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Seafloor sediment classification from single beam echo sounder data using LVQ network

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Abstract Seafloor sediment classification based on echo characteristics obtained from single-beam echosounder is very useful in remote and instant sediment classification. Results of different classification techniques using such data provide robust results when the acoustic beam has a normal incidence with the seabottom. This may not always be true and show poor classification, with the data acquired during rough sea periods corresponding to both oblique and normal incidence of the acoustic pulse, due to roll and pitch motion of the ship. In the present study, an attempt is made to exploit the artificial neural network (ANN) techniques for better classification with such data. Learning Vector Quantisation (LVQ) is a supervised learning algorithm of ANN that is found to be an effective tool and show good performance. The input data to the network include the roughness index (E1) and hardness index (E2) derived from echo characteristics. The network utilizes the competitive learning, a distance function in the first layer and a linear function in the second layer. The network was tried with a different size of hidden neurons and training data size to see the influence on classification. It is found that with ten neurons in the first layer and four neurons in the second layer good performance in classification for the data was achieved.

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Introduction

There are a good number of techniques used to exploit the acoustic backscatter energy from single beam echosounder in remote marine sediment classification. The techniques are mostly based on statistical properties (Legendre et al. 2002), eg., echo shape (Schlagintweit 1993; Prager et al. 1995; Heald and Pace 1996), fractals (Tegowski and Lubiniewski 2000) and some are based on fuzzy neural networks (Dung and Stepnowsk 2000). In single beam echosounders, the data pertain to normal incidence of the acoustic signal. Usually single or multiple echoes are considered. In the present work, the data based on first and second echoes are taken into account for the analysis. The advantage of a single beam echosounder is that it is cheap and a commonly available equipment for any survey ship/boat. With additional provision for recording the first and second echo data can provide some information about the seabottom characteristics. Unlike multibeam echosounders, which provides spatial coverage, the single beam echosounder gives information of the seabed below the survey track lines, due to normal incidence of the acoustic pulse. In case of a multibeam echosounder, a relatively expensive system, provides information on backscatter energy for different grazing angles of acoustic beams, covering some swath on either side of the track lines, will be exploited to characterize the seabed. In the present study, we deal with single-beam echosounder data only.

Usually, echosounder data are acquired along the survey tracks during the calm sea periods. When the sea is calm, the beam is at a normal incident angle. When sea is rough, the beam is at inclined angle due to the heave and roll motion of the ship, causing changes both in shape and travel time of the echo signal and resulting incorrect depths. In general, most of the approaches in sediment classification are calibrated over the known seabed to assign the limits of feature vectors extracted from echo characteristics, in order to classify any area under investigation. Two feature vectors, roughness index (E1) and hardness index (E2), derived from first echo and second echo respectively, are most commonly used (Fig. 1a). E1 is the energy or area under the stretching portion of the first echo, representing roughness index, while E2 is energy of the second echo represent the hardness index as well as acoustic impedance of the seabed. There are two systems commercially available, namely RoxAnn and QTC utilize the concept of E1 and E2 for sediment classification. However they have not revealed any formula for estimating E1 and E2. Similar concepts were adopted for classification from the multi-frequency echosounder data (Justy et al. 2000) using acoustic pressure estimated from the algorithm (Heald and Pace 1996) given below,

$$p_{obs}^2 = p_o^2 \int_{\theta a}^{\theta_b} (m_s(\theta_1) G^2(\theta_1)(R_0')^4) dA_1$$

where, p_o is the source pressure at a distance of 1m from the source, $dA_1 = 2\pi R_0^{\prime 2} \tan\theta_1 d\theta_1, R_0^1 = R_0\sqrt{1+\tan^2\theta_1}$, $G(\theta_1)$ is the transducer gain and, $m_s(\theta_1)\alpha\Re^2$ and $m_s(\theta_1)\alpha(\sigma/T)^2$, where $\Re^2$ is acoustic pressure reflection coefficient, σ the rms height of the surface roughness and T, the correlation length of the surface roughness, θ_1 is the incident angle of the acoustic wave on the bottom. To estimate the roughness (E1), the integration limits for (θ_a, θ_b) in the equation are taken between 20° and 31.6° for 38 kHz, after falling edge of the first echo pulse, whereas for hardness (E2), integration of the complete envelope of the second acoustic bottom scatter are taken (Justy et al. 2000).

The ranges of E1 and E2 vary with sediment type as they comprise of different physical properties and grain sizes. A typical distribution map of E1 vs. E2 for different sediment type is shown in Fig. 1b and one can guess the type of sediment based on their distribution, whenever a new data set is presented.

The earlier mentioned techniques are effective for normal incidence data of a single-beam echosounder. However the same is not true with the data acquired during rough seas, as they represent both normal and inclined beams, resulting a totally different nature of echoes for the same sediment type. Such data (E1, E2) distribution appears to be outliers when compared with corresponding normal incidence data. Thus efficiency of the most of approaches becomes poor with such data.

The objective of this work is to exploit artificial neural network (ANN) techniques for effective sediment classification, even with noisy echo data due to oblique incidence. In the present study, learning vector quantization (LVQ), a supervised companion of self-organized feature map (SOFM) of neural networks, whose capabilities are proven in many application fields such as pattern classification and data compression, is used in sediment classification. Experimental data with ground truth are used to train and validate the network model.

E1and E2 were obtained from a RoxAnn Unit, interfaced to an echosounder with 40kHz operational frequency, of Marimatech make. The echo data were collected at 10 locations over the seabed mainly composed of four type of sediments, i.e silty-clay, silty-sand, clayey-silt and sand. The data were divided into two sets, of which the first part was used for network learning and the second part as test

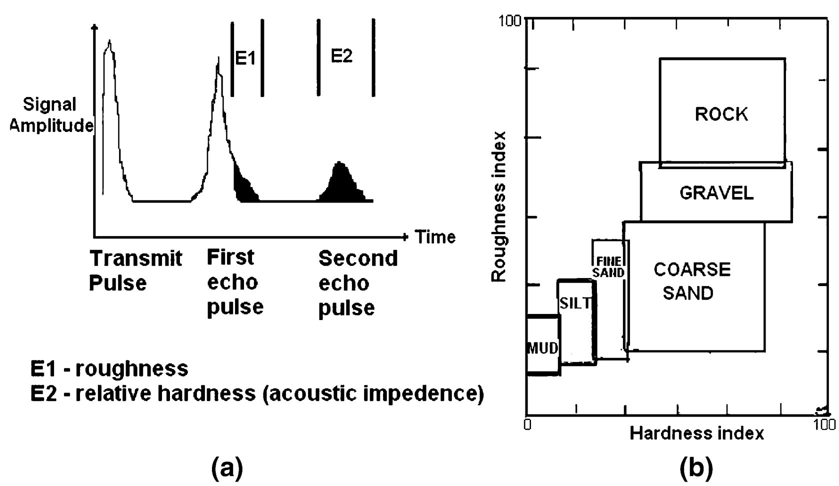

Fig. 1 (**a**) E1 and E2 representation from the echo (**b**) boxes showing E1 and E2 variation corresponding to different sediment type

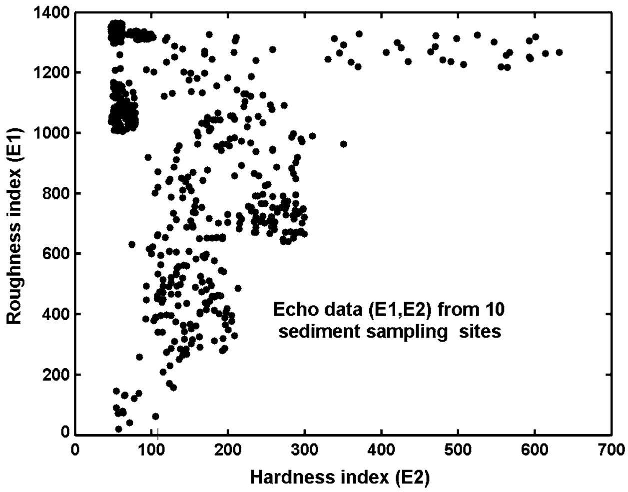

Fig. 2 Distribution of (E1, E2) data used for training the network

data set. Figure 2 shows the E1 vs. E2 data used for network training. It can be noticed that the scattering of points over wide range, unlike normal incidence data.

Learning vector quantisation network

Neural network training algorithms based on competitive learning (Rumelhart and Lelland 1986) are frequently used to solve classification problems. When little a priori knowledge about the statistical properties of the training set is available, the use of an unsupervised approach is advisable (Kohonen 1988). However the number of classes into which the pattern space must be divided is known in advance, such information can be used during the training phase. One of the most commonly used paradigms of such classifiers, developed by Kohonen (1990) is the so called Learning Vector Quantisation, which is actually a family of variants of basic algorithm.

LVQ is a supervised classifier and works by using classes generated by the self-organizing feature map (SOFM) algorithm, with the two layer architecture. In LVQ networks there are mainly two stages. In the first stage, the input space is divided into a number of distinct regions, and each region in the input space is represented by set of encoded vectors or weight vectors also called Veronoi vectors according to the nearest-neighbor rule based on the Euclidean metric. This is done by SOFM technique. In the second stage the LVQ provides the mechanism to modify the Veronoi vectors utilizing the class information for improving the classification (Simon Haykin 1999).

In LVQ network the first layer is the competitive layer and the second is a linear layer (Fig. 3). The competitive layer learns to classify input vectors usually referred as subclasses, while the linear layer transforms the competitive layer's classes into target classification defined by the user. The competitive layer and linear layer will have the number of neurons equal to subclasses and targets respectively. Thus, the neurons in the first layer will always more than the second layer. The schematic of the LVQ network architecture is shown in Fig. 3.

Competitive learning

The neurons of the competitive networks learn to recognize the groups of similar input vectors. The net input vector $\mathbf{n^1}$ of a competitive layer is computed by finding the Euclidean distance using distance function 'ndist' between the input vectors **p** with Rx1 elements and the initial weight vectors **w** of dimension S^1xR, where S^1 is number of neurons in the first layer.

The maximum net input of a neuron will be zero, when the input vector equals that neurons weight vector. The competitive transfer function accepts a net input vector for a layer and returns neuron output as zero for all neurons except for the winner, the neuron associated with the most positive element of the net input $\mathbf{n^1}$, the winner's output as one. Further the weights of the winning neuron are adjusted, so as to move closer to the input. This is done by using Kohonen's learning rule as given below.

$$w_{ij}(q) = w_{ij}(q-1) + \alpha(p(q) - w_{ij}(q-1))$$

where qth weight $w_{ij}(q)$ is the ith row of the input weight matrix corresponding to jth winning neuron and 'α' is the learning rate. The learning rate 'α' to decreases monotonically with the number of iterations. Usually, the value will be initially set at small and decreases further with iterations during weights updating. The Kohonen's rule allows the weights of a neuron to learn an input vector, and because of this, it is useful in recognition applications. In this process, the weights of the winning neuron is updated more close to the input vector, resulting the winning neuron more likely to win in the next time when similar vector is presented and less unlikely when a different input vector. When more input vectors presented from a cluster, which will be represented by a neuron or neurons with output of one.

Thus the output of competitive layer $\mathbf{a^1}$ of dimension S^1x1 will have all zeros expecting for winning neurons. The output of the competitive layer $\mathbf{a^1}$ forms the input to the a linear function in the second layer with number of neurons (S^2) equal to input target class, whose output is $\mathbf{a^2}$. This operation basically assigns the target class to the input vector. For execution of this study, neural network tool box of Matlab (Matlab 6.1 2001) was used.

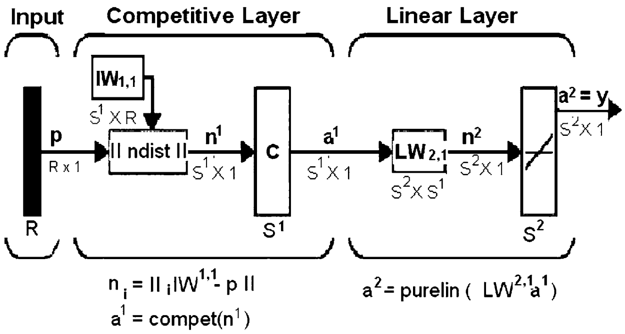

Fig. 3 Architecture of LVQ network

Application of LVQ to echosounder data

The training data comprise of a total of 600 sets of E1 and E2, spread over wide range as seen from the figure. In general at a given site, it is expected to be a narrow and thick cluster, like one at the left top most corner of the figure. But due to rough sea, change in the angle of incidence of acoustic signal results widen the range of E1 and E2 for different type of sediments.

In this study, the network architecture comprises of a one-dimensional grid of 10 neurons in the competitive layer and 4 neurons in the output layer based on a priori knowledge of sediment types ie., target class. Once the network is initialized, the weight vectors are iteratively updated and moved toward the input vectors. The initial weight vectors are initiated with mid values of the range of respective input vectors. The inputs to the LVQ network are range of input vector elements, number of competitive neurons, learning rate and element vector of typical class percentages i.e. the percentage of data of each class with respective to total data under training. Here the learning rate of 0.01 is used.

The efficiency and accuracy of the network also depends on the number of neurons in the competitive layer. The LVQ network used at present requires that the number of neurons to be mentioned in the input before starting the training phase. In fact, the optimal size for such networks mainly depends up on unknown statistical properties of the training set of patterns to be classified, rather than upon the properties of the training set which can be determined in advance such as size and number of input patterns or number of classes into which they must be classified. The performance of the network will be poor, if number of neurons is too low and therefore the network architecture must be reconsidered and new training must be performed. If the number neurons are more i.e., the network is over sized, it will be inefficient in allocation of resources, although possibly accurate, since the processing time required for the network to produce a response is roughly proportional to the number of neurons.

Figure 4 shows that the input vector clusters are represented by different weights (competitive neurons) based on their self similarity. This is done by the first part of the network using competitive layer. This forms the input to the linear layer where the target class (i.e., silty-clay, silty-sand, clayey-silt and sand) is labeled. We noticed that silty-clay and silty-sand show wide range in roughness index and sand shows more variation in the hardness index.

More number of neurons in the competitive layer show slow convergence and require more number of epochs. With 10 number of neurons, the convergence is achieved within 30 epochs. The solid circles indicate the adjusted weight vectors representing each class. In case of more number neurons in the competitive layer, each of the target class will be further represented by sub-clusters or groups by competitive neurons, which will improve the further classification, but time consuming. Since LVQ network requires the number of target classes as input before training, the number of neurons in the competitive layer can be set around that number instead of oversized. In the present study, the network was tried with 5, 10, 15, 20 and 30 neurons in competitive layer and found that the corresponding classification results were 75, 95, 95.2, 95.4 and 95.5% respectively. However the training time increases from one and half times for 15 neurons and more than double time for 30 neurons with respect to ten neurons, without much improving in classification. With five neurons, the results indicate that the number may be insufficient to represent subclasses.

Validation of the network model

Once the network trained with first data set along with target class, the test data is subjected for validation. In

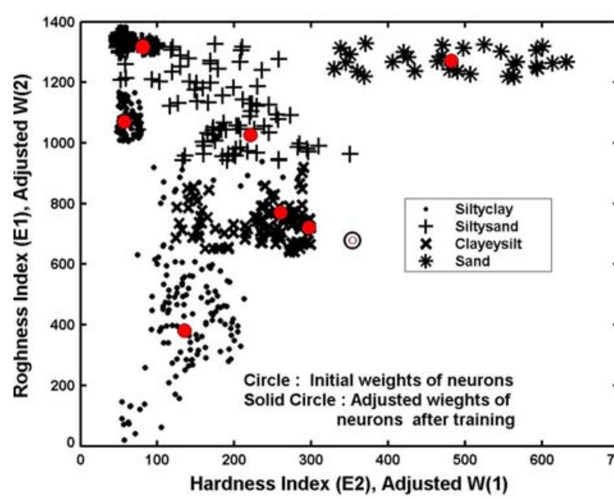

Fig. 4 E1, E2 distribution of the training data showing the adjusted network weight vectors for different sediment types

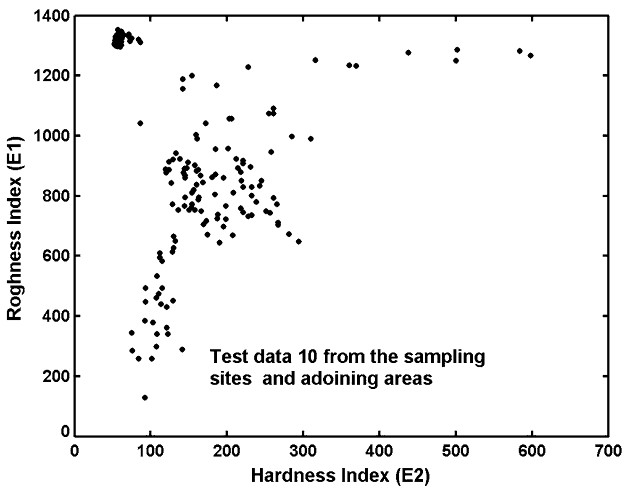

Fig. 5 Test data set (E1, E2) for verification of the network model

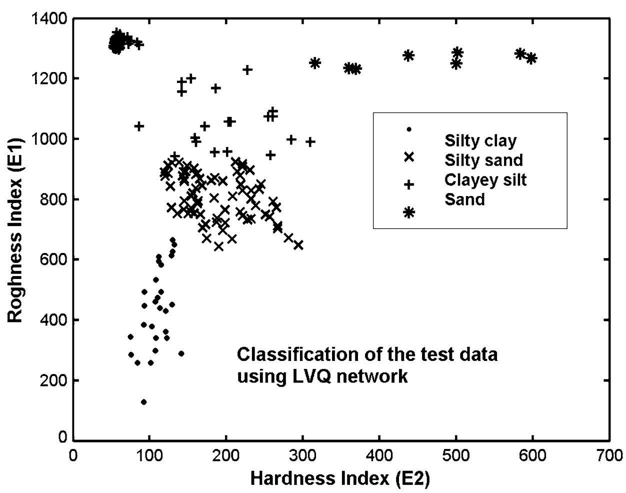

Fig. 6 Sediment classification of the test data from the network

order to verify the model, the untrained test data consist of 200 sets of E1 and E2 (Fig. 5) is subjected to the LVQ network model. The results are promising and 95% of the data were successfully classified (Fig. 6). Only the points, which are overlapping with neighboring class, show deviation and indicate one of the classes. We tried to verify the effect on classification, by interchanging the training data sets and test data sets of E1, E2, and found that the classification was only 72%. This may be due to the training data of 200 sets were insufficient to represent the complete spatial variation of E1 and E2 for each sediment type, unlike in previous case where 600 data sets used as training data. Therefore, the training data distribution must cover and meaningfully represent the each parameter (E1, E2) bounds corresponding to the each class for better classification results, irrespective of data size.

Conclusions

The efficiency of many seafloor classification techniques designed to deal with single-beam echosounder data correspond to normal incidence of the acoustic beam, and this degrades when used with data acquired in rough seas. Such data contain both normal and inclined incidence of acoustic beams due to ship's roll and pitch motion. LVQ algorithm, a supervised learning approach of ANN is found to be quite robust and an effective tool to deal with such data. The results show 95% of data were classified successfully. The performance and efficiency depends on selection of size of neurons in competitive layer, which correspond to the number of sub-classes expected. Performance depends on the selection of training data set, which should represent the region of each of the sediment type, rather than size of the training data set.

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