degree of difference is more crucial in shallow region.

![Figure 5 - Propagation losses of receiver depth 100 m at shallow region (upper) and deep region (lower) with bathymetry data resolutions, 30 m (left), 300 m (middle), and 600 m (right)](image)

![Figure 6 - Propagation losses of receiver depth 100 m at shallow region (upper) and deep region (lower) with bathymetry data sources, KTOPO (left) and ETOPO1 (right)](image)
5. CONCLUSIONS

In deep water, where there may exist shadow and convergence zones, we have to consider the DR and ROD simultaneously to measure sensor performance completely. In the study area, we find that the two parameters, DR and ROD, show reverse patterns in general. Concerning the environmental effects, we can see that the performances are highly dependent on the sensor receiving depths. That is, shallow and deep depths of a passive sensor show high correlations with the 1-st and 2-nd EOF modes, which reflect seasonal and meso-scale variations of environment, respectively. If we keep the passive sensor depth to be greater than those of seasonal environment changes, we can expect consistent performance throughout a year.

Throughout the simulation of horizontal refractions, acoustic waves clearly respond to bathymetry variations and they refract toward shallower region of bathymetry. The simulations with the bathymetry of high resolution, show similar major patterns in the propagation loss from 30 m to 600 m grid resolution, since the model gives an interpolation over the bathymetry data before simulations. However, the propagation losses are very sensitive to data sources used in simulations, implying that precise bathymetry data set is crucial for estimating horizontal refractions.

REFERENCES

Increasing presence of marine acoustic technology in marine environmental impact assessment

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ABSTRACT

In order to realize the SDGs and carbon neutrality, it is essential to take the global environment into consideration, and marine environmental impact assessment is essential for this purpose. The introduction of power generation facilities using renewable energy, development associated with the effective use of fisheries, tourism, mineral resources, etc., and environmental changes associated with climate change, such as global warming, are recognized as ongoing issues common to the world, and there is concern about the short- and long-term impacts of these environmental changes on the natural and human worlds. Our research group has been working on a new approach to apply marine acoustic technologies, e.g. high-resolution acoustic video camera and high-resolution sub-bottom profiler, to environmental assessment since around 2013. In this talk, we will introduce some case studies of these efforts and future issues.

Keywords: Ultrasound, Marine environment, Assessment

1. INTRODUCTION

Changes in the marine environment due to anthropogenic activities, such as ocean acidification, eutrophication, deoxygenation, and pollutions, are recognized as a significant, ongoing, global issue [1]. In order to evaluate short- and long-term effects, data on the baseline biodiversity, its quantitative distribution, and the ecology of various species are essential. Acoustic systems with various operating frequencies are commonly used for the monitoring of marine environment. Our research group have newly developed some acoustic systems to visualize the marine creatures in and under the water [2-5].

2. High-resolution acoustic video camera

The high-resolution imaging sonar termed Dual-frequency IDentification SONar (DIDSON) has produced near-video-quality images by simultaneously transmitting and receiving multiple acoustic beams. High-resolution imaging sonar can also provide high-resolution, 3D acoustic data in water and has been applied to the survey of aquatic plants in shallow lakes. This device is suitable for the monitoring of fish behavior (Fig. 1) and surveying of vegetation [6].

3. High-resolution sub-bottom profiling system

Acoustic systems with various operating frequencies are commonly used for detecting objects buried in marine sediments, for example buried wooden shipwrecks under the seabed was visualized using chirp signals with 1.5–13 kHz swept pulses. Recently, a new monitoring tool, named 3D acoustic “coring” system, was developed and used for the precise survey of buried plant roots with outer diameters of 5–10 cm using the ultrasound of 100 kHz center frequency [2]. Even higher frequency signals with center frequencies of 130–1000 kHz are starting to be used for laboratory-based tests to reveal bivalves and other small buried objects, including soft gummy worms [7]. Recently, the visualization of large infauna in the sediment at deep sea area with using an acoustic coring system for deep sea (Fig. 2, A-core-2000) [5].

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REFERENCES

Effects of weak shear rigidity of the seabed on acoustic fields in water

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ABSTRACT

Surficial marine sediments are often characterized by weak shear rigidity, with shear waves been much slower than compressional ones. Mathematically, weak shear is a singular perturbation of the wave field in the no-shear (fluid) problem. Physically, weak shear leads to several wave phenomena, some of which require bottom-coupled vector sensors to be observed, while others affect the acoustic field throughout the water column. This paper investigates coupling between compressional and shear waves in continuously and discretely stratified solids with weak shear rigidity. Asymptotic and perturbation techniques are employed to study coupling in continuously stratified solids. Results for the seabed modeled as a stack of homogeneous layers are obtained as limiting forms of exact solutions. Additional sound attenuation results from radiation of shear waves into the seabed. The radiation attenuation of acoustic normal modes is found to be drastically different over homogeneous and layered seabeds, with density stratification emerging as the most important factor. Efficiency of the wave coupling within a continuously stratified layer strongly depends on the relative change in the shear modulus and mass density over spatial scales of the order of the shear wavelength. At low acoustic frequencies, radiation attenuation may be comparable in magnitude to compressional wave absorption.

Keywords: Sound Attenuation, Shear Waves, Shallow-Water Waveguide

1. INTRODUCTION

The shear wave speed is much smaller than the compressional wave speed and the sound speed in water in many types of marine sediments, while the evanescent compressional wave field in propagating modes is often negligible deep in the seabed, where the shear speed is large. Under these conditions, the seabed is typically described as a stratified fluid in the sound propagation modeling, with the shear wave effects presumably included via “effective” values of the sound speed, density, and the attenuation coefficient of compressional waves in the fluid bottom. While such a model may be acceptable for calculation of mode phase and group velocities, it may be insufficient for predicting sound attenuation.

In underwater waveguides, shear-wave contributions to sound attenuation are most significant for bottom-interacting normal modes that propagate over a seabed, where shear speed is less than the phase speed of the mode. In propagating normal modes, compressional waves become evanescent in the seabed and carry acoustic energy horizontally as long as dissipation is negligible. In contrast, shear waves are not evanescent and transport energy deep into the seabed. In the absence of dissipation, coupling to shear waves is the only mechanism of exponential attenuation of propagating normal modes in range-independent waveguides.

Understanding and accurate evaluation of the shear wave contributions to sound attenuation are necessary for modeling and interpretation of the sound transmission loss in shallow-water waveguides and for sonar performance predictions from low to mid-frequencies. Quantifying the shear-wave contributions to attenuation of normal modes is important for modeling and interpretation of the power spectra, modal content, and vertical directionality of low-frequency ambient sound in shallow water as well as in applications of noise interferometry to passive remote sensing of the coastal ocean. An accurate prediction of the shear-wave contribution to sound attenuation at different frequencies is required to interpret the empirical models of the linear and non-linear power-law frequency

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dependencies of the attenuation and evaluate applicability of the physics-based models of wave propagation in the porous seabed, such as Biot theory and Buckingham’s viscous grain shearing theory.

Shear wave contributions to sound attenuation in the discretely stratified seabed with weak shear rigidity have been investigated in the recent paper (1). The present work extends the analysis presented in (1) to include continuously stratified marine sediments.

2. MAIN FINDINGS

Weak shear rigidity of stratified marine sediments is found to have a much stronger effect on dispersion of bottom-interacting normal modes and especially on sound attenuation than was previously surmised based on oversimplified seabed models (2–5). With the effects of the weak shear being larger and more intricate than previously predicted, applicability of the effective fluid bottom models and the effect of shear waves on the experimentally measured frequency dependence of the sound dissipation need to be re-assessed.

Acoustic effects of shear rigidity originate from coupling between sound and shear waves at the seafloor and within inhomogeneous seabed. Coupling between compressional and shear waves at interfaces within the bottom is shown to be far more efficient than the coupling at the water-sediment interface. In terms of the small ratio of the shear to compressional wave speeds in soft sediments, first-order contributions to mode travel time and attenuation result from the P and SV wave coupling in the stratified seabed with density discontinuities. These first-order effects are generally much stronger and, because of shear wave interference, have a more complicated frequency dependence than previously studied second-order effects on mode travel times and third-order attenuation effects in the case of homogeneous solid seabed or bottom with constant density. In discretely stratified sediments, the acoustic effects of weak shear tend to be most pronounced at lower frequencies, with the frequency scale being controlled by the shear wave travel time within individual sediment layers, the rate of change of the sediment properties with depth, and the shear wave dissipation.

When sediment parameters vary continuously within the layers, coupling of compressional and shear waves is enabled by gradients of density and the compressional wave speed, with the density gradients playing the main role in conversion from compressional to shear waves. In addition to the local conversion efficiency, shear wave field is also affected by interference of the shear waves generated at different points. The interference tends to be destructive at high frequencies. Overall efficiency of the wave coupling within a continuously stratified layer strongly depends on the relative change in the shear modulus and mass density over spatial scales of the order of the shear wavelength.

The primary implications of this work are for geoacoustic inversions and especially for measurements of the intrinsic (volume) dissipation of compressional and shear waves. To capture the first-order shear effects correctly, geoacoustic models must include a realistic description of density variation in the seabed in addition to compressional and shear speed profiles. A higher vertical spatial resolution than in the fluid bottom models is required, particularly for the density and shear speed.

The shear effects are much stronger in the seabed containing dissimilar surficial layers than in a seabed with averaged parameters. Our results suggest that, for narrow-band signals, the shear-wave contributions to sound attenuation in the bottom can be overly sensitive to uncertain and spatially varying details of sediment stratification, making broadband and/or long-range measurements preferrable. At low frequencies, shear-wave contributions to sound attenuation in stratified sediments remain significant even for very low shear speeds. Because of their non-negligible magnitude and non-monotonic frequency dependence, great care needs to be exercised in characterizing and separating the contributions to measured attenuation due to compressional-to-shear wave conversion, in order to reliably evaluate the frequency dependence of the intrinsic dissipation of compressional waves.

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Physics-aided data-driven modal ocean acoustic propagation modeling

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ABSTRACT
Modeling acoustic propagation accurately is vital to numerous oceanic applications. However, physics-based acoustic propagation models require accurate prior environmental knowledge, which is often hard and expensive to acquire. Such a requirement can be relaxed by using data-driven machine learning techniques. Unfortunately, they are data-hungry and extrapolate poorly. We can potentially train machine learning algorithms with a lot less data and get them to extrapolate well by imposing constraints based on our knowledge of acoustic propagation. Our previous work proposed a physics-based data-aided high-frequency acoustic propagation modeling recipe based on the ray theory to do precisely this. The promising results obtained motivate us to further tailor the recipe for low-frequency applications. The theory of normal modes tends to be a more appropriate choice to model acoustic propagation at low frequencies. In this paper, we incorporate a modal acoustic propagation model in the structure of a neural network. We demonstrate the superiority of such an algorithm in estimating acoustic field, as compared with conventional data-driven machine learning techniques. We also show that this technique allows us to extract information about the environment, such as estimating the sound speed profile from acoustic observations.

Keywords: Normal mode, Acoustic propagation model, Data-aided acoustic modeling, SciML.

1 INTRODUCTION
Understanding acoustic propagation in the ocean is crucial for numerous applications, such as communication channel estimation [1], underwater source localization [2] and geo-acoustic inversion [3]. Oceans offer rich multipath environments that exhibit complicated constructive and destructive interference patterns. Conventional ocean acoustic propagation models solve the acoustic wave equation [3] using various mathematical techniques and simplifying approximations. While conventional models have matured over the past few decades, a key limitation for their effective use is the requirement of having full and accurate prior environmental knowledge. Accurately measuring required environmental parameters such as sound speed profile (SSP), seabed properties and sea surface properties, is often hard and expensive in practice.

Advances in data-driven machine learning (ML) resolve many problems that can not be addressed by conventional models. Modeling acoustic propagation through data-driven ML approaches does not need environmental knowledge. However, classical ML techniques are data-hungry and extrapolate poorly, and therefore poorly suited for most oceanic applications where data is difficult to obtain and consequently sparse. Recently, a synergistic strategy that embeds underlying domain knowledge into data-driven ML has emerged to handle such a dichotomy. This emerging technique is in the field of scientific machine learning (SciML) [5, 6]. Physics-informed neural networks (PINNs) [7], a popular strategy in SciML, encode scientific domain knowledge in the form of partial differential equations (PDEs). The PDEs are added as additional regularization terms in standard loss functions. There are a few recent works that preliminarily demonstrate the feasibilities of PINNs in learning solutions to the acoustic wave equation [8–11]. However, the use of SciML in the context of ocean acoustic modeling has not yet been extensively explored.
Augmenting the loss function is one of the possible strategies in SciML to inform a neural network (NN) by underlying domain knowledge, but is not the only effective one. Embedding the domain knowledge of acoustic propagation in structures of NNs, and using ML algorithms to train the NNs to solve the simplified wave equation also yields a promising strategy. Our previous work [12] extensively investigates this idea in high-frequency acoustic propagation modeling problems based on the ray theory [13]. It demonstrates the applicability and superiority of the proposed ray-based data-aided acoustic propagation modeling recipe in various case studies by benchmarking against classical ML techniques.

Ray theory applies a high-frequency approximation to solve the acoustic wave equation analytically [13], and is therefore not very accurate at low frequencies where the approximation is invalid. Normal mode models [14] are suitable and efficient alternatives for low-frequency oceanic applications. In this paper, we tailor the propagation modeling recipe based on the normal mode theory. We illustrate the proposed mode-based modeling framework in various scenarios and demonstrate its use in ocean acoustic field estimation problems and a SSP inversion problem. The proposed framework is flexible to incorporate any known domain knowledge, and can also embed smaller standard NNs to model unknown parameters. Moreover, it is data-efficient and generalizes well as compared to classical ML models.

2 METHOD
2.1 Normal mode theory

The acoustic wave equation is a second-order partial differential equation that describes acoustic propagation [13]:

\[
\frac{\partial^2 p}{\partial t^2} = c^2 \nabla^2 p,
\]

where \( p \) denotes acoustic pressure, \( t \) represents time and \( c \) is sound speed.

We consider an acoustic propagation modeling problem due to a point source in a horizontally stratified (range-independent) two-dimensional (2D) ocean waveguide. A harmonic wave is a feasible solution to (1):

\[
p(r, z, t) = \hat{p}(r, z)e^{i \omega t},
\]

where \( \hat{p}(r, z) \) is complex pressure amplitude at a location with range \( r \) and depth \( z \), and \( \omega = 2\pi f \) denotes angular frequency. Substituting (2) back into (1) leads to the Helmholtz equation [4]:

\[
k^2(z) \hat{p}(r, z) + \nabla^2 \hat{p}(r, z) = 0,
\]

where \( k(z) = \frac{\omega}{c(z)} \) represents wavenumber at depth \( z \).

Classical normal mode models apply the separation of variables [15] to express acoustic field at location \( (r, z) \) as a combination of a depth-dependent term and a range-dependent term:

\[
\hat{p}(r, z) = \Psi(z)\Phi(r).
\]

We substitute (4) into (3). After rearranging and simplifying, we obtain the modal equation [14]:

\[
\rho(z) \frac{d}{dz} \left( \frac{1}{\rho(z)} \frac{d\Psi(z)}{dz} \right) + \tilde{k}_z^2(z)\Psi(z) = 0,
\]

where

\[
\tilde{k}_z^2(z) = k^2(z) - k_r^2,
\]

and \( \rho(z) \) is density and \( k_r \) represents horizontal wavenumber.

The modal equation derived in (5) is in the form of a classical Sturm-Liouville eigenvalue problem [16]. Theoretically, there are an infinite number of distinct mode solutions \( (\Psi(z) \) and \( k_r \) to the modal equation (5). Normalized mode solutions form a complete set so that solutions to the wave equation can be represented as an infinite sum of the normal modes:

\[
\hat{p}(r, z) = \sum_{m=1}^{\infty} \Psi_m(z)\Phi_m(r),
\]
where \( m \) denotes \( m^{th} \) mode. The range-dependent term \( \Phi_m(r) \) has a standard form in terms of the Hankel function [13]:

\[
\Phi_m(r) = \frac{i}{4\rho(z_s)} \Psi_m(z_s) H_0^{(1,2)}(k_m r),
\]

(8)

where \( z_s \) denotes source depth and \( H_0^{(1,2)} \) refers to the Hankel function of first or second kind. The choice depends on radiation conditions. We adopt the Hankel function of the first kind since we assume energy is radiating outwards as \( r \) approaches \( \infty \). The asymptotic approximation to the Hankel function is often used in literature and (8) is approximated by:

\[
\Phi_m(r) \approx \frac{i}{\rho(z_s) \sqrt{8\pi r}} e^{-\frac{\pi}{2} i} \Psi_m(z_s) \frac{e^{ik_m r}}{\sqrt{k_m}}.
\]

(9)

Popular normal mode models, such as Kraken [17], seek all significant eigenfunction solutions \( \Psi_m(z) \) and corresponding eigenvalues \( k_m \) to the modal equation (5) while satisfying boundary conditions and environment setup.

### 2.2 Mode basis neural network

An imaginary \( k_m \) makes \( e^{ik_m r} \) an exponentially decaying term with respect to propagation range \( r \). A real \( k_m \) leads to a propagating mode that oscillates instead. The infinite sum in (7) can be approximated as a \( n \)-mode finite sum in far-field:

\[
\hat{\rho}(r, z) \approx \frac{i}{\rho(z_s) \sqrt{8\pi r}} e^{-\frac{\pi}{2} i} \sum_{m=1}^{n} \Psi_m(z_s) \Psi_m(z_s) \frac{e^{ik_m r}}{\sqrt{k_m}}.
\]

(10)

Although analytical solutions to (5) are not always available, general field solutions based on the normal mode theory approximately follow [14]:

\[
\hat{\rho}(r, z) \approx \sum_{m=1}^{n} \left( A_m e^{ik_m z} + B_m e^{-ik_m z} \right) \Phi_m(r),
\]

(11)

where \( A_m \) and \( B_m \) are scaling factors to make sure boundary conditions and environment setup are satisfied.

Even though the approximated field expression is provided in (11), the mode parameters \( A_m, B_m, k_m \) and \( k_m \) associated with each mode are calculable only if boundary conditions and all required environmental parameters are accurately known. Any missing environmental parameter prevents the application of the conventional normal mode model, or requires the modeler to estimate the parameter through other means (e.g. matched field processing). Such a requirement greatly limits practical uses of normal mode models as operating environments may not always be well understood.

We propose a *mode basis neural network* (MBNN) framework to enable the use of normal mode modeling in situations where accurate environmental knowledge is unavailable. The idea of encoding the physics of acoustic propagation into structures of data-driven ML has been extensively explored in our previous work [12], where we detail a hybrid modeling framework based on the ray theory for high-frequency underwater acoustic propagation modeling. Following a similar approach, in the MBNN framework, we encode the domain knowledge of acoustic propagation based on the normal mode theory into the structure of a standard NN to model low-frequency acoustic propagation in oceans. The MBNN model is differentiable so that well-developed automatic differentiation techniques [18] can be utilized to find optimal unknown mode parameters, providing acoustic measurements and corresponding measurement locations as training data.

The MBNN framework allows numerical propagation models based on the normal mode theory to be data-driven. At the same time, the structure of MBNN encodes essential physics and therefore improves the model’s data efficiency and generalizability as compared to classical data-driven ML techniques. This leverages complementary strengths of data-driven ML and physics-based models to handle practical scenarios of partially known physics and limited data availability.

We illustrate our MBNN model formulation through two examples of 2D ocean waveguides with isovelocity SSP (Section 2.2.1) and non-isovelocity SSP (Section 2.2.2) respectively:
2.2.1 Isovelocity ocean waveguides

We consider an isovelocity ocean waveguide that has a constant sound speed $c$ and density $\rho$ with a water depth $D$. A general eigenfunction solution to (5) in this isovelocity ocean waveguide follows [14]:

$$\Psi_m(z) = A_m \sin(k_{zm}z) + B_m \cos(k_{zm}z).$$

We assume a pressure-release surface:

$$\Psi(0) = 0,$$

and a rigid bottom:

$$\left. \frac{d\Psi}{dz} \right|_{z=D} = 0.$$

Such boundary conditions further simplify (12) to:

$$\Psi_m(z) = \sqrt{\frac{2\rho}{D}} \sin(k_{zm}z).$$

The corresponding eigenvalue $k_{zm}$ is derived as:

$$k_{zm} = \sqrt{\left( \frac{\omega}{c} \right)^2 - \left( \frac{m + 0.5}{D} \right)^2}, m = 1, 2, \ldots, n.$$  \hfill (16)

We assume that we do not know the exact values of $c$, $\rho$ and $D$. Due to missing environmental knowledge, conventional normal mode models cannot estimate acoustic fields. Fortunately, our proposed MBNN model can automatically learn the best-fitted values of the unknown mode parameters from acoustic data. We train a minimal set of unknown mode parameters and numerically calculate other unknowns using underlying physics to make sure our method generalizes well.

We denote the minimal unknown mode parameters whose values are yet to learn from acoustic observations as MBNN model trainable parameters:

$$\mathcal{T} = \{c, \rho, D\}.$$ \hfill (17)

We minimize the square difference between the estimated pressure amplitude $\hat{p}(r, z; \mathcal{T})$ and the acoustic field measurement $\hat{p}$ at a measurement location $(r, z)$ by tuning $\mathcal{T}$. The loss function is defined as:

$$L(r, z, \hat{p}; \mathcal{T}) = |\hat{p}(r, z; \mathcal{T}) - \hat{p}|^2.$$ \hfill (18)

Equation (18) is normally summed over a batch of training data in each iteration as per ML standards [19]. With the optimal trainable parameters $\mathcal{T}^*$ learnt from acoustic observations, we can readily estimate acoustic fields using (6), (10), (15) and (16).

2.2.2 Non-isovelocity ocean waveguides

**Known SSP** The MBNN framework is capable of modeling non-isovelocity ocean waveguides as well. As the modal equation cannot be analytically solved for ocean waveguides with non-isovelocity SSPs, approximate solutions are necessary. We use the WKB approximation [20] – one of the most widely used approximation techniques in normal mode literature, to approximate the depth-dependent term:

$$\Psi_m(z) \approx A_m \frac{e^{\int_0^z k_{zm}(s)ds}}{\sqrt{k_{zm}(z)}} + B_m \frac{e^{-i\int_0^z k_{zm}(s)ds}}{\sqrt{k_{zm}(z)}},$$ \hfill (19)

where

$$k_{zm}(z) = \sqrt{\left( \frac{\omega}{c(z)} \right)^2 - k_{zm}^2}.$$ \hfill (20)
We assume boundary conditions are unknown. This missing information introduces more unknown model parameters as compared to the isovelocity waveguide case in Section 2.2.1. When SSP is provided, we can use acoustic observations to find the optimal value of the trainable parameters:

\[ \mathcal{F} = \{A, B, k_c\}, \]  

(21)

where \( A = (A_1, A_2, \ldots, A_n) \), \( B = (B_1, B_2, \ldots, B_n) \), and \( k_c = (k_{c1}, k_{c2}, \ldots, k_{cm}) \).

The missing environmental knowledge makes it hard to estimate the number of contributing modes \( n \) precisely. When \( A \) and \( B \) are parts of the trainable parameters \( \mathcal{F} \), conservatively setting \( n \) to an upper bound of its possible range and adding \( L_1 \)-norm regularization terms of \( A \) and \( B \) to encourage sparse solutions can help in model convergence. The loss function is updated to:

\[ L(r, z, \hat{\rho}; \mathcal{F}) = |\hat{\rho}(r, z; \mathcal{F}) - \hat{\rho}|^2 + \alpha \|A\|_1 + \beta \|B\|_1, \]

(22)

where \( \alpha \) and \( \beta \) control the regularizations. With the trained optimal model parameters \( \mathcal{F}^* \), acoustic fields in a non-isovelocity ocean waveguide with known SSP can be estimated using (10), (19) and (20).

**Unknown SSP** The detailed SSP across the water column is often unknown. The unknown SSP makes the calculation of \( k_{zm}(z) \) infeasible, even though the eigenvalue \( k_{zm} \) is provided. The MBNN is flexible to incorporate with standard NNs to model unknown physics. For example, we can implement a 1-input 1-output NN to model the SSP. We name the NN which models SSP as sound speed neural network (SSNN). Fig. 1 illustrates the overall structure of the MBNN framework that incorporates SSNN.

In order to train the SSNN, the trainable parameter \( \mathcal{F} \) defined in (21) is modified to:

\[ \mathcal{F} = \{A, B, k_c, S\}, \]

(23)

where \( S \) contains all parameters (weights and bias) in the SSNN model. Calculating \( k_{zm}(z) \) is feasible now using the trained SSNN:

\[ k_{zm}(z) = \sqrt{\frac{\omega^2}{\text{SSNN}(z)^2} - k_{zm}^2}, \]

(24)

where SSNN\( (z) \) is the estimated sound speed at depth \( z \).

We employ the same loss function defined in (22) to learn optimal \( \mathcal{F}^* \). We then use (10) and (19) with (24) to estimate acoustic fields in a non-isovelocity ocean waveguide with unknown SSP.
2.2.3 Generalization to other mode models
We have illustrated a few MBNN formulations in range-independent ocean waveguides and demonstrated how flexible the proposed modeling framework is in different scenarios. It is worth noting that formulations of normal mode models are application and environment specific. The idea of our MBNN modeling framework generalizes well to tackle different scenarios and can be applied to any variant of classical normal mode models. For example, the MBNN framework can incorporate adiabatic mode methods or coupled mode methods to model range-dependent environments [21–23].

Fig. 2 describes the steps involved in the MBNN model training stage and field estimation stage. For any ocean environment, the key is to have an analytical field solution or an approximated field solution based on the normal mode theory, and use a small number of acoustic measurements as training data to find the optimal MBNN trainable parameters $\mathcal{F}^*$. We can calculate other necessary physical quantities based on the trained MBNN parameters so as to estimate acoustic fields at locations of interest.

3 SIMULATION STUDIES
In [24], the authors study acoustic propagation and hydrological conditions at the Hans glacier front in Svalbard. This paper lays a foundation for several follow-up studies at the glacier [25–27]. We loosely use the environment described in this paper as the basis for our simulation studies to illustrate how one might model the acoustic propagation in a location where full environmental knowledge may be unavailable.

We assume that a work boat anchors at a location 1 km from the glacier. It carries an acoustic modem that emits 500 Hz continuous wave signals for acoustic communication and environmental monitoring. A peer survey boat executes exploration tasks in a region that is further away from the glacier. The bathymetry is approximately flat with a constant water depth of 25 m in the region in which the peer vessel operates. Fig. 3 depicts a schematic of the simulated environment. We use the Kraken normal mode model [28] to generate synthetic acoustic measurements in the simulated environment (with full environmental knowledge).

We then consider a scenario where the bottom properties and boundary conditions are unknown (and so unavailable to the model). We aim to model acoustic propagation from the work boat to a nearby region around the peer vessel in Section 3.1 and infer the SSP using acoustic measurements collected at a constant depth in Section 3.2.

In both cases, we need to train our MBNN using the simulated data. We randomly split the acoustic measurements\(^1\) into a training dataset and a validation dataset based on a 70% : 30% ratio. The training dataset

\(^1\)The synthetic acoustic measurements used in simulation studies are peak-to-peak values from hydrophone output in millivolts.
3.1 Acoustic field estimation

We consider two acoustic field estimation problems, one with known SSP and one with unknown SSP. We assume a 24-element vertical hydrophone array with a 1 m inter-element spacing to the peer vessel to collect acoustic field measurements in the measurement region. We wish to accurately estimate acoustic field in an area, without having to make measurements at all points in that area. To illustrate how this can be done, we define a *measurement region* where we make several measurements, and two 100 m regions on both sides of the measurement region as *extended region* to demonstrate field extrapolation. The measurement region and extended region together form the *area of interest* (AOI).

In [30], the authors find that the use of PINN does not benefit acoustic field estimation performance as compared to standard ML models. Our preliminary evaluation of PINN for this application agrees with this finding. We thus benchmark the field estimation performance of the proposed MBNN framework against two classical data-driven ML techniques – Gaussian process regression (GPR) and deep neural network (DNN).
Table 1. Acoustic field estimation performance of the three models using a different number of profile measurements in the field estimation problem with known SSP.

<table>
<thead>
<tr>
<th>Model</th>
<th>Estimated field pattern with profile #1</th>
<th>Estimated field pattern with profiles #1 &amp; #2</th>
<th>Estimated field pattern with profiles #1–#3</th>
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<td><img src="image1" alt="Field pattern MBNN profile #1" /></td>
<td><img src="image2" alt="Field pattern MBNN profiles #1 &amp; #2" /></td>
<td><img src="image3" alt="Field pattern MBNN profiles #1–#3" /></td>
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<td>[4.67]</td>
<td>[4.80]</td>
<td>[1.19]</td>
</tr>
<tr>
<td>GPR</td>
<td><img src="image4" alt="Field pattern GPR profile #1" /></td>
<td><img src="image5" alt="Field pattern GPR profiles #1 &amp; #2" /></td>
<td><img src="image6" alt="Field pattern GPR profiles #1–#3" /></td>
</tr>
<tr>
<td></td>
<td>[8.12]</td>
<td>[7.50]</td>
<td>[2.10]</td>
</tr>
<tr>
<td>DNN</td>
<td><img src="image7" alt="Field pattern DNN profile #1" /></td>
<td><img src="image8" alt="Field pattern DNN profiles #1 &amp; #2" /></td>
<td><img src="image9" alt="Field pattern DNN profiles #1–#3" /></td>
</tr>
<tr>
<td></td>
<td>[8.89]</td>
<td>[6.51]</td>
<td>[4.59]</td>
</tr>
</tbody>
</table>

design a composite kernel of a squared exponential isotropic kernel and a Matérn 5/2 ARD kernel for GPR, and implement a 2-input 1-output DNN with 3 hidden layers and ReLU activation function. We randomly initialize the MBNN and the DNN model parameters in each run. The hyper-parameters of the GPR model are fine-tuned by minimizing validation error. We carry out 10 Monte Carlo simulations for MBNN and DNN models, and present the field estimation results with the smallest validation error.

3.1.1 Field estimation with knowledge of SSP

We consider an ocean waveguide with a known non-isovelocity SSP, unknown seabed properties and unknown boundary conditions. We use the WKB approximation to formulate the MBNN model based on (10), (19) and (20). We use acoustic measurements to find optimal values of the trainable parameters $\mathcal{F}_\theta$ defined in (21).

We deploy the hydrophone array to collect acoustic measurements in a 2 m $\times$ 23 m measurement region at three profiles, each spaced by a 1 m range in between. Fig. 4 shows ground truth field pattern in the AOI and the three profiles where we collect the measurements. In order to investigate the field estimation performance, we use the Kraken model to generate 464,600 test data with a resolution of 0.1 m in range and depth within...
the AOI. We investigate data efficiency of the three models by estimating the field patterns in the AOI using measurements collected at one profile (24 measurements), two profiles (48 measurements) or three profiles (72 measurements) in the measurement region.

Table 1 shows the estimated field patterns and the corresponding root-mean-square (RMS) test errors in the AOI when different amounts of acoustic measurements are given. When acoustic measurements made at profile #1 & #2 are provided, the GPR and DNN models fail to extrapolate field patterns due to insufficient training data. The field estimated by the MBNN shows a rough field pattern with low fidelity. When the measurements made at profile #1 – #3 are provided, the field estimated by the MBNN model aligns well with the ground truth field pattern. The GPR can extrapolate more details in the extended region. The DNN still performs poorly in extrapolation. The corresponding RMS test errors presented also justify our observations that the MBNN model outperforms the GPR and DNN models in terms of data efficiency and extrapolation performance.

3.1.2 Field estimation without knowledge of SSP

Sound speed in an ocean waveguide is measured by sending a conductivity, temperature and depth (CTD) sensor at various depths. When either the CTD sensor or equipment to survey sound speed at various depths is lacking, we do not know the exact SSP. In this case, we assume that no sound speed measurement is available due to the lack of a CTD sensor. Instead, we only have a rough understanding of a reasonable range that the SSP may fall in. Our conservative initial guess of the SSP is that it falls in a 100 m/s range between 1,400 m/s and 1,500 m/s and SSP variation should not exceed 35 m/s over the 25 m water depth.

Figure 6. The estimated field patterns in the measurement region when SSP is unknown. Panel (a) shows the ground truth field pattern. Panels (b)–(d) show the estimated fields by the MBNN, GPR and DNN models.
Figure 7. The estimated field patterns in the AOI when SSP is unknown. Panel (a) shows the ground truth field pattern. Panels (b)–(d) show the extrapolated fields by the MBNN, GPR and DNN models.

Table 2. Acoustic field estimation performance of the three models in the field estimation problem with unknown SSP.

<table>
<thead>
<tr>
<th>Model</th>
<th>RMS test error (mV_pp)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>In measurement region</td>
</tr>
<tr>
<td>MBNN</td>
<td>0.039</td>
</tr>
<tr>
<td>GPR</td>
<td>0.011</td>
</tr>
<tr>
<td>DNN</td>
<td>0.10</td>
</tr>
</tbody>
</table>

Figure 8. The learnt SSP with the ground truth SSP in the field estimation problem. The SSNN is trained using acoustic measurements sampled across the water column in the measurement region.

One may expect that more acoustic data is required to train the MBNN framework as the size of trainable parameter \( \mathcal{F} \) increases as compared to the previous scenario. As shown in Fig. 5, we uniformly collect 1,224 acoustic measurements (24 elements/profile × 51 profiles) within a 50 m × 23 m measurement region. We assume the detailed SSP and seabed properties are unknown. We use a simple 1-input 1-output NN (SSNN) with 1 hidden layer and ReLU activation function to learn the SSP in the water column. We formulate the MBNN model based on the WKB approximation as (10), (19) and (24). We aim to estimate the acoustic field pattern in the AOI by learning the optimal trainable parameters \( \mathcal{F}^* \) defined in (23) through acoustic measurements. We generate 575,000 acoustic measurements, with a resolution of 0.1 m in range and depth, as the test dataset over the AOI to rigorously quantify the field estimation performance.
Figure 9. The trajectory of AUV labelled as an arrow in the inversion of SSP application.

Figure 10. The learnt SSP with the ground truth SSP in the SSP inversion application using acoustic measurements made at a nearly constant depth and a few sound speed measurements.

As shown in Fig. 6, all of the three models can interpolate acoustic fields in the measurement region well. However, field patterns extrapolated in the extended region shown in Fig. 7 highlight the superiority of our proposed MBNN framework over the GPR and DNN models. The test errors shown in Table 2 support the observations we draw from Fig. 6 and Fig. 7. Although estimation of the SSP might not be of interest to the field estimation problem, the learnt SSP by the SSNN is close to the ground truth SSP in the 100 m/s span as shown in Fig. 8. It demonstrates the flexibility of the MBNN model to incorporate with standard NNs to model unknown physics.

3.2 Inversion for entire SSP
In Section 3.1.2, we have demonstrated that our proposed MBNN model can learn the SSP reasonably well using the acoustic field measurements collected at 50 profiles when a CTD sensor is not provided. However, consider a scenario where measurements are not available through the entire water column, but rather at a few shallow depths only. Could one estimate the SSP in the entire water column with just a few shallow measurements? The MBNN framework can incorporate standard NNs to model unknown physics – in this case, the SSP. This makes the MBNN framework a useful tool for solving various inverse problems related to acoustic propagation modeling.

To illustrate the idea, we assume that an autonomous underwater vehicle (AUV) equipped with an acoustic sensor and CTD is deployed from the peer vessel and dives to an operating depth of 4 m. It then operates at a constant depth of 4 m, and therefore does not have access to profiles through the water column to make either CTD or acoustic measurements. Fig. 9 indicates the AUV’s trajectory in the measurement region. The AUV uniformly makes 5 sound speed measurements at depths between the water surface and the operating depth of
4 m. We aim to learn the entire SSP using the acoustic field measurements collected at a nearly constant depth with the aid of just a few sound speed measurements made at shallow depths.

We assume boundary conditions and seabed properties are unknown. We use the same model formulation, trainable parameters and initial guess of the SSP defined in Section 3.1.2. The lack of strong spatial diversity of the collected field measurements makes this inversion problem particularly challenging.

The learnt SSP, benchmarked against the ground truth SSP, is shown in Fig. 10. We constrain the SSNN using the speed sound measurements made at the water surface, 1 m, 2 m, 3 m and 4 m in the loss function. The learnt SSP over 25 m depth is very close to the ground truth SSP, even for depths where no acoustic field measurement and sound speed measurement are provided. Training the MBNN model using acoustic measurements with stronger field variation can potentially reduce the training data size and improve the inversion accuracy.

4 CONCLUSION

Conventional normal mode propagation models, although are widely used, require accurate prior environmental knowledge. Environmental uncertainties thus significantly affect model estimation performance and thus limit its applicability in practice. We proposed a physics-based data-aided modal acoustic propagation modeling framework based on the normal mode theory. The proposed framework embeds the normal model theory of acoustic propagation into the structure of a NN, so as to enable a data-efficient propagation modeling framework. The proposed model is flexible to incorporate any known environmental knowledge and standard NNs to model unknown physics. At the same time, it extrapolates well and brings interpretability to the trained model parameters. We demonstrate the proposed modeling framework through several simulated application examples, and by benchmarking against classical ML techniques.

References


Research On Shallow Water Acoustics In Lake Kinneret (Israel)

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ABSTRACT

Results of study of shallow water sound propagation carried out by the team of University of Haifa, are presented including results of experiments and the corresponding theoretical modeling:

- long range low and mid frequency (0.3 – 10 kHz) sound propagation with reception by vertical line array.
- mode composition and mode coupling were measured and modeled;
- reflection and reverberation in the presence of gassy sediment using wideband source and receivers, both single hydrophone and VLA;
- noise including shipping noise measurements and analysis.

Key words: shallow water acoustics, experiments in lake

1. INTRODUCTION

Freshwater Lake Kinneret (Sea of Galilee, Israel) is located in the North of Israel, its size is about 12x24 km, maximum depth was about 40 m. Sound speed profile (temperature profile) in the water column changes seasonally (Fig. 2b). Near the lake there is Limnological Lab (IOLR) having a few research vessels, a large set of oceanographic tools, including two anchored platforms (Ecorafts), buoys etc. It means that the lake is good testing field for research in shallow water acoustics.

![Bathymetry and Sound Speed Profile](image)

Figure 1. Bathymetry of Lake Kinneret (left) and sound speed profile (right)

2. EXPERIMENTS

2.1. Oceanographic observations and characteristics, important for acoustical research

Oceanographic survey included measurements of temperature profiles (CTD and thermistor string, bathymetry (echosounder), and currents/internal waves (ADCP). These measurements were carried out from moving vessel and stationary anchoring (during one year). Also direct measurements of sediment properties were done using frozen cores.

3.1. Acoustical measurements
a) Long-range propagation of wideband signals (200 Hz – 10 kHz) was studied using moving research vessel and VLA fixed in the deepest place of the lake for different parameters of signal up to distance 5-7 km. Typical spectrograms for different distances source-receiver is shown in the Figure 2. We can see transition from ray formed pattern to mode decomposition

![Figure 2. Spectrograms for distances 5 km (left) and 500 m (right)](image)

b) Reflection and reverberation of wideband signals. In the Fig.3 typical sequence of received pulses where the first pulse (red color) denotes direct signal and the following pulses correspond to different reflections from bottom and surface. Calculation of this sequence with fitting parameters, characterizing bottom allows us to find, for example, methane bubbles concentration

![Figure 3. Sequence of reflected pulses received by single hydrophone](image)

c) Shipping noise. Experiments on the measurements and usage of shipping noise were carried out in 2019-2022. The first option was measurements using vertical line array and moving ship (R/V Hermona) during 5 min. After frequency filtering it is possible to select modes (see example in the Fig. 4)

![Figure 4. Two waveguide modes at the frequency 48 Hz](image)

Yere we can find attenuation coefficients of waveguide modes and use the fitting procedure to estimate parameters of bottom.

d) Research of currents and internal waves using ADCPs. Currents in the lake were studied using fixed and towed Acoustical Doppler Current Profilers. There were two fixed ADCPs which recorded variations of currents during 1 year. The corresponding pattern shows manifestation of internal Kelwin waves. Moving ADCP was used as well to find cyclonic and anti-cyclonic currents in the lake.

ACKNOWLEDGMENTS

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Retrieval of the dispersion curves of waveguide modes using shipping noise recorded by two vertical line arrays

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ABSTRACT
A technique is proposed for estimating the dispersion characteristics of waveguide modes based on a comparison of the shipping noise recorded by two synchronized vertical line arrays. Using the proposed approach, an experimental study of the modal structure of a low-frequency sound field in a shallow-water waveguide (Lake Kinneret, Israel) with a gas-saturated bottom was carried out in a wide frequency band from 20 to 250 Hz. Bottom of the lake is rich in methane bubbles (~ 1% by volume) and, consequently, has low sound speed of the order of 100 m/s. The receiving system was two 27-m vertical arrays located at a distance ~40 m from each other in 40.4 m-deep water. The noise source, a research vessel, was moving along a straight line in the vertical plane containing the arrays up to 1 km range from them. The proposed approach made it possible to determine the frequency dependences of the phase speed for the first 12 modes, and these dependences turned out to be close to those for a waveguide with a perfectly soft bottom, except at the frequencies in the vicinity of the mode cutoffs.

Keywords: Shipping noise, Correlation function

1. INTRODUCTION. EXPERIMENT

In the Figure 1 layout of experiment is shown which was carried out in the central part of Lake Kinneret, where the depth is approximately 40.4 m; the sound velocity profile is characterized by a noticeable jump at a depth of 10–15 m. The bottom of the water area is covered with gas-saturated sediments. The receiving system consisted of two vertical synchronized chains of hydrophones fixed on the bottom near a moored platform, spaced approximately = 40 m from each other, the western (W), and the other, the eastern (E). Each chain consisted of 10 hydrophones placed at an interval 3 m, covering the depth range from 10 to 37 m.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure1.png}
\caption{Scheme of experiment}
\end{figure}

Fig. 1 shows the movement of the noise signal source, the R/V Hermona, along a straight line through both arrays, with the eastern chain always closest to the vessel. The study considers a time interval of ~5 min,

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during which the vessel moved at a speed of 4 m/s away from the arrays to a maximum distance of 1000 m. Figure 2 (left) shows an example of the noise spectrum of the ship.

2. DATA PROCESSING AND RESULTS

We consider the field from a noise source recorded by the two arrays (E, W), $P^E(t, z_j)$ and $P^W(t, z_j)$, where $z_j$ - hydrophone depth, $t$ - "fast" time in the time interval of the ship's movement. The corresponding spectrograms are $P^E(\omega, T, z_j)$ and $P^W(\omega, T, z_j)$, frequency $\omega = 2\pi f$ and "slow" time $T$ in the interval from 0 to 5 min. Expansion coefficients of the spectrograms over waveguide modes $\psi(z_j, \omega, q)$, as functions of the parameter $q$, frequency $\omega$, and slow time $T$, where discrete depths of 10 hydrophones $A^E(\omega, T, q) = \sum_{j=1}^{N} P^E(\omega, T, z_j)\psi(z_j, \omega, q)\Delta z$, $A^W(\omega, T, q) = \sum_{j=1}^{N} P^W(\omega, T, z_j)\psi(z_j, \omega, q)\Delta z$

Figure 2. Spectrum of shipping engine (left) and function $R(\omega, q)$, white lines are dispersion curves (right)

Ratio of the amplitudes $A^E$ and $A^W$, taking into account the compensation of the phase shift at the distance $\Delta r$ between the antennas, take the real part and average over the slow time (or over the distance from the antennas to the ship), which will give:

$$R(\omega, q) = \langle Re\left(\frac{A^E(\omega, T, q)}{A^W(\omega, T, q)}\exp(iq\Delta r)\right)\rangle_T$$

Function $R$ in coordinates $(\omega, v_{ph})$ where $v_{ph} = \omega/q$ is phase speed, is shown in the Fig.2 (right). White lines show dispersion curves for waveguide with $c_0 = \min(c(z))$ and soft bottom $v_{ph,m}(\omega) = \frac{\omega}{\sqrt{(2\omega/c_0)^2 - (\pi m/T)^2}}$

If we are able to identify waveguide modes then we can choose waveguide parameters to get the best agreement between dispersion curves, selected in experiment and theoretical dispersion curves for fitting parameters.

So, the paper proposes a new approach to separating normal modes and estimating their parameters by analyzing ship noise recorded by two synchronized closely spaced arrays. The advantage of this approach is that there is no need to know the exact coordinates and speed of the ship: it suffices to know only that it is.

Note that the experiment described above in Kinneret Lake is the first attempt to use this approach. The same method can apparently be applied in shallow water with an arbitrary trajectory of a noisy vessel, if this trajectory is known. Due to the nature of the signal processing, a high degree of accuracy in describing the ship’s trajectory is not required. This approach proved to be robust with respect to observed strong pseudoacoustic noise.

ACKNOWLEDGMENT

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Seismo-acoustic wave propagation generated by the detonation of UXOs of large charge weights in a shallow water environment

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ABSTRACT
Unexploded historical ordnance (UXO) from World War II, that is discovered almost every week close to the French coast, must be destroyed quickly after discovery to ensure the safety of divers and ships. The favored destruction method is countermining, i.e., the use of a high-order detonation conducted by exploding an additional donor charge placed adjacent to the UXO. In the framework of a UXO countermine campaign conducted in the Rade d’Hyères (Mediterranean Sea, France) in December 2018, hydro-acoustic and seismic recording systems have been deployed to record the explosion-induced waves in water and the seismic signals on the shore, respectively (POSA project). In this expanded abstract, we present the main observations and focus on the impact of the shallow water environment (whose water depth is less than 50 m), and more specifically on the impact of the unconsolidated sedimentary layer, on the recorded signals induced by the detonation of charges with weights ranging from 80 to 680 kg TNT-equivalent. We also discuss the acoustic-to-seismic wave conversions.

Keywords: Underwater explosion, wave propagation, seismo-acoustic signals

1. INTRODUCTION
Unexploded historical ordnance (UXO) from World War II are discovered almost every week close to the north-western and south-eastern coasts of metropolitan France. Quickly after their discovery, the French Navy Mine Warfare Office (FNMWO) must destroy the munitions to ensure the safety of divers and ships. The favored destruction method is countermine, i.e., to use a high-order detonation conducted by exploding an additional donor charge placed adjacent to the UXO. Depending on whether the UXO is safe to move, such countermine occurs at specific safe locations or at the location of the discovery.

The risks for people in charge of the UXO countermine are well known by the FNMWO experts.

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In contrast, it is difficult to reliably evaluate the possible consequences of underwater explosions on the marine environment and on the buildings located on the coast. Indeed, they depend mostly on the environment geology and on the characteristics (weight and location) of the explosive charges and, hence, on the detonation-induced wave propagation. Large underwater explosions may trigger small-scale landslides that could, in turn, generate large waves on the shore or damage infrastructures (pipelines, optic fibers). Therefore, there is a need for developing a decision support tool for the risk assessment regarding inland infrastructures before the clearance of UXO of large weights.

One of the main goals of the POSA project, partly funded by the French Navy, was to pave the way for reliably assessing the risk of building damage on the adjacent shore, induced by the detonation of large-charge UXO (of between 80 and 680 kg TNT-equivalent weights) in a variable shallow water environment with a water depth less than 50-100 m. While the wave propagation generated by the detonation of small charges (usually, smaller than a few-kilograms TNT-equivalent weight) is quite well studied in the open literature (e.g., [1-3]), to the best of our knowledge, very few works are concerned with charges of a few-hundred-kilograms TNT-equivalent weight and located in coastal waters with a depth close to 50-100 m (e.g., [4-7]). In that respect, the POSA project can be considered a pioneer work.

To understand how the seabed (and possibly, the viscoelastic sedimentary layer with a varying thickness) and the water column (with a varying depth) influence the propagation of the seismo-acoustic waves that are generated by the UXO detonation and that reach the coast, we have relied on a multidisciplinary cross-study including real data obtained within the framework of controlled countermining campaigns, and numerical simulations of the seismo-acoustic propagation using a spectral-element method. The countermining campaigns were conducted in December 2018 in the Mediterranean Sea in the Rade d’Hyères (south-eastern part of France). The real data have been collected by acoustic recording systems (namely, two hydrophones and one shock gauge) and by a relatively dense array of seismic stations (velocimeters, conventional accelerometers, and MicroElectroMechanical Systems (MEMS) accelerometers) located on the shore at a maximum of 15 km from the underwater explosion locations. Most of the results obtained from the analysis of the real acoustic and seismic data and from the numerical simulations are reported in a two-companion paper [8,9] and in a paper currently under review [10].

The present extended abstract summarizes some of the main results of the POSA project. Section 2 briefly describes the POSA experiment conducted in the Rade d’Hyères in December 2018. We refer the reader to [8,9] for further details. Section 3 then presents some of the acoustic and seismic explosion-induced signals collected by the acoustic and seismic recording systems, and also discusses the impact of the charge characteristics on the recorded signals, as well as the impact of the location of the explosion (on the seabed vs. in the water column). Finally, Section 4 investigates the influence of the environment geology on the seismic explosion-induced signals recorded on the shore.

2. THE POSA EXPERIMENT

2.1 Characteristics of the experiment site

The Rade d’Hyères is approximately 15 km long in the E/W direction and 10 km wide in the N/S direction. The water depth within the bay is less than 70 m (Fig.1a) and the sound speed in water was assumed constant and equal to 1507 m/s. The seabed, whose physical and geometrical properties vary spatially, is composed of unconsolidated sediments lying over a bedrock. The sedimentary cover is generally less than 5 m thick within the bay, but locally reaches 30 m close to the western part of the shore (Fig.1b). Except close to this deep sedimentary basin, the sediment properties are globally constant within the bay: measured density \( \rho_{\text{sed}} = 1550-2000 \text{ kg/m}^3 \), measured P-wave velocity \( V_{\text{P,sed}} = 1625-1750 \text{ m/s} \), measured P-wave attenuation \( \alpha_{\text{P,sed}} = 0.49-0.69 \text{ dB/m/kHz} \), estimated S-wave velocity \( V_{\text{S,sed}} \approx 200 \text{ m/s} \), estimated S-wave attenuation \( \alpha_{\text{S,sed}} = 40 \text{ dB/m/kHz} \). Depending on the nature of rocks, the density, P- and S-wave velocities in the bedrock vary within the bay: measured density \( \rho_{\text{rock}} = 2600-2650 \text{ kg/m}^3 \), measured P-wave velocity \( V_{\text{P,rock}} = 4100-4450 \text{ m/s} \), measured S-wave velocity \( V_{\text{S,rock}} = 2700-2910 \text{ m/s} \). In the absence of information on their variation with depth, the rock properties were assumed to be constant with depth.

2.2 Characteristics of the detonated charges

Eight explosive charges of TNT-equivalent weights ranging from 80 to 680 kg were detonated at two specific locations in the bay (labeled 3TY and 3TZ, respectively, in Fig.1). The first seven (S1-
S7) charges were placed on the sea bottom, while the last one (S8) was placed in a container in the water column at ~11 m below the sea surface. The source distance from the shore ranges from 6 to 13 km. At the locations 3TY and 3TZ, the water depth was 46 m and 29 m, respectively. We refer the reader to [8] for further details.

Fig. 1. The experiment site, namely the Rade d’Hyères in the Mediterranean Sea (south-eastern part of France): (a) bathymetry, (b) 3D map of the sediment thickness. The two locations, labeled 3TY and 3TZ, are the locations where the UXO were detonated during the campaign of December 2018. The locations of the temporary seismological stations deployed along the shore are labeled PS01-PS19.

2.3 Hydro-acoustic and seismic experiments

The hydro-acoustic recording system consisted of a shock-gauge transducer T11-Neptune Sonar, with a nominal charge sensitivity of 0.07 pC/kPa, and two hydrophones Hi-Tech model HTI-96, with nominal sensitivities of ~210 dB re 1 V/μPa (hereafter, referred to hydrophone H210) and ~240 dB re 1 V/μPa (hereafter, referred to hydrophone H240), respectively. The two hydrophones have flat responses (within 3 dB) over the frequency band 0.002-30 kHz. The shock-gauge transducer was placed at a water depth of ~10 m below the sea surface and at fairly close horizontal distances (~110-270 m) from the explosive charge locations, whereas the two hydrophones were suspended at a water depth of ~10 m and at distances equal to ~400 or 2800 m and ~3000 or 5900 m from the shot locations, respectively. We refer the reader to [8] for further details.

The shock-transducer signals were recorded continuously, and the signal digitization occurred at a sampling rate of 625 kHz, giving a time resolution of 1.6 μs. As the maximum pressure level that was recorded during the experiments was around 1 MPa, i.e. well below the limit of the measurement system, there was no clipping. The hydrophone signals were recorded continuously, and the signal digitization occurred at a sampling rate of 78.125 kHz, giving a time resolution of 12.8 μs. The limit of the whole measurement system was 6.68 kPa for the hydrophone H210 and 214.5 kPa for the hydrophone H240. We refer the reader to [8] for further details.

A temporary seismic network consisting of 20 three-component medium to broadband velocimeters and accelerometers was deployed all along the shore on 17 sites at distances ranging from 6 to 13 km from the explosion locations (Fig. 1a). The seismological stations recorded continuously during their installation period, including the seismic ground motion generated by explosions. The seismic signals were recorded with sampling rates of 250 samples per second (sps) (velocimeters) and 500 sps (accelerometers), respectively, and then band-pass filtered between 0.1 and 45 Hz (for 250 sps signals) or between 0.1 and 110 Hz (for 500 sps signals). We refer the reader to [8] for further details.

One of the originalities of the POSA experiment is the use of eight MEMS (MicroElectroMechanical Systems) accelerometers (Sercel DSU3-SA) in complement to the conventional velocimeters and accelerometers. Besides their low cost, these instruments have the great advantage of being easily installed in remote locations without external power sources. Two of the eight MEMS accelerometers were collocated with conventional seismic stations at the rocky site PS05 and at the sandy site PS13 (Fig. 1a).

3. ACOUSTIC AND SEISMIC EXPLOSION-INDUCED SIGNALS

3.1 Acoustic signals

Time-series data generated by the explosion of a charge of 80 kg TNT-equivalent and recorded by
the shock gauge transducer T11 are shown at different time scales in Fig. 2. The signal associated with the shock wave highlights the typical feature of a shock waveform, namely an instantaneous pressure rise (with a peak pressure at 0.15 s) followed by an exponential pressure decay (Fig. 2c). The first bubble pulse arrives ~ 0.30 s after the primary shock arrival (Fig. 2a), which is consistent with empirical predictions [1]. The signal arriving at ~ 0.152 s (Figs. 2b and 2c) is associated with the waves reflected by the free sea surface and received before the completion of the bubble pulse from the direct wave. The signal associated with the shock wave generated by the explosions on the seabed has the same waveform, whatever the TNT-equivalent charge weight [8]. However, the shock waveform is very different for the case of an explosive charge located in the water column, namely, the exponential pressure decay following the pressure rise is largely missing because of a so-called « cut-off » (i.e. a fast pressure drop), which is consistent with the results reported in the literature (see discussion in [8]).

Fig. 2. Signal generated by the explosion of an 80 kg TNT-equivalent charge on the seabed at 3TY, and recorded by the shock gauge transducer T11 located at 110 m from the source. Because of pyrotechnic delay, time 0.15 s cannot be considered as a reliable arrival time of the shock wave after detonation.

Time-series data generated by the explosion of a charge of 80 kg TNT-equivalent and recorded by the two hydrophones H240 and H210 are provided in Fig. 3. The signal associated with the shock wave arrives at ~ 0.15 s. The first bubble pulse arrives ~ 0.30 s after this primary shock arrival on the two signals recorded by the two hydrophones. The complexity of the longer range signal recorded by the hydrophone H210, compared to the shorter range signal received at the hydrophone H240, is due to the effects of the shallow water environment on the wave propagation, mainly waveguide dispersion. For the sake of brevity of this expanded abstract, we choose not to present all the signals recorded by the hydrophones, since the signals have similar waveforms for similar detonation conditions, i.e. for similar charge weights and for similar shallow water environments. Nevertheless, the signal waveforms depend on the charge location at a same experiment site. The signals associated with the bubble pulse have globally higher amplitudes when the charge is located in a container in the water column, rather than on the seabed, even if the charge detonated in water is of smaller weight. For further details, we refer the reader to [8].

Fig. 3. Signals generated by the explosion S3 (80 kg TNT-equivalent charge) located on the seabed at the location 3TY, and recorded by the two hydrophones H240 and H210 located at 326 m and 2983 m, respectively, from the source. For a better comparison, both signals are blocked on the same arrival time for the shock wave. Note also that the beginning of the shock wave signal (highest amplitude) recorded by the hydrophone H210 is slightly clipped.
Spectral analysis was carried out through the estimation of the Power Spectral Density (PSD) for the signals recorded by the shock gauge transducer T11 and the hydrophone H240. For the sake of brevity of this expanded abstract, we choose not to present the different spectra and we refer the reader to [8] for details and figures. Nevertheless, we summarize here the main key points:

i. The signal spectra are consistent for a given charge detonated at the same location (3TZ or 3TY, Fig.1a).

ii. Whatever the charge weight and wherever the explosion location, the spectra of the signals recorded by the shock transducer (located « close » to the explosion) are quite similar and relatively constant below 300 Hz. Above 300 Hz, the spectra exhibit a significant drop.

iii. Whatever the charge weight and wherever the explosion location, the hydrophone, although having a good sensitivity at low frequencies (LF), could hardly record the components with frequencies below 30 Hz, because of the waveguide cutoff frequencies.

iv. A detonation on the seabed generates lower frequencies (globally, up to 30 Hz) than a charge detonation in the water column.

v. The shock wave signal mostly contributes to the HF components of the whole spectrum (frequencies above 100 Hz), whereas the first bubble pulse signal contributes to the LF part (below 100 Hz with a peak around 30 Hz), which is consistent with information reported in the literature (see discussion in [8]). Because of its contribution to the lower frequency part, the bubble pulse signal may be the most appropriate candidate to possibly generate seismic risks, in particular in the presence of sedimentary basins. Indeed, the sedimentary basins may lower the frequency content of the signals while locally amplifying their amplitude. This is the well-known site effect observed in seismology, that can damage buildings.

3.2 Seismic signals

For the sake of brevity of this expanded abstract, we choose not to present all the seismic signals and we refer the reader to [8,10] for details. Nevertheless, in order to show the impact of the weight and the location of the explosive charges on the seismic signals arriving at the shore, we compare the vertical component of the ground acceleration induced by each explosion (S1-S8) and recorded at the same station PS05 (Fig.4a). Firstly, for a given location for explosions (3TY or 3TZ) and for similar conditions (i.e. located on the seafloor), the signals are consistent. Secondly, the ground acceleration is linearly related to the charge weight.

**Fig.4.** (a) Vertical component of the ground acceleration, generated by the explosions S1-S8, and recorded by the velocimeters at the station PS05 (see Fig.1). S1 and S2 correspond to a 80 kg TNT-equivalent charge located at the site 3TZ, S8 to a 80 kg TNT-equivalent charge located at 3TY in the water column (WC), and S3, S7, S6, S5, S4 to a 80, 200, 400, 600, 680 kg TNT-equivalent charge, respectively, located at 3TY on the seabed (SB). The amplitudes are graphically clipped between ±8 mm.s⁻² for clarity of display. (b) Power spectral densities (PSD) of the vertical ground-acceleration components induced by the explosions S3-S8.

Spectral analysis shows that the detonation of charges of weight larger than 80 kg TNT-equivalent generates globally similar spectral responses for the vertical ground-acceleration components recorded on the shoreline (Fig.4b). However, the amplitudes of the spectral responses increase with increasing charge weight. Whatever the source, the most energetic peak at ~ 10 Hz is likely associated
with bulk wave propagation. The secondary peak observed in the 0.8-2 Hz frequency range, but only for the largest charges, is likely associated with interface/surface wave propagation.

Compared to a charge detonation in the water column, a similar detonation on the seabed generates seismic signals of much lower frequencies (< 30 Hz) and higher amplitudes that propagate in the seabed (see e.g. the signals generated by the explosions S3 and S8, both corresponding to an 80 kg TNT-equivalent charge, and the associated spectra in Fig.4). Detonating the charges directly on the seafloor, and not close to, makes the coupling between the source and the seafloor super-efficient [11].

Two empirical laws for the explosion-induced local seismic magnitude, as a function of the charge weight, have been derived in [8] for the cases of a charge detonation in the water column and on the seabed, respectively. These two laws globally follow the same trend, but with a shift of 0.5 in magnitude, since much less energy is transmitted downwards into the ground when the explosion takes place at a shallow water depth. Note that, in the POSA experiment, the charge detonations (up to 680 kg TNT-equivalent) have generated seismic events of at most magnitude 2.9 on the Richter scale.

It is worth noting that the contribution of phases, that are not recorded by conventional sensors at usual sampling rates (i.e. less than 250 gps), could be observed from the high sampling rate data (500 gps) recorded by the MEMS accelerometers. Besides the P and S waves, and the interface/surface waves that follow them, a high-frequency high-amplitude signal with a velocity close to the sound speed in water could also be observed at some stations located on rocky sites with a thin sedimentary cover [10]. This signal likely corresponds to an H-phase (following the IASPEI nomenclature), i.e. a wave packet that propagates within the water column from the source to a location close to the shore (at the cutoff height of the acoustic modes) and that subsequently converts to seismic energy before being recorded by the seismic sensor. In addition, at some seismic stations, an energy packet with an apparent velocity close to the sound velocity in the air could also be observed when the largest charges were detonated on the seabed [10]. This is likely an I-phase (following the IASPEI nomenclature), i.e. an acoustic phase that propagates in the air from the explosion location.

4. INFLUENCE OF THE ENVIRONMENT GEOLOGY ON THE SEISMIC SIGNALS

Fig.5. illustrates the seismic ground motion induced by the detonation of a 400 kg TNT-eq. charge (S6) located on the seabed at the site 3TY and recorded by the network of 20 three-component (3C) velocimeters and accelerometers deployed all along the shore of the Rade d’Hyères (Fig.1a).

The global signal waveforms and durations greatly differ according to the explosion-station distance, and according to the ground properties along the propagation path as well. The sediment thickness seems to have a significant influence since for the stations PS09-PS17 installed on sites with several meters of sediments below, the first P-wave arrival is not as impulsive as the one observed at the other sites. Most importantly, the signal duration is much longer, with the presence of late dispersive signals with a very LF content and, for some stations, large amplitude. The largest amplitudes are generally observed for S waves and surface waves, with amplifications that can be significant on the horizontal components (e.g., stations PS10 and PS17). These characteristics are specific to the well-known site effects induced by the sedimentary basin [10] and can be well explained and illustrated by full-wave numerical simulations of wave propagation [9]. For the sake of illustration, Fig.6 shows how the different types of waves (namely, P and S waves, interface and surface waves of Stoneley-Scholte (SS), and Rayleigh or Rayleigh-Sezawa (Rayl) type) interact with the physical properties and the geometry of the marine environment (including the spatially-varying sedimentary layer), and how they evolve along the propagation path between the explosion location and the station location. However, from Fig.5 no strong conclusion can be drawn from the observed differences in the signal amplitudes. Indeed, several factors, including the source-station distance and the conditions of the station set-up on the rocky or sedimentary sites, may also impact the wave amplitudes.

In [10] we further investigate the importance of the sedimentary cover on the frequency content of the seismic signal recorded at the shore. The thick sediment layer is shown to generate important seismic amplification (H/V ratio up to 20) of the relatively low-frequency energy (1 to 5 Hz). In [10] we evidence that the sedimentary cover has to be taken into account to mitigate potential nuisance on land for large charge weights in shallow water environments.

It is worth noting that, although the largest charge (680 kg TNT-eq.) detonation on the seabed generated a seismic event of magnitude 2.9 on the Richter scale, no infrastructure located on the shore of the Rade d’Hyères was damaged. For the sake of illustration of the seismic response on nearby civil engineering structures, two velocimeters were located at the top and the bottom (station PS01), respectively, of the bell tower of the Ste-Anne church located on Porquerolles Island (Fig.1a). During
the POSA experiment, this masonry structure faced motion amplification in response to the explosion-induced seismic signal, but that deformation was well beyond the damage initiation threshold [8,10].

![Fig.5. 3C ground accelerations (GA) induced by the explosion of a 400 kg TNT eq. charge located at 3TY and recorded at PS01-PS19 (Fig.1a). Each signal amplitude is normalized by the maximum amplitude of the corresponding GA. The signals are low-pass filtered at 20 Hz. All the traces are plotted with the same origin time, and the amplitudes are graphically clipped between ± 5 mm.s⁻² for display clarity. Sandy color: sites with a thin sedimentary layer (0-1 m), red-pink and blue colors: sites with a thick one (see Fig.1b).](image)

**Fig.5.** 3C ground accelerations (GA) induced by the explosion of a 400 kg TNT eq. charge located at 3TY and recorded at PS01-PS19 (Fig.1a). Each signal amplitude is normalized by the maximum amplitude of the corresponding GA. The signals are low-pass filtered at 20 Hz. All the traces are plotted with the same origin time, and the amplitudes are graphically clipped between ± 5 mm.s⁻² for display clarity. Sandy color: sites with a thin sedimentary layer (0-1 m), red-pink and blue colors: sites with a thick one (see Fig.1b).

![Fig.6. (Left) Bathymetry, geometry of the sedimentary layer, and location of the fictitious horizontal receiver array (colored dots) along the line 3TY-PS13. (Right) Focus on the first 10 s of the simulated seismograms related to the horizontal component of the velocity. For the sake of better visualization, the signals obtained at the different offsets are represented at different amplitude scales. See [9] for the explanations of the different labels related to the different kinds of waves. The numerical simulations were performed using a spectral-element method.](image)

**Fig.6.** (Left) Bathymetry, geometry of the sedimentary layer, and location of the fictitious horizontal receiver array (colored dots) along the line 3TY-PS13. (Right) Focus on the first 10 s of the simulated seismograms related to the horizontal component of the velocity. For the sake of better visualization, the signals obtained at the different offsets are represented at different amplitude scales. See [9] for the explanations of the different labels related to the different kinds of waves. The numerical simulations were performed using a spectral-element method.

5. CONCLUSION

This expanded abstract summarizes some of the main results related to recorded acoustic and seismic signals induced by the detonation of large charges (with weights up to 680 kg TNT eq.) in the framework of a UXO countermining campaign conducted in a variable shallow water environment, namely the Rade d’Hyères in the Mediterranean Sea (France) in December 2018 (POSA project). As expected, the acoustic and seismic signal amplitudes increase with increasing charge weight. A detonation on the seabed generates lower frequencies (globally, up to 30 Hz) than a charge detonation in the water column. The variable environment characteristics, in terms of bathymetry, thickness of
the sedimentary layer, and physical properties, have a significant influence on the complex wave propagation towards the shore and on the acoustic-to-seismic conversions. In particular, the presence of sedimentary basins can induce site effects, i.e. large amplification of the S-wave and interface/surface-wave amplitudes, increase in the signal duration and shift of the spectrum towards the very low frequencies.

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REFERENCES

Long-range propagation modeling of offshore pile driving noise based on the configuration of the support structure

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ABSTRACT

Offshore impact pile driving noise is radiated and propagated through the water column and ocean bottom. Predicting noise levels around wind turbine support structures at sea is required to estimate the effects of the noise on marine life. Finite Element (FE) and Parabolic Equation (PE) models were used to predict long-range propagation of noise from the installation of offshore wind turbine foundations. FE analysis produced acoustic pressure outputs at short ranges which were used as a starting field for the PE propagation model. Monopile (axisymmetric model) and jacket with raked pile (3D model) wind turbine support structures were considered. The latter presents a particular complication regarding azimuthal dependency due to the non-axisymmetric geometry of the pile. The MMPE model was modified to accept the FE model’s vertically distributed acoustic pressure output in the vicinity of the pile as its starting field. Frequencies up to several hundred Hz were considered in the modeling since this is the range where most of the acoustic energy from impact pile driving is concentrated. The long-range acoustic pressure field outputs from impact pile driving in a shallow water environment around Block Island, Rhode Island will be presented.

Keywords: Sound Exposure Level, Monopile, Raked pile

1. INTRODUCTION

Acoustic energy is created when impact pile driving is used to construct offshore wind turbine support structure and the sound radiates into the water along different paths. The potential paths include,
1. From the top of the pile where the hammer hits, through the air, into the water.
2. From the top of the pile, down the pile, radiating into the air while travelling down the pile, from air into water.
3. From the top of the pile, down the pile, radiating directly into the water from the length of the pile below waterline.
4. Down the pile radiating into the seabed, travelling through the seabed into the sediment and radiating back into the water.

Acoustic energy arriving from different paths with different phase and time lags creates a pattern of destructive and constructive interference near the pile and water (and bottom) borne energy radiates further away from the pile.

To simulate long range propagation of offshore pile driving noise based on the configuration of the support structure, a combination of Finite Element (FE) and Parabolic Equation (PE) model approach has been used. The FE model is ideal for short range calculations of acoustic pressure from complex structure, but it becomes computationally unsustainable when the size of the model is increased due to the mesh size requirement for long range numerical domain. It is also difficult to handle environmental inputs such as depth dependent sound speed profile or range dependent bathymetry. In contrast, the PE model is ideal for long range propagation, with a starting field and appropriate environmental data. The PE model can handle range dependence of the environmental parameters.

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The Monterey-Miami Parabolic Equation (MMPE) model is used in this study which accepts inputs such as source depth, array length, center frequency, frequency bandwidth and number of frequencies along with environmental inputs which define the medium properties.

In one of the earlier studies, Reinhall & Dahl (1, 2) detailed a numerical approach to predict offshore impact pile driving noise. Other studies which presented numerical approaches to predict long range propagation of noise radiation and investigated potential effects on marine life include Potty et al., (3) Kim et al., (4,5) Miller et al. (6). Wilkes (7) and Amaral et al. (8) used axisymmetric FE model to simulate a line array of point sources along the axis of the vertical pile. To represent a raked pile, they rotated the vertical line array by the inclination angle and calculated the Green’s function. However, this study uses a direct approach based on 3D FE model for four raked piles surrounded by water column and ocean bottom to calculate acoustic pressure. To model four raked piles in FE, we adopted the geometry and the environmental information in Amaral (8). Specifically, we used the geometry, material properties, and environmental parameters from Block Island Wind Farm (BIWF) which is the first offshore wind farm in the U.S. coastal waters. Details of this study will be presented by the following sections.

Section 2. describes FE modeling method and results for the case of axisymmetric and 3D models for the different configuration of offshore wind turbine support structure such as monopile and raked pile. Section 3 presents the generation of starting field for the MMPE model based on the results from FE models and corresponding results for the long-range prediction of acoustic pressure outputs. Section 4 provides the conclusions by discussing the advantages and disadvantages of FE combined with PE approach as one of the methods of long-range propagation model of offshore impact pile driving.

2. Finite Element modeling

To predict the radiated acoustic pressure from the raked pile support structure using FE analysis, the following process has been adopted. At first, monopile support structure was modeled using axisymmetric and the model output were compared with published data from Reinhall and Dahl (2) thereby ensuring that the FE model produces reasonable results. To make computation less intensive, axisymmetric model for modeling the monopile was used by assuming azimuthal independence. Then the axisymmetric model has been extended to same geometry with a 3D model and the acoustic pressure outputs from axisymmetric and 3D were compared. Finally, four raked piles are modeled based on the pile geometry and material properties of the pile, water, and bottom provided by Amaral et al. (8). The acoustic pressure outputs as a function of depth in the vicinity of raked piles are then used as the starting field for the acoustic propagation model (MMPE) to predict the acoustic field at long ranges.

2.1 Benchmark model

We used FE model to simulate Reinhall & Dahl’s work (2) as a benchmark model. FE analysis using Abaqus/CAE used implicit dynamic analysis by applying pressure due to impact loading \( p(t) \) as function of time on top of the pile.

\[
p(t) = 2.1 \times 10^6 e^{-\frac{t}{8.004}} \text{ (pa)}
\] (1)

The length of the pile is 30.2m with thickness 25.4mm and radius 0.762m. The water depth is 12.5m and the sediment depth is 10m. A Vertical Line Array (VLA) measured acoustic pressure outputs the at ranges 8m, 12m, and 15m away from the pile. The water and bottom are modeled as acoustic medium. A Perfectly Matched Layer (PML) was set at the boundary to remove unwanted reflection which simulates infinite acoustic medium. We also set series of nodes in FE model to record acoustic pressure outputs at the same location of VLA.

The FE results provide radiated acoustic pressure in the medium due to impact pile driving at different time steps. Mach wave is generated due to different phase speed in steel, water, and bottom. The angle of Mach wave is 17.22° in the water and 18.9° in the bottom. A calculation of Sound Pressure Level (SPL) for the first Mach wave arrival is compared with Reinhall & Dahl’s measured data (2). The solid lines with different colors represent the result of our FE model and the measured data from Reinhall and Dahl (2) at the VLA locations (8m, 12m, 15m respectively) are shown as rectangles, triangles, and circles in Figure 1 (right panel). It can be seen that the Mach wave from our FE analysis compared well with the published data at the VLA locations (Reinhall and Dahl (2)).
Figure 1 – Acoustic pressure outputs at time \( t = 4, 8, 12, 16 \) milliseconds. (left panel), The first-arrival pressure amplitude in \( \text{dB re } 1 \mu \text{Pa} \) as a function of depth. (right panel)

2.2 FE modeling of monopile

Based on the results of the benchmark model, we modelled monopile support structure using both axisymmetric and 3D elements to confirm that they get similar acoustic pressure outputs. We used the same pile configuration and material properties as in Amaral et al (8) and the material properties used are shown in Table 1.

Table 1 – Material properties inputs to the FE model

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Water</th>
<th>Bottom</th>
<th>Steel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Density ( (\rho, \text{kg/m}^3) )</td>
<td>1025</td>
<td>1850</td>
<td>7850</td>
</tr>
<tr>
<td>Bulk Modulus ( (E, \text{Pa}) )</td>
<td>2,306,250,000</td>
<td>5,994,000,000</td>
<td>-</td>
</tr>
<tr>
<td>Young’s Modulus ( (E, \text{Pa}) )</td>
<td>-</td>
<td>-</td>
<td>210,000,000,000</td>
</tr>
<tr>
<td>Poisson’s ratio</td>
<td>-</td>
<td>-</td>
<td>0.3</td>
</tr>
</tbody>
</table>

The pile length, diameter, and thickness are \( 62.5 \text{m}, 1.524 \text{m}, 0.0445 \text{m} \) respectively. Water depth is \( 24 \text{m} \) and the depth of penetration of the pile into the bottom is \( 14 \text{m} \) and the same loading condition in the benchmark model was used. We applied 89 nodes which are vertically distributed and record acoustic pressure time history at range \( 5 \text{m} \) from the pile support structure. The element spacing in water and bottom as an acoustic medium is \( 50 \text{cm} \) which covers frequency range up to \( 500 \text{Hz} \) based on the mesh size requirement that 5 or 6 elements per shortest wavelength corresponding to highest frequency of interest. In the case of water, sound speed is \( 1500 \text{m/s} \) and wavelength at \( 500 \text{Hz} \) is \( 1.5 \text{m} \). In the FE model, it is possible to solve for higher frequency with finer mesh size, but it requires higher computation power and longer running time.

Figure 2 – Acoustic pressure outputs at time \( t = 9, 12 \) milliseconds. (Left panel), the peak SPL and SEL comparison for the case of monopile with 3D and axisymmetric model

Figure 2 shows two different model with same problem of interest the peak SPL (Sound Pressure Level)
and SEL (Sound Exposure Level) were plotted. The peak SPL and SEL are defined as follows,

\[
SPL_{\text{peak}} = 10 \log_{10} \frac{\max ((p(t))^2)}{P_{\text{ref}}} \text{ dB re } 1 \mu Pa
\]

(2)

\[
SEL = 10 \log_{10} \frac{\int |P(f)|^2 df}{P_{\text{ref}}} = 10 \log_{10} \frac{\sum_{n=1}^{N} |P_n(f)|^2 \times df}{P_{\text{ref}}} \text{ dB re } 1 \mu Pa
\]

(3)

Both depth dependent axisymmetric and 3D FE results are relatively similar in water column and ocean bottom, however there are 1~2 dB difference between two models especially in water column (depth 0 meter to 24 meters). We applied all the same parameters for both the models, and the reason for the difference in model outputs is still unknown, and it is going to be explored further in our future study.

2.3 FE modeling of raked pile

The result of axisymmetric model compared well with published data from Reinhall & Dahl (2) and the new axisymmetric model for monopile (Amaral et al., (8)) also compared with 3D model for monopile (within 1 to 2 dB). Having successfully validated our FE model, we proceeded to model four 3D raked piles surrounded by acoustic media such as water and ocean bottom. The Block Island Wind Farm (BIWF) consists of total five 6 Megawatts turbines located three miles southeast of Block Island, Rhode Island, USA. Each turbine foundation has four legs that are referred to as A1, A2, B1, B2 (Figure 3 from (8)). Figure 3 shows the specific dimensions of the single raked pile and water and bottom as an acoustic medium and how four raked piles are modeled in FE assembly module (top and isometric view). To make our 3D raked FE model realistic, four piles were inclined by 13.27° toward center of the jacket type support structure. Four piles and water column and ocean bottom are combined by subtracting overlapped part in water and bottom where raked piles occupied in acoustic medium. It is important to set “tie constraint” between two different surfaces by sharing same physical quantities. For example, steel pile is tied to inside and outside water and bottom, and we applied a total of 21 “tie constraints” in FE model.

The purpose of this study is to predict the characteristics of long-range propagation of inclined (raked) offshore wind farm support structure. Differences in the acoustic field depending on whether the pile is inclined toward the receiver, or it is inclined away from the receiver will also be explored. During the construction of raked impact pile driving, measurement systems such as geophone and towed array and vertical line array are located in the of southeast direction. To compare the differences, we picked the raked pile legs A2 and A1. The leg A2 is inclined toward the receiver and the leg A1 had a different inclination. Also, the distance from leg A2 to the receiver is shorter than that of the leg A1. We defined 89 nodes to record acoustic pressure time history at the edge of the FE model’s numerical domain. This time history will be used as the starting field for the long-range propagation model (modified MMPE model).

The Fourier Transform of acoustic pressure in time domain (p(t)) provided the depth dependent real and imaginary part of acoustic pressure as a function of frequency. This was then used as the
starting field for the MMPE. The frequency band of interest is identified from the result of the plot for the spatial average of the magnitude of complex acoustic pressure on vertically distributed nodes. The dominant frequency as defined in equation (4) and its contribution to long range propagation in water column and ocean bottom are important.

\[
P(f) = \frac{1}{N} \sum_{i=1}^{N} |P_i(f)|
\]  

(4)

Figure 4 shows the spectrum of dominant frequencies for the case of raked pile leg A1 and leg A2. Overall, the pressure magnitude of pile leg A2 is greater than pile leg A1 because the leg A2 is inclined toward in the direction of receiver and the leg A1 is inclined away from receiver. To cover these dominant frequencies, the frequency band of interest of the modified MMPE model is set to 80Hz ~ 1000Hz. The upper high frequency limit corresponds to the mesh size of FE model which is 0.5m.

3. Parabolic equation modeling

The goal of this study is to investigate the long-range propagation from structure borne noise and vibration. It is required to input complex acoustic pressure at each frequency along the pile as a starting field for the modified MMPE. This study modified the MMPE input files and developed a post processing Matlab script to accomplish broadband calculation. The modified code enables the iterative broadband analysis with single run. To define vertically distributed complex acoustic pressure as function of frequency, we took Fourier transform of the acoustic pressure time history, from the implicit dynamic analysis in the FE model, using equation (5). Numerical domain of the FE model (24-meter water and 20-meter bottom) was extended to the numerical domain of the modified MMPE model (24-meter water and 114-meter bottom).

\[
P(f) = \int_{-\infty}^{\infty} p(t) e^{-j\omega t} dt (Pa)
\]  

(5)

Figure 5 – Modified MMPE starting field and corresponding results for a few dominant frequencies
Figure 5 shows MMPE starting field for the frequencies of 206.7Hz, 284.8Hz, 394.7Hz which are a few dominant frequencies within the frequency range of interest. Real and imaginary part of vertically distributed complex acoustic pressure at each frequency were used as the starting field for long-range propagation model MMPE.

The modified MMPE iteratively accepted starting field for different frequencies and calculated acoustic pressure and SPL field output up to a range of 7 kilometers. We applied zero-padding before taking Fourier Transform of acoustic pressure time history to get better frequency resolution. The frequency resolution for the model runs in this study was 0.81Hz and a total of 1130 runs covered frequencies from 80.6Hz to 1000.2Hz. Based on our current FE model with mesh size 50 centimeters, there are significant contribution from 100Hz to 400Hz frequency band and comparatively lower contribution from the frequencies higher than 700Hz. The total energy in the frequency band used in the study, SEL (Sound Exposure Level) in dB re 1μPa², can be approximated as the sum of the magnitude squared of complex acoustic pressure multiplied by frequency spacing as indicated in equation (3).

Figure 6 shows cumulative SEL field output in dB re 1μPa² as a function of depth and range for the case of raked pile leg A1 and A2. Generally, it is observed that the SEL remain high in the water column which indicates that the acoustic energy generated by impact pile driving propagates in water with some penetration into the bottom. The difference between two raked piles inclined toward (leg A2) and away (leg A1) in the direction of receiver can be compared visually from the left and middle panels which are plotted with the same dynamic range. The acoustic energy radiated and propagated by the raked pile leg A2 is more prevailing than the case of the pile leg A1. Quantitatively, we extracted SEL outputs as a function of range at the water-bottom interface. The pile leg A2 has 3 dB higher SEL in average with a maximum of 8 dB difference. The difference is minimum or reversed for the range from 10 meter to 70 meters.

![Figure 6](image)

Figure 6 –SEL output of the raked pile leg A1 and A2 (left and middle panel), The comparison of SEL from raked pile leg A1 and A2 outputs at the water-bottom interface (right panel)

4. Conclusions

This study provides a numerical approach for the long-range propagation modeling of acoustic pressure from the raked pile driving used in the construction of the Block Island Wind Farm in Rhode Island, USA. The starting point was validation of our FE modeling for monopile type offshore impact pile driving with measured data from a previous study (2). Due to monopile’s azimuthal independence, other researchers also used axisymmetric model instead of 3D model for lowering the computational effort. We developed a numerical approach for the raked pile support structure which requires a 3D modeling effort. In order to validate our 3D model, we generated two FE models for monopile (axisymmetric and 3D type element) and compared the FE results from the two models to ensure that the results are acceptable within allowable differences between them. Our goal is to predict the acoustic field, not only in the near field of the pile, but also at long ranges. To do that, two numerical models (FE and PE model) are coupled and with the FE output acting as the starting field for PE. Offshore impact pile driving noise is impulsive in nature and hence we generated vertically distributed acoustic pressure at different frequencies and modified MMPE model to accept it as a starting field for long range prediction of noise.

The results indicate azimuthal dependence of the pressure field based on the direction of inclination of the raked pile in relation to the receiver. The 3D modeling we tried in the paper by providing general approach for developing a coupled FE and PE model is a valuable tool for the prediction of radiated...
noise from offshore pile driving, specifically for non-axisymmetric scenario. Based on detail information such as hammer impact, ocean acoustic environment like bathymetry, range dependent sound speed profile, etc., the result of modeling can be further refined to be more realistic. We also used mesh size for the FE model which is computationally affordable but better computing power can be used, when available, to run finer mesh size quickly.

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As the first named author of this paper, it is important for me getting back to research field in 8 years. A motivation was an invitation letter to attend the ICA 2022 from Professor Stephan Lippert. My doctoral advisors Professor Miller and Potty encouraged me to do research again. I appreciate all their effort and consideration.

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Contemporaneous measurements of mid-frequency transmission and reverberation in shallow water

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ABSTRACT

An acoustic experiment was conducted off Geoje Island in southeast Republic of Korea in May 2017. The purpose is to study uncertainty of mid-frequency sound propagation and reverberation. The environment is in a transitional area bridging a bay setting to the open sea and the oceanographic condition is dominated by strong currents and fronts. Transmission loss (TL) and reverberation level (RL) data were simultaneously collected at 3.5 kHz along two perpendicular tracks each 10-km long. Identical measurements were conducted twice 5 days apart to examine signal repeatability. Sound speed data were taken by CTD casts and a moored thermistor chain. During the test period, sound speed profiles were close to iso-velocity inside the bay, but they were more variable out in the open ocean due possibly to a migrating coastal front. It is found that TL changed more than 10 dB between the two days, whereas the RL stayed more constant. Modeling and analysis on TL satisfactorily explain only part of the TL datasets, highlighting the need to capture and model the changing ocean environment in order to improve mid-frequency SONAR predictions.

Keywords: Transmission loss, Reverberation, oceanography

1. INTRODUCTION

Mid-frequency (1-10 kHz) sound propagation in shallow water often shows strong variability. Understanding the mechanisms responsible for such variability is a long-term goal. To that end, environmental measurements at the right scales should go hand-in-hand with acoustics measurements in order to learn the driving physical mechanisms through model/data comparisons. This was the goal of KOREX-17 (KOrean Reverberation EXperiment-2017), an experiment conducted off the island of Geoje, Republic of Korea, 23-31 May 2017. It was a joint effort with participation of three groups: Agency for Defense Development (ADD), The Applied Physics Laboratory, University of Washington (APL-UW), and Hanyang University (HYU). The experiment was performed onboard the ADD research vessel, the R/V Mirae. One of the objectives of this experiment was to measure both shallow water transmission loss (TL) and reverberation level (RL) at the same time under different environmental conditions to understand the sources of variability in both measurements.

2. Oceanic and acoustic measurements

Acoustic propagation and reverberation measurements as well as supporting oceanographic measurements are described below. In addition, bottom data for the experimental site were made available by the Korea Institute of Geoscience and Mineral (KIGAM). Meteorological data collected by the Korea Meteorological Agency (KMA) were also available for the test period.
2.1 Oceanic measurement

The test site is in a small bay off Geoje Island southeast of the Republic of Korea as shown in figure-1 (a). Water depth in the test site varies from 25 m inside the bay and drops to about 65m outside the bay as shown in figure-1 (b).

Multiple CTD casts were made inside the bay near the stationary acoustic source, which is described later. They were also made at two other locations outside the bay, one 10 km due east, the other 10 km due south. They are at the end of the two TL measurement tracks given later. From 23 to 26 May, a thermistor chain, which consists of six Seabird SBE-39s at depths 3m, 10m, 20m, 30m, 40m, and 50m, respectively, was moored at the entrance of the bay as marked by the red square in figure-1(c). The thermistor-chain data are unavailable for a period when a strong current pushed the chain to the seafloor.

Weather data were available through the ocean data buoy operated by KMA, which is located further NE from the test site marked by the green circle in figure-1 (c). Sediment distribution at the vicinity of the test site is in figure-1 (d): Gravely muddy sand is found inside the bay and near the bay entrance, and muddy sand is found outside the bay and offshore.

Figure-2 shows sound speed profiles (SSP’s) collected during the experiment period. Daily SSPs show very similar profiles except for those taken on 25 May where a surface mixed layer is present, and the layer structure is variable.
Figure-2. Sound speed profiles by CTD casts during the experiment period. (a) 23, (b) 24, (c) 25, (d) 26, (e) 27, (f) 29, (g) 30 and (h) 31 May 2017.

Figure-3 shows the thermistor-chains time series of temperature vs. depth over time. Several observations are here noted: First, the temperature structure in the water column is close to iso-thermal except for those for the 25 May and the 26 May when the water column has a warm layer with variable thickness near the surface. Second, there is a mild warmer water intrusion with a six-hour period, which suggests this site is strongly influenced by the tidal currents in the region. Third, several data gaps of varying duration occur, some of them longer than 4 hours. These are found to be due to very strong currents which overcame mooring buoyancy, resulting in loss of usable data.

During the observation period, warmer surface water intrusions happened several times which had temperatures greater 15 degrees C. The depth of the intrusions varied from 15 m to 35 m. The arrows in the figure indicate times when the first set of TL experiments was conducted.
Figure-3. Moored thermistor-chain data from 23 to 27 May 2017. The two arrows indicate time of TL measurements on the 25 May. Data gaps indicate missing data due to period of strong tidal force that pushed the chain to the seafloor.

Other relevant oceanic data available for the region are from the ocean data buoy operated by KMA (see figure-1 (c)). They include wind speed and direction, sea surface temperature (SST) and wave direction and significant wave height, as shown in figure-4. The sampling interval of the buoy data is one hour.

Wind direction was mostly westward and wind speed was 0 ~ 5 m/s during the entire experiment period as shown in figure-4 (a) and (b). SST varies from 16.5 to 18 °C and shows diurnal variation (figure-4 (c)). Overall, the SST in the first three days was constant at 18 °C and gradually lowered to 16.5 °C hence after. Figure-4 (d) shows wave direction and wave height, and figure-4 (e) shows significant wave height. Wave height was less than 1 m during the experiment period except for the period 26 to 27 May when the wave height is 1-1.5 m. This calm sea surface condition from the buoy is consistent with observations by sight at the experiment location.

Figure-4. Wind, sea surface temperature (SST), and wave from 00:00, 23 to 24:00, 31 May 2017 observed by the ocean data buoy operated by the KMA.
2.2 Acoustic measurements

Figure-5 (a) shows the TL tracks, marked by the red lines. Monostatic reverberation was measured using the ARMS (Autonomous Reverberation Measurement System) along the tow tracks. As shown in figure-5(b), it is a bottom lander consisting of a directional source transmitting 3.5 kHz sound with 100-Hz bandwidth. The beamwidth at 3.5 kHz is ~20 degrees. The source level is 200 dB and its source elements are at 2-m above the seafloor. While the ARMS can be programmed to scan 270-degree azimuth angles, it was pointed at fixed directions for the data discussed in this paper. The ARMS has 4 receive channels with a horizontal aperture of 1m. The ARMS source-receiver combined beamwidth is 11 degrees for backscatter at 3.5 kHz.

The ARMS is deployed inside the bay, shown as a black dot in figure-5 (a). TL is measured between 1 and 10 km using ARMS as source and a self-recording hydrophone (SRH) as receiver towed at 23 m depth, as shown in figure-5 (c). TL experiment was performed along the east-west and north-south tracks on 25 May and repeated on the 30 May.

Figure 5. (a) Two tow tracks marked by the red lines for TL measurement. (b) ARMS. (c) Self Recording Hydrophone (SRH) under tow body.

Figure-6 shows bottom profiles of the tow-tracks for both the E-W and N-S directions, which were collected by the fathometer on the R/V Mirae. It also shows SSPs measured at the ends of each of the two tow tracks just before and after each tow. The SSPs near the source location at both tracks of 25 and 30 May are close to iso-velocity and the SSPs at the offshore ends show greater variability.
3. Transmission loss Analysis

3.1 Measured TL and RL

When the ARMS transmits toward the south, the TL is measured in the N-S direction; when the ARMS transmits toward the east, the TL is measured in the E-W direction. Figure 7 is a summary plot.
of the four TL measurements: two on 25 May, of which one for the N-S tow, and the other for the E-W tow. The same measurements were repeated on 30 May. Of the four TL curves, the one taken on the 25 May along the E-W tow (upper right of figure-7) has a lower loss, whereas the other three are similar in level with greater than 10 dB higher loss. Interestingly, the corresponding reverberation measurements shown in Figure-8 show much less difference among the four data curves.

Figure 8. RL measured. Left: ARMS pointing to the south direction, right: ARMS to the east direction.

3.2 TL modeling

The Parabolic Equation (PE) method is used to model TL at 3500 Hz. Measured water depth (Figure-6) is used for the strong down-slope environment. The bottom parameters are not measured. In modeling, a half-space fluid half-space is assumed with the following parameters: the sound speed is 1630 m/s, sediment density-to-water density ratio is 1.8 and the attenuation coefficient is 0.5 dB per wavelength. A range of other sediment parameters are tried, including range-dependency, but it does not alter TL significantly.

The water column sound speed profile is based on the CTD and thermistor data. Range-independent modeling was first tried using each and all available SSPs, then range-dependent modeling was conducted where linear interpolation of SSPs in range is employed. The simulation results from using these different SSPs differ only slightly. The model curves in figure-7 are ones which are based on the range-interpolated SSPs.

TL measured on the 25 May along the E-W tow track agrees well with the modeled TL (top right of Figure-7). However, TL measured along the N-S track is nearly 20 dB greater than the predicted TL beyond the 5-km range for both days. TL measured on the 30 May along the E-W track also shows as much as 15 dB difference between model and data.

As noted earlier, a warm surface layer is intermittently measured by the thermistor and CTD casts. This surface layer is suspected to be caused by a strong current intrusion. The intermittency implies that the sound speed field in the test area is time-dependent and space-dependent. The lack of such information may have contributed to the model failure for the N-S tow on the 25 May. The lack of thermistor data for the 30 May clearly hampers the modeling for TL for that day.

4. Summary and discussion

The simultaneous measurements of TL and RL on two different days at the same site show two interesting results: (1) The TL has strong intra-day and inter-day variability as demonstrated in Figure-7. (2) The RL has much less variability. One might have surmised that RL should have shown stronger variability than TL because RL involves two-way TL. The measurements show the opposite. The
reason is not known, although it can be speculated that TL variability is more sensitive to sound speed variations near the surface, whereas RL is less so because its sound energy only comes from those ray paths which interact with the bottom.

The lack of success in modeling effort highlights the need for understanding ocean variability. Because the TL measurements were taken along the same tracks, the difference in TL between the two different days indicates that the origin of TL variability is due to time-dependent ocean conditions.

The fact that the measured RL has smaller variability than TL variability suggests that measurements of RL may not be reliable way to assess TL variability.

Future efforts should be focused on combining ocean measurements and ocean modeling with acoustic measurements and modeling.

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Acoustic Characterization of Stratified Estuaries

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ABSTRACT

Stratified estuaries present unique sampling challenges due to their intense spatial gradients and temporal variability. Narrowband acoustic scattering techniques have been used for decades as a tool for remote imaging of physical processes in energetic coastal environments, on spatial and temporal scales difficult to probe with in situ measurements. However, it has been challenging to infer quantitative information from the measured backscatter. Emerging broadband techniques result in increased spatial resolution spectral classification and quantification capabilities. Broadband backscattering collected in the Connecticut River Estuary over more than a decade, together with recent measurements from the James River, Mobile Bay, and Columbia River, have illustrated the potential of broadband acoustics for quantitative remote-sensing of microstructure intensity, as well as other processes, over relevant spatial and temporal scales. The importance of stratification, shear instability, and fronts in determining the coherence of acoustics signals for forward looking sonar imaging applications, as well as the impact of these features on acoustic communications and navigation, is under active investigation. Finally, novel platforms for deployment of broadband sonars, including the use of AUVs and towed platforms, have resulted in new advances in acoustic methods that support high-resolution observations of estuarine processes. [Work supported by ONR].

Keywords: Broadband Backscattering, Estuaries

1. INTRODUCTION

Estuarine environments, where fresh water discharge meets the denser ambient ocean water, are often characterized by strong spatial gradients in water velocity, density and sound speed, and intense mixing. Understanding estuarine mixing, circulation, and exchange flow remain important questions in estuarine oceanography [1].

High-frequency acoustic backscattering techniques, spanning 10s to 100s of kHz provide a unique and powerful tool to rapidly and remotely investigate the physical properties of the ocean interior over a large range of important spatial and temporal scales. These techniques have been commonly used to image physical processes that occur in the ocean interior, including, for example, internal waves [2-4], hydraulic jumps [5], bubbles [6-8], double-diffusion [9,10], thermohaline interfaces [11], oceanic pycnoclines [12], Langmuir circulation [13], suspended sediments [14,15], and microstructure (4,16,17). From an acoustics perspective, microstructure refers to fluctuations in temperature and salinity, resulting in fluctuations in sound speed and density, which in turn scatter sound, and occur at scales from sub-millimeter to tens of centimeters. Over the last decade or so, with the emergency of broadband acoustic scattering techniques [16, 18], significant advancements have been made in the ability to resolve small spatial scales relevant to estuarine mixing, fronts, and shear instability [17, 19, 20], and in spectral classification of different estuarine processes [8, 17].

2. METHODS

2.1 Estuarine Acoustics and the Under Sea Remote Sensing Program

High-frequency, broadband acoustic scattering techniques have been used by the author since 2008 to study the structure, dynamics, and mixing in the Connecticut River Estuary, USA [17, 19]. A current ONR-funded program, the Under Sea Remote Sensing (USRS) program, is aimed at using acoustic
remote sensing techniques to extend these studies to a variety of different estuarine environments, such as the James River Estuary, Mobile Bay, and the Columbia River Estuary, which span a wide range of the conditions that may be encountered in estuarine environments. Specific focus areas include the three-dimensional structure of surface fronts. Surface fronts are common features in many coastal environments where buoyant fresh water discharge meets ambient ocean waters. Convergence at these fronts entrains bubbles where strong downwelling and shear can further entrain and transport these bubbles. These bubbles represent strong acoustic targets with unique spectral fingerprints. Many of these processes, particularly the strong vertical and horizontal sound speed gradients, have a significant impact on the propagation and coherence of sound across a range of frequencies, with ramifications for sonar performance and acoustic communications. A secondary goal of the USRS program is to enhance the performance of AUVs, and other platforms, in challenging estuarine environments [21], and to continue the development of acoustic techniques for quantification of three-dimensional flow features, for example, by developing high-frequency multibeam sonars for estuarine studies.

Spectral characterization and high-resolution imaging of plume front

Figure 1. Broadband acoustic scattering from an plume front in the Connecticut River in 2017 obtained from upwards looking sonar on a REMUS 100 AUV.

2.2 Acoustic Instruments

A Kongsberg Marine Simrad EK80 WBT-Tube scientific echosounder was used with the ES70-7CD (50-90 kHz, 7° full beam width) and ES120-7CD (90-160 kHz, 7° full beam width) broadband transducers to perform the ship-board acoustic measurements. The transducers were pole mounted over the side of the MV Dawn Treader, together with a 1.2 MHz RDI Workhorse ADCP, and a 500 kHz M3 Kongsberg multibeam. Typical operating speeds ranged from 3-6 knots. Also deployed from the MV Dawn Treader was a towed CTD array comprised of 8 RBR Concerto CTDs with approximately .5m depth spacing and a v-wing towed underwater depressor (Boston Engineering model 460) to keep the towed array vertical. A REMUS-100 AUV (Hydridoid Inc.) was deployed with an upward looking Kongsberg Marine Simrad EK80 WBT-Mini scientific echosounder with an ES200-7CDK- Split 3(160-2600 kHz, 7° full beam width) and an ES333-7CD-Single (280-420 kHz, 7° full beam width) broadband transducers.

3. RESULTS

A number of results are published in references [8,17,19,20, 21]. Highlights of the measurements of acoustic scattering from bubbles entrained in estuarine plume fronts are shown in Figure 1 and highlights of high-frequency scattering from shear instability observed during ebb tides in the CT River Estuary are shown in Figure 2.
Figure 2. Spectral characterization and high-resolution imaging of shear instability in the Connecticut River Estuary obtained in 2017. On the bottom right is a 500-kHz multi-beam image of a similar shear instability.

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REFERENCES

Subsurface ducts and their impact on sound propagation off the Washington coast

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ABSTRACT
Data from an underwater glider taken off the U.S. West Coast near Washington State often show the existence of a subsurface duct, which may impact sound propagation. The depth of the minimum sound speed in the duct can vary from 30 m to 130 m. The vertical extent of the duct can vary from 10 m to 60 m. Available oceanographic models do not routinely predict the presence of these ducts, but efforts are underway to enable that capability. This paper examines the impact of such ducts on 3.5 kHz sound propagation. Using measured and modeled sound speed fields as input, the Parabolic Equation method is employed to evaluate transmission loss for different scenarios. It is found that subsurface ducts could have a strong impact on passive and active sonar. Improved ocean modeling can greatly improve sonar performance in the presence of subsurface ducts.

Keywords: Duct, Subsurface duct, Transmission Loss

1. INTRODUCTION
Subsurface ducts, or secondary ducts, have been observed by moorings and gliders off the Washington coast of the United States. They consist of a layer of ocean water that has slower sound speed, hence enabling long-range propagation of sound waves above a certain frequency in this layer. Such ducts have also been observed elsewhere, notably in the northeast Pacific off the Canadian coast [1], the Beaufort Sea [2], and off New Jersey coast of the United States [3, 4]. The presence of such subsurface ducts and their temporal evolution need to be considered in underwater acoustics applications. For this purpose, reliable oceanographic models which can provide forecast or hindcast of subsurface ducts are an effective tool. However, the detailed mechanisms which generate and maintain the ducts are not well understood, making ocean modeling of subsurface ducts an on-going research topic.

Experimental oceanographic and acoustic research focused on the subsurface ducts off the Washington coast is currently underway. This paper summarizes some of the results from acoustic simulations conducted in preparation for field efforts. The acoustic simulations are performed using the Parabolic Equation method at 3500 Hz. The measured sound speed field along an east-west transect by an underwater glider is used to represent the ocean environment for the simulations. Sound speed fields for the same transect and same time from two ocean models are used for comparisons. The purpose for this study is twofold: to investigate effects of subsurface ducts on mid-frequency sound propagation, and to assess the status of current ocean modeling capabilities on subsurface ducts.

2. SOUND SPEED FIELD DATA
2.1 Glider Data
The underwater glider, henceforth called the glider, in this paper refers to a coastal glider operated by the Ocean Observatories Initiative (OOI) [5]. The glider data employed in this analysis was taken 6–16 October 2018 along a 250-km transect off the Washington coast. The left panel of Figure 1 shows the glider transect,
which spans from the west on the continental slope in deep water to the east on the continental shelf in shallow water. While the left panel of Figure 2 shows the sound speed field along the entire transect, the right panel of Figure 1 gives the top 200-m portion of the sound speed profile taken at the 60 km from the western end of the transect. A subsurface duct is found throughout most of this transect with the minimum sound speed of the duct changing between 40–80 m depth. The thickness of the duct is between 30 m and 60 m. The duct has apparent range-dependence and complex depth-dependence. For example, the profile at the 60 km range on the right panel of Figure 1 has a double duct that has two minima, one near 70 m, the other near 140 m. The duct gradually tapers off toward shore. Above the duct, the surface mixed layer which reaches approximately 20-m depth has sound speed more than 15 m/s higher than the minimum within the duct. Immediately below the duct, the sound speed reaches a local maximum which is 2–3 m/s faster than the duct minimum. The sound speed at deeper depths is typical for October and is dictated by decreasing temperature and increasing pressure.

Figure 1 – Glider transect from 03:15, 06 Oct 2018 to 17:32, 16 Oct 2018 (left). Sound speed profiles (right) from the glider and two corresponding models at single point (corresponding to 60 km range in Figure 2).

It took the glider approximately 10 days to finish collecting data along this transect, therefore, the sound speed field displayed in left panel of Figure 2 is not a true ‘snapshot’ of the actual sound speed field, but rather an aliased version of it. The acoustic simulations reported in this paper are based on the following assumptions: (i) The sound speed field from the glider data is treated as a snapshot and any range-dependency of the field due to the finite speed of the glider is neglected. (ii) The glider data do not cover depths very close to the sea surface; the missing near-surface data is filled-in with a constant value that equals the

Figure 2 – Sound speed field measured by glider (left), GLORYS model (middle) and HYCOM model (right). The red curve is the seafloor. Colorbar is in m/s.
shallowest glider data point. In other words, the top layer of water is assumed fully mixed. (iii) The glider data do not cover depths close to the seafloor; the missing near-bottom data is filled in by extrapolation using the deepest portions of the glider data.

2.2 GLORYS12V1 Model Data

This model data product will be referred hereafter to as GLORYS. Details are given in [6], and the data is downloaded from Copernicus Marine Services [7]. The sound speed field determined from daily averaged temperature and salinity data in the GLORYS product along the same glider transect is employed for acoustic simulations. This reanalysis product has 1/12° horizontal resolution and 50 vertical layers. To match the glider data in the time domain, the model sound-speed field is constructed from the reanalysis output for the same day when the glider data was collected at a given location along the transect. Compared to the glider data, the GLORYS sound speed field (middle panel of Figure 2 and right panel of Figure 1) also shows the presence of a subsurface duct at similar depth, although the duct strength is weaker: the layer beneath the duct has sound speed 1.5 m/s greater than the duct minimum, less than that of the glider data. The GLORYS duct is also spatially smoother, which is largely the result of the model’s relatively coarse horizontal resolution. The basic features of the surface mixed layer and sound speed field beneath the duct are similar to those seen in the glider data, but not as persistent in range as in the glider data. It should be noted that GLORYS is a reanalysis product with assimilation of observational data.

2.3 HYCOM Model Data

There are several versions of HYCOM (Hybrid Coordinate Ocean Model). The model data employed in this paper is from the NOAA website given in [8]. The HYCOM model data is available every three hours with 40 vertical layers and with a horizontal grid spacing of 1/12°. The HYCOM sound speed field is from a single time slice at 12:00 UTC on 6 October 2018. While this sound speed field (right panel of Figure 2 and right panel of Figure 1) shows similar near-surface and deep-water profiles as those in the glider data, the subsurface duct is hardly present.

2.4 Acoustic Simulations

Sound transmission simulations are conducted using the three sound fields as input. All acoustic results reported are at 3500 Hz and are simulated using the PE (Parabolic Equation) method. The geoacoustic seafloor properties along the transect are not known. For this simulation effort, the sediment is assumed to be a homogeneous, fine sand half-space with sound speed 1630 m/s, sediment-to-water density ratio of 1.8, and attenuation coefficient of 0.5 dB per wavelength. For each of the remaining figures, the color bar gives the sound intensity in dB, except in the upper left in Figures 6 and 7 where it gives the sound speed in m/s.

The following two scenarios are investigated: (i) sound source depth-dependence where the source is placed above the duct, in the duct, and below the duct, respectively. (ii) Duct range-dependence where the sound source is at a fixed depth inside the duct but at different horizontal positions along the glider transect. In (i), results based on the glider data and the two model ocean data are compared. In (ii), results based on glider data are compared only to those based on the GLORYS model product.

Figures 3–5 compare the simulation results for scenario (i) where the sound source is placed at 60 km from the western end of the glider transect (see Figure 2), and its 4 depths are at 50 m which is above the duct, 100 m which is close to the duct axis, 140 m which is close to the minimum of the lower double duct, and 150 m which is below the duct. The reason for choosing 60 km as the starting range for the simulations is that this is the only area where the GLORYS model gives apparent subsurface duct, and HYCOM shows a hint of it. The results based on the glider data (Fig. 3) show the following features: (1) When the source is above or below the duct, the duct does not have an obvious effect on sound propagation, whereas when the source is in the duct, guided propagation results. (2) How tightly the duct confines the sound energy in depth strongly depends on source location relative to the duct axis. (3) The complex structure of the sound speed profile at the source depth causes the sound to be trapped at different depths of the water column, as evidenced in the cases for source depth at 100 m and 140 m in Figure 3. This is apparently the result of the double duct discussed earlier.

Results based on the GLORYS model (Fig. 4) show similar source depth effects as those from the glider data, but the trapped sound energy is weaker. The reason being that the GLORYS modeled duct is weaker than that from the glider as seen in Figure 2 as discussed before.

With the subsurface duct being largely missing, results using HYCOM data (Fig. 5) show only some intermittent trapping of sound near the depth of 100 m.
Figure 3 – Sound pressure squared for sound source at different depths using glider data. The high sound intensity near the 100-km range is due to bottom reflection.

Figure 4 – Sound pressure squared for sound source at different depths using GLORYS data.
Figures 6 and 7 compare the simulation results for scenario (ii) where the sound source is at 150-m depth but is placed at different positions along the glider transect, starting at the 10 km range. As seen in the top left panel of Figure 6, the subsurface duct in this portion has complex range-dependence and the lower boundary of the duct extends beyond the 160 m depth. The interesting feature from the glider data (Fig. 6) is sound refraction, or mode coupling: guided sound energy spreads vertically between 70 m and 150 m at ranges shorter than 50 km, but behaves differently beyond the 50-km range, due to the range-dependence of the duct. The simulations for the same case based on the GLORYS data (Fig. 7) do not show sound trapped by the subsurface duct because the duct depth is shallower at the chosen range.
Figure 6 – Glider sound speed field (upper left) and sound pressure squared for source at fixed depth, but at different positions along the glider transect. High intensity near the 50-km and 90-km ranges are due to bottom reflections.
2.5 Discussion

Simulations of acoustic propagation based on the glider sound speed field show that 3.5 kHz sound is well trapped in the subsurface duct if the sound source is in it. Once trapped, the sound tends to remain in the duct, even when the duct is range dependent. For a moving source, the trapped sound can be at different depth, depending on local sound speed profile at the source locations.

The GLORYS model shows the presence of the subsurface duct, but the duct is weaker and with less horizontal persistence. The modeled depth of the duct can be different from that of the glider data. Acoustic simulations based on these models partly capture the guided propagation seen in the glider data. Because they contain little range-dependence, the phenomena of mode coupling are not captured. The HYCOM model however has just some very weak indications of a duct.

The simulation results show that the GLORYS ocean model partly captures the characteristics of the subsurface duct, indicating the viability of employing ocean models to assist underwater acoustic applications. The HYCOM model largely missed the subsurface duct. Future model developments should focus on several areas: (1) Investigate the generation conditions of subsurface ducts. (2) With limited spatial and temporal model resolution, investigate how to characterize the variability of subsurface ducts in space and time. (3) Investigate the consequences of data assimilation to model forecasts of subsurface ducts.

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Numerical simulations of wavefields generated by UXO counter-mining: study of the transition from shallow to deep water

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ABSTRACT
Explosive devices from World War II are discovered almost every week on the French coasts and they must be destroyed by the French Navy Mine Warfare Office. The consequences of the counter-mining on the marine environment are complex to evaluate. In a previous work, we focus on the impact of the seismoacoustic waves generated by such explosions on the infrastructures located on the coast and illustrate the importance of interface waves in this context. In this presentation, we address a different perspective of this problem and analyze the wavefields generated by the counter-mining of unexploded ordnances towards deep waters. For this purpose, we performed several numerical simulations using 2D time-domain spectral-element software which allows for accurate handling of the characteristics of the complex marine environment (complex bathymetry and elastic sediments). We will focus on the role of the steep transition from shallow to deep water which takes place in the area where the counter-mining is triggered and on the influence of a thin sedimentary layer on the generated wavefields.

Keywords: Counter-mining, UXO, Wave propagation, Interface wave, Numerical modeling

1 INTRODUCTION
Historical unexploded ordnances (UXO) from World War II are discovered almost weekly near the coasts of northwest and southeast France. Soon after their discovery, they must be destroyed to ensure the safety of divers and ships. The preferred method of destruction is counter-mining, i.e. the use of a higher-order detonation carried out by the explosion of an additional donor charge placed near the UXO. Depending on whether the UXO can be safely moved, this counter-mining takes place at specific safe locations or at the discovery site. In a previous work [1, 2], we evaluated the risk of damage to buildings on the adjacent shoreline induced by the detonation of highly charged UXO in a variable shallow water environment. The importance of environmental characteristics was emphasized and in particular the need to consider the elasticity of marine sediments to account for interface waves. In this extended abstract, as a complement to that work, we study the structure of acoustic wavefields generated towards the deep water to investigate how acoustic energy is distributed in the water column in that direction.

In this extended abstract, we first build a 2D model corresponding to the transition from shallow to deep water in the same area where we previously performed experiments. Then, this model is used to perform numerical simulations in the time domain of acoustic and seismic wave propagation. Finally, the results of these numerical simulations are analyzed and some conclusions are drawn.

2 CONFIGURATION
We first identified a bathymetric profile corresponding to a transition path to deep water in the rade d’Hyères (Mediterranean Sea), where the experiments reported in previous works [1, 2] took place. This path is shown in Figure 1. Note that there is a steep transition from shallow to deep water. At the beginning of the path, the depth of the water column is almost constant and equal to 46m. Towards the middle of the path, the depth is 240m to finally ends at 800m. After designing the computational domain, a mesh of it is created using quadrilateral elements with the Gmsh software [3].

Numerical simulations are then performed using the open-source software SPECFEM2D which implements a spectral-element method. It is based upon a high-order piecewise polynomial approximation of the

1https://github.com/geodynamics/specfem2d
weak formulation of the wave equation and combines the accuracy of the pseudospectral method with the flexibility of the finite-element method. In this method, the wavefield is represented in terms of high-degree Lagrange interpolants, and integrals are computed based upon Gauss–Lobatto–Legendre quadrature. This combination leads to a perfectly diagonal mass matrix, which in turn leads to a fully explicit time scheme that lends itself very well to numerical simulations on parallel computers. It is particularly well suited to handling complex geometries and interface conditions. As a consequence, the accurate simulation of surface wave propagation is straightforward without any additional cost. This is a very important feature in our configuration since the influence of an interface wave of the Stoneley-Scholte type is known to be important. The numerical simulations are performed using the cylindrical coordinate system.

Two source positions are considered. The first position is “proud on the bottom”. In this configuration the charges are placed on the sea bottom. This position corresponds to the majority of the experiments which were done. The second position is “under barrel”. In this position, the UXOs are gathered in a barrel immersed at a depth of 11m under the sea surface. This source position is used to avoid the generation of vibrations at shore but is likely to generate more acoustic energy inside the water column.

We consider Very Low-Frequency acoustic propagation (VLF) by using a source time signal of the Ricker wavelet type with a central frequency of 25 Hz.

The bottom of the ocean is considered as an elastic medium. The physical characteristics are:

- Water: $\rho = 1000$ kg/m$^3$, $c_p = 1477$ m/s
- Bottom: $\rho = 2600$ kg/m$^3$, $c_p = 4100$ m/s, $c_s = 2700$ m/s

where $\rho$, $c_p$ and $c_s$ are respectively the density, the velocity of longitudinal waves and the velocity of shear waves.

3 NUMERICAL RESULTS

In this section, we present the numerical results obtained with the configuration presented in section 2. Figure 2 represents snapshots of the acoustic energy distribution in the water column for two source positions, namely “proud on the bottom” and “under barrel”. It can be seen that, when the water depth increases strongly, the way the acoustic energy is spreading into the water column is very different depending on the source position suggesting a very different structure of the acoustic wavefield.

3.1 Analysis of simulated time signals

To investigate more in detail the structure of the acoustic wavefield which is generated with the two source positions, we present in Figure 3 the signals received at several vertical arrays situated along the path towards deep waters. The vertical arrays have different lengths because they span the entire water column at different distances from the source for which the water depth is different.
3.2 Sound exposure levels

The Sound Exposure Level (SEL) is another physical parameter useful for the evaluation of the impact of the acoustic wavefield on the marine fauna. This parameter is given by the following relation:

$$SEL = 10\log \left( \int_0^T p^2(t)dt \right)$$
where $T$ is the length of the time signal.

It can be easily evaluated from time domain numerical simulations. In this subsection, we compare the SEL variations for the two source positions (“proud on the bottom” and “under barrel”).

We first evaluate the SEL variations with depth on several vertical arrays situated at different distances to the source (see Figure 4).

![Figure 4. Variation of the SEL on vertical arrays spanning the entire water column for six different distances to the source.](image)

For all vertical arrays, it can be noted that the SEL values for the “proud on the bottom” source are always greater than the SEL values for the “under barrel” source. This result is counter-intuitive and puts in light the strong effect produced by the interface wave. A 10 dB gap is present in the vicinity of the interface between water and sediments. In addition, a variation with depth of the SEL values is observed suggesting that it cannot be considered as constant in this configuration as usually guessed in the literature.

In a second step, we investigate the evolution of the SEL values with range at a given depth.

![Figure 5. Variation of SEL with source-receiver distance for three different depths.](image)

Figure 5 confirms the results of Figure 4 showing that when the receiver gets close to the interface the difference between the SEL produced by the two sources can be more than 10 dB. This difference is higher in the shallow water zone but remains non negligible even when reaching deeper waters.
4 CONCLUSION
In this extended abstract, we studied the propagation of acoustic waves generated by the counter-mining of UXOs in shallow water. Specifically, we investigated the structure of the acoustic wavefield which propagates towards deep waters. It was found that the interface waves generated during disposal are critical highlighting the absolute necessity of considering the elasticity of sediments in this type of studies.

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Temporal variability of mid-frequency sonar in a deep bay

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ABSTRACT
Mid-frequency (2-10 kHz) sound propagation and reverberation are sensitive to temporal changes in the ocean environment which can produce significant signal variability on timescales ranging from minutes to hours. To study this temporal variability, an experiment was conducted in January 2020 in Dabob Bay using fixed source and receivers to measure transmission loss, reverberation level, and ambient noise over a 10-day period. Over the course of the experiment, several storms passed over the site producing significant surface waves and an influx of cold, fresh water which formed a surface layer, the structure and thickness of which varied over time. The surface roughness and freshwater layer, as well as a significant tidal exchange, were the major drivers of mid-frequency acoustic intensity variability observed within the bay. Despite the confined nature of the bay, the significant variation in the depth (30-185 m) makes the environment similar in many respects to the ocean shelf. This talk provides an overview of the variability of the acoustic measurements made over the course of the experiment, relates that variability to environmental factors, and discusses how those factors would manifest in the ocean environment.

Keywords: Mid-frequency sonar, transmission loss, reverberation

1. INTRODUCTION
A major challenge in the use of mid-frequency (2-10 kHz) sonar for passive and active target detection is signal uncertainty. For passive sonar, it is not uncommon to encounter 20 dB or greater transmission loss (TL) variability in the matter of hours, even minutes (1). For active sonar, signal excess suffers two-way TL uncertainty as well as varying reverberation. In addition, in some applications, active sonar performance relies heavily on TL estimates to make sonar predictions. This signal uncertainty comes from lack of knowledge of environment, which includes sea surface roughness, entrained bubbles, water column variability due to changing oceanographic conditions, and bottom complexity. Unlike low-frequency sonar, where the wavelengths are on the order of meters, mid-frequency sonar wavelengths are 10s of centimeters and variations in environmental properties at these length scales will have a larger impact on mid-frequency propagation and reverberation. It can be difficult to assess the relative importance of different sources of environmental variability at these length-scales since they are not only difficult to measure over large areas, but multiple sources of variability may be impacting propagation at the same time. For sonar performance prediction based on ocean modeling, even if the impacts of environmental variability are well understood, the relevant length-scales are smaller than the resolution of most ocean models and it’s unclear whether the model fidelity could ever reach the point where they could be predicted deterministically.

To systematically investigate such uncertainty issues, it would be desirable to have a testbed where repeated experiments can be performed during different seasons and under varying wind, tide, ambient noise, and other oceanographic conditions. There are several open ocean sites that have seen repeated acoustic experiments such as the Atlantic coast of Florida (2) and the New England shelf (3). The difficulty with an open ocean site is that they can be challenging to access frequently due to distance from shore, comprehensive environmental characterization requires extensive, repeated measurements, and in some seasons, the weather conditions may not permit access at all. Sheltered bodies of water such as lakes, bays, and lagoons allow for easier access and the potential for the long-term installation of measurement equipment, but by their very nature, the environmental conditions in these waters can

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be very different from those encountered in the open ocean. By careful selection of a sheltered site, however, it may be possible to study the variability of mid-frequency sonar due to variations under a subset of environmental conditions. This not only isolates the mechanisms driving variability and uncertainty but also reduces the extent of the environmental characterization needed to understand those mechanisms.

As a first step towards the goal of developing a mid-frequency sonar testbed, a mid-frequency propagation and reverberation experiment was conducted in Dabob Bay, WA. Dabob Bay is a 185-m-deep fjord extending 20 km to the north from its entrance at the Hood Canal in Puget Sound. The orientation of the Hood Canal and Dabob Bay are such that during the January time frame of the experiment, prevailing winds blow north along the canal and into the bay with sufficient fetch to generate significant wind-driven waves which propagate up the length of the Bay. The wind waves, along with the injection of fresh, cold water from river and streams into the bay, produces an environment where the combined effects of a variable surface acoustic duct and rough sea surface on mid-frequency propagation and reverberation can be studied. This paper provides an overview of the experiment, highlights several acoustic observations of TL and reverberation level (RL) variability during the experiment, and discusses the potential for future experiments within the bay.

2. EXPERIMENT OVERVIEW

This paper will focus on measurements made using two acoustic systems deployed as shown in Figure 1 in Dabob Bay during 21-30 January 2022. The Autonomous Reverberation Measurement System (ARMS), shown in Figure 1, is a bottom lander with a directional source and 4-element receive array. The source and receive array are mounted on a motorized rotation stage and the system can be programmed to transmit and collect reverberation data over a 270-degree azimuthal range. The system can transmit pulses at 3-6 kHz with a maximum source level of 210 dB. For the Dabob Bay experiment, the ARMS transmitted 1-sec-long LFM pulses with a center frequency of 3.5 kHz, a source level of 200 dB, and bandwidths ranging from 100 Hz to 3000 Hz. The ARMS was deployed in shallow water at approximately 50 m depth near the northern end of the bay. The ARMS source has a 1.2-m-wide horizontal aperture and when combined with the horizontal array of 4 elements separated by 0.46 m, this produces a combined beam pattern that is 11 degrees wide at the 3 dB down and sidelobes at -22 dB. The second system was a moored vertical line array (VLA) with 10 hydrophones distributed over 37 m and which could be moved as a group to different depths in the water column. The array was moored at roughly 180 m depth and 5.5 km to the southeast of the ARMS such that the bearing from
the ARMS to the VLA was roughly parallel to the long axis of the bay. For the measurements discussed here, the ARMS was typically oriented so that it was transmitting in the direction of the VLA.

Near the location of the ARMS, several oceanographic instruments were deployed to monitor the environment over the course of the experiment. These included an upward-looking ADCP deployed in 30 m water on a bottom lander, a thermistor chain consisting of 10 sensors evenly spaced and deployed in 60 m of water, and a Datawell Waverider buoy which continuously recorded wave spectra data over most of the experiment. In addition to these stationary instruments, a series of CTD casts were periodically made at 500 m intervals along the line connecting the ARMS and the VLA. These measurements provided a rough estimate of horizontal variability of the sound speed as a function of depth along the propagation path between the source and receive array.

![Figure 2](image)

**Figure 2** – (a) Omnidirectional wave spectra recorded by the Datawell Waverider buoy over the course of the experiment. (b) Rose plot showing distribution of RMS wave heights and direction. (c) Sound speed field measured between the ARMS and the VLA on 27 January 2020.

The decision to conduct the experiment during January was based upon historical meteorological data which showed that during the winter, there are frequent storms, and the associated wind blows predominately from the southwest. This causes waves to build up along the Hood Canal and into Dabob Bay. This was indeed the case during the 2020 experiment as can be seen in the omnidirectional wave spectrum (Figure 2a), where frequent wave events can be seen, and the distribution of wave directions (Figure 2b) which appear to be predominantly from the southwest. The wave buoy was deployed near the ARMS, in shallow water, and we believe that the incoming waves were refracted shoreward as they approached the buoy. In the deeper waters of the bay, the waves were aligned closer to the ARMS-VLA line and the acoustic propagation path between the two systems is approximately parallel to the wind wave direction.

Another consequence of the frequent storms is the influx of cold, fresh water into the bay from streams and rivers. This incoming water formed a low sound speed layer near the surface of the water column, as can be seen in the CTD measurements shown in Figure 2c, and the boundary separating the cold, fresh water and the underlying warm, brackish water, varied over the course of the experiment between 8-15 m. Below the fresh water layer, the sound speed increases as a function of depth and below 100 m it is governed by increasing pressure and constant temperature. The sound speed profile within the bay is also consistent with historical measurements taken during January and February.

While no sediment characterization was performed as part of the 2020 experiment, historic measurements within the bay indicate that above 100 m, the sediment is predominantly silty sand while below 100 m, the sediment is silt (4). Sub-bottom profiling and passive fathometer measurements suggest that the deep silt sediments are in a roughly 7 m thick layer above a harder,
3. VARIABILITY OF TRANSMISSION LOSS AND REVERBERATION LEVEL

During most of the experiment, the ARMS was oriented so that the main lobe of the directional array was aligned with the VLA. The ARMS was programmed to transmit a 1-sec-long pulse every 20 s while the VLA was continuously receiving. An example of the TL measured on a single hydrophone at 44 m depth for each ping over a 12-hour period on 28 January 2020 is shown in Figure 3a. Both the ARMS and the hydrophone were located near the same depth and towards the bottom of the thermocline. Consequently, the measured signal is dominated by sound that is trapped in the surface duct as can be seen in the ray trace in Figure 2b where only rays with launch angles from -4 to 4 degrees are shown. Above and below these launch angles, the rays are no longer trapped, reflect from the seafloor, and at the VLA, their arrivals are distributed sparsely throughout the water column. This is consistent with the field intensity simulated using the parabolic equation which is shown in Figure 3c.

![Figure 3a](image1.png)

### Figure 3 – (a) TL measured on a hydrophone at 44 m depth (red) and the incoherent average over all 8 hydrophones distributed between 19 m and 56 m (black). The pings transmitted by ARMS were 3.5 kHz center frequency, 100 Hz bandwidth, 1-s-long LFM pulses. The lower plot shows the RMS wave height measured over the (b) Ray trace for the sound speed shown in Figure 1c for rays with launch angles between ±4 degrees. (c) Intensity field calculated using a parabolic equation solver for 3.5 kHz.

In the TL for the single hydrophone shown in Figure 3a, there are two types of variability present; large fluctuations where the TL changes by 10-15 dB over time-scales on the order of 30 min and smaller fluctuations that occur over very short time scales. Comparison of the TL time series with the RMS wave height measured over the same period indicates that these small fluctuations occur when the sea surface is rough. A possible explanation for these fluctuations could be that the sea surface roughness produces small changes in the propagation paths for those rays that interact with the surface. This in turn produces phases shifts in the eigenrays arriving at the hydrophone which leads to random intensity fluctuations due to the interference of the rays. We expect no appreciable increase in the TL as a result, an expectation that is consistent with the data. In the Kirchhoff approximation, the coherent reflection coefficient is $e^{-\frac{\chi^2}{2}}$, where $\chi = 2kh\sin\theta$, k is the wavenumber, h is the RMS roughness,
and $\theta$ is the grazing angle with the surface. For the center frequency of 3.5 kHz, the measured RMS roughness of 0.1 m, and assuming a grazing angle of 4 degrees, the reflection coefficient is 0.98 or a loss of 0.18 dB per surface interaction. Given that the ray trace indicates that sound trapped in the surface duct has only 2-3 interactions with the surface between ARMS and the VLA, any increase in TL due to the rough surface is negligible.

The larger fluctuations which occur over larger timescales, with the intensity varying over 15-60 min. These fluctuations aren’t correlated with the presence of the rough surface and are most likely due to tidal fluctuations and changes in the surface duct. The tidal range was 3 m over the course of the measurements shown in Figure 3a and preliminary PE simulations have shown that this may be contributing to these larger fluctuations. Of equal or greater importance, however, may be changes in the surface duct which are due in large part to changes in the influx of fresh water from rivers and streams feeding into the bay. ADCP and CTD measurements show that the depth of the boundary separating the fresh and brackish water increased by 2.5 m over the first 4 hours of the measurements and then fluctuated with increasing and decreasing in 2-hour intervals. These changes in thickness were also accompanied by small vertical and horizontal differences in sound speed within the duct, again driven by the influx of fresh water.

Unlike the variations induced by the surface roughness, these longer time variations appear to suggest large scale changes are being induced in the intensity field structure. For example, the ray trace in Figure 3b indicates that along the length of the surface duct, the rays, and hence the intensity field, form patterns similar to convergence zones. Changes in the width of the fresh water layer may expand or contract these patterns, changing the vertical intensity pattern at the range of the VLA.

These large fluctuations in TL can be reduced 5-10 dB by incoherently averaging over the intensity measured across the hydrophones in the array as shown by the black points in Figure 3a. Given that the sound travelling inside the duct does not interact with the seafloor and experiences little loss as a result, the net flux of energy through the vertical aperture should not change with small compressions of and variations within the duct. The remaining fluctuations are likely the result of the sparseness of the array. This mean loss can be estimated by assuming cylindrical spreading loss and taking into account the angular portion of the total energy from the source that is trapped in the duct:

$$\langle TL \rangle \approx 10 \log_{10} R - 20 \log_{10} \left( \frac{\Delta \phi}{180^\circ} \right) = 64.4 \text{ dB},$$

where $R = 5.5 \text{ km}$ and $\Delta \phi = 8^\circ$, consistent with the mean level in Figure 3b.

Figure 4 – (a) Polar plot of reverberation measured on ARMS in Dabob Bay. (b) Comparison of the mean reverberation measured along the ARMS to VLA line over two-hour periods when the RMS sea surface height was $h \approx 0$ m (black) and when $h = 0.12$ m. (c) Comparison of incoherent mean (blue) and coherent mean (red) of the reverberation measured during the calm period. (d) Comparison of incoherent mean (blue) and coherent mean (red) of the reverberation measured during the rough period.
Using the ARMS as a source for the propagation measurements described above, made it possible to simultaneously measure monostatic reverberation associated with each of the transmitted pings. In addition, to these fixed bearing transmissions, the ARMS was also programmed to collect reverberation over its full 270-degree measurement range to provide a polar plot of reverberation shown in Figure 4a. This angular measurement helps to understand the reverberation features in Figure 4b which shows the incoherent average of the reverberation measured when the ARMS transmitting towards the VLA, indicated by the black circle in Figure 4a. At ranges less than 1.5 km, the reverberation is high and can be associated with scattering from the sediment, likely sand, on the slope where the ARMS was deployed. Beyond 1.5 km, the reverberation begins to drop off until 4.5 km, where the outer edge and side lobes of the source/receive array beam pattern is reflected from Pulali Point, indicated by the black arrow in Figure 4a.

Unlike the TL measurements on the VLA in the upper water column, the reverberation is driven not with sound trapped in the duct, but instead with sound leaving at steeper grazing angles and which scatter from the bay floor. As a result, the sound is weakly affected by the tides, layer thickness, or changes in the sound speed within the duct. This sound does interact with the sea surface, so the variations in the TL due to the rough sea surface will impact the RL as well. In Figure 4b, the mean reverberation measured when the bay is calm does not decrease as the roughness increases. This is consistent with the observation that the roughness does not appreciably increase the TL. The roughness does have the effect of “smoothing” the reverberation; while the overall RL level is maintained, the small-scale structures in the curve are missing. See for example the change in response between 3-4 km and 5-6 km in Figure 4b.

These changes can be partially understood by looking at the coherent vs. incoherent mean reverberation during the calm and rough periods. Figure 4c shows the incoherent mean and the coherent mean of the reverberation over a two-hour calm period. In this case, the two RL curves are very similar and hence there is high ping-to-ping correlation. When the surface roughness comes up, the variability in the TL observed on the VLA manifests as a blurring or smearing of the seafloor scattering. While this does not impact the overall shape of the RL curve, it will have an impact on the ability of the mid-frequency sonar to resolve a target.

The reverberation scan in Fig. 4(a) shows several strong highlights around the shores of the bay when the ARMS beam is aimed close to perpendicular to shore. While these highlights are expected, the quantitative scattering level at those highlight spots are not fully modeled and understood. Doing so will provide understanding of bottom scattering mechanisms in this unique setting where acquiring measurements of bottom properties is relatively easy. In addition, these stationary strong scattering features can serve as known targets. Measurements of scattering strength from these targets under varying wind and seasonal conditions can help shed light on propagation variability.

The analysis so far indicates that for this winter environment, only those rays propagating at relative steep angles interact with the bottom. Isolating those ray arrivals on the TL can provide clean data for inverting bottom properties. Similar inversions can also be attempted using RL data which is due to scattering by high angle rays.

Finally, and perhaps most importantly, such simultaneous TL/RL measurements offer realistic opportunities to jointly model transmission and reverberation. Historically, few such joint measurements are conducted. Consequently, TL and RL modeling are often considered separate problems, and consistency of the models are seldomly checked. Only by doing so with confidence can one hope to utilize RL data to make estimates of TL for active sonar.

4. Future Experiments

For studying rough surface impacts on TL and RL, Dabob Bay provides an easily accessible, repeatable testbed. Using the same equipment as deployed in the 2020 experiment, the impacts of the rough sea surface on broadband TL and RL can be studied. Also, by moving the source or VLA to different locations, the angle between the acoustic propagation path and the wind wave direction. The case where the acoustic propagation and wind wave directions are perpendicular is of particular interest since common 2-D modeling approaches, such as rough surface PE, fail to capture the impacts of the wave field in this case. Moving beyond the 2020 experiment, if a longer VLA is deployed, preferably one that spans the water column, the propagating acoustic field can be differentiated into different angles, and spatial coherence under different wind and wave conditions can be fully examined.
Historical measurements indicate that the sound speed profile in the bay evolves over the course of the year, with a secondary ducts forming in the Spring and Fall. During these periods, the bay would be a natural laboratory to study the impacts of the duct on transmission loss and target detection using the scattered return from the shoreline as discussed in the previous section.

5. SUMMARY

This paper highlights several of the measurements and observations from a 2020 experiment in Dabob Bay where mid-frequency transmission loss and reverberation level were measured simultaneously. By conducting the experiment in the bay during a period when regular winds generated waves along the acoustic propagation path, the impact of the waves on TL and RL could be separated from variability due to tidal and fresh water intrusion. Joint TL and RL modeling remains to be done, but the extensive environmental characterization and the separation of the different sources of environmental variability, should simplify the modeling approaches necessary to reconcile the TL and RL measurements.

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Sub-Surface Shear Wave Velocity Images by Ocean Ambient Noise

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ABSTRACT

Sub-surface shear wave velocity images are particularly interesting for geotechnical engineering, assessment of geohazards and reservoir characterization, and production monitoring. This study analyzes one-hour ocean ambient noise recorded by a Permanent Reservoir Monitoring System for sub-surface characterization. The recorded noise is very short with strong directional interference resulting in a bias in travel-time measures between a pair of sensors using seismic interferometry. A pre-processing technique, an adapted eigenvalue-based filter, is applied to the noise recordings to suppress the interference and obtain reliable Green’s functions. Scholte-wave phase velocity dispersion curves are extracted from the retrieved Green’s functions. With a limited recording time, detailed images of the shear-wave velocity structure below the recording system are obtained by a nonlinear inversion. This study demonstrates the effectiveness of the pre-processing technique and shows the potential of the technique in ambient noise processing and passive seismic interferometry.

Keywords: Passive seismic interferometry, Dispersion curves, Green’s function, Shear wave velocity images

1. INTRODUCTION

Knowledge of sub-surface shear-wave velocities is of importance for geotechnical engineering, assessment of geohazards and reservoir characterization, and production monitoring [1-2]. Shear-wave velocity can be estimated from dispersion curves of seismic interface waves by active seismic measurements [3-4]. An alternative is to use passive seismic interferometry that uses the ocean ambient noise cross-correlations recorded by receiver pairs to reconstruct the subsurface impulse response. An estimate of the Green’s function between the receivers can be obtained. The waves in the Green’s function usually carry useful information about the environment between the receivers. As an environmental-friendly passive imaging technique, passive seismic interferometry significantly enhances the importance of naturally occurring ambient noise. It makes it possible to image subsurface structure and monitor temporal sub-surface changes [5]. This technique requires that the noise field be diffuse and equipartitioned [6]. However, the noise field in the real world is usually contaminated by strong, directional sources, introducing biases into the retrieved Green’s functions. Wu et al. [7] reviewed the techniques, and they proposed an adapted eigenvalue-based filter (AEF) to suppress the interference of strong directional sources and improve the quality of the estimate of the Green’s function. In this paper, the proposed AEF is applied to perform shear-wave velocity images on a very short recording of ocean ambient noise that was severely contaminated by strong interference.

2. DATA ANALYSES

The data used in this study contains 1.02 hours of ocean ambient noise recorded by a permanent reservoir monitoring (PRM) system installed by Equinor at the Grane oil field in the North Sea [7]. The PRM system consists of 17 cables from 1.5 km to 12.85 km. The cable spacing is 300 m, and the sensor spacing is 50 m. The sampling frequency is 500 Hz, and the water depth is 125 m. Each sensor station consists of 4 components (pressure and three components of particle velocity). Only the pressure component is analyzed in this paper. The noise recordings are severely contaminated by strong directional events (airgun signals, earthquakes, and other events with higher energy than the background noise), as shown in Figure 1. The AEF is applied to the sample covariance matrix \( \hat{R}(f) \) to suppress the noise and retrieve reliable noise cross-correlations.
\[
\hat{R}(f) = \sum_{k=1}^{K} \hat{\lambda}_k \hat{\nu}_k \hat{\nu}_k^H + \sum_{k=K+1}^{N'} \hat{\lambda}_k \hat{\nu}_k \hat{\nu}_k^H + \sum_{k=N'+1}^{N} \hat{\lambda}_k \hat{\nu}_k \hat{\nu}_k^H \\
= \hat{\lambda}_s + \hat{\lambda}_d + \hat{\lambda}_i
\]

where \( \hat{\lambda}_s \) is related to the strong directional noise, \( \hat{\lambda}_d \) to the diffused noise, and \( \hat{\lambda}_i \) to the uncorrelated noise [8]. The key is to determine the eigenvalues \( K \) and \( N \) values. Figure 2 illustrates the energy distribution of beamforming of a gather (30 sensors) before (left column) and after (right column) applying the AEF. It is clearly shown that there are strong directional events in Figure 2(a) and 2(c), while it is more uniformly distributed after applying the AEF (Figure 2(b) and 2(d)). Reliable Green’s functions of a gather (30 sensors) can be retrieved, and the dispersion curves can be extracted. With 25-sensor overlapping, 537 gathers are obtained, and 537 sets of dispersion curves are extracted for the entire PRM system.

3. RESULTS AND DISCUSSION

Nonlinear inversion, adaptive simplex simulated annealing (ASSA) [9], is applied to the extracted 537 sets of dispersion curves (only fundamental mode is used) to perform 3D shear-wave velocity structure in the area of the PRM system. It is assumed that the geoacoustic model is a homogenous layered model. The shear-wave velocity and layer thickness of each layer are estimated parameters, and P-wave velocity and density in each layer are related to shear-wave velocity by the empirical formulas [8]. The shear-wave velocity images beneath the PRM system are obtained. The inversion results indicate a 4-layered sub-bottom structure: the top layer is a thin and soft layer with a thickness of \(~15\) m and a shear-wave velocity of \(~300\) m/s; the thickness and shear-wave velocity of the second and the third layers are \(~100\) m and \(~500-600\) m/s, and \(~260\) m and \(~800-900\) m/s, respectively. The interfaces of the top layers are clear, and the shear-wave velocity distribution is relatively homogeneous over range. The layer thickness of the bottom layer is larger than 500 m, and it is a high-velocity layer with a shear-wave velocity spanning 900-1300 m/s. The velocity value can be even higher in several areas, indicating a more complicated structure than the top three layers. The estimated shear wave velocity sub-structure is compared with the active-source reflection tomography [10] in the same field, and they are very similar. However, the active-source reflection method gives better resolution due to its higher energy level.

4. CONCLUSIONS

Shear-wave velocity tomography of the sub-surface is performed using only 1.02 hours of ocean ambient noise. The noise is severely contaminated by strong directional events. An adapted eigenvalue-based filter (AEF) is proposed to suppress the severe interference. The technique shows good effects both in beamforming and noise cross-correlation results. The nonlinear inversion is used to perform the sub-surface shear-wave velocity tomography. The inversion results indicate a four-layer sub-bottom structure with a generally increasing velocity as depth. The distribution of the velocity values in the first three layers is relatively homogeneous, while the fourth layer shows a more complicated distribution, indicating a heterogeneous structure under 500 m. The comparison of the imaging result with the active-source reflection method demonstrates that the tomography obtained in this paper is reasonable and encouraging even though the ambient noise is short and contaminated.
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Geoacoustic inversion at sea made easy using simple hand-deployable acoustic systems

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ABSTRACT
Ocean acoustic experiments often rely on complex experimental assets. Standard equipment used for geoacoustic inversion usually includes at least a horizontal or vertical line array of hydrophones and a powerful sound source (e.g., a towed transducer or an explosive/implosive system), as well as a large research vessel. In this article, we propose a simple and low-cost pair of experimental assets to collect marine acoustic data for geoacoustic inversion: a “TOSSIT” sensor mooring and a “RIUSS” (Rupture Induced, Underwater Sound Source). The TOSSIT is a hand-deployable tetherless bottom lander with a single-hydrophone recorder and an acoustic release, while the RIUSS is an expendable hand-deployable acoustic source system that produces a high-amplitude impulsive signal. The combination of RIUSS and TOSSIT enables state-of-art single-hydrophone geoacoustic inversion, e.g. using warping and trans-dimensional methods. To validate the system, a geoacoustic experiment was performed using these assets from a comparatively small and inexpensive fishing vessel in March 2021 on the New England Mud Patch. Inversion results compare favorably with previous results obtained using data collected with standard equipment on the same track during the 2017 Seabed Characterization Experiment.

Keywords: Acoustic instrumentation, Geoacoustic inversion, New England Mud Patch, SBCEX, warping

1. INTRODUCTION
In shallow water and littoral environments, sound propagation is greatly influenced by the seabed properties. Estimating these properties \textit{in situ} using ocean acoustics is an active research field, and various geoacoustic inversion methods have been developed. Standard equipment used for geoacoustic inversion usually includes at least a horizontal or vertical line array of hydrophones and a powerful sound source (e.g., a towed transducer or an explosive/implosive system), as well as a large research vessel. The deployment of such systems is often challenging and expensive, which effectively reduces the number of arrays that can be deployed for a given experiment, and the number of experiments that can be performed over a given time period.

In this article, we propose a simple and low-cost pair of experimental assets to collect marine data for geoacoustic inversion: it relies on the use of a “TOSSIT” passive acoustic mooring and a “RIUSS” (Rupture Induced, Underwater Sound Source).
2. **TOSSIT**

A TOSSIT is a custom-made mooring developed at the Woods Hole Oceanographic Institution (WHOI). It consists of a Soundtrap acoustic recorder (ST300) and a VEMCO acoustic release (V2R). It is mounted on a rope-free and shackle-free frame.

The TOSSIT's simple rope-less concept removes strumming noise and entanglement risk for marine life. Thanks to their simplicity, TOSSITs can easily be deployed from small (e.g. rigid-hull inflatable) boats or from large oceanographic vessels. All the TOSSIT components are depth rated to at least 500 m.

Figure 1 shows a TOSSIT picture as well as its assembly design. A detailed description of the TOSSIT can be found in Ref. [1].

![Figure 1: A TOSSIT mooring.](image)

3. **RIUSS**

The RIUSS is a simple device used to create high amplitude, broadband acoustic pulses for underwater acoustics experiments and surveys [2]. It uses a submersible vacuum chamber and a rupture disc, which is an expendable diaphragm that breaks under a given static pressure.

A RIUSS is a fully mechanical system without any electronic components. To deploy a RIUSS, the unit is simply lowered or dropped through the water column until the pressure differential between the two faces of the disc exceeds that of the disc’s pressure rating. Upon rupture of the disc, a quick inrush of water collapses into the evacuated chamber, which creates a high amplitude, broadband acoustic pulse.

In this article, we consider an expandable version of the RIUSS [3] which can be hand-deployed in a quick and easy expendable manner from any kind of vessel. A picture of this system is shown in Fig. 2.
4. AT SEA EXPERIMENT AND INVERSION

A TOSSIT/RIUSS experiment was performed on May 21 2021 on the New England Mud Patch (NEMP), about 100 km south of Martha’s Vineyard, MA, USA. The experiment was performed from a 22.5 m long scallop fishing vessel, the F/V Kathryn Marie.

Several TOSSIT/RIUSS were deployed by hand by two operators, and two CTD casts were performed using an autonomous instrument attached to a fishing winch. At the end of the experiment, the TOSSIT were recovered by the same operators using a pole with a hook. The whole experiment, once the NEMP experimental site was reached, was run in less than four hours.

The data collected on a single TOSSIT/RIUSS pair is considered here. Time-frequency modal dispersion was estimated using warping. Those dispersion data were subsequently used as input for Bayesian trans-dimensional geoacoustic inversion. The inversion results, which will be presented in detail during the conference, compare favorably to results obtained with data collected on the same track with traditional assets (e.g. a vertical line array) during the 2017 Seabed Characterization Experiment.

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Application of noise interferometry to acoustic characterization of the coastal ocean on different time scales

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ABSTRACT
Noise interferometry takes advantage of uncontrolled, spatially distributed noise sources to extract environmental information by cross-correlating acoustic pressure recorded by hydrophone pairs. Empirical estimates of the Green’s function are obtained from two-point noise cross-correlation functions (NCCFs), which serve as the signal to probe the ocean. For each hydrophone pair, detailed and robust environmental information is retrieved by using the warping transform to separate normal mode components of NCCF and measure their dispersion curves. The methodology has been applied to the data acquired in the Straits of Florida and on the continental shelf off New Jersey. Geoacoustic parameters of the seabed are found from NCCFs evaluated using long averaging times of about 1–2 weeks. Similar averaging times are employed to characterize subseasonal variations in the sound speed profile (SSP) in water. In dynamic environments, these sound speed profiles describe time averages of the sound speed. It is found that long-range NCCFs can be also reliably retrieved with noise averaging times as short as one minute, which suggests the ability to passively monitor ocean dynamics in real time. The inversion results obtained with long and short averaging times will be compared and discussed. [Work supported by NSF, ONR, and MOST.]

Keywords: Noise Interferometry, Time Warping, Passive Inversion

1. INTRODUCTION
Acoustic noise interferometry (NI) (1-3) exploits ambient and shipping noise as a signal to probe the ocean environment and offers a way to measure its physical parameters without using any controlled sound sources. This passive technique relies on time averaging to retrieve empirical Green’s function from noise cross-correlations using hydrophone pairs. We obtain noise cross-correlation functions (NCCFs) on different time scales using the data acquired in two experiments (4, 5). In each experiment, 1–2 weeks of noise were recorded on near-bottom hydrophones, and cross-correlation functions were calculated up to distances of about 8–10 km, or 100 water depths (Sec. 2.1 and Sec. 2.2). A signal processing technique, time-warping transform (6), was applied to extract dispersion curves of normal modes from the obtained NCCFs (Sec. 2.3). The passively measured dispersion curves have been inverted for the geoacoustic properties of ocean bottoms (7, 8), and to characterize the sub-seasonal sound speed variations (9) (Sec. 3).

2. EXPERIMENTS AND NOISE CROSS-CORRELATION FUNCTIONS (NCCFs)

2.1 Florida Straits 2012 Experiment (FL12) with one NCCF from 6-day noise time series
The experimental site of FL12 noise interferometry experiment is illustrated in Fig. 1(a). The acoustic noise recorded by two hydrophones A and B, separated horizontally by 5.01 km on the continental shelf close to the 100-m isobath in the Straits of Florida [Fig. 1(b)] were employed to construct the NCCF shown in Fig. 1(c). The negative- and positive-time-delay parts of the NCCF, abbreviated as N-NCCF and P-NCCF, respectively, approximate the Green’s functions, which

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correspond to sound propagation in opposite directions between hydrophones A and B. The largest NCCF amplitudes and best signal-to-noise ratio (SNR) for retrieving the empirical Green’s functions are found at time delays 3.20 s < |τ| < 3.80 s as the signal portions within the dashed-box indicated in Fig. 1(c). With NI, this two-point cross-correlation function of noise from hydrophones A and B serve as the probing signals and replace the Green’s function measured in traditional active acoustic remote sensing.

2.2 Shallow Water 2006 Experiment (SW06) with 32 NCCFs from 15-day noise records

The multi-institutional SW06 experiment was carried out on a continental shelf about 120 nm from New York Harbor illustrated in Fig 1(d). The SW06 site is known for strong and rapid variations of the sound speed in the water column due to energetic internal gravity waves, including internal tides to make the application of NI more challenging. In the previous Sec. 2.1, only one hydrophone pair was employed to develop one NCCF. Here a single hydrophone receiving unit (SHRU) and a horizontal line array (HLA) of 32 hydrophones shown in Fig. 1(e) were employed. The spacing of HLA hydrophones is 15 m, and the distance between SHRU and the HLA hydrophones ranges between 3.4 and 3.8 km. With 32 hydrophone pairs, 32 NCCFs illustrated in Fig. 1(f) were obtained.

2.3 Time warping to retrieve normal mode travel times from NCCF

A single-receiver modal filtering method, the time-warping transform, was applied to a NCCF to separate contributions of individual normal modes and extract the modal dispersion curves. The dispersion curves are sensitive to environment and thus suitable as input data for an inverse problem to retrieve geoaoustic properties of ocean bottom, the sound speed profile (SSP) in the water column, etc.

The negative-time-delay part, N-NCCF between SHRU and the first HLA hydrophone in Fig.1(f) was used as an input signal to interrogate the ocean environment, with its modal decomposition process illustrated in Fig. 2 to retrieve mode 2 dispersion curve as an example. This procedure was repeated, and frequency dependence of the travel time was determined for the first three modes using optimum, mode-, and HLA hydrophone-specific time-frequency masks for all measured N-NCCFs in Fig. 1(f).
3. INVERSION RESULTS AND CONCLUSION

3.1 Geoacoustic inversion

Assuming a geoacoustic model with five unknown parameters [Fig. 3(a)], the noise cross-correlations obtained in the SW06 experiment were employed to characterize the ocean bottom. The travel times and group speeds of normal modes were passively measured from the NCCFs of 15-day averaging by the time warping technique outlined in Sec. 2.3. Mode dispersion curves were inverted to estimate the five unknown geoacoustic parameters. As an illustration of the inversion process, Figure 3(b) presents a sensitivity analysis of the model-data mismatch to sound speed in the sediment layer. The inversion results from SW06 are largely consistent with earlier geoacoustic inversions employing controlled sound sources in the same general area (10).

3.2 Sound speed profile (SSP) inversion

Temporal variations of the water-column SSP have been evaluated using the noise measurements in two consecutive 15-day observation periods, 08/03–08/17 and 08/18–09/01/2006 [Fig. 3(c)], and the geoacoustic model, which was obtained (8) from the noise time series acquired in the second observation period. Assuming the time-averaged SSPs [Fig. 3(d)] in the second observation period to be known, we further inverted the differences between the dispersion curves obtained from the two 15-day datasets for the variation of the time averaged SSP during the SW06 experiment. As shown in Fig. 3(d), the passively inverted $SSP_1$ is close to the ground truth $SSP_1$, which is provided by the time average of the SSPs that were measured in situ during the first observation period (9).

3.3 Conclusion

It is demonstrated that noise interferometry can be successfully used to acoustically characterize the seafloor and time-averaged SSP on continental shelves at different time scales despite strong sound speed variations.
Figure 3 – Geoacoustic parameters and time-averaged sound speed profile inversion results by employing noise only. (a) The geoacoustic model implied in the inversion process with the SSP in water and the water depth assumed to be known. The unknown parameters to be determined are geoacoustic characteristics of the fluid seabed: sediment layer thickness $H$, sound speeds $c_s$ and $c_b$ in the sediment and basement, and the ratios $\rho_s$ and $\rho_b$ of the densities of sediment and basement to that of water. (b) Sensitivity of the data-model mismatch to individual parameters of the environmental model, using sediment sound speed $c_s$ as an example. The red circle indicates the position of the cost function minimum and the best inferred value. The red dashed line corresponds to the error bound. (c) Time-dependence of the sound speed in water measured in the SW06 experiment using a thermistor chain located near the HLA position shown in Fig.1(e). The first and second 15-day observation periods are indicated by the blue and red boxes, respectively. (d) Comparison of the reference 15-day average SSP$_2$, ground-truth SSP$_1$, and the retrieved ssp$_1$ with error bars superimposed.

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Geoacoustic inversion using air gun sounds measured by a single hydrophone in the East Siberian Sea

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ABSTRACT
Korea Polar Research Institute had operated after installing a bottom-moored single hydrophone in the East Siberian continental margin in the Arctic Ocean for about one year from August 2019 for long-term underwater noise monitoring. In addition, a seismic survey using an air gun was conducted in September 2019, and the air gun sounds were received by the hydrophone. The modal dispersion curves were observed in the result of spectrogram analysis of the air-gun signals received at distances of several tens of km between the sound source and the hydrophone. We extracted the dispersion curves from the spectrogram using a time-warping signal processing. Inversion of geoacoustic parameters such as sound speed and density in the sediment layer was carried out by minimizing the mismatch between extracted dispersion curves and the replicas predicted by the KRAKEN normal-mode propagation program. The results will be discussed through comparison with the sedimentary environment of the East Siberian Sea.

Keywords: Air gun sounds, Dispersion curves, Geoacoustic inversion, Single hydrophone, Arctic ocean

1. INTRODUCTION
The East Siberian is one of the least studied regions in the Arctic Sea, located between the Laptev Sea and the Chukchi Sea. The East Siberian Sea is a very wide, flat, and shallow hard bottom shelf region with an average water depth of ~58 m (1). In this ocean environment, where the waveguide is nearly range-independent, low-frequency impulsive sound propagating over several kilometers is dispersive and can be described as the sum of several modal components by normal mode theory (2,3). In this study, the seabed geoacoustic parameters was estimated by matching the modal dispersion curves of air gun sounds measured at distances of several tens of km with the model predictions.

2. FIELD MEASUREMENTS
The long-term underwater noise monitoring was conducted in the East Siberian continental margin for one year from August 2019. A single self-recording hydrophone (AURAL-M2, Multi-Electronique Inc., Canada) was deployed 13 m above the seafloor at location 74° 37.327’N, 174° 56.397’E by the icebreaking research vessel R/V Araon, operated by Korea Polar Research Institute. The mooring site was an almost flat area at a depth of 70 m. The acoustic data were sampled at a 32,768 Hz for 10 minutes every hour. A seismic survey using the air gun installed on the R/V Araon was conducted from September 2 to 10, 2019, within the monitoring period. The low-frequency impulsive air gun sounds were received by a single hydrophone every ~11 sec. The conductivity-temperature-depth (CTD) casts were made twice on 14 September to measure the sound speed profiles.

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3. RESULTS

The modal dispersion curve of the received signal can be estimated using time-frequency analysis of the air gun signal received at a distance of several tens of km between the sound source and the hydrophone. Figure 1A and B show the time-series signal and its corresponding spectrogram, respectively, received at a range of 18.7 km. First and second modes are clearly visible and ground wave (4) is clearly presented at frequencies below the Airy phase. To estimate geoacoustic parameters such as sound speed and density in the sediment layer, the dispersion curves were first extracted from the spectrogram of the received signal using a warping method (3,5), and geoacoustic parameters were the estimated by an optimization method matching the extracted dispersion curves with the replicas predicted by the KRAKEN normal-mode program.

![Figure 1](image)

Figure 1 – (A) Time series of the air-gun signal received at 18.7 km range and (B) its spectrogram.

4. CONCLUSIONS

The geoacoustic inversion is carried out by minimizing the mismatch between the dispersion curves extracted using the warping method and the simulated replicas. These inversion results may be valuable in that they provided an indirect measure of geoacoustic parameters of the East Siberian continental margin in the Arctic Ocean.

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Geoacoustic inversion using waveform matching as a preliminary step in dispersion curve analysis to assess bottom attenuation from a single vector sensor

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ABSTRACT
Geoacoustic inversion using dispersion curves is very popular, but such techniques suffer from intrinsic errors associated with the separation of normal modes via time-warping methods which, for example, can be improved using band-pass filter masking. The combination of pressure and vertical velocity dispersion curves from a vector sensor measurement also can improve results. This paper discusses the value added by using waveform matching as a preliminary step to improve the quality of the dispersion curve inversion method and its effect on the inversion performance. In addition, within the waveform matching approach, the estimation of bottom attenuation using the modal phase difference between pressure and vertical velocity is tested. In this analysis, the KRAKEN propagation model is used for synthetic predictions, including components of the vector field. The environment is modeled utilizing sound speed profiles measured during the Monterey Bay 2019 at-sea experiment with a sediment layer overlying a deeper sub-bottom type. Inversion of experimental data is presented with a hybrid optimization approach used to improve the results and reduce uncertainty of the genetic algorithm method.

Keywords: geoacoustic inversion, time-warping, dispersion curves, acoustic vector sensor.

1. INTRODUCTION
In shallow water ocean waveguides, sound propagation presents a dispersive behavior, being greatly influenced by the ocean bottom properties. Such behavior is represented by dispersion curves (DCs) which reflect the dependency of normal mode travel time with frequency, one of the most broadly used features (1,2,3,4) in ocean remote sensing for the geoacoustic inversion of environmental parameters. Normal mode properties can be identified using different approaches, and time-warping (TW) is one that has been increasingly adopted by the acoustics community for modal separation. It is a technique that relies on one sensor using broadband signals, which simplifies the at-sea probing task. Bonnel, et al. present details about TW in (2).

The benefit of utilizing DC features stems from their lack of sensitivity to certain parameters, such as bottom attenuation, source spectrum, or source depth. However, this comes at the cost of neglecting potential information contained in the full time-domain waveform, and at the cost of using data limited to those parts of the DCs obtained using TW. Moreover, DC inversion techniques suffer from intrinsic errors and distortions associated with normal mode separation via TW methods, such as [1] the lack of high resolution in time-frequency analysis, [2] the use of an imperfect TW operator based on the ideal waveguide, which affects performance in more complex environments, and [3] the abrupt transitions included in the processing caused by rectangular windows applied both in the time-domain, before the warping transformation, and in the time-frequency domain using binary masks. Some approaches have been proposed to attenuate such distortions, like the use of a band-pass filter (BPF) mask (5) and utilization of additional acoustic channels included in vector sensors.

Many researchers have studied vector sensors in geoacoustic inversion, beyond their application in direction finding or target tracking. In 2021, Guarino, et al. (5) showed that the modal phase difference between pressure and vertical velocity can be a possible candidate for the estimation of the bottom attenuation coefficient. This has been traditionally estimated, for example, using pressure-only sensors and mode amplitudes, as done by Duan, et al. (6) in 2016. In 2022, Guarino, et al. (7)
discussed the value added by doing multichannel averaging of pressure and vertical velocity DCs to reduce distortions.

This paper expands the analysis done in (7). The former study investigated the averaging hypothesis using synthetic signals and data collected on a single vector sensor deployed on the northern shelf during the Monterey Bay 2019 experiment. The inversion showed that the combination adds value to the pressure-only analysis and improved results.

This work uses the same data and environmental model of (7). The inversion utilizes sound speed profiles measured during the test event and assumes a sediment layer of constant thickness overlying a deeper sub-bottom type. Since data can be contaminated by other sources of error like noise and mode coupling, these effects can worsen DC quality even more.

In this context, this paper incorporates both DC and waveform matching inversion methods as complementary to each other. It discusses the value added by using waveform matching (8) as a preliminary step to improve the performance of the DC inversion, which provides initial estimates of primary geoacoustic parameters, while waveform matching inversion will refine those results to produce a superior solution in the end. The particular way DC and waveform matching approaches are combined in this study is guided by experience acquired from extensive numerical simulations (7) under conditions approximating the conditions encountered in the Monterey Bay experiment. The paper shows that waveform matching can provide a way to check the DC quality and improve DC inversion. It is also shown that waveform matching results can be refined with simultaneous matching of pressure and vertical velocity waveforms, and using the modal phase difference for better estimates of bottom attenuation.

To show this, the KRAKEN (9) normal mode model is applied for synthetic predictions, which include DCs based on group speed, and full-field and individual mode predictions for both pressure and vertical velocity using the adiabatic approximation. To guarantee optimum results, KRAKEN is first calibrated using the parabolic equation model RAM (10) as a reference.

As for the optimization approach, the same structure is used as in (7). Genetic algorithms (GAs) can rapidly locate the region in which the global optimum exists. However, it can be slow to locate the exact local optimum in the region of convergence. A hybrid optimization approach is implemented to expedite convergence.

This paper is organized as follows: the sea test characteristics, environmental model and DC inversion scheme are briefly explained, and details can be found in (7). The inversion scheme for waveform matching is defined. Next, DC inversion is applied using the multichannel combination of pressure and vertical velocity and BPF mask using TW, as shown in (7) to be the best option. Waveform matching is then applied individually for pressure and vertical velocity data, and for both signals simultaneously. After that, the modal phase difference approach is presented and used to refine the waveform matching outcomes. The estimated parameters from both DC inversion and waveform matching inversion are used to generate synthetic DC, and such replicas are compared with the DC from data to evaluate the quality of the DC inversion.

The results show that in the case of this paper, waveform matching inversion performs better than the DC matching inversion, supported by the modal phase difference approach and simultaneous matching. The manuscript concludes with our analysis of experimental data followed by a discussion of results.

2. SEA TEST CHARACTERISTICS AND ENVIRONMENTAL MODEL

This section presents a description of the sea test characteristics and environmental model. More details can be found in (7). The acoustic data were collected in 2019 in Monterey Bay. Figure 1(a) shows a bathymetric map of the experiment location. The location of two yellow markers labeled Shot 3 and Shot 4 correspond to two light bulb [Figure 1(b)] implosions. The environmental model assumes a sediment layer of constant thickness overlying a deeper sub-bottom type, as illustrated in Figure 1(c).

Prior information from two CTD casts is used in this work: CTD6 and CTD5 are taken at the vicinity of the source (light bulb) and receiver (vector sensor). The CTD casts measured all the water column and were modeled as range-dependent. A reference hydrophone near the source was used, which allowed us to estimate the source depth for Shots 3 and 4 of 29.8 and 29.7 m, respectively. A Geospectrum M20-105 vector sensor system was used in the sea test. The sensor itself was suspended from the frame with a nylon rope as shown in Figure 1(d). The system frame was placed on the seafloor at ~85 m depth [Figure 1(c)]. To mitigate flow noise, the system was covered prior to the deployment with a fabric.
As for the effective bottom model (4), the sub-bottom has constant sound speed, density and attenuation coefficient, whereas the sediment layer has all parameters constant except for the sound speed that has a constant gradient. Regarding ground truth information (4), the bottom is composed mainly by mud, very fine sand, and silt according to the California Seafloor Mapping Program (11).

Figure 1 - Overall sea test characteristics. (a) Location of the test event in Monterey Bay, showing the positions of the two light bulb implosions in yellow, CTD castings in white and vector sensor in red. (b) Light bulb system setup. The implosion is carried out sending a messenger from the boat that travels along the rope and breaks the light bulb. (c) Range dependent environmental model used in the analysis. (d) Vector sensor system used in the sea test, model GTI M20-105.

3. INVERSION METHODS

The inversion methods use DCs directly computed by KRAKEN group speed, and full-field and individual mode predictions, which are used for waveform matching and phase difference approaches, applying an adiabatic approximation. Since KRAKEN is a normal mode model, the number of range segments is determined based on the constraint that the maximum bathymetry vertical step must be less than or equal to the highest frequency component wavelength, as shown in (7). Figure 2 shows a comparison between KRAKEN and RAM for calibration purposes for a certain set of environmental parameters, according to Figure 1(c).

Figure 2 – Comparison between KRAKEN and RAM for a certain set of environmental parameters
according to Figure 1(c). Source signature rectangular windowed ranging from 80 to 600 Hz. Both waveforms match consistently for calibration purposes.

The hybrid optimization approach applies two GA instances followed by two Bayesian optimization instances, where the lower and upper bounds of each searched parameter shrink accordingly as the optimization process moves forward. The optimization tools are based on the Matlab function “ga” (12) within the Global Optimization Toolbox and on the function “bayesopt” (13) within the Statistics and Machine Learning Toolbox.

The cost function $d_{DC}$ for the DC inversion is based on the minimization of the mean squared error average between the DC estimate, which is calculated from data, and DC replica travel times with frequency being the independent variable according to

$$d_{DC} = \frac{1}{M} \sum_{m=1}^{M} \frac{1}{N_m} \sum_{i=1}^{N_m} \left[ t_m(f_i) - t_m^r(f_i) + dt \right]^2,$$

where $M$ is the number of modes, $N_m$ is the number of points of a specific mode DC, $t_m$ is the DC estimate travel time, $t_m^r$ is the DC replica travel time and $dt$ is a time shift included as a search parameter when the sea test signals are used to compensate for small range mismatches.

The cost function $d_{WM}$ for the waveform matching is defined as

$$d_{WM} = \frac{1}{M} \sum_{i=1}^{M} \left| y[i + N] - y_r[i] \right|^2 \left( 1 - \frac{|y^T y_r|}{|y||y_r|} \right),$$

where $y$ are data (pressure or vertical velocity), $y_r$ is the replica, and $N$ is a shift included as a search parameter to account for range mismatches. The first term is the root mean square error (RMSE) and the second term includes the correlation coefficient. The calculation is done using only the portion of data where signal is present. The choice for both terms is a way to avoid replicas that have good matching only for the very initial portion of the signal, i.e., to avoid situations where the optimization forces the remaining portion to ~ zero for better RMSE-only results. Therefore, the choice for both terms allows for replicas that do not match the whole signal perfectly, working as a balance between both calculations, with the first part mostly matching amplitude, and the second part mostly matching phase. This approach was found useful for the employed reduced order bottom model.

4. INVERSION OF DATA USING DCs

Data are inverted using shots 3 and 4. Both shots have high SNR for pressure and vertical velocity signals. To illustrate, considering shot 4 the SNR values are 38.3 dB and 31.1 dB, respectively. To improve the separation of modes in the warped-domain, according to Duan, et al. (14), source deconvolution is applied, which is also essential for the frequency components to be generated at the same instant. Details about the pressure and vertical velocity full-field and deconvolved signals can be found in (7). The modes are then separated using TW with a BPF mask, as shown in Figure 3(a) for the pressure signal while Figure 3(b) shows the warped-domain spectrogram for the vertical velocity signal, and Figure 3(c) shows the pressure and vertical velocity retrieved DCs.

![Figure 3 – Shot 4 data. (a) Warped-domain spectrogram for deconvolved pressure signal using BPF mask centered in the line indicated by the connected dots. (b) Warped-domain spectrogram for](image)
deconvolved vertical velocity signal. (c) Deconvolved pressure and vertical velocity retrieved DCs for modes 4, 5, 7, 9, 10.

The warped-time spectrograms and DCs for shot 3 can be found in (7). Table 1 shows the estimated parameters for shots 3 and 4, and Figure 4 shows the DCs and the full-field collected data compared with Table 1’s shot 4 replica. The number of data points for shot 4 in Figure 4(a) varies from 72 to 121 per mode, depending on the mode number. It is limited to those parts of the DCs that was possible to retrieve using TW.

Table 1 – Estimated parameters for shots 3 and 4 using the combination of pressure and vertical velocity DCs. $c_s$ and $c_b$ are the sediment and sub-bottom sound speeds (m/s), $\nabla c_s$ is the sediment sound speed gradient (m/s/m), $\rho_s$ and $\rho_b$ are sediment and sub-bottom densities (g/cm$^3$), $a_s$ and $a_b$ are the sediment and sub-bottom attenuation coefficients (dB/m/kHz), and $H_s$ is the sediment thickness (m).

<table>
<thead>
<tr>
<th>Shot 3</th>
<th>$c_s$ (m/s)</th>
<th>$\nabla c_s$ (m/s/m)</th>
<th>$\rho_s$ (g/cm$^3$)</th>
<th>$a_s$</th>
<th>$H_s$ (m)</th>
<th>$c_b$ (m/s)</th>
<th>$\rho_b$ (g/cm$^3$)</th>
<th>$a_b$</th>
<th>range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shot 3</td>
<td>1574</td>
<td>8.5</td>
<td>1.29</td>
<td>x</td>
<td>5.0</td>
<td>1914</td>
<td>2.0</td>
<td>x</td>
<td>3100</td>
</tr>
<tr>
<td>Shot 4</td>
<td>1577</td>
<td>7.5</td>
<td>1.32</td>
<td>x</td>
<td>6.4</td>
<td>1773</td>
<td>1.6</td>
<td>x</td>
<td>3083</td>
</tr>
</tbody>
</table>

The range estimates in Table 1 are different because shots 3 and 4 were taken at slightly different locations as shown in (7). Figures 4(b,c) show that the parameters found using the DC inversion do not provide a good matching in the time-domain. It can be noticed in the same figure that the replica low order modes travel faster than the ones in data, which suggests, for example, that sediment sound speed is overestimated. This suggests that the DC inversion must be compared with waveform matching, results for which will be presented in a subsequent section. Prior to that comparison, the next section presents the modal phase difference approach.

5. MODAL PHASE DIFFERENCE APPROACH

The modal phase difference is directly related to the modal attenuation coefficient. Following an analogous derivation as in (5), the modal pressure ($p_m$) using the adiabatic approximation is given by (15)

\[
p_m(r,z) \approx \frac{j}{\rho \sqrt{8\pi r}} \frac{e^{-j\frac{\pi}{2}}}{\sqrt{k_m'(r')}} \psi_m(0,z_3) \psi_m(r,z) e^{-j \int_0^{r'} k_m(r') \, dr'}
\]

Figure 4 – Comparison between data and replica for shot 4 estimated parameters. (a) Pressure channel DCs for modes 4, 5, 7, 9, 10. (b) Pressure channel full-field. (c) Vertical velocity channel full-field.
where \( r \) is the range, \( z \) the receiver depth, \( z_s \) the source depth, \( \rho \) the water density, \( \psi_m \) is the mode function, and \( k_m \) the horizontal wavenumber.

The modal vertical velocity (\( u_{zm} \)) is obtained from the modal pressure gradient using the Euler equation

\[
u_{zm} = \frac{1}{j\omega \rho} \frac{\partial p_m}{\partial z}, \tag{4}\]

which is found to be

\[
u_{zm}(r, z) = \frac{p_m}{j\omega \rho} \frac{\partial \psi_m(r, z)}{\partial z}, \tag{5}\]

where \( \omega \) is the angular frequency.

The modal phase difference (\( \Delta \theta \)) can be obtained from the modal vertical intensity (\( I_{zm} \)) given by

\[
I_{zm}(r, z) = \frac{p_m u_{zm}^*}{2} = j \frac{|p_m|^2}{2 \omega \rho} \left[ \frac{\partial \psi_m(r, z)}{\partial z} \right]^* = A e^{j \Delta \theta}. \tag{6}\]

In the case of this paper, \( \psi_m \) is obtained using KRAKEN. However, since the propagation model has been updated to provide both full-field and individual mode components of pressure and vertical velocity in the time-domain, ultimately using Matlab the calculation is done by

\[
\Delta \theta = \text{angle} \left( \text{fft}(p_m) \ast \text{conj} \left( \text{fft}(u_{zm}) \right) \right).\]

In the case of data, the modal phase difference is calculated in the same way, based on the modal pressure and modal vertical velocity signals that are obtained using TW.

6. INVERSION OF DATA USING WAVEFORM MATCHING

The optimization using waveform matching applies the same hybrid optimization approach of the DC matching, except for the cost function that uses Equation 2. The inversion is done using shots 3 and 4, matching pressure and vertical velocity individually, and simultaneously using both signals. In the case of the simultaneous matching, Equation 2 is calculated for each signal, and then the results multiplied. Table 2 shows the estimated parameters.

<table>
<thead>
<tr>
<th>Shot</th>
<th>( c_s ) (m/s)</th>
<th>( \nabla c_s ) (m/s/m)</th>
<th>( \rho_s ) (g/cm³)</th>
<th>( a_s ) (dB/m/kHz)</th>
<th>( H_s ) (m)</th>
<th>( c_h ) (m/s)</th>
<th>( \rho_h ) (g/cm³)</th>
<th>( a_h ) (dB/m/kHz)</th>
<th>Range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>S3 (p)</td>
<td>1500</td>
<td>3.3</td>
<td>1.36</td>
<td>0.10</td>
<td>3.5</td>
<td>1670</td>
<td>2.37</td>
<td>0.39</td>
<td>3100</td>
</tr>
<tr>
<td>S3 (uₚ)</td>
<td>1519</td>
<td>0.7</td>
<td>1.38</td>
<td>0.04</td>
<td>7.9</td>
<td>1673</td>
<td>2.14</td>
<td>1.75</td>
<td>3093</td>
</tr>
<tr>
<td>S4 (p)</td>
<td>1501</td>
<td>4.9</td>
<td>1.51</td>
<td>0.02</td>
<td>3.8</td>
<td>1677</td>
<td>2.29</td>
<td>0.67</td>
<td>3081</td>
</tr>
<tr>
<td>S4 (uₚ)</td>
<td>1508</td>
<td>3.0</td>
<td>1.39</td>
<td>0.06</td>
<td>5.1</td>
<td>1684</td>
<td>2.20</td>
<td>1.43</td>
<td>3089</td>
</tr>
<tr>
<td>S3 (p, uₚ)</td>
<td>1503</td>
<td>7.2</td>
<td>1.55</td>
<td>0.24</td>
<td>4.8</td>
<td>1672</td>
<td>2.31</td>
<td>0.66</td>
<td>3090</td>
</tr>
<tr>
<td>S4 (p, uₚ)</td>
<td>1505</td>
<td>7.7</td>
<td>1.48</td>
<td>0.10</td>
<td>4.1</td>
<td>1672</td>
<td>2.28</td>
<td>0.68</td>
<td>3080</td>
</tr>
</tbody>
</table>

Table 2 shows that the inverted values for shots 3 and 4 using pressure-only have good agreement, whereas using vertical velocity-only, some parameters seem to be overestimated, e.g., \( c_s \), \( H_s \), and \( a_h \). The simplicity of the bottom effective model may be responsible for the increase in \( a_b \), which ends up being correlated with other parameters that are equally erroneously estimated. Therefore, when it comes to the estimation of sediment and sub-bottom attenuation coefficients, the results vary substantially. On the other hand, when simultaneous matching is applied, the results \( S3 (p, uₚ) \) and \( S4 (p, uₚ) \) have better agreement. The modal phase difference between pressure and vertical velocity
is then used to refine the results of Table 2. To illustrate that, shot 4’s mode 5 is used and its waveforms for pressure and vertical velocity are separated from the full-field signals as shown in Figure 5. Next, the modal phase difference is calculated using Equation 6 and the results are shown in Figure 6 for shot 3 in blue and shot 4 in red. Next, KRAKEN is used to generate the individual modes for pressure and vertical velocity for each set of inverted values of Table 2. The phase difference is then calculated using Equation 6, and the results shown in Figure 6(a-f), where data and replica can be compared. $S_4 (p, u_z)$ is the overall best result. Figure 7 shows the comparison of waveforms between data and replica using $S_4 (p, u_z)$ inverted values.

![Figure 5](image_url) - Shot 4’s mode 5 waveforms for pressure and vertical velocity after the separation using TW with BPF mask.

![Figure 6](image_url) - Modal phase difference between pressure and vertical velocity, including shots 3 and 4, and
replicas using parameters of Table 2. (a) $S_3 (p)$. (b) $S_3 (u_z)$. (c) $S_4 (p)$. (d) $S_4 (u_z)$. (e) $S_3 (p, u_z)$. (f) $S_4 (p, u_z)$.

Figure 7 – Comparison of waveforms between data and replica using inverted values $S_4 (p, u_z)$. (a) Pressure with correlation coefficient of 0.92. (b) Vertical velocity with correlation coefficient of 0.78.

7. COMPARISON BETWEEN DC AND WAVEFORM MATCHING INVERSIONS

To compare results from both techniques, the waveform matching estimated parameters $S_4 (p, u_z)$ are used to generate synthetic DCs. Figure 8 shows the comparison considering only the pressure signal.

Figure 8 – Comparison between inversion techniques. (a) The DC replica uses DC inversion estimated parameters. (b) The DC replica uses waveform matching estimated parameters.

The synthetic DCs using waveform matching shown in Figure 8(b) reveal the distortions in data for mode 4 above 200 Hz, mode 5 above 250 Hz, and modes 7 and 9 above 365 Hz. Such distortions are caused by intermodal interference in the warped-domain, more pronounced within the low order modes at higher frequency components since the modes travel more closely together, as shown in the spectrogram of Figure 3(a). This effect ends up overestimating sediment sound speed in the DC inversion from 1505 to 1577 m/s, for instance. Doing the DC inversion again suppressing those portions of data, Table 3 compares DC inversion without suppression, DC inversion with suppression, and waveform matching. As expected, the results improve, getting closer to the ones estimated by the waveform matching.

Table 3 – Comparison of results between DC inversion and waveform matching suppressing parts of the DCs to improve results.

<table>
<thead>
<tr>
<th></th>
<th>$c_s$ (m/s)</th>
<th>$\nabla c_s$ (m/s/m)</th>
<th>$\rho_s$ (g/cm$^3$)</th>
<th>$a_s$ (dB/m/kHz)</th>
<th>$H_s$ (m)</th>
<th>$c_b$ (m/s)</th>
<th>$\rho_b$ (g/cm$^3$)</th>
<th>$a_b$ (dB/m/kHz)</th>
<th>range (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shot 4</td>
<td>1577</td>
<td>7.5</td>
<td>1.32</td>
<td>x</td>
<td>6.4</td>
<td>1773</td>
<td>1.60</td>
<td>x</td>
<td>3083</td>
</tr>
<tr>
<td>(DC no suppression)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shot 4</td>
<td>1509</td>
<td>1.3</td>
<td>1.44</td>
<td>x</td>
<td>3.6</td>
<td>1674</td>
<td>1.76</td>
<td>x</td>
<td>3090</td>
</tr>
<tr>
<td>(DC with suppression)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>S4 ($p, u_z$)</td>
<td>1505</td>
<td>7.7</td>
<td>1.48</td>
<td>0.10</td>
<td>4.1</td>
<td>1672</td>
<td>2.28</td>
<td>0.68</td>
<td>3080</td>
</tr>
<tr>
<td>(waveform matching)</td>
<td></td>
<td></td>
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<td></td>
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</tbody>
</table>
8. DISCUSSION

The DC inversion using TW to separate modes is broadly used (3,14,16). One of its advantages is related to the optimization process that requires less parameters to match, since the travel time of normal modes, for example, is not sensitive to the bottom attenuation. On the other hand, small changes in the environmental parameters cause small changes in the DC shapes, which makes the technique susceptible to the distortions caused by the separation of modes, for signal processing reasons and physical reasons, like noise contamination. Aside from that, the tendency is to maximize the DCs energy content, which means to separate the DCs with the longest duration in time as much as possible to optimize results. However, this paper shows that such distortions can be very subtle. There is no indication in Figure 3(c) of low quality DCs, for example. On the other hand, when the same DCs were put against the waveform matching, the distortions became visible. The suppression of those regions improved results as shown in Table 3 but decreased the energy content of the DCs, making the optimization less sensitive to some parameters, which affected the estimation of sediment sound speed gradient and range, for instance.

As for the waveform matching technique, the bottom reflectivity and attenuation affect the mode amplitudes in the receiver. Then, an erroneous estimation of one can adversely affect the estimation of the other. Therefore, this paper shows that a more robust estimation of bottom attenuation is obtained when a vector sensor is applied, using the modal phase difference between pressure and vertical velocity. In this paper, such calculation was used to refine the estimated parameters of Table 2. However, it can be easily incorporated to the cost function of the optimization process.

Additionally, Figure 7(b) shows that it is harder to match the vertical velocity signal compared to the pressure signal, which is shown in Figure 7(a) with a correlation coefficient of 0.92. That can be related to the simplicity of the bottom effective model. However, the correlation coefficient of 0.78 for the vertical velocity was helpful to the simultaneous matching that generated more stable results as shown in Table 2.

The estimated parameters are consistent with the ground truth information about the region being composed by mud, very fine sand, and silt according to the California Seafloor Mapping Program (11).

Finally, the results suggest based on the environment considered and data analysis of this paper, although waveform matching can be used to improve the DC inversion, when a vector sensor is available for geoacoustic inversion, waveform matching performs better.

9. CONCLUSIONS

This paper discussed the value added by using waveform matching as a preliminary step to improve the performance of the DC inversion method. The separation of modes using TW methods causes distortions to the retrieved DCs, for signal processing or physical reasons, like noise contamination. The results showed that waveform matching can be used to check the quality of the DCs retrieved from data and improve results. Although the waveform matching technique has more parameters to match, like the bottom attenuation coefficient, we show that when a vector sensor is available, waveform matching results can be refined. First, doing the simultaneous matching of pressure and vertical velocity, and second, using the modal phase difference approach. Although in this paper such approach was used to refine results after the inversion, if KRAKENC is used for the waveform matching, full-field and individual mode predictions can be included, and the modal phase difference between pressure and vertical velocity can be incorporated to the cost function of an optimization process, which narrows down the bottom attenuation calculation, avoiding erroneous estimations within correlated parameters. Overall, this study suggests that when a vector sensor is available for geoacoustic inversion, waveform matching can improve results of the DC inversion technique, but in the environment considered in this paper, waveform matching is a better option.

REFERENCES

Model Selection in Quantitative Geoacoustic Inversion and Uncertainty Estimation

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² Applied Ocean Physics and Engineering Department, Woods Hole Oceanographic Institution, Woods Hole, MA, USA

ABSTRACT

This paper examines two important components of quantitative model selection in Bayesian geoacoustic inversion and uncertainty estimation. In particular, the problems of determining an appropriate geoacoustic-profile parameterization and an appropriate data error model are considered and illustrated. Regarding parameterization, rigorous approaches are applied for representing layered and gradient-based profiles, consistent with the information content of the data, based on trans-dimensional (trans-D) and Bernstein-polynomial (BP) formulations, respectively. Trans-D inversion marginalizes over an unknown number of uniform layers, while BP inversion represents smooth gradients in terms of a polynomial of optimal order as determined by the Bayesian information criterion. Regarding the error-model, which specifies the likelihood/misfit function, parametric and non-parametric representations can be formulated, and qualitative and quantitative statistical tests can be applied a posteriori to ensure an appropriate choice. Choices of parameterization and error model are not independent, but must be considered in tandem. The various approaches to model selection (parameterization and error model) are illustrated here for the inversion of modal-dispersion data, and have also been applied to a variety of other data types.

Keywords: Bayesian geoacoustic inversion, quantitative model selection, data error models

1. INTRODUCTION

Knowledge of the geoacoustic properties of seabed sediments is needed to understand and model/predict acoustic propagation in shallow-water environments, as required for a variety of geophysical, geotechnical, biological, and naval applications. Estimating seabed model parameters via the inversion of ocean acoustic measurements (geoacoustic inversion), represents an attractive in situ alternative to direct (invasive) measurements, such as sediment coring, and has been the subject of considerable research. However, geoacoustic inversion represents a nonlinear, non-unique inverse problem for which quantitative estimates and uncertainties require rigorous consideration of the parameterization of the seabed geoacoustic model and the data error model.

In terms of model parameterization, the amount of seabed structure that can be resolved depends on the information content of the acoustic data, which varies with the physics of the seabed acoustic interaction, frequency content, measurement and theory errors, etc. Under-parameterizing the model can preclude seabed structure that could have been resolved, biasing results and under-estimating uncertainties, while over-parameterization can lead to spurious structure and over-estimating uncertainties. Quantitative model selection applied to general model parameterizations ensures the inclusion of seabed structure that is reliably sensed by the data while precluding unjustified structure.

To quantify the information content of acoustic data to resolve seabed structure, a Bayesian inversion formulation is applied that includes rigorous approaches to model selection and data error modelling. Model selection approaches considered here include both layered and gradient representations of seabed profiles using two different methods: (1) trans-dimensional (trans-D)
inversion [1–6], and (2) Bernstein-polynomial (BP) basis functions [6,7], respectively. Trans-D inversion considers the number of seabed layers as an unknown hyper-parameter in the inversion, and applies the reversible jump Markov chain Monte Carlo algorithm to construct a Markov chain that samples from the posterior probability density of the trans-D parameter space. In BP inversion, the Bayesian information criterion (BIC) [7] is applied in model selection to determine polynomial orders consistent with the information content of the data: higher-order BPs can represent more complex structure but include more parameters, which is penalized by the BIC.

The error model considered here assumes a multi-variate Gaussian distribution with unknown variance and covariance; covariance estimation is formulated in terms of trans-D sampling of zeroth- and first-order autoregressive (AR) processes to avoid over- or under-parameterizing the error model [4]. The validity of these assumptions/approaches can examined with qualitative and quantitative residual analyses [6]. Inversion results are considered in terms of marginal probability profiles for geoacoustic properties (marginalized over the number of layers for trans-D inversion), which quantify the resolution of seabed structure versus sub-bottom depth.

The two inversion approaches (trans-D and BP) are applied here to modal dispersion data collected at the New England Mud Patch (NEMP) during the 2017 Seabed Characterization Experiment (SBCEX17) [9]. These data include high-order modes extracted via warping time-frequency analysis [5,10] of a pulsed sound-source signal recorded at a vertical line array (VLA) of hydrophones at a range of approximately 4.5 km along a largely range-independent propagation track. Auxiliary environmental measurements carried out on the NEMP as part of SBCEX17 include high-resolution seismic reflection profiles which provide an indication of the sediment layering structure, and shallow sediment cores, which indicate sediment type at the core sites. These measurements indicate an upper mud layer approximately 10.7 m thick with increasing sand content near the base of layer, above a layer of sand < 1 m thick; deeper layers were also detected with the seismic data but were not sampled in coring. The seismic and core measurements can be used for comparison with the geoacoustic inversion results.

2. RESULTS

The observed modal dispersion data are shown in Fig. 1 in terms of arrival times as a function of frequency for 18 of the first 21 modes. These data were extracted by applying warping time-frequency analysis individually to the source recordings at 14 VLA hydrophones, with modal signal-to-noise ratios (SNRs) assessed to determine which recording (i.e., which receiver depth) best resolved each mode [5]. The SNR was poor for modes 16, 18, and 20 on all VLA receivers, precluding their inclusion.

Figure 1: Observed modal dispersion data (open circles) for 18 of the first 21 modes, with modes identified in (a). Blue lines show the predicted data as sampled in the Bayesian inversions. The data fit for trans-D inversion is shown in (a), and for BP inversion in (b). Modified from [6].
in the data set, likely due to the source depth coinciding with nulls for these modes. This figure also shows the fit to the data achieved by the two inversion approaches: trans-D inversion in Fig. 1(a) and BP inversion in Fig. 1(b). In both cases, the data fit is excellent, with virtually no discernable differences between results for the two inversions.

Figure 2 presents the results of the two approaches to Bayesian inversion and model selection applied to the modal dispersion data, shown in terms of marginal probability profiles for sediment interface depths, sound speed $c$, and density $\rho$. The upper panels show the results of trans-D inversion, which parameterizes geoacoustic profiles in terms of an unknown number of uniform layers, while the lower panels show results for a hybrid inversion, which represents the mud layer in terms of general, smooth gradients parameterized by BPs, overlying deeper layers represented trans-dimensionally. The BIC indicated a fifth-order polynomial for sound speed and a third-order polynomial for density. Figure 2 shows similar geoacoustic profiles for the two inversion approaches, consisting of a nearly uniform upper layer approximately 8 m thick with a low sound speed of about 1470 m/s (with a small increase in the upper 3 m or so), above a region of increasing sound speed from about 8–11, above a high-speed layer from about 11–13 m (~1800 m/s, but with high uncertainties), with a somewhat reduced sound speed (~1700 m/s) below this depth. This structure is in good agreement with the seismic reflection and core measurements (10.7 m mud layer with increasing sand near its base overlying a sand layer) although the layer boundaries indicated by seismic reflectors (dashed lines in Fig. 2) are not clearly resolved by the inversion. Of note, the trans-D inversion results represent the geoacoustic profile over the mud (to ~11 m depth) in terms of layered structure, while the BP inversion represents structure with smooth gradients. The BIC does not indicate a significant preference of one inversion result over the other, indicating that the data are not able to differentiate between the two results.

![Figure 2: Geoacoustic inversion results](image.png)
The trans-D error model for both of the two inversions indicated standard deviations of approximately 2 ms for the modal dispersion data, with some variability between modes; a first-order AR process with coefficient $> 0.5$ was favoured for all modes to characterize the error covariance over frequency. A posteriori statistical tests on data residuals (difference between observed and predicted data) indicate that the assumptions of Gaussian-distributed errors with variances and covariances estimated as part of the inversion are generally valid [6].

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REFERENCES

Broadband Acoustic Characterization of Mesopelagic Fishes

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ABSTRACT

The mesopelagic zone, spanning depths from 200–1000 m, is one of Earth’s largest ecosystems and home to a diverse community of marine animals. Mesopelagic fishes are some of the most abundant vertebrates on Earth, and are thought to play an important role in global ocean biogeochemical cycles. Mesopelagic fishes are difficult to sample, or harvest by commercial fisheries, due to their often remote and inhospitable habitats, and their ability to efficiently avoid trawl nets and cameras. The mesopelagic zone is characterized by deep sound scattering layers which are observed to perform daily vertical migration. There has been increased interest in using narrowband shipboard sonars to survey mesopelagic fishes, though little is known about their target strength. Recent advances in broadband sonars and in situ platforms are being used to fill the technology gap and infer target strengths of these elusive mesopelagic fishes. This talk presents an overview of the work done in this area to date, discusses the key challenges that still remain, and assesses the impact of broadband acoustic techniques in advancing our knowledge of the target strength, abundance, biomass, and distribution of mesopelagic fishes in the Ocean Twilight Zone. [Work supported by NSF and WHOI OTZ Project.]

Keywords: Broadband Acoustic Scattering, Deep Sound Scattering Layer, Daily Vertical Migration

1. INTRODUCTION

The mesopelagic zone, often referred to as the Ocean Twilight Zone (OTZ), is one of the largest habitats on Earth, but there exist major gaps in our knowledge of the biology, adaptations, abundance, and distribution of its inhabitants. The OTZ is made up diverse communities of zooplankton, macrozooplankton, and micronekton, including a variety of small fishes (collectively referred to as “mesopelagic fishes”), cephalopods, crustaceans, and gelatinous organisms, such as siphonophores. Such mesopelagic organisms are often undersampled by conventional nets as some species are patchy and sparse, some can effectively avoid capture by nets, and some are fragile and easily destroyed by net systems [1-3]. As a consequence of this under-sampling, there are major gaps in our knowledge of the biology, adaptations, abundance, and distribution of mesopelagic organisms, and these habitats remain one of the least investigated components of ocean ecosystems [4].

The global biomass estimate of mesopelagic fishes based on net catches is approximately one gigaton [5-6]. This estimate is based on net sampling gear and yet is often used in assessments of ecosystem function and the biogeochemistry of the global ocean [7]. There are estimates that one-quarter of all known fish species in the Southern Ocean live in the mesopelagic and bathypelagic zones [8-9], and it is thought that the fish genus Cyclothone sp. is likely the most abundant vertebrate on earth [10]. Yet mesopelagic fishes have a notoriously effective avoidance behavior and there is evidence they may be under-sampled by as much as a factor of 10 [2,11]. Furthermore, many species of mesopelagic fish migrate at night into the epipelagic zone (0-200m) and Irigoien [11] have shown that mesopelagic fish biomass and primary production are strongly coupled, suggesting the importance of mesopelagic fishes in ocean biogeochemical cycles needs to be revised, and may end up playing a potentially important role in the ocean carbon cycle.

Myctophids (aka lanternfish) are the most widespread mesopelagic fish family [12]. They play a significant role as consumers of zooplankton in oceanic food webs [13], and are an important food source for higher trophic level predators, such as epipelagic and bathypelagic fish [14], including...
deep water fish [15-17], seabirds [18], fur seals [19], squid [20,21], and whales [22,23], some of which are either threatened or endangered. Beaked whales are known to dive and forage to mesopelagic depths [24], and there is a broad association between the dive depths and acoustic scattering layers, but whether they are targeting specific species (e.g., squid vs. myctophids) is unknown [25]. The ability to sample at the same scales as the whales is fundamental to our understanding of predator-prey interactions and the bioenergetics of marine mammals.

While mesopelagic ecosystems are historically under-sampled, their inhabitants lend themselves to effective characterization with acoustical techniques [e.g. 26-28], and potentially with optical techniques. In fact, mesopelagic organisms comprise one of the most “visible” features of the open ocean, the deep scattering layer, observed on ship’s echosounders for many decades [29i]. Layers 10-100s of meters thick blanketing large areas are ubiquitously observed [29ii]. These layers often appear continuous and uniform, an artifact of large acoustic sampling volumes used in shipboard operations. Characterizing the spatial and temporal scales of distribution, abundance, and species composition of these patterns at finer scales is challenging with existing technologies and yet critical to our understanding of the trophic dynamics and ecology of deep-water ecosystems, and potentially to the harvesting of these resources.

A series of recent studies have provided tantalizing insight into the abundance and ecology of mesopelagic fish using narrowband shipboard echosounders, employing typical fisheries acoustics frequencies of 18-200 kHz [e.g. 11-30]. Yet, shipboard acoustics suffer from low range penetration at higher frequencies, limiting the information available on the acoustic frequency response of organisms; from large acoustic sampling volumes at the large depths, leading to complicated frequency responses due to multiple organisms sampled simultaneously; and from uncertainty introduced due to the proximity of the lowest frequencies (typically 18 and 38 kHz) to the resonant frequency of gas-bearing mesopelagic organisms [31]. Furthermore, although biomass is often dominated by various fishes, the proportional contribution to scattering of different organisms is complicated by an acoustically diverse community composition, including both swimbladder-bearing and non-bearing fish (as well as species that transition from gas-bearing to non-bearing as they grow and age), crustaceans, and strongly scattering low-biomass taxa (e.g., siphonophores) [32]. To fully characterize mesopelagic communities using acoustics, high-resolution information is needed on taxa, size, their vertical distribution and any depth-sensitivity to their scattering properties [33]: information best achieved through the concurrent deployment of wide-band acoustic and optics sensors in a deep towed platform [34]. Thus, while mesopelagic ecosystems have historically been challenging to sample with nets, acoustical and optical systems, especially when deployed in combination, represent a powerful and non-destructive sampling approach, with the remote and high-resolution sampling to large ranges offered by acoustics complemented by high-taxonomic resolution afforded by optical approaches.

As coastal fisheries around the world have declined, industrial fishing has spread seaward and deeper [35,36]. Deep-sea fisheries, involving species such as orange roughy, oreos, and cardinalfish, operate globally throughout the world’s oceans, mostly targeting stocks on continental slopes and offshore seamounts. Studies addressing the sustainability of deep-sea fisheries [37] have found that few are sustainable [38]. Most deepwater stocks are overfished or even depleted [39], with unknown impacts on prey and predator populations, including mesopelagic fishes. Yet mesopelagic fishes are thought to be critical in determining the sustainability of deep-sea fisheries [4]. From a fisheries management perspective, mesopelagic and bathypelagic fishes are seen as an underutilized (aka latent) resource. With advances in gear technology, the capability to harvest these resources in an economically feasible way is not far in the future, and there is a fundamental need to acquire even the most basic information on these ecosystems before they become an economic resource.

In recent years, in response to the increasing demands placed on our oceans, NOAA has been working to advance an ecosystem-based approach to management (EBM). The importance of mesopelagic (and bathypelagic) organisms to deep-sea fisheries, and the US implementation of EBM, has been recently recognized [40,41]. It is important to understanding the structure and function of these ecosystems [4,42] to bolster our ability to predict how these communities will respond to fishing efforts and environmental changes brought on by climate change [43].

A wide-band acoustic scattering and two-scale optical imaging system, integrated with a suite of environmental sensors, including an environmental DNA (e-DNA) sampler [44], has been developed at WHOI that addresses the technological void for characterizing mesopelagic ecosystems. This system capitalizes on broadband acoustical approaches with acoustic systems spanning 5-450 kHz
almost continuously, simultaneously providing “full spectrum” information on zooplankton and micronekton, with the lower frequencies optimized for resonance classification of gas-bearing organism, such as myctophids and siphonophores, and the higher frequencies optimized for spectral classification of organism without gas-inclusions, such as euphausiids and salps. The two-scale imaging system provides images of these organisms over a larger 1-m² area for taxa/species-level classification as well as behavioral observation, including imaging larger and mobile micronekton, and will ground-truth the synoptic acoustic data. A holographic camera images smaller organism, spanning 50 μm – 2cm. These acoustical and optical systems are integrated into a towed platform depth-rated to 2,000 m and enabling high-band-width data telemetry and real-time control. This instrument platform has been deployed in a series of oceanographic expeditions in the New England shelf break and slope waters, focused on quantifying the biomass and distribution of zooplankton and micronekton, particularly in relation to environmental variability, such as meso-scale oceanic eddies, fronts, and upwelling regions, and abrupt topography.

![Figure 1. A typical series of dives for the Deep-See towed platform superimposed on the shipboard 18 kHz narrowband acoustic echosounder data during a summer 2019 cruise to the New England Slope Waters. A schematic of the bioacoustics mooring is also shown for reference.]

2. PLATFORMS

A wide-band acoustic backscattering and a two-scale optical imaging towed platform has been developed at WHOI for assessing the distribution and abundance of zooplankton and micronekton in the mesopelagic zone. Although these under-sampled deep regions are the primary focus of this effort, necessitating the large depth-rating (2000 m), the system will be equally useable for epipelagic (0-200m; a region into which many mesopelagic organisms migrate on a diel basis) and shelf break applications. The entire system is towed with the wide-band acoustic system downward looking and the optical imaging system forward looking, to mimic a net sampling system. The optical component of the system complements the acoustical component of the system by allowing individuals to be identified to the taxa/species level, as well as providing information on their size and angle of orientation, aiding with the interpretation of the acoustic returns. The environmental sensors provide vital data concerning the water properties, including temperature and salinity. An eDNA sampling system allows genetic fingerprints of mesopelagic organisms to be obtained.

The towed instrument platform, named “Deep-See”, has been deployed in a series of oceanographic expeditions aimed at understanding the New England shelf break and slope waters in water depths spanning 400 m to 3000m. Fundamental to the design is the integration of the diverse sensors, which allows for simultaneous and accurate characterization of multiple trophic levels. Acoustics alone provides synoptic information, but not at the taxa/species level. Optical imaging, while sampling a smaller volume, provides taxa/species level information. Integrating these two technologies with
environmental sensors provides synoptic taxa/species data correlated with environmental parameters. Pivotal to the acoustic design is the wide range of frequencies (5-450 kHz). Commercially available systems are either optimized for characterization of the frequency responses of zooplankton or fish, but not both. The Deep-See frequencies span a wider range than any commercial system and are optimized for both fish (lower frequencies) and zooplankton (higher frequencies). Also crucial is the use of broadband technology resulting in continuous frequency coverage. The range of frequencies, coupled with use of broadband technology and associated spectral classification, significantly improves the accuracy of characterizing fish and zooplankton over any system commercially available. Another key element is the design of the optical imaging system, simultaneously spanning two scales to accommodate the wide range of organisms sizes: A larger 1-m² outer area with lower resolution for imaging larger organisms more prone to avoidance, such as euphausiids, and a smaller inner area, 2 cm², with high resolution (O(50 µm)) for quantification of smaller organisms, such as copepods or pteropods.

2.1 Wide-Band (5-450 kHz), Split-Beam Acoustic Scattering Systems

The wide frequency coverage requires two separate acoustic sub-systems. The lower portion of the range is optimized for resonance classification of fish [45,46] and the upper portion of the range is optimized for spectral classification of zooplankton [47]. Split-beam technology at all frequencies is used to provide direct measurements of target strength from resolved individual fish and zooplankton. Broadband matched-filter-based signal processing techniques, often referred to in the acoustic scattering community as compressed pulse processing, are used to significantly improve range resolution and signal-to-noise ratios [48,49]. Analysis of the echo data involves classification of swimbladder-bearing fish according to the resonance of their swimbladder (lower frequencies) and classification of the Rayleigh-to-geometric transition of the non-swimbladder-bearing fish and non-gasbearing zooplankton (higher frequencies). Sizes of fish and zooplankton are determined from these resonances or transition frequencies through scattering models. This spectral classification greatly improve characterization (size, numerical density, and patchiness) of fish and zooplankton [45-47].

Figure 2. A) The combined acoustical and optical towed instrument platform. B) “Deep-See” being deployed from the NOAA Ship Henry B. Bigelow. C) Data from the Deep-See Airmar acoustics channel (18-47 kHz) [59]. D) A reconstructed image of a copepod from the holographic camera. E) An image of a Euphausiid from the LAPIS camera system.

2.1.1 Mid-Frequency Acoustic Subsystem (5-47 kHz)

This component was developed at WHOI as split-beam technology is not commercially available in the lower frequency range. This subsystem utilizes is built around a highly flexible, user-specified two-channel EdgeTech sub-bottom profiler system. One channel transmits in the frequency band 5-18 kHz (KT-216D transmitter) and the other interfaces with a custom-designed Airmar source in the frequency band 18.5-47 kHz. EdgeTech built a split-beam receiver array for this project, using a
PVDF-based receiver array. PVDF (Polyvinylidene Fluoride) is a ferroelectric polymer with unique capabilities for the design of acoustic arrays. The split-beam array consists of two concentric circles, split into 4 quadrants, totaling 8 receive elements. Both the outer (1 m diameter) and inner (0.6 m diameter) circular receive arrays are used with the 5 - 18 kHz source, and the smaller circular receive array (inner 4 elements) is used with the 18.5 - 47 kHz transducer. This subsystem was calibrated using a 20-cm diameter spherical Al standard targets following the techniques outlined in Stanton et al. [50]. The signal processing is performed in MATLAB using data acquired from the Edgetech data acquisition system and control software, JStar, which allows for real-time data visualization and integrates GPS/UTC data. The processing involves making a series of phase-coherent operations on the different receive array elements, which results in information on the location of a resolved scatterer in the beam, and subsequently converted into target strength.

2.1.2 High-Frequency Acoustic Subsystem (50-450 kHz)

The high-frequency subsystem utilizes two Kongsberg-Simrad WBT-Tubes and four broadband, split-beam, Simrad transducers. Both WBT-Tubes are controlled in real-time though the same EK80 software from a common topside computer, which integrates shipboard GPS data. This software is triggered by the mid-frequency EdgeTech electronics for the purpose of accurate synchronization. Four octave-bandwidth split-beam (4-quadrant) Simrad transducers with center frequencies at 70, 120, 200, and 333 kHz span the 50-450 kHz frequency band with small gaps (Table 1). All post processing of EK80 data is performed in Matlab with software already developed at WHOI. These high-frequency channels are calibrated using a 38.1mm-diameter Tungsten Carbide spherical standard target following Lavery et al. [51]. There have been a small number of studies using in-situ high-frequency broadband acoustic approaches [52-54].

<table>
<thead>
<tr>
<th>Transducer</th>
<th>Nominal Center Frequency (kHz)</th>
<th>Bandwidth (kHz)</th>
<th>Full Beamwidth (Degrees)</th>
<th>Pulse Duration (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ES70-7CD</td>
<td>70</td>
<td>50-90</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>ES120-7CD</td>
<td>120</td>
<td>90-160</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>ES200-7CD</td>
<td>200</td>
<td>160-260</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>ES333-7CD</td>
<td>333</td>
<td>280-450</td>
<td>7</td>
<td>2</td>
</tr>
</tbody>
</table>

Table 1. High-frequency, split-beam, Simrad transducers mounted on Deep-See.

2.2 Optical Imaging Systems

A two-scale imaging system on Deep-See allows many zooplankton and micronekton to be simultaneously imaged. The larger-scale component images a volume large enough to sample the larger, sparsely distributed, and more mobile organisms such as fish and euphausiids, at the sacrifice of the resolution required to image smaller organisms. The smaller-scale imaging system images a much smaller volume, but with high enough resolution to image and classify the smaller organisms. There have been a number of optical imaging approaches and systems developed for identification and monitoring of small zooplankton [55]. Examples include the 3-D Oasis system [55], the Zooplankton Visualization System [56] and the Video Plankton Recorder [57,58]. However, these plankton-imaging devices sample volumes that are too small to be useful for macrozooplankton and micronekton, necessitating a large-area imaging system. A single-scale large-area plankton imaging system (LAPIS [1]) with close to 1 m² areal coverage was developed over a decade ago and a feasibility demonstration was successfully completed. Through image analysis and computer “training” for automatic classification, the size, shape, orientation, behavior, and abundance of zooplankton and small fish can be determined in real time [58]. Early deployments of this system showed that it was possible to: i) Infer abundance of individuals per cubic meter, using flowmeter data to calculate volume imaged during the tows. ii) Measure animal sizes from the images, based on prior calibration of the field of view. iii) Identify targets to taxa/species, thus allowing species diversity to be assessed. iv) Determine orientation and behavior of swimming organisms, including observations that the swimming orientation of salps was consistent with their diel migration (headed up at night, down in early morning), observations of solitary salps releasing their chains of aggregate offspring in surface waters at night, quantification of the numbers and positions of hyperiid amphipods on salps and other gelatinous organisms, arrangement of tentacles in feeding positions for medusae, siphonophores, and ctenophores, and observations of shock-molting behavior and escape swimming in Euphausia superba schools. However, the original LAPIS system operated over a single larger scale at the sacrifice of
resolution at the smaller scale. Furthermore, significant advances in camera and LED-technology has rendered the strobe-based LAPIS obsolete.

A new system has been developed, extending and updating the LAPIS design previously developed at WHOI [1]. The development includes a 24-MPixel camera imaging an area of 1m$^2$ (1m x 1m) so that the larger organisms can be imaged at lower resolution and a holographic imaging system with an imaging volume of 1m x 2cm x 2cm so that the smaller organisms can be imaged at higher resolution (approximately 50µm). With the two cameras mounted side-by-side, the smaller imaging area is within the boundaries of the larger area, providing some overlapping information. The larger area system is an increase of nearly a factor of four in resolution over the original LAPIS system. Critical to the design of this system is the optimization of the lighting and camera positions, as well as the forward-looking towed approach, which, using flowmeter data to calculate volume imaged during the tows, results in data comparable to abundance data from net tows, except with far greater resolution of spatial patchiness, and more accurate quantification of fragile organisms. Off-the-shelf hardware includes cameras, zoom lens, and LED-strobes. Control is executed by ship-board pc’s through the fiber-optic link, and integrates ship-board GPS.

2.3 Environmental Sensing Systems and Towed Platform

Temperature, conductivity, and depth (CTD) are obtained using a Seabird 49 FastCat CTD, in addition to obtaining depth/roll/pitch of the towed platform in the power and telemetry underwater unit. A 500-kHz M3 Multibeam is also available, either pointing forward to monitor avoidance, or downward looking. An environmental eDNA sampler with 16 separately pumped samples is also integrated to the Deep-See towed platform to allow genetic fingerprinting of mesopelagic organisms. All sensors are deployed on the single towed platform to collect simultaneous, co-located data. The optics, high-frequency acoustics, and environmental sensors especially must be at or near the depths of the organisms. Deep-See is flooded platform towed at speeds between 2-3 kts. The oil-filled junction box (J-Box) is a key part of the system, providing power and control/data telemetry to all systems from the tow cable. Deep-See is towed by the industry standard 0.681" diameter cable with three layers of outer strength windings, three inner electrical conductors (for sensor power) and three single mode optical fibers (ethernet control of sensors and data transfer up to 5 Gb/s). The sensors are controlled remotely from control computers in the control lab on the deck of the ship. Data from individual sensors is transmitted to specific computers and all data have a common timestamp (ship’s GPS).

2.4 Bioacoustics Mooring

To complement the measurements performed with the integrated towed sensor platform Deep-See, a bioacoustics mooring (Fig. 3) was deployed in the New England slope water in 2784 m water depth. The mooring allowed persistent measurements of acoustic backscattering in order to assess the importance of season variability in abundance, distribution, and biomass, as well as the impact of meso-scale physical drivers such as warm-core rings. The mooring consists of an anchor weight, an acoustic release, and a flotation sphere with the Simrad WBAT and broadband 3-sector transducer (ES38-18CDK, bandwidth ~32-43 kHz). The mooring has no surface expression and the float with the bioacoustics sensors was located at approximately 600m depth, upward looking. The autonomous acoustic system collects data for 5 min every 30 minutes in a 2-week cycle.

3. RESULTS

The Deep-See platform has been deployed in New England slope waters to study the OTZ in 2700-3000 m water depth in summer 2018, summer 2019, and summer 2022 from the NOAA Ship Henry B. Bigelow. Published results can be found in references [59-62] and a summary is shown in Figures 1 and 2. The autonomous bioacoustics mooring was deployed from July 2021-March 2022, and June 2022 – present, also in the New England Slope Waters (38 59.1258 N, 70 12. 1387 W, Water Depth 2785). A summary of results is shown in Figure 3.
ACKNOWLEDGEMENTS

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REFERENCES


Preliminary inversions using compressional, shear and interface waves in the New England Mudpatch

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ABSTRACT

The properties of ocean sediments can significantly impact the acoustic propagation in shallow water. To understand the effect of fine-grained sediments on acoustic propagation experiments were conducted in 2017 and 2022 at the New England Mud Patch. The mud patch is a 13,000 square kilometer area covered by a layer of silty mud sediments. This sediment layer is the only area on the entire eastern United States outer shelf where surficial sediments contain more than 30 percent silt plus clay. Hence this area offers a unique location to apply the inversion techniques to investigate the geoacoustic properties of fine-grained sediments.

Data collected during the 2017 Seabed Characterization Experiment (SBCEX-2017) triggered large number of studies and subsequent publications (1, 3, 4). In order to augment this understanding, the 2022 experiment collected more data in the same experimental area. The ongoing data analysis and inversions builds on the understanding gained based on the 2017 experiment. This article highlights some of the data collected and analyzed and presents preliminary results. Specifically, data measured from broadband SUS sources are analyzed in this study. The receiver systems deployed during these experiments include a tetrahedral array of hydrophones and a 3-axis geophone and Ocean Bottom Recorders (OBXs). The geophones and OBXs measure particle velocity in three mutually perpendicular directions and acoustic pressure. Scholte waves on the mud-sand interface were generated by a bottom-mounted transducer. Measurements of SUS signals on the hydrophones and directional sensors will be used to estimate the sediment geoacoustic properties. Preliminary inversions from the 2022 experiment will be compared to previous inversions for the same location. [Work sponsored by Office of Naval Research, Code 322OA].

Keywords: inversion, SUS, dispersion, particle velocity

1. Introduction

The properties of ocean sediments can significantly impact the acoustic propagation in shallow water. To understand the effect of fine-grained sediments on acoustic propagation experiments were conducted in 2017 and 2022 at the New England Mud Patch (NEMP) off the United States East Coast (1). The mud patch is a 13,000 square kilometer area covered by a layer of silty mud sediments. This sediment layer is the only area on the entire eastern United States outer shelf where surficial sediments contain more than 30 percent silt plus clay (2). Hence this area offers a unique location to apply the inversion techniques to investigate the geoacoustic properties of fine-grained sediments.

Data collected during the 2017 Seabed Characterization Experiment (SBCEX-2017) triggered large number of studies and subsequent publications (1, 3, 4). In order to augment this understanding, the 2022 experiment collected more data in the same experimental area. The ongoing data analysis and inversions builds on the understanding gained based on the 2017 experiment. This article highlights some of the data collected and analyzed and presents preliminary results. Specifically, data measured from broadband SUS sources are analyzed in this study. The receiver systems deployed during these experiments include a tetrahedral array of hydrophones and a 3-axis geophone and Ocean Bottom Recorders (OBXs). The geophones and OBXs measure particle velocity in three mutually perpendicular directions and acoustic pressure. Scholte waves on the mud-sand interface were generated by a bottom-mounted transducer. Measurements of SUS signals on the hydrophones and directional sensors will be used to estimate the sediment geoacoustic properties. Preliminary inversions from the 2022 experiment will be compared to previous inversions for the same location. [Work sponsored by Office of Naval Research, Code 322OA].

Keywords: inversion, SUS, dispersion, particle velocity

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perpendicular directions and acoustic pressure. This study focuses on measurements of SUS signals on one of the OBXs, which includes data from a hydrophone and 3-axis geophone.

2. Broadband SUS data and modal dispersion

The locations of the SUS charge and the OBX receiver are shown in figure 1 (panel a). Based on the deployment locations, the range was calculated as 9.95 km. The source to receiver propagation path is oriented at 164° (measured anti-clockwise from the east direction) as shown in figure 1 (panel a).

![Figure 1 - Locations of the source (SUS) and OBX receiver (panel a). The propagation path is oriented 164° measured anti-clockwise from east. The OBX receiver is shown in panel b. The orientations of the inline, cross line and vertical (marked X, Y and Z) axes are also shown in the panel. The azimuth angle (θ) and the elevation angle (φ) are defined in panel c.]

The OBX is a self-contained sensor package consisting of a 3-axis geophone and a co-located hydrophone along with heading sensor, accurate clock, battery and data storage. The OBX measures particle velocity along three mutually perpendicular directions (inline, cross line and vertical – marked as X, Y and Z in figure 1 (panel b)). The OBX data can be used to find the azimuth and elevation angles (as defined in the panel c in figure 1) of the direction of arrival (DOA) of the signal. Data were measured on the OBX at a sampling frequency of 4 kHz.

2.1 OBX data

The broadband data measured on the OBX located 9.75 km from the source is shown in figure 2. The figure shows the vertical, inline, cross line velocity components (in mm/s) and the pressure time series (in Pa) from the hydrophone channel. The OBX was deployed on the seabed and position shown in the figure is the triangulated location after deployment. The OBX has a heading sensor and the heading measured on that sensor was 260° (clockwise from N). This heading can be validated by calculating the DOA from the source and the known source position.
Figure 2 – Broadband data from the OBX. The four subplots (top to bottom) show the vertical, inline and cross line velocity components. The bottom subplot shows the hydrophone data. Note that the inline component is stronger (~ 5 times) compared to vertical and cross line components.

2.2 Modal dispersion

The arrivals corresponding to the different normal modes can be observed in the time-frequency representations of the broadband acoustic signals shown in figure 2. Figure 3 shows the modal dispersion diagrams of the velocity components and the acoustic pressure.

Figure 3 – Time-frequency diagrams of the data shown in figure 2 showing the dispersed arrivals of the normal modes. The four panels correspond to the vertical, inline and cross line components of the velocity and the hydrophone data. Note that inline component is stronger (~ 5 times) compared to vertical and cross line components.
Note that the color scale for the inline component is different from the vertical and crossline components since it comparatively stronger. All of the velocity components and pressure data show the presence of precursor arrivals and strong dispersed arrivals (~1 second long) corresponding to the first four normal modes. The Airy phase (group speed minimum) can be clearly identified in the pressure and the inline velocity component. The velocity components can be used to calculate the DOA and a time-frequency representation (called ‘azigram’) can be constructed to identify the direction of acoustic propagation.

### 2.3 DOA: Azigram

As mentioned earlier the ‘azigram’ provides a visualization of the evolution of DOA as a function of time and frequency. The DOA of the arrivals is calculated using the velocity components as defined in figure 1 (panel c). The time series is divided into a number of segments and the azimuth and elevation angles are calculated as a function of frequency using equation 1. The azimuth calculated as a function of time and frequency is shown in figure 3 (bottom panel). The top panel in figure 3 shows the azimuth at 101 Hz.

![Figure 3 – Time-frequency visualization of the DOA (azimuth) of the acoustic arrivals shown in figure 2. The color indicates the azimuth in degrees as mapped according to the color bar. Top panel shows the azimuth at a single frequency (101 Hz). The source receiver positions are shown in figure 1 (panel a).](image)

The active intensity measures the in-phase product of pressure (P) and velocity ($v_x, v_y$) which indicates the portion of the acoustic field that is actively transporting acoustic energy through the measurement point along the direction of the velocity vector. The azigram $A(n,m)$ is defined as (5),

$$A(n,m) = \tan^{-1}\left\{\frac{I_y(n,m)}{I_x(n,m)}\right\}$$

(1)

Azigram represents the dominant azimuth from which acoustic energy at time chunk $n$ and frequency index $m$ is propagating along the horizontal plane. The active intensity along the x and y direction in equation 1 is defined as shown in equation 2,

$$I_x = \text{Re}\{P(n,m)v_x(n,m)\} \quad \text{and} \quad I_y = \text{Re}\{P(n,m)v_y(n,m)\}$$

(2)

In figure (3) the azimuth is shown only for the times and frequencies at which the active intensity component is dominant. This is done by calculating the Normalized Transport Velocity (NTV) and using that to identify the active part of the acoustic arrivals.
2.4 Normalized Transport Velocity (NTV).

The Normalized Transport Velocity (NTV) is defined as the ratio of the active intensity magnitude to the energy density (5) as shown in equation 3.

\[
NTV = \frac{\left(\frac{\iota^2 + \iota_f^2}{\iota_p}\right)c}{2\rho_0 \left(\frac{u_x^2 + v_y^2}{\iota_p^2}\right) + \left(\frac{1}{2\rho_0 c^2}\right)} 
\] (3)

The magnitude of NTV should lie between 0 and 1; with 1 corresponding to propagating plane wave and 0 corresponding to standing wave. After calculating the azigram using equation 1, the values corresponding to NTV <0.5 has been removed (white areas in figure 3) which preserves the propagating part of the wavefield and removes the rest of the wave types.

The azimuth values shown in figure 3 indicates that the direction of propagation of the acoustic energy corresponding to the broadband source is along the inline axis (X direction) of the OBX (azimuth measured from X axis ~ 0). A slice of the azigram along 101 Hz (dashed line) confirms this as shown in the upper panel in figure 3.

3. Preliminary estimation of geoacoustic model using H/V ratio method

Horizontal to vertical particle velocity ratio (H/V) method (6) calculates the spectral ratio between the horizontal and vertical components of particle velocity measured by a single particle motion sensor. The ratio between the horizontal and vertical axes of the ellipse of particle motion is called ellipticity. The H/V curve exhibits a single peak corresponding to the resonance frequency of the site. For a sensor on the seabed, it is widely accepted that the resonance frequency is linked to a peak in interface wave ellipticity for sites with a large shear-wave impedance contrast between the surficial sediment layers and the underlying bedrock [7]. If the site has multiple layers of sediment, the H/V curve may exhibit multiple peaks. The principle of the method is to calculate the ratio of the horizontal (\(v_x\), \(v_y\)) and vertical (\(v_z\)) Fourier spectra of ambient seismic vibration recordings of a single three-component seismic sensor. The natural frequency (\(f_R\)) of a homogeneous sediment layer of thickness (d) and shear speed (Vs) is approximately given by equation 4.

\[
f_R = \frac{Vs}{4d} 
\] (4)

When the peak frequency is estimated from the H/V curve, the shear speed or the depth to bedrock (depth to impedance mismatch in the case of multiple peaks) can be calculated knowing one of them. Ambient noise data measured on the OBX was used to calculate the H/V ratio and identify the resonances. Since this is a passive technique, an algorithm used extensively in the geophysical community (RayDec algorithm) was used to identify and confirm the presence of Scholte waves. The H/V ratio is then computed from the data using the RayDec algorithm (8) and is shown in figure 4 (black curve). The RayDec algorithm is based on the random decrement technique, which is commonly used to characterize the dynamic parameters, i.e., resonance frequency and damping. This technique isolates the Scholte wave arrivals in the data and uses that to calculate the H/V ratio. The RayDec algorithm is described in detail in [8].

The RayDec algorithm also finds out the DOA of Scholte wave arrivals by searching the data (the vertical and horizontal components of velocity) at various times and frequencies and identifying the 90° phase shift between them (vertical and horizontal components) which is characteristics of the Scholte waves. Right panel in figure 4 shows the frequencies dominated by Scholte waves in the ambient noise data analyzed and the associated azimuths. The azimuth corresponding to the Scholte wave arrivals seems to be 300° which is nearly opposite to the direction of the SUS data propagation direction. Data from this frequency band identified as Scholte wave arrivals are used to calculate the H/V ratio as described earlier.

The H/V ratio can also be predicted using modeled acoustic particle motion in the horizontal and vertical directions. The green curve in figure 4 (left panel) is the H/V ratio calculated using predicted
particle velocities. The particle motions were predicted using Lai-Rix model (9). The inputs to this model are the bottom parameters such as the shear and compressional wave speeds and densities in various layers of sediments, and the layer thicknesses. The model output shown in figure 4 is based on a geoacoustic model as shown in figure 4 (middle panel). The multiple resonant peaks in the data indicates a number of layers of sediment (both in mud and sand depositional packages). The shear speeds in the mud were 25 m/s (0 to 3 m) and 40 m/s (3 to 6 m). Shear speeds in the sand layer below the mud increased from 200 m/s to 250 m/s (in three steps) over a layer thickness of 20 m. The shear speed in the basement was 500 m/s. The compressional wave speeds in the were assumed as 1450 m/s and 1520 m/s in the two mud layers, and in the as 1700 m/s, 1700 m/s and 1750 m/s respectively in the three sand layers. The compressional wave speed in the basement was input as 1800 m/s. Densities varied from 1.65 kg/m³ to 2 kg/m³ in the mud and sand layers.

Figure 4 – The ellipticity (H/V ratio) calculated for the ambient noise data using the RayDec algorithm (black curve). The green curve in the left panel is calculated using predicted Scholte wave motion for a bottom model shown in the middle panel. The right panel shows the frequency band where the Scholte wave arrivals are dominant, and the color corresponds to the azimuth in degrees.

4. CONCLUSIONS

Preliminary analysis of acoustic data measured during the Seabed Characterization Experiment is presented in this paper. The broadband acoustic pressure and particle velocity data show dispersive behavior with adequate signal to noise ratio (SNR) are long ranges (~ 10 km). Standard time-frequency techniques (Fourier and wavelet analyses) were able to extract the modal arrival pattern for the lower order modes. Higher order modes can be identified, and arrival times extracted by the application of high-resolution techniques (warping transform). The orientation of the sensor was measured with good precision by the heading sensor and was validated with DOA estimates using SUS data. H/V ratio technique was applied to ambient noise data using an algorithm (RayDec method) which identifies and uses particle motion data corresponding to Scholte wave arrivals. The Scholte wave arrivals are identified in the 20 to 30 Hz frequency band coming from an azimuth of ~300° which is nearly opposite direction to the SUS arrivals analyzed in this study. The simple sediment description (multiple mud and sand layers over basement) provided estimates of Scholte wave particle motion which then was used to calculate H/V ratio for comparison with data derived H/V ratios. The resonant frequencies in the 0-10 Hz band were matched to a lesser degree compared to the peaks in the 10-20 Hz band. It should be noted that this match was achieved by iterating the model runs without using any inversion algorithm. We plan to continue the inversion with better constraints on the shear speeds and layer thicknesses based on available data (cores, seismic data and prior inversions) and using advanced inversion techniques.

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Extended abstract

Propeller Cavitation Localization applying Sparse Signal Recovery

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ABSTRACT

Conventional cavitation localization methods have problems in terms of accuracy or inability to distinguish adjacent sources because they have low resolution. In this study, we propose a method to apply sparse signal recovery to the localization of cavitation, which can reconstruct the location of the cavitation with high resolution. In many cases, the cavitation noise generated by the propeller has a sparse property, so the cavitation localization problem is suitable for applying the sparse signal recovery technique. The proposed method showed high-resolution and noise robustness due to the advantages and characteristics of the sparse signal recovery method, and these advantages were illustrated in this study as the results of localization.

Keywords: Sparse signal recovery, Cavitation localization

1. INTRODUCTION

Propeller cavitation is a significant source of noise in the marine environment, affecting the survivability of warships as well as the comfort of passengers. It's crucial to identify and detect cavitation in order to lessen the harmful impacts of propeller cavitation. Optical techniques have limitations for locating the locations of the incipient TVCs since the bubbles that create them are too tiny to be seen [1]. As an alternative, acoustic measurements that incorporate noises from developing TVCs have been applied to the cavitation localization [2-4].

There are two types of cavitation localization methods: Matched field processing (MFP)-based methods and sparse signal recovery (SSR)-based methods. MFP-based methods are a traditional and widely used methods for cavitation localization. MFP is a method to generate the virtual pressure field (replica) for the search space and to evaluate the similarity between the replica and acoustic measurements. However, the MFP has a limitation in that it cannot distinguish adjacent sound sources due to its low resolution. Meanwhile, in the case of SSR methods such as CS and SBL, high-resolution results can be obtained, so studies have been conducted to localize cavitation by applying them. Therefore, studies have been conducted to localize cavitation by applying SSR method such as compressive sensing (CS), which can obtain high-resolution results [3-4]. Despite recent advancements, the CS-based methods have a disadvantage that localization performance is dictated by hyper-parameter. On the other hand, SBL is not dependent on the hyper-parameter and is generally known to outperform CS. Herein, we propose an SBL-based cavitation localization method and verify the performance of the proposed method with experimental results.

2. SPARSE REPRESENTATION

Cavitation noise was assumed to be mono-pole source in which sound propagates omnidirectionally. Then, the signal \( y'_m \) received by the \( m \)-th hydrophone can be expressed as

\[
y'_m = e^{-i(2\pi f \xi^c)} \frac{x'^f}{4\pi r'_m} + n'_m,
\]

(1)
where the superscript $f$ is the frequency of the source, $c$ is the sound speed, $r_m$ is the distance from the source to the $m$-th hydrophone, $x^f$ is the source amplitude, and $n^f_m$ is the noise. Assuming that there is a virtual source at each grid point by dividing the three-dimensional search space, the signal vector composed of the $m$-th hydrophone signal can be expressed in the following vector form.

$$y^f = A^f x^f + n^f. \tag{2}$$

$x^f$ is estimated by SBL reconstruction scheme. The final localization result is compiled by adding all $x^f$ obtained in each process.

3. RESULT

To check the validity of the proposed method, a model-scale experimental data that conducted at the Korea Research Institute of Ships and Ocean Engineering (KRISO) is used. The array consists of 7 hydrophones, the grid points were distributed with grid interval 0.02 m over the 3-D search space (x-axis:-0.15 to 0.15 m, y-axis:-0.20 to 0.20 m, z-axis:-0.20 to 0.20 m).

![Figure 1](image-url)

(a) Image from high speed camera, (b) SBL localization result(front view), (c) SBL localization result(side view), (d) MFP localization result(front view), (e) MFP localization result(side view),

Fig 1(a) is image data captured from high speed camera video data, and cavitations are observed in the areas indicated by red and orange circles. Fig 1(b) and Fig 1(c) are front view and side view of SBL localization result, respectively. Fig 1(d) and Fig 1(e) are front view and side view of MFP localization result, respectively. The red dots in Fig 1(b) and Fig 1(c) indicate the positions of the hydrophones, the black circle represents the propeller diameters, and the estimated cavitation positions are indicated by yellow and blue dots.

MFP results (Fig 1(d) and Fig 1(e)) have high ambiguity due to low resolution, making it difficult
to specify the location of cavitation. In addition, it can be seen that the vertical resolution is very poor because the sensors are on the top. On the other side, the results of estimating the location of cavitation by the proposed method (Fig 1(b) and Fig 1(c)) coincide with the cavitation inception area (red circle and orange circle in Fig 1(a)) and have high resolution.

4. CONCLUSION

In this paper, we proposed a method that applies SBL to localize cavitation. Through experimental data results, it was confirmed that the proposed method obtains results with better resolution than conventional method MFP. In addition, MFP has very poor vertical resolution and cannot localize cavitations, whereas the proposed method shows results consistent with images obtained from high speed cameras.

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REFERENCES

Demonstration of a physics-based sediment property inversion algorithm applied to multibeam echosounder data.

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ABSTRACT
Leveraging several decades of research on high-frequency sediment acoustics, a physics-based inversion algorithm has been developed to invert multibeam echosounder data for geoacoustic parameters of the seafloor. This approach begins by generating synthetic data using a sonar-equation model and finds the interface and volume scattering strengths that produce the best fit to the data along each beam. Physics-based scattering models are then fit to the interface scattering strength to determine the roughness spectrum and the reflection coefficient for the sediment. The reflection coefficient is then used to determine the sediment properties via a set of regression relations. To evaluate the performance of the algorithm for a range of sediment types, sonar and ground-truth data were collected in 2019 at 10 sites in Sequim Bay, a shallow, protected bay along the northern coast of the Olympic peninsula in Washington State. A second echosounder survey was conducted in the fall of 2021 to demonstrate the inversion’s ability to map sediment properties over a wide area. Details of the inversion and results from the two field tests will be discussed.

Keywords: Sound, Insulation, Transmission

1. INTRODUCTION
Due to their high-resolution and ease of deployment, multibeam echosounders (MBES) have become popular tools for sediment characterization. These sonar systems, however, have been designed and marketed primarily for the measurement of bathymetry and as a result, inversion of the sonar data typically relies on ad-hoc techniques that attempt to correlate features of the backscattered signal with ground-truth measurements of the seafloor properties. These ground truth measurements can include the vibrocores, grab samples, or images of the seafloor. These approaches are often designed around a single sonar system and migrating the approach to a new sonar can be difficult and potentially lead to differences in the seafloor characterization.

To overcome these issues and reduce the reliance on ground-truth data, a physics-based MBES inversion has been developed which leverages decades of research on high-frequency scattering of sound from the seafloor (1). This inversion builds on previous techniques developed for single-beam echosounders (2,3) and utilizes the time-series of the backscattered pressure along multiple beams to estimate the roughness and volume scattering strength of the sediment, from which the geoacoustic properties of the seafloor can be determined from empirical relations (Figure 1a).

This inversion algorithm has been developed using data from three field tests: The Target and Reverberation Experiment in 2013, the St. Andrews Bay Experiment in 2014, and a field test in Sequim Bay in 2019. In these experiments, both MBES data and ground truth data were collected so that the inversion could be evaluated and improved. A fourth field test in Sequim Bay was conducted in November 2021. This field test focused on the application of the inversion to wide-area survey data to evaluate both the inversion performance and techniques to visualize the inversion output and the uncertainties in that output.

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SEQUIM BAY FIELD TESTS

Sequim Bay is located at the northern end of the Olympic Peninsula in Washington State, U.S.A. The bay is connected at its northern end to the Juan de Fuca Strait through a small opening (see the background satellite image in Figure 1c) and is roughly 1.5 km wide and 3 km long. For the 2019 field test, 10 sites within the northern portion of the bay were chosen to cover a range of sediment types and depths. At each site, ground truth data was collected from diver cores, an in-situ velocimeter, a laser-line profiler, and a conductivity probe. Multibeam echosounder data was also collected along 200-m-long survey lines that passed through each of the sites. An example of the inversion output compared to the ground truth measurements is shown in Figure 1b.

During the 2021 field test, multibeam echosounder data were collected along survey lines which spanned the northern portion of the bay as well as longer lines which extended approximately along the north-south axis of the bay. An example of the inversion output using all of the 2021 survey lines is shown in Figure 1c.

3. SUMMARY

This talk will discuss in greater detail the physics-based inversion algorithm shown in Figure 1a and the results of the Sequim Bay field tests.

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Sparse frequency analysis of passive sonar signals using the adaptive learned iterative thresholding algorithm

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ABSTRACT

In this paper, we introduce the sparse frequency analysis using neural networks based on the iterative solvers of adaptive learned iterative shrinkage thresholding algorithm (Ada-LISTA) that receives pairs of signals and their corresponding dictionaries as inputs, and learns the model. The Ada-LISTA has acceleration benefits of learned solvers and incorporates the dictionary as part of the input data at both training and inference time, allowing for adaptivity to different models. In order to improve the performance of the Ada-LISTA based frequency analysis, we train the model using simulation data (pre-training step), and then reflect the physical characteristic of the real-data, we retrain the model using the real-data with the cost function considering system model of frequency analysis (fine-tuning step). Experiments using the underwater in-situ data measured near the Korea peninsula show the superior restoration performance and processing speed of the Ada-LISTA compared with the performance of the fast Fourier transform and the sparse Bayesian learning.

Keywords: Sparse frequency analysis, Ada-LISTA

1. Introduction

Passive sonar systems received the acoustic signals that emitted from marine objects such as submarine and surface ship, and accurate estimation of frequency components is crucial to identifying the target. The tonal signals which are generated by operation of machinery of ship are composed of the sparse frequency component at low frequency region [1]. The frequency analysis problem can be expressed by a linear equation of the form:

\[ y = Ax + n \]

where \( x \in \mathbb{R}^n \) is the unknown frequency components, \( A \in \mathbb{R}^{m \times n} \) is the dictionary matrix, \( y \in \mathbb{R}^m \) is the received signals which mainly composed of the tonal signals, and \( n \) is the noise.

In order to solve the linear inverse problem with sparsity, compressive sensing and sparse Bayesian learning (SBL) have been used to reconstruct the sparse solution [2-4]. However, they are hard to be applied in real-time owing to high computation complexity. To overcome the limitation, in this study, we apply neural networks based on iterative solvers of adaptive learned iterative shrinkage thresholding algorithm (Ada-LISTA[5]). We compare the restoration performance from fast Fourier transform (FFT), SBL and Ada-LISTA using the underwater in-situ data measured near the Korea peninsula.

2. Methods

To solve (1), we apply the Ada-LISTA [5]:

\[ x_{k+1} = S_{\theta_k+1}((I - \gamma_{k+1}A^T W_1^TW_2A)x_k + \gamma_{k+1}A^T W_1^Ty), \]

where \( W_{1,2} \) are weights, \( \gamma \) is a step size, \( \theta \) is a scalar thresholding value, and \( K \) is number of unfold layer. The unknown parameter \( \Theta = (W_1, W_2, \{\gamma_k, \theta_k\}_{k=1}^K) \) are learned through training the neural
networks using stochastic gradient descent. In order to improve performance, we train the Ada-LISTA with two steps: 1) pre-training step using simulation data, and 2) fine-tuning using real-data. In the first step, the loss function is written as

$$\min_{\Theta} \sum_{i=1}^{N} \| y^{(i)} - A \mathcal{F}_K (y^{(i)}, A; \Theta) \|_2^2 + \| \mathcal{F}_K (y^{(i)}, A; \Theta) - x^{(i)} \|_2^2 + \lambda \| \mathcal{F}_K (y^{(i)}, A; \Theta) \|_1. \quad (3)$$

In second step, the loss function is as

$$\min_{\Theta} \sum_{i=1}^{N} \| y^{(i)} - A \mathcal{F}_K (y^{(i)}, A; \Theta) \|_2^2. \quad (4)$$

$N$ is the number of training example, $\lambda$ is the hyperparameter controlling the sparsity penalty, and $\mathcal{F}(y, A; \Theta)$ outputs frequency components using the Ada-LISTA.

3. Results

The training data in pre-training step are randomly generated using (1); activating frequency component are from 25 to 100, and SNRs vary from -15dB to 15dB. We used 20,000 simulation data and 200 real-data for pre-training and fine-tuning, respectively.

The restoration results from the FFT, Ada-LISTA, and SBL are displayed in Figure 1. The frequency analysis using the FFT is smeared by the overall noise. The Ada-LISTA and SBL improve the detection results in terms of the resolution and denoising; the overall noise is significantly reduced by the sparse estimation, which is beneficial to the detection clarity. For the simulation in Figure 1, the SBL require computational time of 7600 second under the computational environment of Intel(R) Core (TM) i9-9900K CPU, therefore it is hard to be applied in real-time. However, in case of the Ada-LISTA, once the model is trained in advance, we can obtain the frequency analysis results of Figure 1 in almost 0.061 second.

![Figure 1](image)

Figure 1 – Simulation results using in-situ data measured near the Korea peninsula.

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Geoacoustic inversion of an ocean waveguide using Bayesian optimization with a Gaussian process surrogate model

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ABSTRACT
Geoacoustic model optimization and inversion are computationally expensive endeavors. In cases where a parameter grid search is prohibitively expensive, optimization produces an approximated solution through sampling techniques. Recent work proposes sampling with a Bayesian approach that uses a Gaussian process as a surrogate model of the objective function. In this study, the objective function is defined as a Bartlett processor which measures the correlation between a received and replica pressure field on a vertical line array. The replica field is calculated using a propagation model whose parameters are selected from the parameter search space. The surrogate model represents the posterior on the objective function and is updated with each model evaluation. Optimization is performed with sequential model evaluations, with an acquisition function guiding the next point in parameter space to be evaluated. Expected improvement is used as the acquisition function, as it incorporates the uncertainty in the posterior to select the next evaluation point and adaptively balances exploitation (densely sampling around the best observed value of the objective function) and exploration (sampling in areas of high variance in the objective function posterior). Results indicate that Bayesian optimization using a Gaussian process surrogate model converges rapidly on an approximated optimal solution.

Keywords: Estimation, Bayesian, Optimization

1. INTRODUCTION
A popular and conventional approach for underwater acoustic source localization is matched field processing (MFP), which uses beamforming to match a sound pressure field \( \mathbf{d} \) measured by an array with replica fields \( \mathbf{d}^* \) produced by a forward acoustic propagation model with parameters \( \mathbf{m} \).[1]–[3] The conventional beamformer output is the Bartlett processor:

\[
f(\mathbf{m}) = \left| \mathbf{w}^H \mathbf{d} \right|^2
\]

where \( \mathbf{w} = \mathbf{d}^*/||\mathbf{d}^*|| \). Where the measured and replica fields are most highly correlated indicates the best estimate \( \hat{\mathbf{m}} \) of the source’s range and depth. MFP uses a grid search through the parameters \( \mathbf{m} \) to find the maximum correlation produced by the Bartlett processor. One of the downsides to MFP is that it is computationally intensive, consisting of an exhaustive grid search through parameter space, in this case range and depth. Another limitation to grid search is that the sampling is restricted to the points on the grid and may miss important features that do not lie on the grid. Finally, the information used in MFP is not used for subsequent decision making about where to sample next.

To improve sampling efficiency and utilize the information learned upon each sample evaluation, we use a Bayesian optimization method to estimate the optimal parameters. Previous Bayesian optimization techniques include simulated annealing and genetic algorithms, though these techniques are also computationally intensive and rely on Monte Carlo sampling of the objective function.[4], [5] In this study we treat the objective function in a Bayesian approach that incorporates previous sample results in the decision of where to sample next, thereby improving sampling efficiency and converging on the optimal solution more rapidly.[6]–[8]
noisy observations and the noise process whose observations are characterized by a Gaussian process is defined as a Gaussian process.

2.1 Gaussian Process Surrogate Model

The objective of the optimization is to maximize the objective function in Eq. (1) to find the optimal parameters by:

$$\hat{m} = \text{argmax}_m [f(m)].$$

To accomplish this, we simplify the optimization by approximating the objective function with a Gaussian process, which is characterized by the posterior distribution of the objective function. A Gaussian process is defined as a collection of random variables, any finite number of which are jointly distributed. Consider $N$ samples from $D$-dimensional parameter space $X_{D \times N} = [x_1, ..., x_N]$ whose observations are $f = [f(x_1), ..., f(x_N)]^T$; the Gaussian process is described by a mean function:

$$\mu = \mathbb{E}[f] = [\mu_1(x), ..., \mu_N(x)]^T,$$

where $\mu(x)$ is the mean at $x$; and a covariance function:

$$\Sigma_{ij} = \mathbb{E}[(f(x_i) - \mu(x_i))(f(x_j) - \mu(x_j))]^T = K(x_i, x_j),$$

where $K$ is a kernel function measuring the similarity between two samples $x_i$ and $x_j$. The Gaussian process is thus described as $f \sim \mathcal{N}(\mu, \Sigma)$. Consider a dataset of observations with added Gaussian noise $\mathcal{D} = \{(x_n, y_n), n = 1:N \} = \{X, y\}$ where $y_n = f(x_n) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \sigma^2)$. The joint distribution of the noisy observations and the noise-free predictive distribution at new points $\{X_s, f_s\}$ is:

$$p(y, f, X_s, f_s) = \mathcal{N}\left(\begin{bmatrix} \mu_X & \mu_f \end{bmatrix}, \begin{bmatrix} K_{XX} & K_{Xf} \\ K_{fX} & K_{ff} \end{bmatrix}\right),$$

where $\mu$ and $\mu_s$ are the mean functions at $X$ and $X_s$, respectively; and

$$\begin{align*}
K_\sigma &= K_{XX} + \sigma^2 I = K(X, X)_{N \times N} + \sigma^2 I \\
K_{Xf} &= K(X, X_s)_{N \times N_s} \\
K_{fX} &= K(X_s, X)_{N_s \times N} \\
K_{ff} &= K(X_s, X_s)_{N_s \times N_s}.
\end{align*}$$

The posterior predictive distribution at $X_s$ is:

$$p(f_s|\mathcal{D}, X_s) = \mathcal{N}(f_s|\mu_s, \Sigma_s)$$

where

$$\begin{align*}
\mu_s &= \mathbb{E}[f_s|\mathcal{D}, X_s] = m(X_s) + K_{Xs}^T K_\sigma^{-1} (y - \mu_X) \\
\Sigma_s &= K_{ss} - K_{Xs}^T K_\sigma^{-1} K_{Xs}.
\end{align*}$$

Figure 1. (a) Ambiguity surface from matched field processing (MFP) for a 201 Hz source located at 3 km range and 62 m depth. (b) Ambiguity surface sliced at the source depth of 62 m.

2. SEQUENTIAL OPTIMIZATION METHOD
Figure 2. Top panels: the Gaussian process posterior distribution (blue) of the true objective function (red). Bottom panels: expected improvement acquisition function. The next sample point is denoted by the black vertical dotted line.

The kernel function is one of the design parameters and can be treated as a hyperparameter.\[9\] For this study, the Matern kernel with $\nu = 5/2$ provided the best results. Hyperparameters that require tuning are the variance and the lengthscale in the Matern kernel, which are obtained by calculating the marginal likelihood given the parameters and performing gradient descent to find the optimal hyperparameters.\[9\], \[10\]

2.2 Acquisition Function

The next important component to this method is to algorithmically determine which point in parameter space to evaluate next. Acquisition functions seek to balance exploitation of the best observed values so far with exploration of regions where little is known. In this study, we utilize the expected improvement (EI) algorithm \[6\], \[11\]as it robustly balances between exploitation and exploration, thus avoiding convergence on local optima and sufficiently exploring regions of high variance. Expected improvement is defined as:

$$
\alpha_{\text{EI}}(x) = (m(x) - f') \text{CDF}(f'; m(x), \sigma^2(x)) + \sigma(x) \mathcal{N}(f; m(x), \sigma^2(x))
$$

(12)

Where $f'$ is the best observed value so far and the CDF is the cumulative distribution function at $x$. The point which is to be evaluated next is given by:

$$
\mathbf{x}_* = \underset{x}{\text{argmax}}[\alpha(x)].
$$

(13)

Figure 2 shows the Bayesian optimization in progress over four different iterations. In each iteration, the top panel shows the mean function of the Gaussian process plotted with a blue line and the standard deviation plotted with a shaded blue curve; the true objective function is in red, and samples are indicated with black “x” marks. In the bottom panel, the EI acquisition function is plotted. The vertical black dotted line indicates where the next sample will be evaluated, as determined by the maximum value of the acquisition function. In this example, the optimization locates the optimal solution after 50 iterations.
3. RESULTS

Initial simulations indicate rapid convergence on one-dimensional range estimation problems and two-dimensional range-depth localization problems. Further simulations are being conducted for additional geoaoustic parameters to estimate ocean bottom layers and their properties. These simulations are conducted using the KRAKEN normal mode propagation model.[12] In addition to simulations, this technique is being applied to real data collected during the SWELLEX96 underwater acoustics experiment, which took place off the coast of Southern California. The impacts of various configurations such as noise levels and source range are under investigation.

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ABSTRACT
This work presents an estimation method for direction-of-arrivals (DOAs) based on sparse signal processing. Sparse methods for DOA aim to express beamforming output as a sparse signal in the angular domain and achieve high resolution. The proposed method obtains sparse solutions through an iterative covariance-fitting using alternating projections and is a gridless sparse method. Compared to gridless sparse DOA estimators, the proposed method is computationally efficient and deals with non-uniformly configured linear arrays. In addition, high-resolution and reliable DOA estimation is achieved even with single-snapshot data and coherent sources. We evaluate the method using data from a real ocean experiment. The real data involve a time sequence of single snapshot data, stationary sources over multiple snapshots but coherent due to multipath effects, and co-prime array configuration, a popular non-uniform linear array.

Keywords: Direction-of-arrival (DOA) estimation, Sparse signal recovery, Variational Bayesian estimation

1 INTRODUCTION
The problem of direction-of-arrival (DOA) estimation, beamforming, is to retrieve the direction of (usually few) sound sources from measurements of the wavefield with an array of sensors. Sparse signal processing, including compressive sensing, reconstructs signals from measurements using sparsity [2]. Compressive beamforming [3, 4, 5, 6, 7] obtains a sparse solution that provides sharp estimates of the beamforming spectrum. The advantages of compressive beamforming are 1) it offers higher resolution than traditional methods, 2) it handles any number of snapshots, including a single snapshot, 3) it is not sensitive to coherent arrivals, and 4) its extensions are applicable, e.g., sequential processing [8, 9].

We solve the compressive beamforming with gridless sparse processing [10, 11]. The gridless method overcomes the basis mismatch [12, 13, 14] and does not assume that the true DOAs lie on angular search grids. Challenges of the gridless method involve accelerating solvers and handling arbitrary array geometries.

We propose a method using alternating projections (AP) [15, 16] for gridless sparse DOA estimation based on covariance fitting, AP-Covariance. Covariance fitting-based sparse processing constructs a structured matrix that has the best fit to a sample covariance matrix (SCM) and pursues the DOAs. AP-Covariance has the objective and constraint of obtaining a low-rank positive semi-definite (PSD) Toeplitz matrix for a DOA-dependent SCM. AP consists of a sequence of two projections: low-rank Toeplitz projection and PSD projection.

We study the performance of AP-Covariance with single- and multiple-snapshot data, incoherent and coherent arrivals, and non-uniform linear arrays.

2 ARRAY DATA MODEL
We consider narrowband sources with \( K \) DOAs \( \theta_k \in [-90^\circ, 90^\circ] \) are in the far-field of a uniform linear array (ULA) with \( M \) sensors. Let the \( k \)th DOA of the complex source amplitude for the \( m \)th snapshot \( s_{k,m} \in \mathbb{C} \),
becomes,

\[
\mathbf{Y} = \sum_{k=1}^{K} a(\theta_k) \mathbf{s}_k^T + \mathbf{E} = \sum_{k=1}^{K} c_k \mathbf{a}(\theta_k) \phi_k^T + \mathbf{E},
\]

(1)

\[
\hat{\mathbf{R}} = \mathbf{YY}^H / L,
\]

(2)

where \( \mathbf{s}_k = [s_{k,1} \ldots s_{k,L}]^T \in \mathbb{C}^L \), \( c_k = ||\mathbf{s}_k||_2 > 0 \), \( \phi_k = c_k^{-1} \mathbf{s}_k \in \mathbb{C}^L \) with \( ||\phi_k||_2 = 1 \), \( \mathbf{E} \in \mathbb{C}^{M \times L} \) is the additive noise, and the steering vector,

\[
\mathbf{a}(\theta) = \left[ e^{-j \frac{2\pi}{\lambda} d_1 \sin \theta} \ldots e^{-j \frac{2\pi}{\lambda} d_M \sin \theta} \right]^T \in \mathbb{C}^M,
\]

(3)

where \( \lambda \) is the wavelength. The distance between sensors 1 and \( m \) is \( d_m = \delta_m d \), \( m = 1, \ldots, M \), where \( \delta_m \) is a scale factor in units of sensor-spacing \( d \) (here, \( d = \lambda / 2 \)). A uniform linear array (ULA) has \( \delta = [0, 1 \ldots M - 1]^T \), and a non-uniform linear array (NUA) consists of real number \( \delta_m \).

3 GRIDLESS SPARSE DOA ESTIMATION

Assuming the sources \( \mathbf{s}_k \) and the noise \( \mathbf{E} \) are uncorrelated and \( \mathbb{E}\{\mathbf{s}_l\} = \text{diag}(\mathbf{p}) \) and \( \mathbb{E}\{\mathbf{e}_l\} = \sigma^2 \mathbf{I} \), the SCM (2) becomes,

\[
\hat{\mathbf{R}} = \sum_{k=1}^{K} c_k^2 \mathbf{a}(\theta_k) \mathbf{a}^H(\theta_k) + \sigma^2 \mathbf{I} = \text{A} \text{diag}(\mathbf{p}) \mathbf{A}^H + \sigma^2 \mathbf{I}.
\]

(4)

Without correlated terms, (2) converges to (4) as \( L \to \infty \) [17]. DOAs are estimated from \( \hat{\mathbf{R}} \) under statistical assumptions [18, 19, 20, 21].

Gridless sparse DOA estimation based on covariance fitting uses a parameter \( \mathbf{R} \in \mathbb{C}^{M \times M} \) and fits it to SCM \( \hat{\mathbf{R}} = \text{A} \text{diag}(\mathbf{p}) \mathbf{A}^H + \sigma^2 \mathbf{I} \) (4). The covariance fitting (handles both nonsingular and singular \( (L < M) \) \( \hat{\mathbf{R}} \)) is accomplished by minimizing \( \| \mathbf{R}^{-\frac{1}{2}} (\hat{\mathbf{R}} - \mathbf{R}) \|_F^2 \) [18, p. 553], [22].

Sparse processing is achieved minimizing principal components in \( \mathbf{Y} \) (1), expressed using the atomic \( l_0 \) norm [13] as

\[
\| \mathbf{Y}^* \|_{l_0,0} = \inf_{\mathbf{c}_k, \theta_k, \phi_k} \left\{ \mathbf{K} : \mathbf{Y}^* = \sum_{k=1}^{K} c_k \mathbf{a}(\theta_k) \phi_k^T \right\}.
\]

(5)

Minimizing (5) is equivalent to minimizing the rank of \( \mathbf{R}^* = \mathbf{Y}^* \mathbf{Y}^* / L \) [13, 18]. Given (4), covariance fitting-based gridless sparse DOA estimation solves the rank minimization

\[
\min_{\mathbf{R}, \mathbf{Z}} \text{rank}(\mathbf{R} - \sigma^2 \mathbf{I}) \quad \text{subject to} \quad \mathbf{P} = \begin{bmatrix} \mathbf{R} & \mathbf{R} \\ \mathbf{R} & \mathbf{Z} \end{bmatrix} \geq 0.
\]

(6)

For the details and a convex relaxation method, see [1].

4 ALTERNATING PROJECTIONS

We formulate the problem (6) with the objective, projecting \( \mathbf{R} \) in a low-rank Toeplitz matrix, and the constraint, projecting \( \mathbf{R} \) in a PSD matrix. AP-Covariance consists of PSD projection and \( K \)-rank Toeplitz projection.

4.1 PSD projection

The projection of \( \mathbf{P} \) onto the PSD set \( \mathcal{P} \) is achieved from the eigendecomposition of \( \mathbf{P} \in \mathbb{C}^{2M \times 2M} \) with its eigenvalues \( \mu_i \) and eigenvectors \( \mathbf{q}_i \), \( \mathbf{P} = \sum_{i=1}^{2M} \mu_i \mathbf{q}_i \mathbf{q}_i^H \) [15, 16],

\[
P_{\mathcal{P}}(\mathbf{P}) = \sum_{i=1}^{2M} \max(0, \mu_i) \mathbf{q}_i \mathbf{q}_i^H.
\]

(7)
Figure 1. DOA estimation using acoustic data from the SWellEx-96 experiment. Single-snapshot processing for (a) CBF, (b) AP-Covariance. (c) Multi-snapshot processing for CBF, MUSIC, SBL, and AP-Covariance. (d) The full ULA structure. (e) Co-prime array processing for CBF, MUSIC, SBL, and AP-Covariance. (f) The co-prime array structure.

4.2 $K$-rank Toeplitz projection

The projection of $\mathbf{R}$ onto the $K$-rank Toeplitz set $\mathcal{R}$ is achieved [23, 24],

$$P_{\mathcal{R}}(\mathbf{R}) = \sum_{k=1}^{K} c_k^2 \mathbf{a}(\hat{\theta}_k) \mathbf{a}^H(\hat{\theta}_k) = \hat{\mathbf{A}} \text{diag}(\hat{\mathbf{p}}) \hat{\mathbf{A}}^H,$$

$$(8)$$

$$\hat{\mathbf{p}} = \text{diag}(\hat{\mathbf{A}}^H \mathbf{R} (\hat{\mathbf{A}}^H)^H),$$

$$(9)$$

where $\hat{\mathbf{A}} = [\mathbf{a}(\hat{\theta}_1) \ldots \mathbf{a}(\hat{\theta}_K)] \in \mathbb{C}^{M \times K}$. $\hat{\mathbf{A}}^\dagger$ is the Moore-Penrose pseudo-inverse, and diag($\mathbf{A}$) is the column vector containing the diagonal elements of matrix $\mathbf{A}$.

The factorization (8) is the Vandermonde decomposition [18, Sec. 11.6.2], which recovers DOAs. AP-Covariance iteratively updates $\mathbf{R}$ projecting it onto SCM (7) and formulating it into the low-rank Toeplitz matrix (8). The procedure for AP-Covariance is summarized in [1, Secs. IV and V].

5 EXPERIMENTAL RESULTS

The gridless sparse method demonstrates DOA estimation performance on ocean acoustic measurements for source tracking. The data is from the the SWellEx-96 (shallow water evaluation cell experiment 1996) experiment [9, 25, 26], conducted approximately 12 km from the tip of Point Loma near San Diego, CA. During the Event S5, from 23:15–00:30 GMT on 10–11 May, two sources, a shallow and a deep, were towed simultaneously from 8.65 km southwest to 2.90 km northeast of the vertical uniform linear array (VLA). The VLA has $M = 64$ sensors with spacing $d = 1.875$ m and was spanning 94.125–212.25 m depth. (Element 43 was corrupted and thus excluded.)
We focus on the deep source towed at 54 m depth at frequency 148 Hz. The data have a sampling frequency of 1500 Hz. The duration data covers 0.5 min before and 1 min after the point when the source was closest to the VLA, and the data is divided into 63% overlapping 87 snapshots. Each snapshot data is Fourier transformed with $2^{12}$ samples.

The performance results are shown for a single snapshot, multi-snapshot with coherent arrivals, and a co-prime array, see Fig. 1. The figure includes results for CBF, MUSIC, SBL, and AP-Covariance. AP-Covariance works well with single-snapshot [Fig. 1(b)], and sparse signal processing, SBL and AP-Covariance, work well with multi-snapshot data with coherent arrivals [Fig. 1(c)]. The co-prime array has $M_1 = 21$, $M_2 = 2$ ($M = 24$) [Fig. 1(e)–(f)]. Using co-prime arrays, we can reduce the number of sensors and obtain good results. AP-Covariance and SBL can accurately estimate DOAs using the co-prime array.

6 CONCLUSION

We have proposed a gridless sparse DOA estimator, which deals with a single snapshot, multiple snapshots with coherent arrivals, and arbitrary array geometries. Our evaluation based on real data indicates favorable performance compared to previous methods. For more results and derivation, please see [1].

ACKNOWLEDGEMENTS

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Effect of Water Column Variability on Normal-Mode Based Geo-Acoustic Inversion

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ABSTRACT

Normal mode characteristics of broadband acoustic signals have been utilized in estimating the sound speed and attenuation in sediment at the New England Mud Patch during the 2017 Seabed Characterization Experiment (SBCEX2017), which was conducted when the water column had an almost depth-independent temperature profile. From early May to early June of 2022, when the water column showed strong temporal and spatial fluctuations, researchers revisited the New England Mud Patch and performed a series of experiments (SBCEX2022) using the same experimental setup as that of SBCEX2017. The environment measurements and acoustic data from both SBCEX2017 and SBCEX2022 enable us to study the effect of water column variability on geo-acoustic inversion. In this research, the effect of water column variability is examined by (1) comparing the difference of measured water column temperature profiles and (2) evaluating the variation of the normal mode characteristics (e.g. Airy phase structure and modal arrival time) due to the different water column conditions. Finally, the appropriate inversion approaches minimizing the water column effect are discussed. [Work supported by ONR Ocean Acoustics.]

Keywords: Normal mode, Geoaoustic inversion, SBCEX

1. INTRODUCTION

Normal mode characteristics of broadband acoustic signals have been utilized in estimating the sound speed and attenuation in sediment at the New England Mud Patch during the 2017 Seabed Characterization Experiment (SBCEX2017) [1-4]. The SBCEX2017 was conducted from early March to early April of 2017 when the water column was well mixed and had an almost depth-independent temperature profile. From early May to early June of 2022, a following experiment (SBCEX2022) was performed at the SBCEX2017 site, but in a different water column environment with strong temporal and spatial fluctuations. As a part of the SBCEX2022, broadband signals were transmitted and received using the same source-receiver configuration as that of SBCEX2017. One of the rationales for this unique experimental design is to study the effect of water column variability on normal-mode based geo-acoustic inversion. This research focuses on the low-frequency analysis including the Airy phase region of normal modes. The measured water column temperature profiles from both SBCEX2017 and SBCEX2022 are presented in Sec. 2, followed by the analysis of normal mode arrivals and discussion in Sec. 3.

2. WATER COLUMN TEMPERATURE PROFILES

A vertical line array equipped with acoustic hydrophones and environmental sensors was deployed at the same location during both SBCEX2017 and SBCEX2022 by the University of Delaware. The detailed information about the array can be found in Ref. [1,2]. The left panel of Figure 1 shows the measured temperature profiles as a function of geo-time during SBCEX2017 (top panel) and SBCEX2022 (bottom panel). The right panel of Figure 1 are the selected examples of the temperature profile as a function of depth for SBCEX2017 and SBCEX2022. The times of measurements of these two temperature profiles are indicated by the back dash lines in the left top and bottom panel, respectively. It is noted that these two temperature profiles will be used as inputs for the calculation of modal arrival times in Sec. 3.

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The following information can be obtained from Figure 1. (a, left top panel) The water column was well mixed and had a depth independent water column temperature profile during most of the SBCEX2017. The water temperature varied from 4°C to 6°C. (b, left bottom panel) The water column in SBCEX2022 was much stratified due to the surface warming and a bottom warm layer. The water temperature ranged from 8°C to 14°C and higher than that in SBCEX2017. The difference of measured water column temperature profiles cause the variation of the normal mode characteristics (e.g. Airy phase structure and modal arrival time), which is evaluated in Sec. 3.

Figure 1. The measured temperature profiles as a function of geo-time during SBCEX2017 (left top panel) and SBCEX2022 (left bottom panel). Right panel: the selected examples of the temperature profile as a function of depth for SBCEX2017 and SBCEX2022. The times of measurements are indicated by the back dash lines in the left top and bottom panel, respectively.

3. WATER COLUMN EFFECT ON NORMAL MODE ARRIVALS

In this section, the variation of the normal mode characteristics is studied using the different temperature profiles from SBCEX2017 and SBCEX2022. In particular, the two profiles in the right panel of Figure 1 are used as examples. It is noted that these two profiles correspond to two SUS charges detonated and received using the same experimental configuration during SBCEX2017 and SBCEX2022, respectively. This research focuses on the numerical simulation and the acoustic data analysis will be reported in a separate paper.

Figure 2 shows the calculated modal arrival times for the first three modes below 80Hz using the temperature profiles in the right panel of Figure 1. The input parameters for the sediment are the same for the two cases. In other words, the arrival time difference is only due to the water column changes. The source-receiver distance is 15.45km and the details of the input parameters for the calculation of modal arrival times can be found in Ref. [1, 2].

The results in Figure 2 indicate that (1) the normal modes travelled faster in SBCEX2022 due to the warmer water column, (2) the Airy frequency corresponding to the minimum group velocity for each mode is not sensitive to the water column variation, but sensitive to the sound speed in the sediment [1]. The calculated Airy frequency is listed in Table 1. (3) the cut-off frequencies are very close for the two cases. Based on (2) and (3), the model arrivals below Airy frequency could be used in a very dynamic water column environment for geo-acoustic inversion. The resulting inversion algorithm could minimize the water column effect.

<table>
<thead>
<tr>
<th>Mode 1</th>
<th>Mode 2</th>
<th>Mode 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>SBCEX2017</td>
<td>12 Hz</td>
<td>28 Hz</td>
</tr>
<tr>
<td>SBCEX2022</td>
<td>12 Hz</td>
<td>28 Hz</td>
</tr>
</tbody>
</table>
Figure 2. Comparison of modal arrival time using the water column temperature profiles from SBCEX2017 and SBCEX2022.

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Distortions of the vector sensor measurements by diffraction of sound

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ABSTRACT

Deployment of acoustic receivers from mobile, autonomous platforms offers significant new opportunities for long-term, cost-effective observations of acoustic fields in the ocean and atmosphere. In ocean acoustics, the autonomous platforms include unmanned underwater vehicles and float-equipped moorings. Acoustic observations from free-flying stratospheric and tropospheric balloons play an increasingly important role in atmospheric sciences. The acoustic quantities measured by a mounted sensor differ from their values in the free field because of wave scattering from the platform carrying the sensor. While the effect of large “platforms” such as solid ground, seabed, or ship hull on mounted sensors has been studied in some detail, measurement distortions due to compact platforms, dimensions of which are of the order of acoustic wavelength or smaller, remain poorly understood. Using platforms with simple geometric shapes to streamline the diffraction analysis, this paper quantifies the effects of acoustically compact platforms on scalar and vector sensors. It is found that vector sensors are more susceptible to the distortions than pressure sensors. Strong distortions of particle velocity are likely to occur under conditions representative of the atmospheric and underwater applications. Possible approaches to compensation of the distortions and retrieval of the free-field acoustic quantities will be discussed.

Keywords: Vector Sensors, Sound Scattering, Infrasound

1. INTRODUCTION

Measured acoustic quantities deviate from their ambient values because of the sound diffraction by, or scattering from, the platform used to deploy the sensors in the water column. In underwater acoustics, the relation between ambient fields and the measurements made with mounted hydrophones and vector sensors is usually studied with the platform modeled as an infinite plane or a layered structure. This is a good approximation at high- and mid-frequencies and for hull-mounted sensors. However, at the low frequencies of primary interest in noise interferometry and seismo-acoustics, the entire platform may be small compared to the wavelength. The platform may be acoustically compact even at mid-frequencies when sensors are carried by gliders or autonomous underwater vehicles. The relation between ambient acoustic fields and measurements made by various sensors mounted on a compact underwater platform has been investigated theoretically in the recent paper (1) in a geometrically simple setting that admits an analytic treatment of sound diffraction. The present paper expands the analysis presented in (1) to include balloon-borne infrasound sensors in the atmosphere.

There is a growing interest in the atmospheric sciences community in supplementing ground-based and satellite observations by measurements at different altitudes in the atmosphere by placing various sensors, including microbarometers and accelerometers, on free-flying, long-living balloons. Placing additional sensors at stratospheric heights promises new insights into acoustic-gravity wave fields in the atmosphere and their coupling to physical processes in the ocean, solid earth, and ice shelves as well as advances in detection and characterization of natural and man-made infrasonic sources. Using balloon-borne acoustic-gravity wave and infrasound sensors is also actively studied for exploration of Venus and other planets. While allowing the measurements to be made at desired altitudes and suppressing the flow noise by moving with the wind, balloons also scatter waves and inevitably distort the ambient wave field. It is demonstrated in the present paper that balloon-induced measurement distortions are rather different from the well-understood effect of a rigid boundary on ground-based
2. CONCLUSIONS

It is sometimes argued, incorrectly, that the spatial scale of acoustic field variation is of the order of wavelength, and therefore small probes do not distort the ambient field. In fact, diffraction can significantly affect low-frequency acoustic fields in a vicinity of a compact object even when the object is small compared to the wavelength.

In the underwater acoustics context, we have shown that strong, frequency-dependent pressure perturbations occur in the vicinity of a small sphere when its compressibility is large compared to that of water. This leads to strong distortions in measurements when a hydrophone is placed near floats that employ thin, gas-filled shells. On the other hand, floats made of syntactic foam-type materials create only modest distortions of the free-field, low-frequency acoustic pressure values. Frequency dependence of the measurement distortions that occur on compact platforms proves to be rather different than in the previously studied limit of platforms that are large compared to wavelength.

Scattering-induced low-frequency perturbations in oscillatory velocity and acceleration are generally much larger than pressure perturbations in the vicinity of sub-wavelength objects, leading to strong distortions of vector sensor measurements. Distortions of measurements of the tangential to the platform and normal components of oscillatory velocity by mounted vector sensors prove to be rather different. As a result, mounted vector sensors correctly measure neither the direction nor amplitude of the free-field oscillatory velocity. We have shown, however, that, away from resonances, the scattering-induced distortions in low-frequency vector sensor measurements can be readily corrected for, without any a priori information about the ambient acoustic field.

In application to balloon-borne infrasound sensors in the atmosphere, neither zero- and super-pressure helium balloons nor high-altitude hot air balloons are predicted to support a Minnaert resonance. This is beneficial for broadband wave measurements. Platform-induced distortions of the ambient wave field are found to be non-negligible for stratospheric balloons. This is illustrated in Figure 1.

![Figure 1](image-url)  
Figure 1 – Frequency dependence of the response of a balloon-borne radial velocity sensor

The figure shows the ratio of measured and ambient values of the radial velocity for different wave
frequencies and three directions of a plane wave arrival: from nadir (red curves), 75° from nadir (green) and 60° from zenith (blue); $k$ is the acoustic wavenumber. The vector sensor is located beneath a zero-pressure spherical helium balloon of radius $a$ at the distance $r = 1.5a$ (solid lines) or $r = 2a$ (dashed lines) from its center (panels a and b) and $r = a$ (solid lines) or $r = 3a$ (dashed lines) from its center (panels c and d). Panels b and d show details of low-frequency behavior.

The natural frequencies of gondola suspension that fall into the infrasonic frequency range are an important factor controlling ambient wave field distortion by the high-altitude balloons. Infrasound diffraction and balloon vibration effects should be considered together with propagation (2, 3) and wind-induced absorption anisotropy (4) effects in order to understand the differences between measurements (2, 3) that are made with airborne and ground-level sensors.

Distortion of the ambient acoustic field by a sensor platform does not necessarily degrade the sensor performance. When understood and accurately modeled, amplitude distortions can be exploited to increase sensor sensitivity in a desired frequency band. Low-frequency phase distortions can be exploited to improve source bearing estimates.

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Underwater acoustic communication using a vector sensor from a moving source in shallow water

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ABSTRACT

For the optimal performance of underwater acoustic communication, it is important to minimize the effect of the Inter-Symbol Interference due to the delay spread of the multipath channels formed by multiple interactions with the ocean boundaries. The multipath channels have time-varying characteristics due to temporal variations of ocean environments. Especially, the communication channels on moving platforms have high Doppler frequency shifts and low channel coherence times due to spatial environment changes. Recently, acoustic vector sensors have been applied to underwater acoustic communication. A vector sensor can simultaneously measure x, y, and z-components of acoustic vector quantities as well as acoustic pressure with different channel characteristics and signal-to-noise ratios, and therefore, it can be used as a single-input multiple-output communication system. Underwater acoustic communication experiments using an acoustic vector receiver were conducted off the coast of Geoje island in Southeast Korea during the Korea Reverberation Experiment (KOREX-17) in May 2017. In this talk, communication techniques that can give the best performance using acoustic pressure signal and particle velocity signals measured by a single vector sensor in time-varying channel are investigated.

Keywords: Underwater acoustic communication, Acoustic vector sensor, Directionality.

1. INTRODUCTION

In shallow-water acoustic communication, various techniques utilizing spatial diversity gain, such as Multichannel combining with Decision feedback equalizer (M-DFE) (1-3) and multichannel Time Reversal combining with Decision Feedback Equalizer (TR-DFE) (4-7), have been studied to overcome the large delay spread induced by Inter-symbol Interference (ISI) by time-varying multipaths in shallow water. A spatially separated receiver array is required to improve spatial diversity gain. For this reason, a receiver array used in an underwater communication system is difficult to be accommodated in a compact underwater communication platform.

Acoustic vector sensor can measure three orthogonal components of acoustic vector quantities, such as acoustic particle velocity and acceleration, as well as acoustic pressure, making it a good alternative for applications on small platforms (8-10). In the case of a separated hydrophone array, the acoustic pressure signal received from each channel has multipath characteristics with different delay times and amplitudes. On the other hands, vector channels obtained a single vector sensor exhibit the channel characteristics with different amplitudes but similar delay times. Therefore, when using a single vector sensor, the communication performance can be improved only through the gain by the directionality of the vector channel, i.e., Directional diversity gain. In this paper, the underwater
acoustic communication performance using a single vector sensor was verified through experimental data acquired during the KOREX-17.

2. COMMUNICATION EXPERIMENT USING A SINGLE VECTOR SENSOR

Underwater acoustic communication experiment was conducted off the south coast of Geoje island of Korea in May 2017. An omni-directional transducer (Neptune D-11) was used as an acoustic source, which was deployed at a depth of 13 m from the R/V Mirae and then towed away from the vector sensor system while transmitting communication signals. The communication signals were measured by in-situ acoustic vector receiver of Applied Physics Lab., Univ. of Washington, for which the combined pressure and accelerometer-based vector sensor was positioned 1 m above the seafloor at a water depth of 29 m. During the experiment, the horizontal range between the source and the vector sensor measured by the GPS increased from 143 to 670 m.

The communication packet was composed of a linear frequency-modulated (LFM) signal and communication sequence. The LFM signal had signal duration of 0.1 s and bandwidth of 2.5-3.5 kHz, which was used to synchronize the communication sequence. The communication sequence is a quadrature phase-shift keying (QPSK) modulated signal lasting 8 s with a carrier frequency of 3 kHz and a symbol rate of 500 symbols/s. The total communication signals consisted of 4000 symbols including a sequence of 400 training symbols prior to the information symbols.

3. RESULTS

In order to compensate for the Doppler shift caused by the movement of the acoustic source, an initial Doppler shift was estimated from the training symbols of the acoustic pressure signal, the received acoustic pressure and the three components of acoustic particle velocities were resampled in passband. After that, a noise normalization process was performed since the noise levels of the acoustic pressure and the particle velocity channels were different. Then, three types of time reversal techniques were used for communication demodulation: Passive time reversal (PTR), Block-based time reversal (BTR) and Bidirectional block-based time reversal (BiBTR). In a time-varying channel environment, the communication performance of the PTR may be degraded, and in this case, the BTR generally performs better than the PTR. Because the channel impulse responses of particle velocities and acoustic pressure measured at a single point have similar delay times, directional diversity of particle velocity channels can provide relatively lower gains than spatial diversity by spatially separated receiver array.

![Figure 1](image)

Figure 1 – The comparison of communication performances of (a) Passive time reversal with resampling process, (b) Block-based time reversal and (c) Bidirectional block-based time reversal obtained with a vector sensor for a Doppler shift of -0.62 Hz.

In this talk, we propose BiBTR, which combines BTR and Bidirectional equalization. The Bidirectional equalization can exploit the difference in error propagation of nonlinear equalizer as a form of diversity, as it combines the soft outputs of forward and backward equalizations. Figure 1 shows the comparison of communication performances by three types of time reversal methods using acoustic pressure and particle velocity signals in the case of Doppler shift of -0.63 Hz. Delay spread of the pressure signal channel was ~12 ms in this case. In all three methods, a single-phase tracking and Decision Feedback Equalization (DFE) with adaptive algorithm of Recursive least squares were
applied. The number of feedforward filter taps in the DFE was set to sufficiently cover the channel delay, and the number of feedback filter taps was half the number of the feedforward filter taps. The block size of symbol for the BTR was 200 symbols (0.4 s). The results showed that the BiBTR communication system with resampling process provides the best performance with error-free and an output signal-to-noise ratio (SNR) of 14.4 dB.

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Abs-0629

Potential and kinetic energy of underwater noise measured below a passing vessel and response to sub-bottom layering

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Abstract

For underwater sound energy emitted by a passing vessel and received at a relatively steep angles, such as vessel directly overhead, there can be a significant excess in potential acoustic energy relative to kinetic energy with the opposite also occurring. Observations when expressed as a ratio of kinetic to potential energy in decibels are interpretable upon inspection, yielding an estimate of the sensor height above the seabed, and information on properties of the seabed. The effect was studied as part of the recently completed experiment on the New England Mud Patch. The R/V Neil Armstrong underwent controlled transits directly overhead a vector sensor, positioned about 1.5 m above the seabed. A model for kinetic and potential energy developed from method of images combined with a layered seabed, is used to invert the data. The low-speed mud-layer is identified along with higher-speed transition layer separating the mud substrate from a sediment basement. The inverted seabed parameters consistent with other recent studies. Observations made in Puget Sound over a higher-impedance seabed near the Kingston Arch are also presented to illustrate the standing wave features of such data.

Keywords: Underwater Acoustics, Kinetic and Potential Energy

1. INTRODUCTION

When a vessel passes directly above, it can dominate the underwater sound field below. At closest point of approach (CPA) the sound field is reinforced by multiple reflections from the seafloor and sea-surface establishing a standing wave. Under such CPA conditions, potential energy can be an order of magnitude greater than kinetic energy in certain frequency bands. Given that ship noise is a broadband source, the ratio between potential, $E_p$, and kinetic, $E_k$, energy presents a frequency pattern, linked primarily to the position above the seafloor and the geoacoustic properties and structure of the marine sediments.

Here, such conditions are addressed in controlled experiments where two research vessels conduct transits directly above a vector sensor, positioned about 1.5 m above the seabed, resulting in a CPA range of 0 (Fig. 1). One case involves R/V Neil Armstrong (length 73 m) operating in waters of depth 75--80 m within the New England Mud Patch (NEMP) and the other R/V Robertson (length 18 m) operating in waters of depth 42 m in Puget Sound. The noise in the 50-2000 Hz band shows a distinct pattern in the energy ratio; differences are due to the sediment type and layering within the seabed at the two experimental sites.

2. MODEL

The method of images is used to compute an approximate Green's function $g(z,z_0,f)$ for a harmonic source (time dependence $\exp(-i\omega t)$ being suppressed) near the air-water interface depth at $z_0$, and receiver directly below it at depth $z=z_r$, within a waveguide of depth $H$ (see Fig. 1). This is modified from an exact form (1) for a rigid, or infinite impedance, boundary condition at the seabed, by setting the receiver range equal to 0 and replacing the reflection coefficient $R_b = 1$ with finite impedance, frequency dependent form $R_b(f)$, to be evaluated at normal incidence (grazing angle 90°).

The impedance translation theorem (2) is used to construct the plane-wave reflection coefficient for fluid seabed consisting of two layers of thickness $L_i$, $i = 1,2$ characterized by density $\rho_i$ and sound speed, $c_i$, and terminated by a half space characterized by $\rho_3$ and $c_3$. 
3. INVERSION AND RESULTS

For comparison with the deterministic model the vertical component of kinetic energy $E_{kz}$ is parsed into active and reactive components, their sum called coherent vertical kinetic energy. This is kinetic energy associated with the combination of vertical velocity precisely in phase with pressure (active) and precisely in-quadrature or 90° out of phase with pressure (reactive) (3). We notionally define the difference between total and coherent kinetic energy as diffuse kinetic energy, although further interpretation of this quantity is beyond the scope of this study, and it is not fundamental to understanding these results. The process of isolating coherent vertical kinetic energy in noisy data involves the squared coherence between pressure and vertical velocity.

A geoacoustic inversion is applied to the ratio data expressed in decibels as function of frequency, using a Bayesian framework (4), with model-data mismatch equal to the decibel difference between each sequence which tends to be approximately centered about 0 dB.

Results of inverting the observations from Puget Sound (water sound speed 1478 m/s) reproduces key features of the data (Fig. 2a), such as approximate decibel range and frequency variation. The model is based on the following inverted geoacoustic parameters: $c_1=1750$ m/s $L_1 = 3.65$ m, $c_2 = 2230$ m/s $L_2 = 0.45$ m, $c_3 = 2720$ m/s, which is consistent with a shallow Holocene (5) sediment layer over harder substrate.

For the NEMP observations Sound (water sound speed 1486 m/s) again the model tends to reproduce key features of the data (Fig. 2b). The model is based on the following inverted geoacoustic parameters: $c_1=1440$ m/s $L_1 = 10$ m, $c_2 = 1590$ m/s $L_2 = 2.6$ m, $c_3 = 1640$ m/s. A prominent feature of the seabed in this location is the low-speed mud layer commencing at the water-seabed interface with thickness of order 10 m (6).
Figure 2. (a) Results for Puget Sound: Model (red, dashed line) for ratio $E_{kz}$ to $E_p$ as a function of frequency and expressed in decibels compared with observations (black line). (b) Results for the NEMP.

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Modal-MUSIC for passive mode extraction on a partially-spanning array

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ABSTRACT
Modes extracted from data can be used as input for geoacoustic inversion or for source localization. There are a number of active source methods for mode extraction. However, passive mode extraction from surface noise has been limited to the case of full water-column spanning arrays, in which case the orthogonality of the modes permits their separation with the singular value decomposition of the covariance matrix. With knowledge of the sound speed profile (SSP) in the water column, the Multiple Signal Classification (MUSIC) algorithm can be adapted to the problem of mode (rather than plane wave) extraction: “modal MUSIC”. Modal-MUSIC has no requirement that the modes be orthogonal on the array, and the modes can theoretically be extracted whenever the number of array elements exceeds the number of modes. The method is demonstrated by extracting modes from simulated and real data.

Keywords: Normal modes, passive mode extraction, underwater acoustics

1 INTRODUCTION
Normal modes are a convenient and sparse description of low-frequency underwater acoustic fields. In a range-independent, knowledge of the normal modes $\Phi_i(z)$ and their associated horizontal wavenumbers $k_i$ is sufficient to model the field between any source-receiver pair in the water. Mode extraction methods estimate the normal modes and the wavenumbers from data, either using the field produced by ship/surface noise or by an active source. Once the modes have been extracted, they can be used as input for applications of localization and geoacoustic inversion [1, 2, 3, 4]. Modal-MUSIC is a passive mode extraction method for partially-spanning arrays, using noise from a ship-of-opportunity.

From a modeling perspective, normal modes are typically computed by solving a boundary value problem (BVP) framed by the sound speed profile (SSP) in the water column, the surface boundary condition (which can be modeled as pressure release), and a geoacoustic model consisting of a physical description of the medium beneath the seafloor. The shooting method [5] is one numerical approach that solves the BVP by numerically integrating solutions down from the surface for candidate eigenvalues (wavenumbers). The value of the candidate solution is compared to the boundary conditions at the bottom, and the eigenvalue is adjusted until the candidate mode satisfies the physics enforced by a geoacoustic model. Rather than using a geacoustic model, modal-MUSIC compares candidate solutions from shooting to the data from a ship-of-opportunity using the MUSIC algorithm. This requires knowledge of the SSP from the surface down to the bottom of the array. The modes supported by the waveguide and excited by the source show up as peaks in the modal-MUSIC spectrum.

2 MUSIC
MUSIC is a subspace-based array processing method for identifying and classifying an unknown number of radiating sources [9]. The data are assumed to follow a linear model

$$d = As + n,$$

where $d$ is a vector containing the measurements made on the array, $A$ is a matrix whose columns are the signal waveforms sampled by the array, $s$ is a vector of the source amplitudes, and $n$ is the noise, which is
assumed to be uncorrelated white Gaussian noise with covariance matrix \( \sigma_n^2 I \) (\( I \) is the identity matrix). If there are \( N \) array sensors and \( M \) sources, then \( d \) is \( N \times 1 \), \( A \) is \( N \times M \), \( s \) is \( M \times 1 \), and \( n \) is \( N \times 1 \). For the plane wave estimation problem, the \( j \)th column of \( A \) is the plane wave associated with the \( j \)th source sampled at the array locations.

The data covariance matrix obeys

\[
E(dd^H) = A^H E(ss^H) A + \sigma_n^2 I,
\]

where \( E \) denotes expectation and \( (\cdot)^H \) denotes complex transpose. Assuming that \( M < N \) and that none of the sources are fully correlated, there will be \( N - M \) repeating eigenvalues of value \( \sigma_n^2 \) [9]. The corresponding “noise eigenvectors” will be orthogonal to the columns of \( A \). Collecting the noise eigenvectors into a matrix \( E_n \) and denote the plane wave associated with source angle \( \theta \) sampled on the array as \( a(\theta) \), then the MUSIC spectrum is

\[
P_{MU}(\theta) = \left[ a(\theta)^H E_n E_n^H a(\theta) \right]^{-1},
\]

and will have peaks at the source angles.

### 3 MODAL-MUSIC

In a range-independent underwater acoustic environment, the signal radiated by a moving source, filtered to a single frequency, can be written in the same form (1). However, now the columns of \( A \) are the normal modes evaluated on the array rather than plane waves, and the signal time series \( s(t) \) now contains time dependence of each mode. Viewed another way, each mode can be thought of as a virtual source that has a time dependence determined by its horizontal wavenumber and the motion of the source. The waveform produced by each virtual source on the array is no longer a plane wave, but rather the associated normal mode wavefunction sampled at the array depths.

Although for a coherent source/environment the modes are statistically dependent, as the source moves in range they will become uncorrelated. This means that \( E(ss^H) \) will have full rank as long as the source moves a significant range (see [6] for details). Therefore the eigenvalues of the covariance matrix due to a moving source will allow for identification of the noise subspace (which is then organized as the column space of the matrix \( E_n \)). The noise subspace will be orthogonal to the normal modes \( \Phi_i \) supported by the waveguide and excited by the source.

Finally, to compute the modal-MUSIC spectrum as (3), we need a means of computing the “array manifold”. To do so, we use knowledge of the water column sound speed profile to numerically integrate normal modes from the pressure release surface down to the bottom of the array via the shooting method [5]. This allows us to compute \( \Phi(k_r) \) for any horizontal wavenumber \( k_r \) on a mesh in the water column. By sampling the candidate normal modes at the array depths, stored in a vector \( \Phi(k_r) \), the modal-MUSIC spectrum can be computed as

\[
P_{MoMU}(k_r) = \left[ \Phi(k_r)^H E_n E_n^H \Phi(k_r) \right]^{-1}.
\]

The spectrum will have peaks at the horizontal wavenumbers of the medium. No information on the source range is required for the method to work, besides the knowledge that it has transited a significant range. Therefore the method is suitable for application to noise from a ship-of-opportunity.

### 4 Final remarks

The shooting method combined with knowledge of the water column SSP allows one to compute normal modes in the water column for any horizontal wavenumber \( k_r \). Typically, a geoacoustic model is then used to select the normal modes that satisfy the physical constraints imposed by the seafloor. By viewing each normal mode excited in the waveguide as a virtual source, the mode extraction problem becomes a signal estimation problem relevant for the MUSIC algorithm. Modal-MUSIC combines the shooting method with MUSIC, using data from a ship-of-opportunity to select the modes that are actually present in the waveguide (as opposed to using a geoacoustic model). The extracted modes can be used for source localization or geoacoustic inversion.
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Enhancement of Green’s function using the waveguide invariant theory

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ABSTRACT
This paper presents a method to achieve signal-to-noise ratio (SNR) improvements of the Green’s function. This work is motivated by a recent paper [Song and Byun, J. Acoust. Soc. Am \textbf{149}, 2150-2158 (2020)] that derived an analytic relation between Green’s functions at adjacent ranges using the waveguide invariant, $\beta$. For a known value of $\beta$, Green’s functions from multiple ranges can be extrapolated to a single range. Subsequently, the extrapolated Green’s functions are coherently combined to enhance a Green’s function with low SNR. The proposed method is demonstrated for a ship of opportunity moving radially away from the vertical array at ranges of 2.06-2.16 km in 100-m water depth.

Keywords: Green’s function, Waveguide invariant, SAVEX15

1. INTRODUCTION
Acoustic waves in an ocean waveguide are greatly influenced by the characteristics of the underwater sound channel. Thus, the environment’s physical characteristics (i.e., the Green’s function) between the source and receiver is typically required for various remote sensing applications (1). Ray-based blind deconvolution (RBD) can be an excellent method to estimate the Green’s function with low computational complexity (2-4). However, usually the signal of interest is recorded along with undesired signals (noise), as a result, it can be challenging to estimate the Green’s function properly.

In this letter, we present a method for improving the signal-to-noise ratio (SNR) of the Green’s function using the waveguide invariant. This work is motivated by a recent report that derived a simple analytic relation using the waveguide invariant, denoted by $\beta(5,6)$, to extrapolate Green’s functions to adjacent ranges(7). Our approach is to exploit this relationship to extrapolate Green’s functions from adjacent ranges to a single range. The extrapolated Green’s functions then can be coherently combined to enhance a Green’s function with low SNR. The performance of the proposed method is examined through a recent shallow water experiment conducted in the northeastern East China Sea (ECS) [Shallow water Acoustic Variability EXperiment (SAVEX15)].

2. SAVEX15
SAVEX15 was conducted in the northeastern ECS using R/V Onnuri during May 2015(8). The experimental site has a nearly flat sandy bottom and a water depth of approximately 100 m. Both fixed and towed source transmissions were carried out to two moored vertical line arrays (VLAs) over ranges of 1-10 km.

To investigate the approach proposed, we analyze a segment of data during a source-tow run on JD 146 (May 26). The schematic of the source-tow run is illustrated in Figure 1(a). The bottom-
moored VLA consisted of 16 elements spanning 56.25 m aperture with 3.75-m element spacing, covering about half the water column (from 25 to 81.25 m) in about 100-m deep water. The SSP displayed in Figure 1(a) is an average of two CTD (conductivity, temperature, and depth) casts collected around JD 146. The R/V Onnuri was towing two broadband sources (3-10 kHz and 12-32 kHz) simultaneously at a speed of 1.5 m/s along the radial track (2060-2160 m) as shown in Figure 1(b). Here our interest is in the Green’s function from the R/V radiating low frequency random noise (e.g., < 1 kHz) which did not interfere with the high frequency waveforms broadcast by the two controlled sources (3-10 kHz and 12-32 kHz) at 50-m depth.

The simulated Green’s function in the frequency band of interest (200-900 Hz) for a point source near the surface (5 m) at range 2060 m is displayed in Figure 2(a). A normal mode program(9) is used to simulate the Green’s function assuming a range independent environment with a simple half-space sandy bottom whose geoaoustic parameters are indicated in Figure 1(a).

The Green’s function from the source of opportunity can be estimated via ray-based blind deconvolution (RBD)(2-4). A 2-s window ship noise (200-900 Hz) was used to obtain the Green’s function for the selected track in Figure 1(b). The Green’s function estimated along the VLA at 2060 m range is shown in Figure 2(b). Compared to the simulated Green’s function in Figure 2(a), the first five wavefront arrival structures are in great agreement with simulated Green’s function, whereas the following arrivals are highly attenuated and too weak to distinguish between noise.

![Figure 1](image-url)

Figure 1 – (a) Schematic of a source-tow run on JD 146 (May 26). (a) Global Positioning System (GPS) ship track of the R/V Onnuri, transiting radially away from the VLA (black) at a speed of 1.5 m/s.

3. COMBINING THE GREEN'S FUNCTION

The combined Green’s function can be expressed as the sum of Green’s functions of adjacent ranges extrapolated to a single range \( r_0 \) via waveguide invariant, as follows

\[
g_c(r_0, t) = \frac{1}{N + 1} \sum_{i=0}^{N} [g(r_i, \alpha_i t) \ast \delta(t - \Delta r_i/c)]
\]

where \( N \) is the number of adjacent ranges \( (i = 0 \ldots N) \). The term in the bracket denotes the Green’s functions extrapolated to \( r_0 \) by a two-step procedure(7): (1) resampling the Green’s function with a factor of \( \alpha = 1 + \beta (\Delta r/r) \) and (2) a time-delay, where \( c \) is the nominal speed of sound 1500 m/s.

In this paper, we take a Green’s function at range 2060 m as a reference \( (r_0) \) and extrapolate 100-m of Green’s functions to a closer range (i.e., \( \Delta r < 0 \)) to coherently combine, which requires a temporal dilation along with a time advance of the range varying eigenray arrival times. The combined Green’s function is presented in Figure 2(c). Compared to the original in Figure 2(b), the eigenray arrival times of the five early groups show good agreement.

The processing gain (PG) of combining the Green’s function can be expressed as a function of the SNRs of the original and combined Green’s function \( \text{PG} = 10 \log_{10}\text{SNR}_{\text{c}}/\text{SNR}_{\text{org}} \), where the SNR is defined as the ratio of the signal power to the noise floor(10). We select a segment where the ray arrival no longer arrives as the noise floor \( (t > 200 \text{ ms}) \). Using 100-m of adjacent Green’s functions (i.e., \( N = 11 \)), the performance is about 10 dB. The SNR improvement is remarkable, as the arrivals masked by noise can be recognized.
4. SUMMARY

The relationship between Green’s functions at adjacent ranges can be derived by the waveguide invariant: \( g(r + \Delta r, t) \approx g(r, \alpha t) \ast \delta(t - \Delta r/c) \), where \( \alpha = 1 + \beta (\Delta r/r) \). In this paper the feasibility of improving the SNR of the Green’s function is investigated using this relationship. 100-m of extrapolated Green’s function were coherently combined for enhancement of about 10 dB. The proposed method was demonstrated for a ship of opportunity moving radially away from the vertical array at 1.5 m/s at range 2060-2160 m in 100-m shallow water.

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Deep learning-based dispersion curve detector in the spectrogram

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ABSTRACT
A time-warping transform is a nonlinear resampling method that compensates for dispersion curve and is used for mode separation. This method has the advantage that mode separation is possible in a single hydrophone and it is usually robust against mismatch between the warping operator and the ocean environment. However, this transform can degrade mode separation performance in the case where the observed mode pattern is completely different from the ideal dispersion curve or where the source is unknown. The range mismatch also affects the accuracy of mode separation. In this proceedings, a dispersion curve line detector based on deep learning is proposed to evade these problems. The proposed network is based on a U-Net and the data of spectrograms and corresponding dispersion curve are made by KRAKEN. We show the deep learning is useful in detecting a dispersion curve.

Keywords: Normal Mode, Time-warping transform, Deep learning, U-Net, Segmentation

1 INTRODUCTION
The time-warping transform is the method for estimating the dispersion curve of an impulse signal with a single hydrophone (1), that enables inversion of ocean environmental factors and source localization (2, 3, 4). By the warping transform, the modal phase in the received field is transformed into the constant for time, which makes the mode-picking easier. The warping method is known to be robust to environmental mismatch, but there may be a concern of performance degradation in environments such as strong reflection or refracting environments. This is due to the warping operator based on the ideal waveguide (5). Also as another drawback, the time-warping transform needs some manual works through trial and error in order to separate the modes in time-frequency domain.

In this work, we propose a dispersion curve segmentation network that directly detects the dispersion curve of an impulsive source in a properly modal-differentiated spectrogram image. This network is based on so-called model-guided deep learning (6), considering the difficulty of data collection and the lack of good data in the underwater environments. U-Net (7) is chosen as basic network for deep-learning. The physics-informed data (or modeled data) guides the U-Net to estimate the dispersion curve. Considering the incorrect knowledges of ocean environmental factors, the datasets are simulated with KRAKEN in various ocean environments chosen randomly. Such a procedure makes the deep-learning network robust to the environmental mismatch and can improve the performance of generalization.

The outline of this proceedings is as follows; Section 2 describes U-Net network, datasets, and preprocessing. Section 3 shows the results of curve detection in the ocean environments with iso-speed profile and negative gradient sound speed profile (8). Also, we shows the application to the real data. Section 4 is the conclusions.
2 DEEP LEARNING NETWORK AND TRAINING STRATEGIES

2.1 Dataset

The datasets are generated with the normal mode program KRAKEN (9). We simulate them in the frequency range of 50 to 200 Hz. The SNR is set to be 3 dB. Noisy data is found to be useful to strengthen the robustness of deep learning network. Two range-independent ocean environments are used for learning as shown in Figure 1. For each environment, we randomly select the ocean environmental factors like sound speed profile, bottom depth, geoacoustic property, source depth, receiver depth, source-receiver range. A total of 750 ocean environments are prepared for the simulation in all cases. Note that this sample size is very small considering the complexity of ocean environment.

2.1.1 Dataset: Data

The datasets are respectively generated from two different ocean environments, called Pekeris environment and thermocline environment in this proceedings. These environments are displayed in Figure 1. With the ocean environmental factors selected randomly, KRAKEN performs Monte-Carlo simulation for two kinds of ocean environments. When generating datasets, we remove the modes of small energy, which may be drowned out in the noise in the long-range propagation. The time-frequency spectrograms are plotted with each mode, not only all effective modes. For example, if there are three mode groups in an ocean environment, total four spectrograms are generated.

2.1.2 Dataset: Preprocessing

A spectrogram is generated via a short-time Fourier transform (STFT) with 1024 frequency bins, 30 overlap size, and Hamming window of 31 length for 0.6 second time snippet. The spectrogram is normalized by its absolute highest peak. Using a spline interpolation, the image size of spectrogram is mapped into 128 by 128.
Table 1. Dataset configuration. Mean F1 score for multi-modal is evaluated with all effective mode curves and the term of ‘single-modal’ means that of each mode curve.

<table>
<thead>
<tr>
<th>Environment</th>
<th>Train set</th>
<th>Validation set</th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pekeris environment</td>
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<td>A subset of modes</td>
<td>A complete set of modes</td>
</tr>
<tr>
<td></td>
<td>4156</td>
<td>461</td>
<td>1188</td>
</tr>
<tr>
<td>The pressure field</td>
<td>0.92</td>
<td>0.89</td>
<td>0.89</td>
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<tr>
<td>The number of data</td>
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<td>0.89</td>
<td>0.81</td>
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<tr>
<td>Mean F1 score</td>
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<tr>
<td>Mean F1 score for multi-modal</td>
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<td>0.89</td>
<td>0.81</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Thermocline environment</th>
<th>Train set</th>
<th>Validation set</th>
<th>Test set</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A subset of modes</td>
<td>A subset of modes</td>
<td>A complete set of modes</td>
</tr>
<tr>
<td></td>
<td>4298</td>
<td>477</td>
<td>1230</td>
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<tr>
<td>The pressure field</td>
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<td>0.77</td>
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<tr>
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<tr>
<td>Mean F1 score</td>
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<td>0.77</td>
<td>0.88</td>
</tr>
<tr>
<td>Mean F1 score for single-modal</td>
<td>0.88</td>
<td>0.77</td>
<td>0.88</td>
</tr>
</tbody>
</table>

2.1.3 Dataset: Label
The labeling (true frequency-time curve) can be directly calculated from the KRAKEN. We plot the frequency-time curves in the 128 by 128 image, where one pixel corresponds to one point in the curve.

2.2 Deep learning network: U-Net
U-Net with RGB channels is used as deep learning network for curve detection. The size of input and output image in the network is the same as 128 by 128. Basically, the U-Net learns datasets proceeding in the direction of minimizing dice loss (10). The final layer of U-Net performs a pixel-level class classification via softmax. To improve the learning ability, the image augmentation technique is applied with random translation of the spectrogram for the time and frequency axis. Learning rate, batch size, and number of epoch are 1e-5, 32, and 500, respectively.

The datasets are split into 64% training sets, 16% validation sets, and 20% test sets, based on environmental data. Table 1 shows the dataset configuration and the F1 score for each dataset. Note that the number of datasets is different from the number of ocean environments generated since the spectrograms for each mode are used as dataset as previously mentioned. From Table 1, it can be shown that the U-Net can be used as a good mode curve detector in the frequency-time spectrogram.

3 RESULTS
In this section, we show the predicted results using test sets in the same environment, the generalized results using the unseen environment, and a real data in unseen environment. All simulated test sets in this section are assumed to have the horizontal distance of 10 km between the source and receiver. The bottom sound speed, bottom density, and bottom attenuation are 1640 m/s, 1.62 g/cm³, and 0.05 dB/λ, respectively (8). The water depth is commonly 80 m and each sound speed profile is displayed in Figures 2, 4, and 6. In addition, the SNRs of those data is varying from 0, 3, and 6 dB to evaluate the performance of trained network in noisy environments.
3.1 Test dataset in Pekeris environment

Figure 2 shows the sound speed profile and the mode characteristics of test dataset. The source and receiver depth is assumed to be 70m and 10m. Five propagating modes excites without a refraction mode. Figure 3 shows the prediction results using an U-Net trained with Pekeris-based datasets (PU-Net) and an U-Net trained with thermocline-based datasets (TU-Net). The red line represents the predicted curve and the green line does the true curve. The black line indicates pixels perfectly matching of prediction and true value. The PU-Net shows better performance than the TU-Net for all cases. However, TU-Net predicts the dispersion curve well, especially for higher SNR, although it has not seen the Pekeris environment.
Figure 4. Thermocline environment. Here, the red dotted line represents the maximum sound speed. In Figure 4(b) and (c), each mode curve is plotted with solid line (blue: refraction mode, black: reflection mode).

Figure 5. Prediction in the thermocline environment (red pixel: prediction, green pixel: true value). The black pixels indicate completely matched pixels. In the figure, ‘dB’ means the SNR.

3.2 Test dataset in thermocline environment

In the thermocline environment, the sound speed profile and the mode characteristics of test dataset are shown in Figure 4. The modes under the red dotted line are refractive (Modes 1 and 2). This environment causes more complex time-frequency pattern of modes (8). The source and receiver depth are assumed to be 10m and 75m. Figure 5 shows the prediction results for two U-Nets (PU-Net and TU-Net) and SNRs. Different from previous example, TU-Net has better performance than PU-Net. It is not perfect, but the TU-Net correctly estimates the refractive modes for higher SNRs. The PU-Net finds the mode-pattern but the F1-score is not as high as that of TU-Net.
3.3 Test dataset in the ocean environment with a negative gradient sound speed profile
This section is to test the generalization performance of PU-Net and TU-Net. A negative gradient sound speed profile is used to generate the test dataset as shown in Figure 6(a). The source and receiver depth are 40m and 70m. In Figure 6(b), 3 out of 8 modes are refractive modes represented by blue solid line. Figure 7 shows the prediction results. The PU-Net tends to be false-negative in a noisy environment as previous examples. On the other hand, the TU-Net is more pronounced in false-positive than the PU-Net. Also, there is a tendency not to classify the segments of modes 1 and 2 for the high-frequency range. And, the F1-score of TU-Net is generally higher.
3.4 Real data: Right whale gunshot
Finally, we evaluate that the trained U-Nets works well with real data. The used data is a right whale gunshot data acquired by D. Wright in the southeastern Bering Sea in 2013\(^{(4, 11)}\). This original data has largest energy independent of water propagating modes below 20Hz. It is found that this largest energy affects the normalization of image and degenerates the performance of U-Net. So, a high pass filter with 25Hz cutoff frequency is applied into the original data to remove the unnecessary part. Figure 8 shows the prediction results by time-warping transform, PU-Net and TU-Net. The deep-learning networks show better results than time-warping transform. Especially, the TU-Net finds all 4 modes as time-warping transform. The results of U-Nets are more like an ideal dispersion curve and seem to provide rich information than the time-warping transform.

4 CONCLUSIONS
In the proceedings, we propose the U-Net extracting the dispersive curve of impulsive source from the spectrogram. Deep knowledges for estimating the dispersion curve are guided by underwater acoustic normal mode propagation model, KRAKEN. This procedure of model-guided deep-learning will be more appropriate in the underwater environments, where it is difficult to collect clean and complete data due to the environmental mismatch and data complexity. For three simulated data and one real data, the trained deep-learning network shows good performance in the learned and unlearned environments. We expect that the proposed deep-learning procedure can complement the time-warping method for mode separation.

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