

Estimation of Mean Grain Size of Seafloor Sediments using Neural Network

Chanchal De ^{a,1}, Bishwajit Chakraborty ^b

^aG-FAST, P-1, Metcalfe House,
Delhi – 110054 (INDIA)

^bNational Institute of Oceanography,
Council of Scientific and Industrial Research,
Dona Paula, Goa - 403 004 (INDIA)

Abstract

The feasibility of an artificial neural network based approach is investigated to estimate the values of mean grain size of seafloor sediments using four dominant echo features, extracted from acoustic backscatter data. The acoustic backscatter data were collected using a dual-frequency (33 and 210 kHz) single-beam, normal-incidence echo sounder at twenty locations in the central part of the western continental shelf of India. Statistically significant correlations are observed between the estimated average values of mean grain size of sediments and the ground-truth data at both the frequencies. The results indicate that once a multi-layer perceptron model is trained with back-propagation algorithm, the values of mean grain size can reasonably be estimated in an experimental area. The study also revealed that the consistency among the estimated values of mean grain size at different acoustic frequencies is considerably improved with the neural network based method as compared to that with a model-based approach.

Keywords Mean grain size, neural networks, acoustic backscatter, echo features

Introduction

¹ **Corresponding Author** (chanchal_dey@yahoo.com)

A quantitative knowledge of mean grain size of seafloor sediment is of great importance for a wide range of applications in the field of marine geology, marine engineering, hydrographic, and environmental monitoring. The most reliable and accurate assessment on mean grain size of seafloor sediments can be obtained from the laboratory analyses of sediment samples. However, collection of sediment samples with grabs and/or cores or *in-situ* measurements is expensive as well as time consuming process. In addition, this conventional approach can give information on the seafloor characteristics only at pre-selected discrete locations in an experimental area. As an alternative approach, remote sensing by acoustic means has long been recognized as a rapid and cost-effective method for characterization and classification of seafloor sediments over a wide area of interest. The acoustic remote sensing essentially relies on the backscatter strength of the acoustic signal reflected from the seafloor. Since the backscatter strength contains information on the properties of the material at which the signal is scattered, it can be used for assessing the mean grain size of seafloor sediments. Acoustic backscatter data, obtained from common seafloor depth measurements equipments such as single-beam and multi-beam echo sounders, could be used for this purpose. A number of approaches concerning the characterization and classification of seafloor are available in literature (Jackson et al. 1986a; de Moustier and Alexandrou 1991; Pouliquen and Lurton 1992; Jackson and Briggs 1992; de Moustier and Matsumoto 1993; Lyons et al. 1994; Legendre et al. 2002; Sternlicht and de Moustier 2003a; Chakraborty et al. 2000; Hutin et al. 2005; Zhou and Chen 2005, van Walree et al. 2005; Chiocci et al. 2011). These approaches can be grouped into two basic categories namely model-based methods and model-free techniques. Model-based methods often utilize physics-based acoustic backscatter models to estimate the characteristic parameters of the seafloor sediments through inversions by maximizing the match between the measured and the modeled signals (Gott and Martinez 1993; Sternlicht and de Moustier 2003b; De and Chakraborty 2011). However, the accuracy of the inversion result greatly depends on the scattering theory employed in the forward backscatter model. Furthermore, the presence of benthic flora and fauna, morphological features, and the density fluctuations within sediment volume can also influence the process of echo formation and thus imposes additional challenges in the estimation of the seafloor characteristic parameters from acoustic measurements at different frequencies (Lyons and Orsi 1998; van Walree et al. 2006). In contrast, model-free techniques such as statistical methods and neural network approaches are used for characterization and classification of seafloor sediments using echo characteristic features (or echo features) that are extracted from the acoustic backscatter signal reflected from the seafloor (Orlowski 1984; Pace and Gao

1988; Chivers et al. 1990; Stewart et al. 1994; Tegowski and Lubniewski 2000, 2002; Chakraborty et al. 2003b, 2007; van Walree et al. 2005, De and Chakraborty 2009). However, in model-free approaches, ground-truth measurements from sediment samples are essential to interpret the results (obtained from the backscatter signal) by associating with the true sediment properties.

Acoustic backscatter strength from the seafloor is primarily controlled by the contrast in acoustic impedances between water and sediment, contributions from the seafloor interface roughness, the sediment volume inhomogeneity or layering, and the acoustic frequency used for measurements. The effect of seafloor interface roughness on scattering is relatively more important at higher acoustic frequencies, whereas, the scattering due to sediment volume inhomogeneity is relatively more significant at lower acoustic frequencies. In soft sediments, after penetrating into the sediment, the acoustic energy is likely to be scattered from the buried inhomogeneities (coarse sand particles, pebbles, shell hash, gas bubbles etc.) or buried layers. The intensity of the scattered energy depends on the sizes of these buried inhomogeneities relative to the impinging acoustic wavelength and is expected to decrease with an increasing acoustic frequency because of the enhanced absorption inside the sediment volume. As a result, various complex dynamic processes affect the interaction and scattering of acoustic energies from the seafloor and interpretation of backscatter data mainly depends on the level of understanding of the scattering mechanism of acoustic energies from the seafloor. Thus, studies on validation and applicability of various theoretical models over a wide range of acoustic frequencies are indispensable (Jackson et al. 1986b; Jackson and Briggs 1992; Jackson et al. 1996; Sternlicht and de Moustier 2003a, 2003b; van Walree et al. 2006; Snellen et al. 2011; De and Chakraborty 2011). If a forward model is sufficiently close to the true sediment model, inversion algorithms using a physics-based model can provide true solutions of the seafloor characteristic parameters. Recently, an investigation on the applicability of a physics-based temporal backscatter model to estimate the seafloor sediment parameters at two conventional frequencies (33 and 210 kHz) of a single-beam echo sounder revealed that a single power-law relief spectrum (usually assumed in backscatter models) might be too simple to describe the seafloor scattering mechanism over a wide range of acoustic frequencies (De and Chakraborty 2011). In addition, laboratory experiments under controlled conditions revealed that there is a significant difference in the backscatter strength measured with two acoustic frequencies over two sediments with different mean grain sizes and this persistent difference in the frequency range 150 kHz to 2 MHz could be explained by a ratio of mean grain size to wavelength (Ivakin and Sessarego 2007). Recent field experiments also revealed that above 150-200 kHz a new scattering mechanism is coming

into play for the backscatter data collected from the Sediment Acoustic eXperiments conducted in 1999 (SAX99) and 2004 (SAX04) in the northeastern Gulf of Mexico (Williams et al. 2002, 2009). Therefore, estimation of the seafloor sediment characteristic parameters from the frequency-dependent acoustic backscatter energy warrants detailed understanding of the changing scattering mechanism above 150 kHz due to the variations in physical properties of the seafloor sediments at different scales, lateral inhomogeneity of sub-bottom layers, and their density gradients.

Hence, a model-free approach using artificial neural networks is exploited in this paper to estimate the values of mean grain size of seafloor sediments using the acoustic backscatter data at 33 and 210 kHz. The model-free approaches using artificial neural networks provide the most promising alternative to various conventional classification methods. Different techniques based on neural networks have successfully been demonstrated earlier for classification of seafloor (Ghosh et al. 1992; Alexandrou and Pantartzis 1993; Stewart et al. 1994; Michalopoulou et al. 1995; Stepnowski et al. 2003; Chakraborty 2003a, 2004; De and Chakraborty 2009, 2010). These self-adaptive, non-linear, data-driven models are capable of adjusting itself to the input data without any explicit expression of the underlying model and successfully used for seafloor classification in the real world (Chakraborty et al. 2001, 2003a, 2003b; Zhou and Chen 2005). In general, echo features, extracted from the acoustic backscatter data, are used in neural network based techniques for seafloor classification. Proper selection of echo features is an important criterion to save the computational time as well as to achieve improved success in the classification using a neural network based approach (De and Chakraborty 2010). The aim of this paper is to investigate the feasibility of a neural network based approach to estimate the values of mean grain size of sediments at two acoustic frequencies without exploring the physics responsible for the acoustic interaction with the seafloor and the scattering mechanism at different frequencies. The values of mean grain size of sediments thus estimated are compared with that estimated from a model-based approach (De and Chakraborty 2011). Though earlier model-based study by De and Chakraborty (2011) deals with the estimation of the values of four seafloor parameters, in this paper, only the value of mean grain size is estimated using the neural network based method because of non-availability of the ground-truth data on other seafloor parameters in the experimental area. Furthermore, in the absence of ground-truth data, the effectiveness of the neural model is investigated to predict the values of mean grain size for seafloor sediments at five unknown locations.

Measurements

Acoustic backscatter echo data were acquired at 20 locations along three tracks (Fig. 1) in the central part of the western continental shelf of India in the Arabian Sea using a hull-mounted Reson Navitronic NS-420 normal-incidence, single-beam echo sounder operated at 33 and 210 kHz. The pulse lengths of the transmitted continuous wave pulse signals are 0.97 and 0.61 ms, respectively, for 33 and 210 kHz. The widths (-3 dB) of the conical shaped beam of the echo sounder are 20° and 9° respectively, for 33 and 210 kHz. Acoustic backscatter data were acquired at each location when the ship was stopped for collection of sediment samples. In the initial pre-processing stage, the echo data (after removing the received signals with saturated voltage) are subjected to Hilbert Transform to obtain the echo envelopes. Due to the transducer heave motion and small variations of seafloor depth over consecutive pings (while recording the backscatter data), initial rise times of the envelopes are not same for all the echoes collected at a particular location. Therefore, it is essential to use stable acoustic signals for further analyses. To obtain stable acoustic signals, backscatter echo envelopes are first aligned and then averaged using 20 successive envelopes with 95% overlap (i.e., the echoes are averaged in a moving average sense with sequences 1-20, 2-21, and so on till the end of the number of consistent echo envelopes available in the dataset) (De and Chakraborty 2009).

The shapes of the acoustic signals scattered from the seafloor vary significantly with the seafloor depth because of the variation of footprint size of the transmitted beam, even if the seafloor sediment remains unchanged. An echo recorded at a greater depth (compared to a reference depth) is stretched along the time axis and an echo recorded at a lesser depth (compared to the reference depth) is compressed along the time axis. To overcome this difficulty, time adjustments are made on the averaged echo envelopes at a reference seafloor depth of 50m, which is the approximate average of all the spot depth measurements (Pouliquen 2004). Finally, four echo features are extracted from the normalized averaged echoes. These features are backscatter strength, statistical time-spread, statistical skewness, and Hausdroff dimension. Backscatter strength, the ratio in decibels (dB) of the sound intensity backscattered from a unit seafloor area and the incident intensity at a unit distance from the source, is computed from the measured acoustic data (Chakraborty et al. 2007). The statistical echo shape parameters, time-spread and statistical skewness, are calculated from the second and the third central moments respectively, in the time domain (van Walree et al. 2005). The fourth echo feature Hausdroff

dimension (fractal dimension) is a measure of the complexity of the seafloor echo envelope (Tegowski and Lubniewski 2000).

Sediment samples were collected using a Van-Veen grab sampler at the same 20 locations, where the backscatter echo data were acquired, in order to obtain ground-truth values on mean grain size of the seafloor sediments as well as the sediment types. The grain sizes are commonly expressed either in millimeters or in phi (ϕ) units and these two units are related as $d = -\log_2(D_g)$, where D_g is the grain diameter in millimeters and d is the corresponding value in ϕ units. The mean grain size of sediments (hereafter referred to as M_ϕ) in ϕ units is calculated as $M_\phi = (d_{16} + d_{50} + d_{84})/3$, where d_x is the grain size in ϕ units at which $x\%$ of the grain sizes are smaller than d_x in the sediment sample. Laboratory analyses of the surficial sediment samples revealed that four types of seafloor sediments, namely clayey-silt, silt, silty-sand, and sand, are available in the experimental area. The ground-truth values of M_ϕ for clayey-silt and silt sediments vary within $5.83-6.79\phi$ and $6.20-6.50\phi$, respectively, whereas for silty-sand and sand samples, the values of M_ϕ vary within $1.99-4.02\phi$ and $1.16-2.42\phi$, respectively.

Estimation of mean grain size of sediments using a neural network

An artificial neural network is a nonlinear information processing system that uses mathematical algorithms to learn the relationships and the hidden patterns in a given dataset. Multi-layer perceptron neural network trained with back-propagation algorithm is one of the most widely used neural network models for characterization and classification of seafloor sediments (Alexandrou and Pantartzis 1993; Stewart et al. 1994; Michalopoulou et al. 1995; Chakraborty et al. 2003a). In this paper, a multi-layer perceptron model is used to estimate the values of M_ϕ using the four echo features, extracted from the acoustic backscatter data. A typical network consists of an input layer, one or more hidden layers, and an output layer. In a typical operation, each neuron of a network receives inputs from other interconnected neurons and/or from the external source and finally the processed information is obtained through the output layer. The neurons in the hidden layers enable a network to learn complex patterns of the input data applied to the network. During the process, each neuron in a layer receives the collective weighted information from the neurons in the previous layer and finally an activation function is applied to modify the sum of the weighted input signal to produce the output signal. This process is called learning

or training of a network and the input data used for this purpose is called the training data. This training process essentially adjusts the weights of interconnecting neurons in various layers of a network with an objective to achieve an expected output response at an acceptable level. Back-propagation is an efficient learning method to capture the inherent characteristics of a given set of input-output pairs. In back-propagation, the deviation of the actual output from the expected response is propagated backwards through the network from output to input layer through the hidden layer(s) and the network performs a nonlinear optimization to minimize the error between the actual and the expected outputs. More information on the theory of neural networks can be found in Masters 1993 and Haykin 2003.

A uniform scaling is essential in neural network analysis for equalizing the importance of all the input-output variables. In this study, at each layer of the network, hyperbolic tangent sigmoid functions are used as activation functions for nonlinear conversion of the summed inputs. Thus, input and output data are scaled in such a way that all the values lie within a range -1 to $+1$ (MATLAB 7.0, 2004). In addition, scaling of data is carried out in such a way that the data used in training are proportional with that used for testing the network. Though various partial derivative based back-propagation algorithms are available, in this paper, a resilient back-propagation algorithm is used as a training algorithm (Reidmiller and Braun 1993). As mentioned, sigmoid transfer functions are generally used in the hidden layers of a multi-layer perceptron network. If the inputs to these functions are large, the slopes of these functions approach to zero. In partial derivative based back-propagation algorithms, a small gradient makes small changes during the adjustment of weights and biases, even if the weights and biases are far their optimum values. The advantage of a resilient back-propagation algorithm is that only the sign of the derivative is used to determine the direction of weights update; and the magnitude of the derivative does not play any role in the weights update. For training a network with resilient back-propagation algorithm, a function '*trainrp*', available in Neural Network Toolbox of MATLAB (2004), is used here. The training algorithm uses the mean square error minimization scheme to minimize the error between the actual output from a network and the expected outputs.

De and Chakraborty (2010) investigated the relative importance of seven echo features (extracted from the acoustic backscatter data) for classification of seafloor sediments using a multi-layer perceptron network trained with back-propagation algorithm. Dual frequency (33 and 210 kHz) acoustic backscatter echo data, collected from an experimental area in the Arabian Sea, were used in that study. The study demonstrated that the best performance of a neural network based sediment classifier could be

achieved if a proper set of input echo features is selected. The use of more number of echo features in the input dataset compared to the optimum number of features does not increase the success rate of a neural classifier. However, the computational time increases considerably. The study also revealed that backscatter strength, time-spread, statistical skewness, and Hausdroff dimension are the most dominant echo features (when used as a set) to a neural network based sediment classifier at 33 and 210 kHz in the experimental area (De and Chakraborty, 2010). It was demonstrated that if the above-mentioned 4 features are used together as an input to a neural network based sediment classifier, the highest percentage of success could be achieved. The same acoustic backscatter data, which were used earlier to investigate the dominant echo features for seafloor classification (De and Chakraborty 2010), are used in this study also. As a result, in this paper, these four dominant echo features, backscatter strength, time-spread, statistical skewness, and Hausdroff dimension, are selected as a set of input parameters to the network for estimating the values of M_ϕ .

In this paper, a network structure consisting of an input layer, two hidden layers, and an output layer are used to estimate the values of M_ϕ . The number of neurons in the input and output layer are equal to the number of inputs parameters (i.e., four) and the number of output parameter (i.e., one) respectively. The number of neurons in the hidden layer(s) of a network is usually optimized by trial and error methods. A network with optimum size is less likely to learn the noise in the training dataset, and may therefore generalize better to a new dataset applied to the network (Haykin 2003). Initially, a network architecture consisting of an input layer, one hidden layer, and an output layer is experimented with the number of neurons in the hidden layer varying from 1 to 55 to decide the optimum number of neurons in the first hidden layer. Subsequently, the number of neurons in the second hidden layer is varied from 1 to 30 for optimization. From these experiments, the numbers of neurons in the first and second hidden layers are optimized as 25 and 10 for both the frequencies. No significant improvements in the results are observed by increasing the number of hidden neurons beyond the optimum number. As a result, in this paper, a network configuration [4-25-10-1] is optimized for the estimation of the values of M_ϕ . Having optimized the network architecture, the percentage of data used for training the network is optimized by varying it from 5% to 40% of the total dataset. If the training dataset increased beyond 15% of the total dataset, no significant improvements in the success rates are observed during the testing of the network. As a result, in this paper, 15% of the total dataset is used as a training dataset and the remaining 85% of the total dataset is used as a testing dataset for both the frequencies.

The performance of a network (i.e., the percentage of success in estimating the true values of M_ϕ during training and testing) is evaluated by computing the ratio of the number of data points giving ‘true estimation’ to the total number of data points used for training or testing. If the estimated value of M_ϕ falls within a range of $\pm 5\%$ deviation from the ground-truth value for a particular sediment, it is considered as the ‘true estimation’. Thus, if the estimated value of M_ϕ lies within a range of $1.16 \pm 0.06\phi$ for a sandy sediment sample with a ground-truth value 1.16ϕ , it is considered as the ‘true estimation’ during training or testing. This $\pm 5\%$ tolerance value (from the ground-truth value) is chosen arbitrarily to compute the percentage of success during training and testing of the network. However, it is observed that the final result depends on the values of interconnecting weights chosen initially during the training of a network (if other computational parameters are kept unchanged). Therefore, a particular network is trained and tested 10 times with 10 different sets of randomly generated initial weights. The number ten is chosen arbitrarily to take into account the variations of initial weights on the performances of the neural network. Subsequently, an average percentage of success is computed by taking the average of these 10 sets of results. The neural network toolbox available in MATLAB 7.0 (2004) is used in this paper.

Initially, the total dataset (comprising of echo features from all the sample locations) is used for training and testing of the network. As mentioned earlier, 15% of the total dataset is optimally used as training dataset and the remaining 85% of the total dataset is used as a testing dataset for both the frequencies. The estimated values of M_ϕ obtained from this experiment are compared with the ground-truth data as well as with that estimated from a model-based method. The details of the model-based approach and the discussion on the estimated values of M_ϕ using the model are available in another paper (De and Chakraborty 2011). The values of M_ϕ obtained from this model-based approach are used for comparison study in this paper. Furthermore, the network is trained with the data from 15 sample locations and subsequently, the values of M_ϕ are estimated for all the 20 samples using the trained network. The results are compared with the ground-truth data to explore the effectiveness of this model-free technique to predict the values of M_ϕ at five unknown samples for real-time applications while a research vessel is underway.

Results and Discussion

An average value of M_ϕ is computed by taking the mean of all the estimated values for a particular sediment sample using the neural network [4-25-10-1]. Subsequently, an overall average value of M_ϕ is computed by taking the mean of 10 sets of average values of M_ϕ obtained from the network trained with 10 different sets of interconnecting weights. These overall average values of M_ϕ are used for comparing the results with the ground-truth data as well as with that obtained from a model-based approach (as mentioned earlier).

The estimated average values of M_ϕ for surficial seafloor sediments obtained from a neural network based model are expected to correlate with the laboratory-measured values of M_ϕ (i.e., ground-truth data). The linear regression analysis between the estimated average values of M_ϕ and the laboratory-measured values of M_ϕ is shown in Fig. 2. The analysis revealed that the determination coefficients (r^2) are 0.9879 and 0.9979, respectively for 33 and 210 kHz. The p -values associated with these correlations indicate that these correlations are statistically significant at 5% level of significance (computed using student's t -distribution). The analysis also indicates that these regression lines are capable to explain about 99% of the variances in the estimation of M_ϕ using the neural network model at both the frequencies. Furthermore, the results indicate that the least square line obtained from the best fit of the 210 kHz estimation gives the best evaluation of M_ϕ when compared with the 1:1 straight line (i.e., the line with unit correlation coefficient). It is also observed that the estimated average values of M_ϕ for coarse sediments (i.e., silty-sand and sand samples with $M_\phi < 4\phi$) have relatively more fluctuations (evident from the error bars in Fig. 2) as compared to the fine sediments (i.e., clayey-silt and silt sediments with $M_\phi \geq 4\phi$). In addition, the fluctuations associated with the estimated values of M_ϕ for silty-sand samples are comparatively bigger than that of sand samples. Earlier model-based inversion study in the present experimental area revealed that the inverted values of M_ϕ using 33 kHz data provided relatively improved estimations over the 210 kHz data (De and Chakraborty 2011). The model-based study also revealed that the least square line obtained from the best fit of the M_ϕ values at 33 kHz inversions showed improved results when compared with the 1:1 straight line. The values of r^2 ,

obtained from the linear regression analysis between the laboratory-measured values of M_ϕ and the inverted average values of M_ϕ , were 0.9544 and 0.9184, respectively for 33 and 210 kHz (De and Chakraborty 2011). In contrast, the estimations from neural network analysis (as presented in this paper) indicate that the value of r^2 is marginally lower for 33 kHz as compared to 210 kHz (Fig. 2). This comparison shows that the neural network based approach is capable to estimate the values of M_ϕ more accurately as compared to the model-based approach.

Fig. 3 shows the consistency among the values of M_ϕ estimated from the model-based approach and the neural network based approach using 33 and 210 kHz backscatter data. The consistency among the average values of M_ϕ obtained from the model-based approach at 33 and 210 kHz is comparatively lower because of the possible change in the mechanism of scattering phenomena at different acoustic frequencies (which may not be incorporated in the model, as mentioned earlier). The value of r^2 obtained from the regression analysis of the inverted values of M_ϕ at 33 and 210 kHz using the model-based approach is 0.9178 (Fig. 3). In contrast, the consistency among the estimated values of M_ϕ obtained from the neural network based approach at 33 and 210 kHz is relatively higher ($r^2 = 0.9916$). As a result, in the absence of a suitable backscatter model, capable to explain the detailed mechanism of scattering from the seafloor at different acoustic frequencies, the neural network based approach may be feasible and advantageous to estimate the values of M_ϕ in an experimental area at 33 and 210 kHz.

The average estimated values of M_ϕ and the percentages of success for ‘true estimation’ are given in Table 1 for two cases: (1) Case A - the network is trained with the data chosen from all the 20 sample locations, (2) Case B - the network is trained with the data chosen from 15 sample locations only and the values of M_ϕ are estimated for all the 20 samples. The asterisk (*) marks (in Case B) indicate that the data from these sample locations are not used for training the network. The regression analysis for the Case B, between the laboratory-measured values of M_ϕ and the average estimated values of M_ϕ using the neural network based method at all the 20 sample locations, indicate that the statistically significant (computed using student’s t -distribution) values of r^2 are 0.9815 and 0.9898 respectively, for 33 and 210 kHz. The values of r^2 at both the frequencies are decreased in comparison with those

obtained from the same network trained with the data chosen from all the sample locations (Case A). However, the regression models (for Case B) can still explain about 98-99% of the variances in the estimations of M_ϕ . Though the success rate for ‘true estimation’ (as shown in Table 1) degrades for all the unknown samples, the effectiveness of the network to predict the values of M_ϕ for soft sediments is comparatively better than that for coarse sediments.

Conclusion

This study demonstrates that in the absence of detailed understanding on the mechanism of the seafloor scattering phenomena as well as the accurate model to interpret the backscatter data at different acoustic frequencies, neural network based approach is advantageous for estimating the values of mean grain size of sediments in the frequency range 33-210 kHz. In general, estimation of the values of mean grain size using a physics-based model through an inversion algorithm is computationally demanding. In contrast, the values of M_ϕ could be estimated using a neural network based approach at much shorter computational time. The results revealed that the performance of the neural network based approach at 210 kHz is relatively better as compared to that at 33 kHz. In the absence of independent ground-truth information, it is feasible to characterize the prevailing seafloor sediments using the model-free approach. In addition, neural network based approaches may be useful for rapid assessment of the characteristics of seafloor sediments while a research vessel is underway. Furthermore, these model-free approaches could be effectively used to decide the possible locations for further collection of ground-truth samples in real time in a wide experimental area.

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Figure Captions

- Fig. 1** Study area showing sediment sample locations and the sediment types. The depth contours are in meters.
- Fig. 2** Scatter plot showing the correlation between the laboratory-measured values of M_ϕ and the estimated average values of M_ϕ obtained from the neural network [4-25-10-1] using 33 and 210 kHz data. Diagonal dotted lines indicate the 1:1 line. The error bars indicate one standard deviation in either direction. The values of determination coefficients (r^2) are also indicated in the plot.
- Fig. 3** Scatter plot showing the consistency among the values of M_ϕ estimated from a model-based approach and the neural network (NN) based approach using 33 and 210 kHz data. The values of determination coefficients (r^2) are indicated in the plot.

Table Caption

- Table 1** Estimated average values of M_ϕ and percentages of success for ‘true estimation’ obtained from the neural network based approach

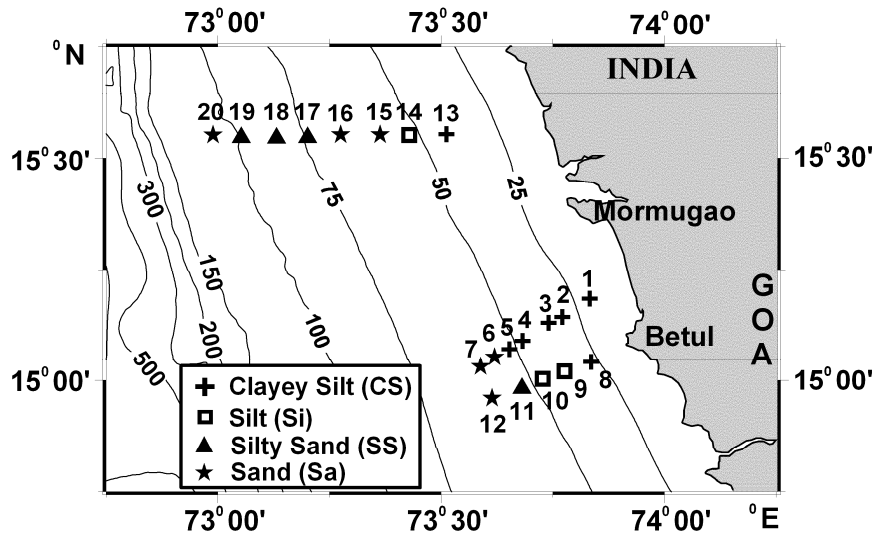


Fig. 1.

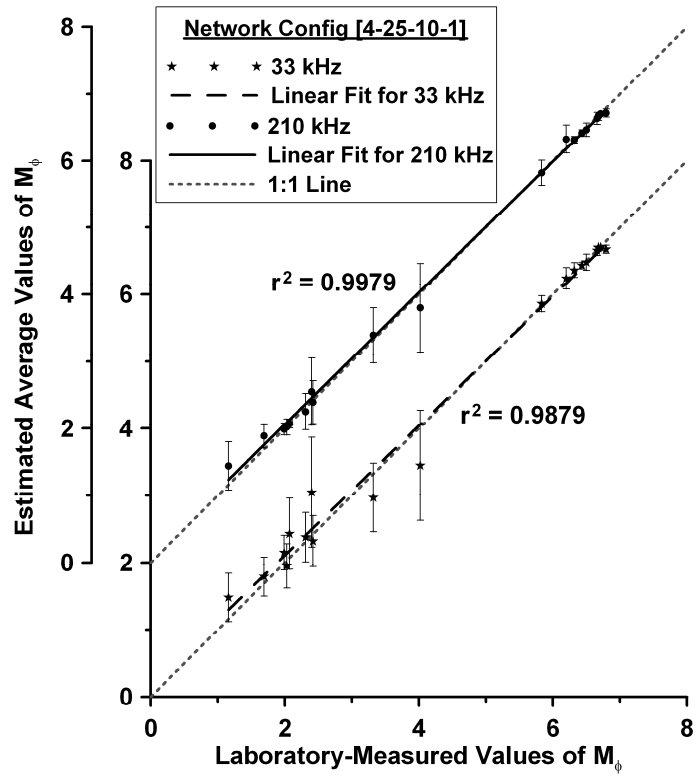


Fig. 2

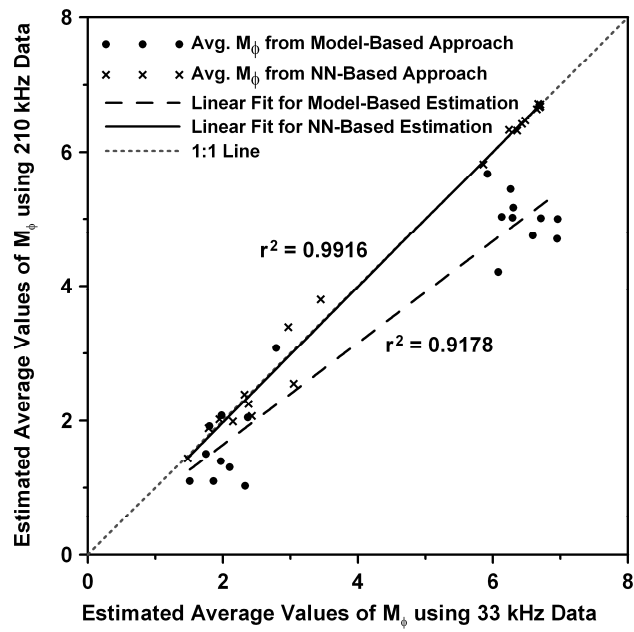


Fig. 3

Table 1 Estimated average values of M_ϕ and percentages of success for ‘true estimation’ obtained from the neural network based approach

Stn No.	Case A				Case B				Laboratory-Measured M_ϕ	True Sed. Type
	33 kHz		210 kHz		33 kHz		210 kHz			
	Avg M_ϕ	% Success	Avg M_ϕ	% Success	Avg M_ϕ	% Success	Avg M_ϕ	% Success		
1	6.70	100	6.71	100	6.71	99	6.71	100	6.71	CS
2	6.70	100	6.68	100	6.71*	100	6.67*	100	6.68	CS
3	6.69	100	6.67	100	6.70	100	6.67	100	6.67	CS
4	6.36	96	6.32	100	6.53*	45	6.38*	49	6.32	CS
5	5.86	95	5.82	87	5.87	90	5.88	91	5.83	CS
8	6.65	100	6.64	97	6.18*	67	6.46*	73	6.66	CS
13	6.67	98	6.72	98	6.71	99	6.75	99	6.79	CS
9	6.43	100	6.42	100	6.43	100	6.40	99	6.42	Si
10	6.48	98	6.47	98	6.02*	64	5.78*	36	6.50	Si
14	6.24	91	6.33	80	6.04	84	6.39	68	6.20	Si
11	3.45	28	3.8	50	3.43	30	3.71	56	4.02	SS
17	3.05	25	2.55	62	3.06	24	2.54	64	2.40	SS
18	2.15	41	1.99	86	2.15	37	1.99	92	1.99	SS
19	2.97	24	3.39	61	2.98	23	3.30	70	3.32	SS
6	1.79	70	1.89	29	1.73	68	1.68	40	1.69	Sa
7	2.38	68	2.25	48	2.40	63	2.22	56	2.31	Sa
12	1.95	23	2.02	77	1.71*	11	1.56*	17	2.03	Sa
15	2.32	53	2.39	51	2.35	63	2.37	72	2.42	Sa
16	1.48	19	1.44	42	1.49	25	1.43	59	1.16	Sa
20	2.43	23	2.07	94	2.41	24	2.08	100	2.07	Sa

Case A – data chosen from all the 20 sample locations are used for training the network,

Case B – data chosen from 15 sample locations only are used for training the network,

Asterisk marks (*) - No data is used for training from these 5 sample locations in the Case B (and are referred to as unknown samples in the text),

Sediment types: CS - Clayey Silt; Si – Silt; SS - Silty Sand; Sa - Sand