

Fine scale analyses of a coralline bank mapped using multi-beam backscatter data

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Abstract—In this work, we have developed a classification technique to characterize the seafloor of the Gaveshani (coralline) bank area using multi-beam backscatter data. Soft-computational techniques like the artificial neural networks (ANNs) based unsupervised self-organizing maps (SOM) architecture is used to determine the existence of six classes. Thereafter, 55 segments were identified for data segmentation, employing six profiles selected from the backscatter maps, using the fuzzy c-means (FCM) algorithms. The gridded map of the segmented seafloor backscatter data was overlaid on the co-registered backscatter map to understand the distribution of the overlying sediment material on the bank.

Keywords—seafloor; coralline bank; backscatter; ANN; SOM; FCM.

I. INTRODUCTION

Multibeam echo-sounding systems (MBES) allow synchronized acquisition of high-resolution seafloor backscatter and bathymetric data [1], [2]. The processed bathymetry [3] and backscatter data [4] can help detect large-scale as well as fine-scale seafloor roughness. As most the seafloor models require stationary input data, preprocessing of bathymetric and backscatter data is essential before initiating modeling. Soft-computing techniques can be used as an alternative for dimensional reduction applications, representing input vectors to a specific output [5]. Soft-computing techniques including artificial neural networks (ANNs) offer solutions for computationally intricate tasks. The ANN-based self-organizing map (SOM) architecture can exercise unsupervised competitive learning on an unknown data set (input) onto coarser clusters, i.e., primary classifications. For real time survey applications, the SOM can be utilized to formulate a decision regarding the number of data class. The recently developed technique utilizing ANN and SOM, is now being applied to Gaveshani bank [6]. The bank is located approximately 100 km from the Karnataka coast, off Malpe (Fig. 1). The bank is about 1500 m wide and located at a depth of 38 m. It has a pinnacle, the tip of which is at a depth of 32 m [7]. The seafloor surrounding the bank appears to be flat with a low gradient and apparently the main topographic feature of the bank is the abruptly rising periphery. The sediments composition of the seafloor around the bank are silty sand, predominantly carbonate, consisting of foraminifera shells, mollusks fragments and corals. In this paper the bank and the contiguous area around were subjected to the newly developed seafloor classification technique to understand the distribution of the overlying sediment material.

II. MATERIALS

The bathymetry and backscatter data for the present study was acquired using the Simrad Kongsberg EM1002 MBES operating at 95 kHz. A total of 1200 data points of the processed MBES backscatter data were used from 6 selected profiles. The water depth of the survey area varies from 80 m around the bank, to 40 m on the top of it. The extent of the study area that comprises of the coralling bank and contiguous area is nearly 3.5 km². The calibrated backscatter map presented in the figure shows variation in backscatter on the top of the bank, and the entire map consists of 28800 pixels. The bathymetry data was processed using Neptune software incorporating corrections for propagation, refraction errors and tide. The backscatter data was processed using

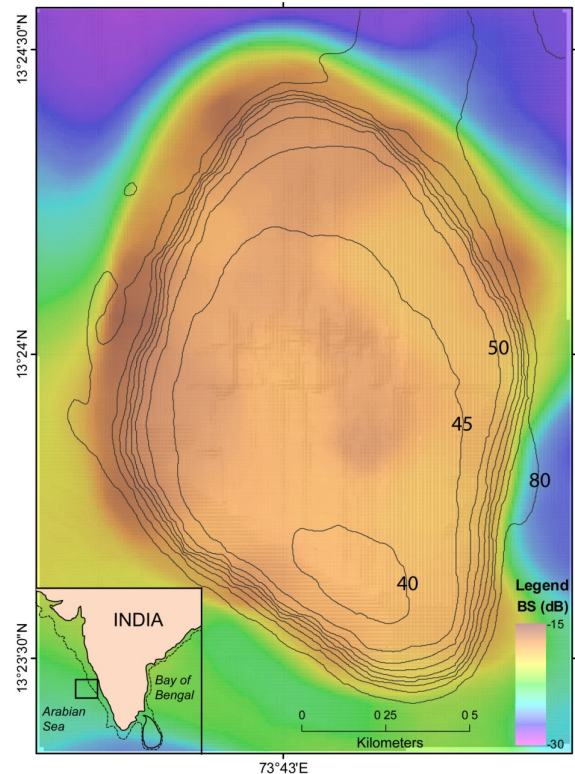


Fig. 1. Backscatter map of the study area showing 40-80 m isobaths with an interval of 5 m depth. Inset shows outline of the coast and continental margins of India.

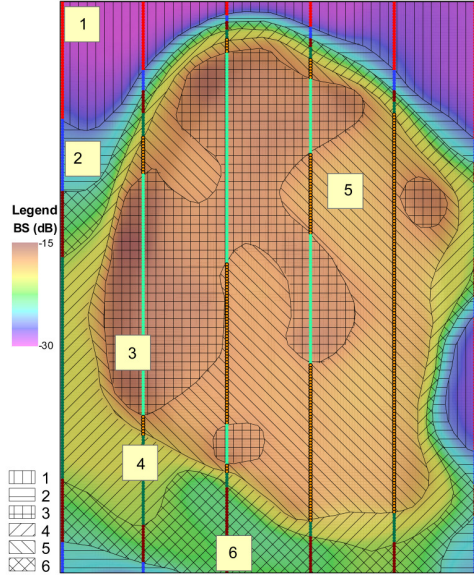


Fig. 2. Six backscatter profiles classified into six different classes overlaid on rasterized backscatter that is also being estimated using the segmented profiles of the five classes.

PROBASI II [8] for data normalization, and subsequently imported to CFLOOR (Cfloor AS) software for gridding (resolution: 10 x 10 m) and improved visualization.

The backscattering strength of the area ranged from -29 to -15 dB. Generally, angular backscatter data strength exhibit higher values at normal incidence compared to the outer-beam angles particularly in the case of smooth seafloor. Such backscatter data exhibit artifacts at the time of data acquisition. After carrying out sonar related preprocessing of the backscatter data, the artifacts along the centre beam path were removed by using MATLAB based median filter [9]. As a result, off-line corrections are occasionally made use of, to compensate for the outer-beams backscatter strength data in such a way that the effect of angular backscatter strength is removed. Improvement in the image data quality was seen after utilizing the four stage image processing technique. The work developed here demonstrate that the employed data processing technique can efficiently classify the survey area using linear data traces (backscatter / bathymetric) varying along the geographical south to the north (Fig. 2). These traces are referred as a “profiles”. Six such profiles were used in the present work. Each profile extracted from the backscatter map of the study area holds 200 data points each, and the distance between two consecutive data points (along the profile) is nearly 10 m. The uniform separation between the six parallel profiles is ~ 300 m.

III. METHODS

The soft computing technique making use of SOM and Fuzzy C-means (FCM), have been applied to the data acquired around the Gaveshani Bank [6]. Six backscatter profiles from the backscatter data were subjected to preprocessing as

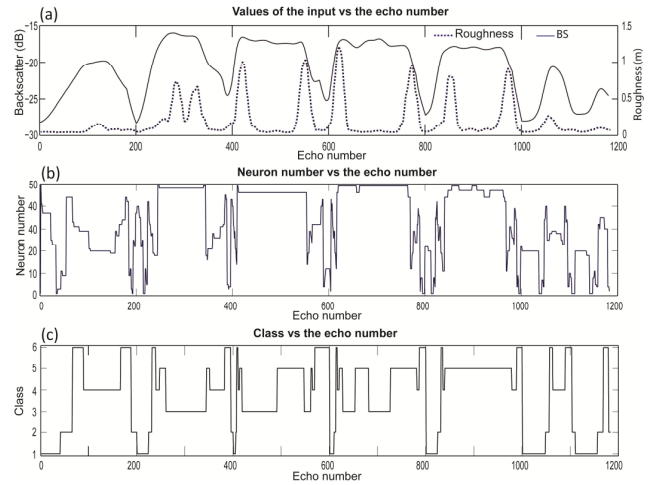


Fig. 3. (a) Representative plot of the input values (backscatter and roughness) from the six backscatter data profiles, (b) Firing neurons correspond to the SOM output of the two input feature vectors for above data, (c) Classification of the data points using FCM.

described in [4]. A moving average type of filter is applied to smooth out short-term fluctuations. The corresponding depth values associated with backscatter data were used to obtain the local seafloor roughness. The “roughness” parameter can be considered as the deviation of the depth value about the local linear trend of the data. Large deviations with respect to the local linear trends are indicative of rough seafloor surface, other wise the surface can be considered smooth. Large scale roughness parameter was estimated for every nine data points (~ 90 m) from the depth data profiles (Fig. 3a). As regards the profile segmentation application carried out here, the backscatter and depth data respectively represent the fine and large scale roughness aspects of the seafloor, and these two characteristics are then used as input feature vectors for the SOM network.

The SOM network consisting of 50 output neurons grid, accepts the feature vectors representing the backscatter and roughness parameters as input, to estimate the number of classes in the data. The neurons in the grid compete among themselves to get activated on presenting the input data to SOM. In order to determine the number of classes using SOM architecture, input feature vectors of each data point are presented, and the closest neurons were selected to be the firing neurons for the input data. Initially, two input feature vectors are presented as a training sample. Once the training is completed, the excited neurons during the testing processes are plotted (Fig. 3b). If the testing results throw up the winning neuron within a group of trained neuron, it is assumed that it belongs to the same class as the data where it was trained else the training/testing process is reinitiated. The representative percentages of the number of times the neurons have been fired for the entire data set are plotted as bar diagram with respect to the number of neurons. The maximum numbers of classes that exist are equal or above the number of occurrences i.e., 20% of the highest neuron firing (Fig. 4a). The testing and training process for the entire data set is repeated ~ 100 times. The neuron numbers produced during

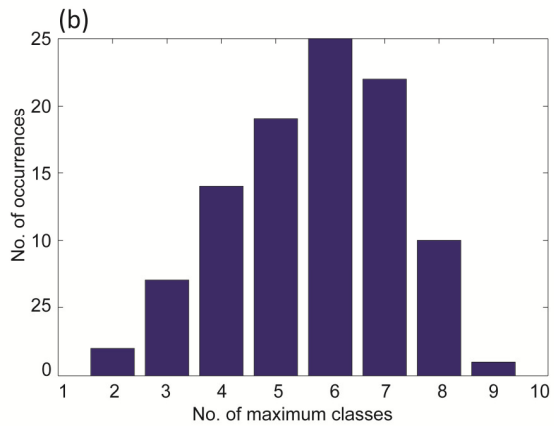
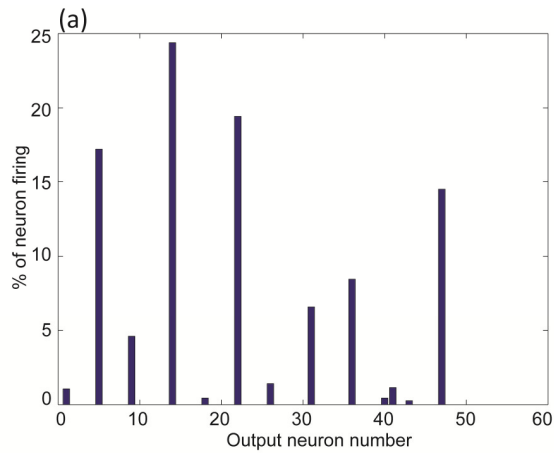


Fig.4. (a) The six bars above the 20% of the number of neuron firings depict the six classes obtained from one training-testing processing, (b) histograms of the number of occurrences of maximum number of classes obtained from the ~ 100 training-testing process employing SOM analysis, indicating the no. of classes available in the datasets.

the multiple training-testing processes using the SOM are plotted in a histogram indicating the six major classes (Fig. 4b). Thereafter, fuzzy C-means (FCM) method [9] is employed utilizing the estimated number of data classes, for segmentation of the backscatter data of the profiles. The six classes generated from the training and testing of the firing neurons correspond to the six segmented sets of the backscatter data from the profiles. The FCM generated segmented profiles (color coded) overlaid on the backscatter map are presented (Fig. 2).

The output of the soft computational technique (SOM and FCM) could be validated employing different techniques. The histogram of backscatter data from the six profiles were fitted using multi-modal curves considering each curve as Gaussian distribution. The mixtures of the normal distribution of the six components are presented (Fig. 5). The distribution supports the fact that the backscatter data exhibits the corresponding number of available classes in the dataset as a means to validate the SOM based study.

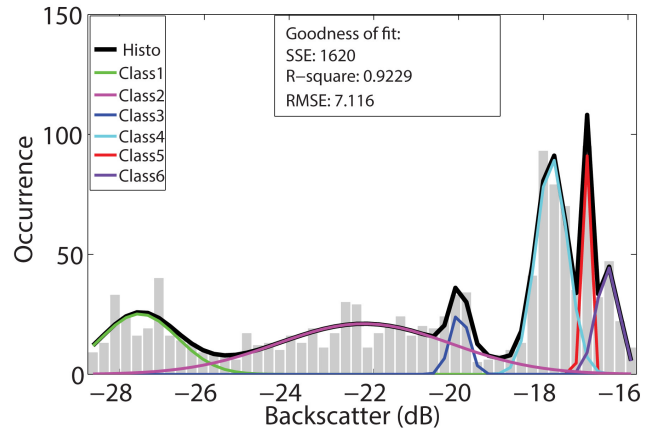


Fig.5. Occurrences of backscatter strength (dB) with respect to the rasterized backscatter pixels (dB) of the study area and the fitted multi-modal curves of the total and the six PDF components.

IV. RESULTS

SOM helps to ascertain the number of classes by counting the occurrences of number of prominent neurons (Fig. 4a). At the onetime training-testing process of the profile data, the highest neuron firings occurred at the neuron position 14, and the rest were observed at 5, 22, 31, 35 and 47 as shown in (Fig. 4a). The training-testing process is repeated for a number of times (~ 100) for the entire datasets of the six profiles. For each training-testing process, the numbers of classes are determined from the histogram plot of numbers of occurrences versus the number of classes (Fig. 4b). The number of classes occurring maximum number of times (at the end of repeated cycle for entire data) is considered as the total number of classes existing in the data. This process provides the number of classes available in a given dataset without any prior information.

V. CONCLUSION

The acoustic backscatter strength of the Gaveshani coralline bank ranges from -30 to -15 dB. The high backscatter (> -20 dB) can be attributed to the coral growth, sediment type and the relief. Generally the coarse grained sediment along with abundant shell material reveal high backscatter strength. Towards the higher depth (> 80 m) where the seafloor gradient is gentle, the backscatter strengths are generally low (< -22 dB).

In the present study the seafloor classification technique developed for backscatter and bathymetry data acquired with MBES system has been successfully applied to the Gaveshani Bank, off the coast of Karnataka. The technique is capable of providing real-time seafloor roughness information using limited sampling data. The application of the soft-computational method could be employed to determine the presence of six classes from the six backscatter and bathymetric profile data of the coralline bank. The presence of six classes has been further validated employing a multimodal curve fitting to the histograms generated using the backscatter data profiles. This obliquely suggests a coherent rationale for the utilization of just two features for the seafloor

classification, such as backscatter 'pixel' as well as 'roughness' parameter of the depth data. The data-driven approach for segmentation of backscatter map based on the SOM and FCM could be used to analyze the fine-scale roughness parameters. The successful outcome of this technique indicates potential for its exploitation to calibrated sonar image profiles for real-time classification and characterization, which can considerably reduce the data acquisition time. The technique would also be useful for geological applications with sparse survey data.

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