Sediment Characterization from Acoustic Echo Sounding Using an Artificial Neural Network

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ABSTRACT

In 2018, an experiment was conducted for sediment characterization off the coast of Qingdao, China, using hydrographic systems. In this experiment, single-beam and multibeam echo sounders were towed along the ship track, which was approximately 120 km long and covered three main sediment types, i.e., clayey silt, sandy silt, and silty sand. This study emphasizes the potential of using an artificial neural network (ANN) and the multibeam backscatter data for performing acoustic sediment characterization. The index of impedance (IOI) of the sediment as inverted from the single-beam sonar data is shown to be consistent with the core sampling distribution, which is used to label the mean angular response curves extracted from the multibeam data in ANN training. First, the ANN is trained to map the relation between the mean angular response curves and IOI using a training dataset; then, it is applied to a testing dataset to predict the IOI of the sediment. For data processing, 80% of the available data are used for training, whereas the remaining 20% are used for testing. The preliminary results denote that the prediction accuracy on testing dataset can up to 90% within the absolute error tolerance of 0.1, showing the feasibility of using an ANN for performing sediment characterization using multibeam data.

1 INTRODUCTION

Sediment characterization is an important area of research in the ocean environment, marine geology, and ocean engineering fields. Instead of traditional mechanical drilling sampling, many studies have focused on indirectly evaluating the sediment properties using various acoustic echo sounding and classification techniques (Jackson, Winebrenner, and Ishimaru 1986). Initially, a single-beam echo sounder (SBES) can be used to provide oriented signals in the nadir direction to distinguish among the properties of different types of sediments. Therefore, data-driven methods and model-based approaches are consecutively employed using the full received SBES echo or parameters that describe the shape of the echo signals (Siemes et al. 2010). However, a multibeam echo sounder (MBES), which simultaneously collects the bathymetry and seafloor backscatter data, is preferred over an SBES because of the larger coverage and higher spatial resolution of the swath. For performing seafloor classification and characterization, the collected datasets are generally analyzed to produce backscatter mosaics and angular response curves, and different approaches involving the MBES data are discussed based on these data analyses. These methods can be broadly classified as phenomenological or predictive modeling (Parnum and Gavrilov 2011). In a phenomenological approach (e.g., clustering analysis), data are divided into statistically similar regions without denoting the actual physical properties of the seafloor (Parnum and Gavrilov 2011), whereas predictive modeling can provide the physical properties of the seafloor (Fonseca and Mayer 2007).

An artificial neural network (ANN) is an information processing technique, and the excellent self-adaptability and nonlinear mapping capabilities of the ANNs make them outstanding in many fields, including pattern recognition, regression, fitting, and optimization (Bianco et al. 2019). Recently, ANNs have gradually become promising for application in underwater acoustics, such as for underwater source ranging (Huang et al. 2018) and geoacoustic inversion (Marsh and Brown 2009), and some studies (Marsh and Brown 2009, De 2012) have used ANNs to classify sediments and study the MBES images and angular backscatter data. When compared with classical sediment classification, which involves a time-consuming trial-and-error process to find the appropriate features (Berthold et al. 2017), an ANN can automatically extract the relevant features from the training data. This method requires a complete dataset with desired outputs (labels) representing the ground-truth information such as sediment type and property parameters; however, the acquisition of ground-truth information is considerably difficult in underwater acoustics. All the collected data cannot be labeled by considering the sediment samples as the ground truth, which is extremely time consuming and expensive.

Our idea is that the inverted sediment parameters obtained from model-based inversion of SBES could be used to supplement traditional core sampling. Herein, we consider the inverted parameters as labels for multibeam backscatter data in an ANN, which is theoretically feasible because of the good agreement of the analysis results with respect to the SBES and MBES data (Siemes et al. 2010) during independent processing. The remainder of this study is organized as follows. Section 2 describes the experiment and data preprocessing. After giving an description of backpropagation neural network (BPNN) in section 3, section 4 presents the application process and results. Section 5 concludes thisstudy.

2 YELLOW SEA EXPERIMENT

In August 2018, an experiment was conducted using hydrographic systems for performing sediment characterization in the Yellow Sea off the coast of Qingdao in China. The results that have been obtained previously based on core sampling are presented in Fig. 1. The ship track of the experiment (the red dashed line in Fig. 1) began at point B and ended at point A (Fig. 1), covering a distance of approximately 120 km and three main sediment types, i.e., clayey silt, sandy silt, and silty sand. The sediment was mainly silt on the first half of the ship track and sand on the second half; the depth of the seafloor in the study area was 30–40 m. In this experiment, an SBES and MBES were simultaneously used to measure the sediment properties and were operated at 25 and 200 kHz, respectively. Despite the different operating frequencies, the analysis results based on the MBES backscatter values and the SBES echo envelopes were observed to be correlated to some extent.(Parnum et al. 2009).

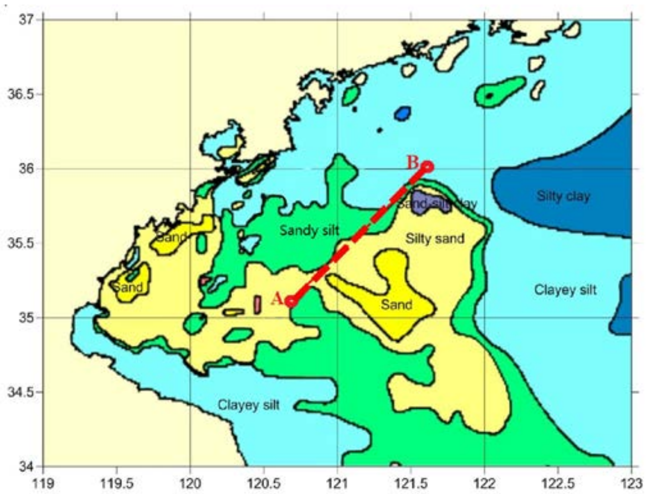

Figure 1: Core-sample type distribution, where the red line denotes the track of the experiment survey.

2.1 MBES Data Preprocessing

The multibeam sonar system used in this experiment was a NORBIT WBMS Bathy 200 MBES that primarily measured the backscatter intensities in each of its 512 beams, with a swath coverage of 135°. These acoustic intensities backscattered from the seafloor are useful to determine the physical properties of the sediment such as the substrate sediment type and parameters. Figure 2 shows the data for the raw recorded backscatter intensity; here, we select only the data with beam angles of 0°–60°, i.e., approximately 230 beams from one side of the swath.

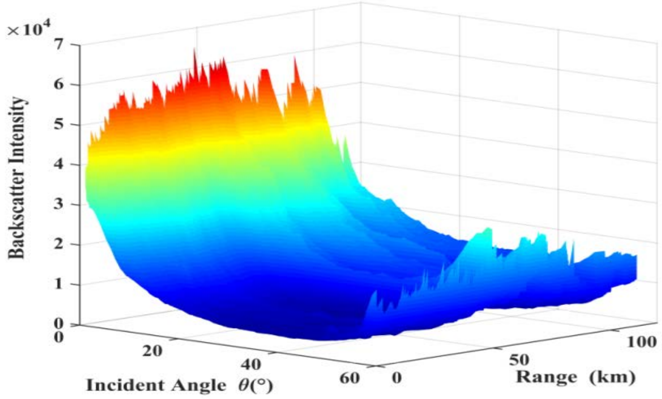

Figure 2: Received echo backscatter intensity

Theoretically, according to the active sonar equation (Hellequin, Boucher, and Lurton 2003), the echo level (EL) of the raw recorded signal can be transformed into the backscatter strength (BS), which is considered to be the quantity that characterizes the bottom reflectivity.

$$\mathrm{BS} = \mathrm{EL} - \mathrm{SL} + 2\mathrm{TL} - \mathrm{BA} - G_R - S_H - D_R - D_T, \tag{1}$$

where SL is the MBES's source level, $2\mathrm{TL}$ is the two-way transmission loss (comprising the spherical spreading of the signal and the absorption loss in water), BA is the radiated or backscatter area (which is bounded by the beam geometry and depends on the along-track resolution Φ_x, across-track resolution Φ_x, transmitter pulse length τ, and several other factors), G_R is the constant processing gain, S_H is the acoustic sensitivity of the receiver array, and D_R and D_T are the receiver and transmitter beam patterns, respectively.

However, the lack of absolute calibration parameters makes it difficult in practice to obtain the absolute BS as calculated from Eq. (1). Practically, the BS is likely to be sufficiently reliable to reflect the differences among various sediment types (Haris et al. 2011); therefore, by ignoring the constant and unknown terms in the sonar equation (e.g., c, τ, Φ_x, Φ_x, G_R, S_H), the relative backscatter strength (BS) of the seafloor can be obtained as

$$\mathrm{BS} \propto \mathrm{EL} + 2\mathrm{TL} - \mathrm{BA}. \tag{2}$$

To use the ANN method, we average the 230 beams in 0°–60° of BS to reduce the number of dimensions. The BS values are averaged for every 1° and for every 10° in each ping, reducing the length of the angular response curve of each ping to 60 and 6, respectively, which is convenient for ANN training. All the processed BS values of every 100 pings are averaged in the logarithmic domain with 80% overlap. This averaging among pings eliminates the influence of abnormal data points and provides mean angular BS curves because of backscatter fluctuations. Figure 3 shows the processed relative BS values versus the beam angle.

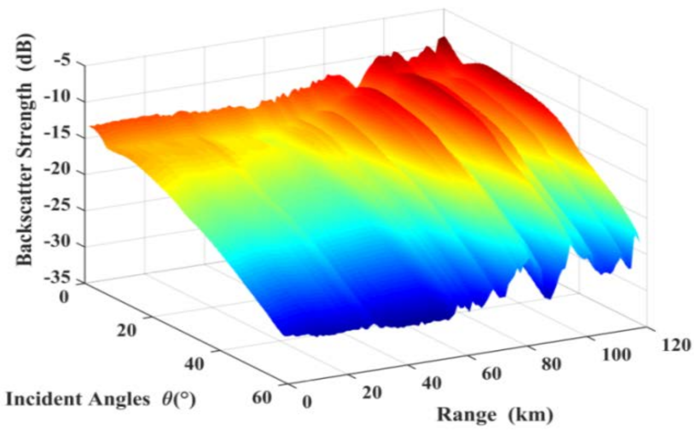

Figure 3: Processed relative backscatter strength (BS) obtained from the raw data in Fig. 2.

2.2 SBES Inversion Results

The SBES backscatter envelopes are processed for obtaining the sediment properties. After snap averaging, arrival-time aligning, and threshold smoothing, the processed signals are used to estimate the index of impedance (IOI) based on a high-frequency backscatter model and a simulated annealing optimization algorithm (see Lu et al. (2019) for details). The inversion results are presented in Fig. 4 and are used as the ground truth to label the MBES backscatter data, which are observed to generally vary in accordance with the core sampling distribution in Fig. 1.

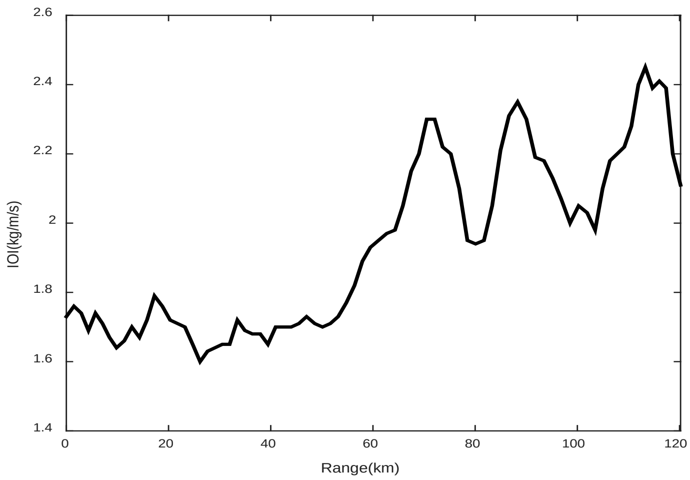

Figure 4: Index of impedance (IOI) inverted from the single-beam sonar envelopes.

3 ARTIFICIAL NEURAL NETWORKS

3.1 BPNN Description

BPNN is also known as multilayer feedforward neural network based on the error backpropagation (BP) algorithm. BPNN has been used to characterize and classify the seafloor sediments because of their excellent self-adaptability and nonlinear mapping capabilities.

A typical three-layer fully connected neural network is illustrated in Fig. 5. This network includes one input layer, two hidden layers, and one output layer, and the information flows from the inputs to the outputs (labels) based on the intermediate calculations. First, the input of each layer of neurons is multiplied by the weight, called weight connection. Next, the signal is transformed by an nonlinear activation function and then input to the next layer of neurons (Bianco et al. 2019).

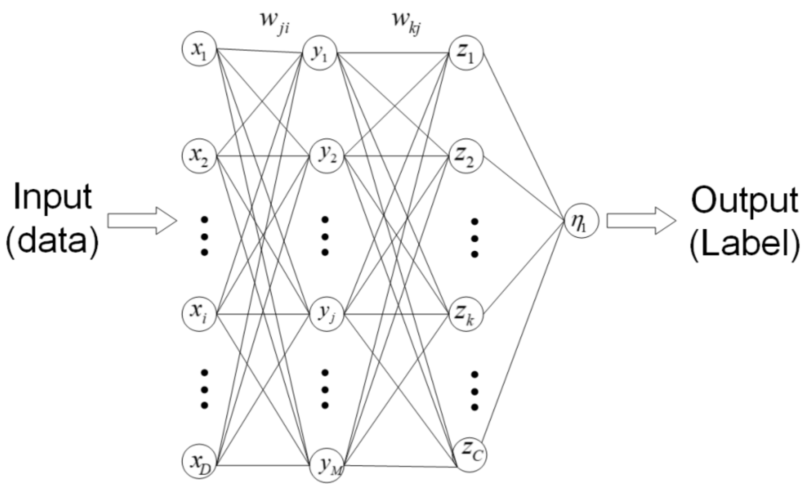

Figure 5: Typical three-layer fully connected backpropagation neural network (BPNN).

The number of neurons in the two hidden layers is set as 10 and 30. With respect to input layer, the number of neurons represents the dimension of trained BS values, respectively 60 and 6. Similar to input layer, the 1 neuron in the output layer means the IOI used as output or label.

The entire neural network process is divided into two parts, i.e., training and testing. During the training process, the angular backscatter curves of the MBES backscatter data are used as the input, and the sediment IOI provides the corresponding training labels. Subsequently, the network learns the mapping relation between the input and the labels. The weights of all the neuron connections in the network are fixed after the training process; in other words, the relation between the inputted MBES backscatter data and IOI is learned and memorized. The trained network is applied to the testing dataset for estimating the IOI.

3.2 Preventing Overfitting

Two strategies are used to prevent overfitting during the ANN training process, among which the first strategy is early stopping. The validation part is separated from the training data to monitor the training errors. Unlike the training part, which is used to train the network and update the connection weight, the validation part is set to monitor the error produced during the training process. If the training error decreases but the validation error increases, it is likely that overfitting has occurred; therefore, the training process is stopped early, regardless of whether the error threshold has been reached. Furthermore, the multibeam backscatter data are enhanced by adding noise to the processed BS values, considerably expanding the training dataset. More general features of the sediment type will be learned from this expanded dataset, effectively preventing overfitting and providing improved generalization performance.

4 SEAFLOOR CHARACTERIZATION USING BPNN

4.1 Application

Herein, the dataset from the entire ship track is divided into training and testing datasets, with 80% of the data being used for BPNN training and 20% being used for testing. Using an improved backpropagation algorithm for training network, i.e., the Levenberg–Marquardt (LM) algorithm, the performance function used in the BPNN is the mean squared error (MSE) function. The entire training and testing processes are performed several times to prevent random initialization from influencing the connection weights.

To assess the feasibility of using an ANN for performing sediment characterization, we use a classical multivariate statistical technique, i.e., multiple linear regression (MLR), for performing comparison (Parnum 2012). Unlike the nonlinearity of the neural networks, MLR seeks linear mapping to describe the relation between independent variables and output through a series of known data, and this linear equation is used to predict the results.

4.2 Results

The predicted results using different approaches (MLR and ANN) are presented along with different processed angular BS values (different average angle ranges). Within an absolute error tolerance of 0.1, the predictive accuracy obtained using the testing dataset is presented in Table 1 for the MLR and ANN methods, using the origin BS values and noised BS values, respectively. When compared with MLR, the predictive accuracy of ANN is higher, showing the feasibility of using an ANN to estimate the sediment parameters. Furthermore, the ANN trained using the noised BS data exhibited a higher predictive accuracy than that of normal data, because the addition of noise considerably expanded the training dataset; thus, more general features will be learned.

The IOI values as obtained from the BPNN are shown in Fig. 6. The good linear fitting between the predicted and label values exhibits high correlation. When trained with noised BS values, the MSE shown in Fig. 7 gradually converges with an increase in epochs during the training, validating, and testing processes, and the downward trends of these three stages indicate that overfitting was avoided.

Table 1: Predictive accuracy using the multiple linear regression (MLR) and artificial neural network (ANN) methods.

BS values averaged for every 10 degree			BS values averaged for every 1 degree		
MLR (Normal data)	ANN (Normal data)	ANN (Noised data)	MLR (Normal data)	ANN (Normal data)	ANN (Noised data)
64.82%	89%	96%	67.13%	91%	96.7%

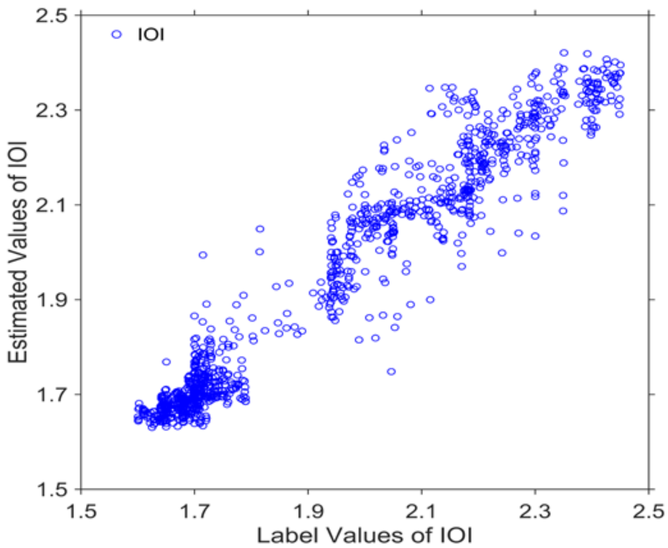

Figure 6: Linear fitting between the label and predicted IOI values.

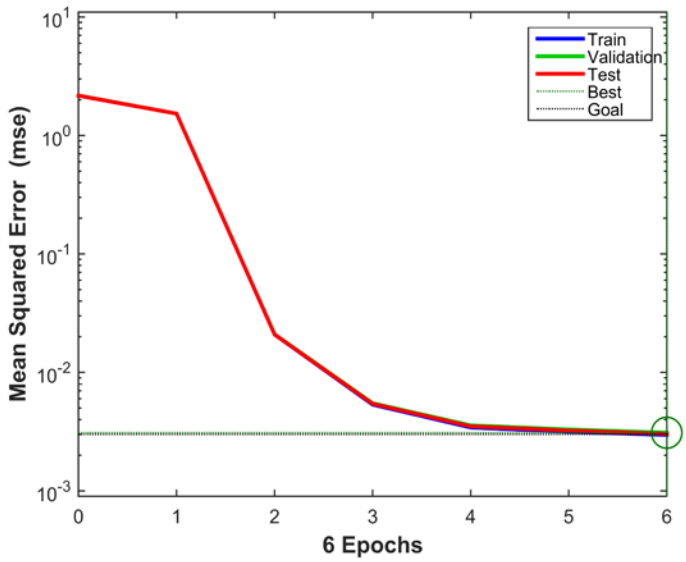

Figure 7: Mean squared error performance versus epochs.

5 CONCLUSION

In this study, a BPNN is used to estimate the IOI of the surface seafloor sediment from the MBES backscatter data, with the IOI inverted from the SBES data being used to label the MBES backscatter data during the training process. However, the results suggest some problems. First, the IOI inverted from the SBES is not necessarily accurate; second, even for the given sediment type, the IOI may slightly differ among different seafloor regions. Therefore, the mapping relation between the acoustic echo signals and sediment properties as developed using a previous neural network may fail to work when applied to a new environment. Further work is being conducted to find more consolidated labels for obtaining more reliable characterization results.

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