Sub-Bottom Imager (SBI) sub-seabed anomaly detection using deep learning

Introduction

Accurate detection of sub-seabed anomalies, such as unexploded ordnance (UXO), boulders, buried cables, and pipelines, remains a critical challenge in marine geophysics. The SBI 3D sub-bottom acoustic imaging has addressed this need by combining linear hydrophone arrays with Inertial Navigation Systems (INS) to enable coherent Synthetic Aperture Sonar (SAS) processing. This technique has become a standard in the industry for generating high-resolution sub-seabed imagery.

With data acquisition speeds ranging from 1 to 3.7 m/s, the Kraken Robotics SBI acoustic platform can rapidly collect large volumes of data. However, manual interpretation of these datasets can be time-consuming and resource-intensive. To address this, deep learning methods are increasingly being adopted to improve processing efficiency, reduce the need for large interpretation teams, and minimise human bias.

Following the methodology proposed by Mishra (2021), which integrates recurrent neural networks (RNNs) and discrete wavelet transforms for enhanced automated seismic facies characterisation, volumetric data from the SBI were processed to detect acoustic anomalies and identify sub-seabed sedimentary layers. This was implemented using RNN architectures in MATLAB, leveraging its deep learning and signal processing capabilities.

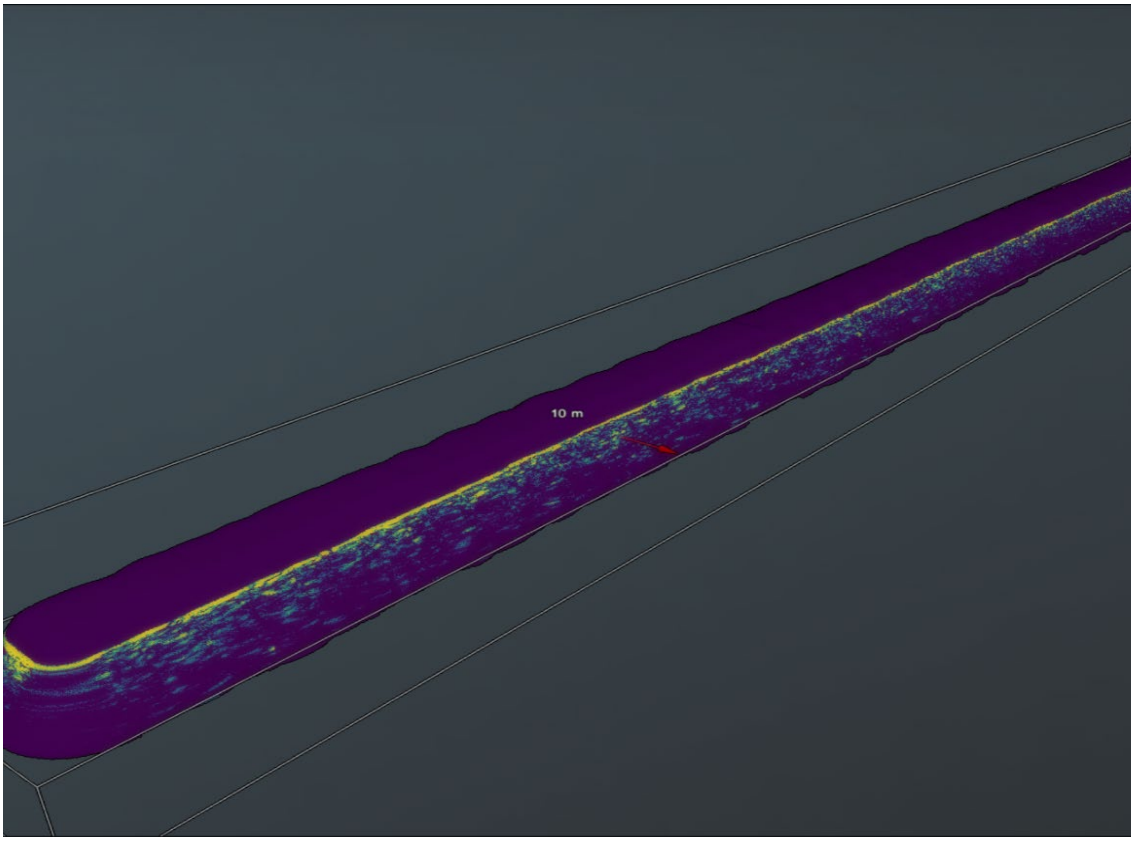

Figure 1 *SBI 3D SAS rendered volume is displayed in the visualisation software NaviModel.*

Sub-Bottom Imager Technology

The SBI is a mobile acoustic platform (Figure 2) that can be deployed in various configurations, including as an ROV (Remotely Operated Vehicle), pole-mounted system, or integrated into a towfish. It is designed for rapid and accurate acquisition of acoustic data used to visualise the sub-seabed.

The system features three 4.5–12.5 kHz projectors and a 40-channel linear array, both mounted at the front of the platform. During operation, the projectors continuously illuminate the sub-seabed, while the linear array captures the returning acoustic reflections. An onboard Inertial Navigation System (INS) corrects for both linear and angular motion.

Synthetic Aperture Sonar (SAS) processing is applied to the acoustic returns, combined with corrected positioning data, to generate a 3D volumetric dataset. This dataset comprises voxels containing spatial coordinates (x, y, z), acoustic intensity, and contribution count (Dinn, 2012). SAS imaging involves summing multiple pings using a synthetic narrow beam array, which enhances signal coherence and improves the signal-to-reverberation ratio, which is key to resolving weak acoustic signals.

The resulting volumetric data is saved in Kraken Robotics' proprietary SAS format. However, for this study, the data was exported in 3D SEG-Y format, post-processed, and then imported into MATLAB for analysis.

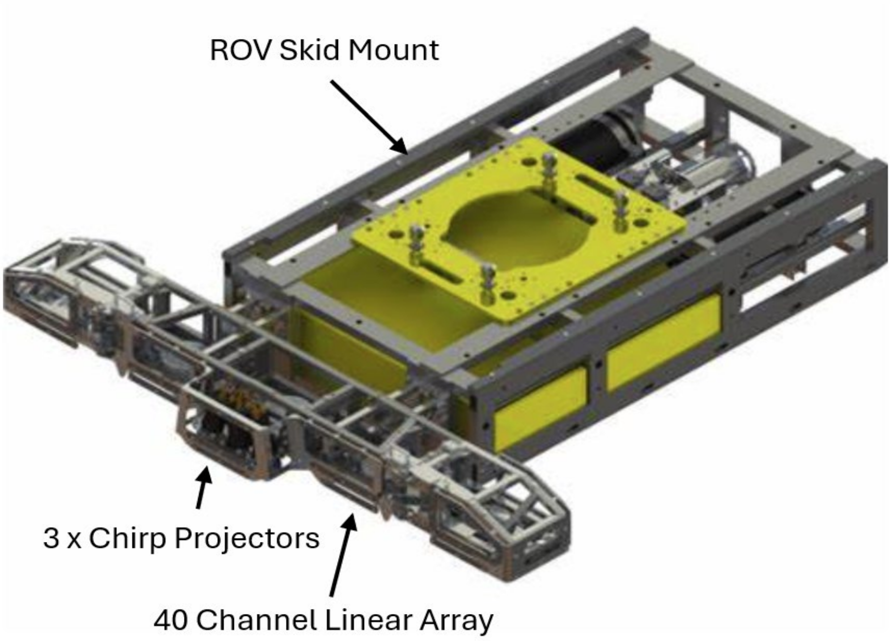

Figure 2 *Sub-Bottom Imager with ROV Skid Mount. The front-mounted chirp projectors and hydrophones are seen as they would be during SBI operations. The INS system would be mounted on the skid or frame and referenced to the common reference point (CRP) in the center of the linear array.*

Data Processing and Labelling

The data used in this study was imaged using Kraken Robotics' SAS Renderer (Figure 1). Following imaging, a vertical gain of 5 dB/m was applied to balance the acoustic amplitude throughout the volume. The resulting dataset had dimensions of 5 m × 170 m × 5.4 m, with a voxel size of 10 cm. The volume was exported in SEG-Y format and imported into ZoomSpace, Kraken Robotics' proprietary seismic processing software. The SEG-Y data matrix was reshaped into a 50 × 1700 × 54 double-precision array and subsequently imported into MATLAB's Volume Segmenter (Figure 3). Labelling was performed across each Inline (50 slices) and Crossline (1700 slices).

Figure 3 displays the labelled data along Inline 25, where the volume was segmented into three primary units: Water Column, Sedimentary Layer 1, and Sedimentary Layer 2. The region's geology has been interpreted as high to very high-strength clay. Within Layer 1, several discrete anomalies were identified and labelled based on their acoustic intensity, forming a distinct 'anomalous' unit. The elevated acoustic intensity observed in Sedimentary Layer 2 is attributed to a combination of stratigraphic features and acoustic multiples.

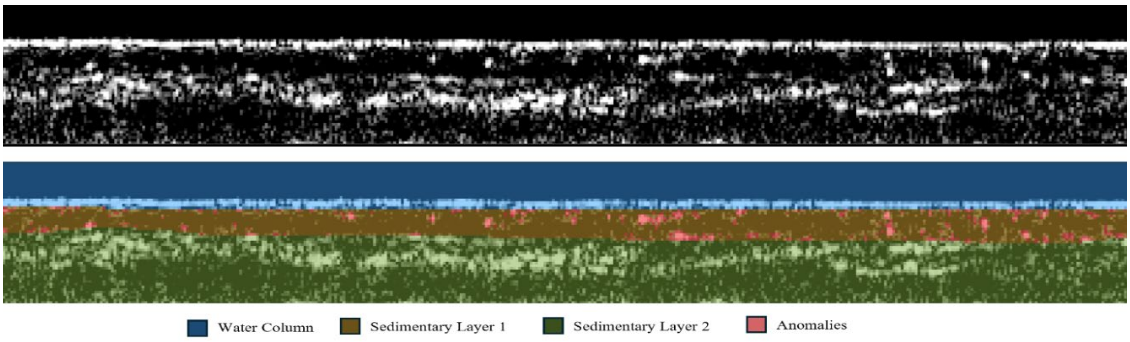

Figure 3 *SBI 3-D SAS Rendered Data in cross-section (top) and labelled data (bottom) as visualised in MATLAB's volume segmenter.*

Deep Learning Architecture

The architecture chosen follows Mishra (2021), which uses a combination of 2D U-Net convolutional neural networks (CNNs) in the XZ and YZ planes of the seismic data, along with a signal-based method using acoustic traces and a Recurrent Neural Network (RNN) architecture to classify sedimentary facies and targets of interest. To reduce overfitting, the technique utilises wavelet multiresolution analysis (MRA) within MATLAB, specifically the 'fk14' wavelet, by decomposing each trace by frequency content into five channels per trace, which enhances network training by capturing spatial correlations across a 3x3 trace grid in the XY plane. The use of the signal wavelet is key to this method to capture the uniqueness of the wavelet of a specific class, sedimentary layer, or target and use it to differentiate between the features. The volume dimensions, classes, and class weights were modified to fit the specifications of the SBI data set. The network architecture, designed using MATLAB's Deep Network Designer (Mishra, 2021), optimises classification performance for a wide range of geological applications and is supported by GPU-accelerated training.

Results

To evaluate the accuracy of the classification, a confusion matrix (Figure 4) was created using a subset of the data and the deep learning network. The results show an accuracy greater than 90% among 3 of 4 classes, whereas sedimentary layer 1 was misclassified as the class Anomalies 17.8% of the time.

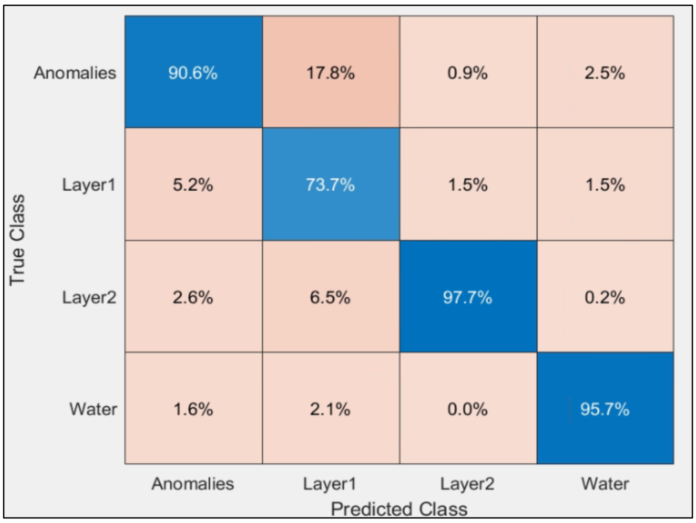

Figure 4 *Accuracy between the labelled and predicted classes is displayed in a confusion matrix. There is a high degree of accuracy shown for most of the classes, while sedimentary layer 1 is frequently misclassified as an anomaly.*

Figure 5 overlays the predicted data with the SBI SAS data. As seen above in the confusion matrix, there is good differentiation between the water column and the two sedimentary units. The high-intensity anomalies, which are suggestive of boulders and cobble-size geohazards, have been identified successfully in this 45 m by 5.4 m cross-section of data. Further refinement of the labelled data and/or modifying the class weights may improve the accuracy.

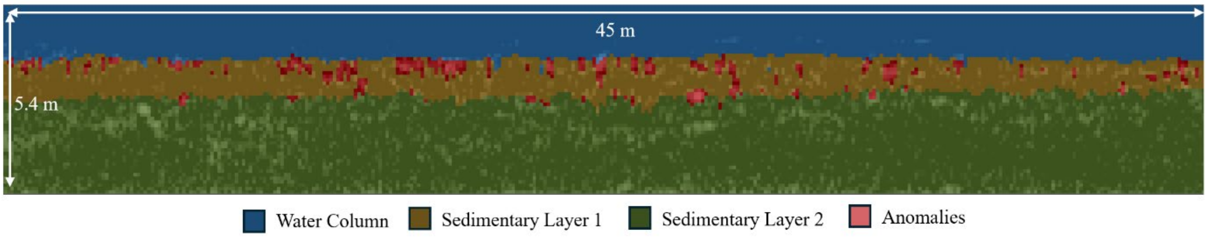

Figure 5 *Predicted data after classification using sample SBI data and labelled data.*

Conclusions

The adaptation of the MathWorks deep learning and signal-based method for the detection of geohazards appears to have merit for its application to anomaly detection using SBI data. The classification results demonstrate strong overall performance, with over 90% accuracy achieved in three out of the four classes. However, sedimentary layer 1 was misclassified as the Anomalies class at a high degree of misclassification of 17.8%, likely due to similarities in signal characteristics between the two. This misclassification highlights the challenge of distinguishing between geologically similar facies and suggests that further refinement, such as improved feature separation, class-specific augmentation by refining labels or sampling, or targeted model tuning, may be needed to improve discrimination between these classes. Despite this, the model effectively differentiates the water column and sedimentary units and successfully identifies high-intensity anomalies associated with potential geohazards, indicating its practical utility for subsurface interpretation.

Acknowledgements

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References

Dinn, G. [2012] Field experience with a new sub-bottom investigation tool: Acoustic 3-D imaging of the sub-seabed. *OCEANS 2012 MTS/IEEE Yeosu*, 1–6.

Mishra, A. [2021] Seismic Facies Classification with Wavelets and Deep Learning. GitHub repository, accessed 22 January 2025, at https://github.com/mathworks/Seismic-Facies-Classification-with-Wavelets-and-Deep-Learning/.