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Segmentation and classification of shallow subbottom acoustic images using image processing and neural networks

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Summary

Subbottom acoustic profiler provides acoustic imaging of the subbottom structure of the upper sediment layers of the seabed and it is commonly used in geological and offshore geo-engineering applications. Delineation of the subbottom structure from a noisy acoustic data and classification of the sediment strata is challenging with the conventional signal processing techniques. Image processing techniques utilise the spatial variability of the image characteristics, known for their potential in medical imaging and pattern recognition applications. In the present study, they is found to be good in demarcating the boundaries of the sediment layers associated with weak acoustic reflectivity, hidden in the noisy background. The study deals with application of image processing techniques, like segmentation in identification of subbottom features, extraction of textural feature vectors using grey level co-occurrence matrix statistics for different sediment strata inferred. Utilising the feature vectors, an SOM unsupervised neural network model was used in classification of the sediment type of different strata of a four layered structure inferred from an image. The model was also tested for its consistency, with repeated runs with different configuration. Successful classification of a few untrained test images representing similar environment using the network model as expected.

Keywords: *Subbottom profiler, Image processing, segmentation, textural analysis, SOM, neural networks, classification*

Introduction

Hull-mounted or towed subbottom profilers usually operated relatively at a very high frequency compared to low frequency sources used in seismic exploration, provide high resolution shallow subbottom acoustic image data pertains to normal incidence of acoustic signals. Due to increase in attenuation of acoustic energy at high frequencies, the depth of penetration into the bottom ranges from a few tens of meters to a few hundred meters depending on the type of sediments. The data are very use full in offshore geotechnical, geo-engineering and geological applications, in resolving the upper layers sediment structures, studies on dynamics of sedimentation, compaction, and qualitative information on physical/acoustic properties of sediments, neotectonic activity, and shallow basement configuration. Despite, enough care taken by different operational settings of the equipment during data acquisition at sea, quite often, the images are noisy, due to sea state and oceanographic acoustic propagation conditions, including ambient noise. This results masking of the subbottom structures/features associated with a weak reflecting interfaces, which has significant role in the above mentioned applications. The commercially available software supplied along with the equipment have limited capability in addressing such issues. Therefore, there is a need of better processing techniques to delineate such features.

In the present studies, we have considered a sample image data containing the subbottom features masked by a strong noisy background (Fig.1). Our objective was to process the data with appropriate image processing techniques to identify the clear demarcation of the subbottom sediment layering configuration, extraction of feature vectors associated with the different sediment layers inferred and build a neural network model in classification of these layers based on their feature vectors. Further the network model is to be tested for its validation with new images (not used in network training) representing similar environment.

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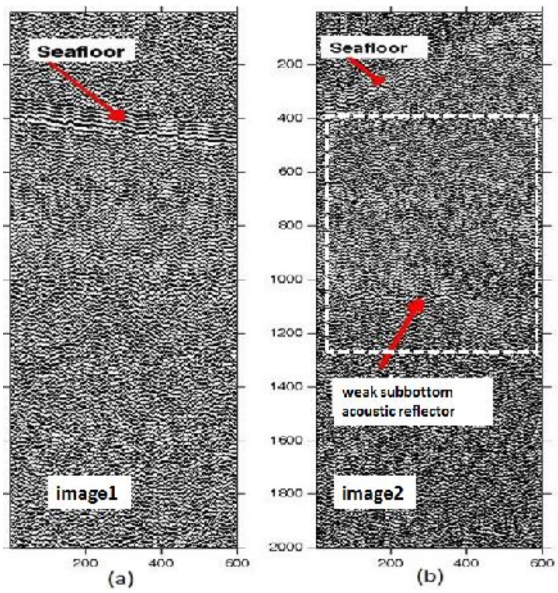

Figure 1. Subbottom profiler images at two offshore sites

A good number of techniques employed in image processing, exploiting the spatial variability of signal intensities (represented in terms pixel values in the image) are known for detection of anomalous features with high precision, associated with a very weak signals, particularly in biomedical, remote sensing applications and other high precision imaging areas. Different segmentation techniques commonly used in pattern recognition has a potential application in the present study in demarcation of the boundaries of the sediment layers. A neighbourhood based technique adopted in the study was found to be reasonably good for this purpose. The textural properties of the sub-images representing the inferred sediment layers were studied using Grey Level co occurrence Matrix (GLCM) and derived the image properties, like, correlation, homogeneity, contrast and energy. GLCM provides the information on spatial distribution of the image intensities and their relation across the image, different for different textures of the image. Further the GLCM properties obtained were used as textural feature vectors in classification. In the absence of ground truth on the type sediment varying with vertical depth, attempt was made to classify the vertical section of the bottom acoustically. Therefore, a Self Organisation Map (SOM), an unsupervised learning neural network model was used in classification of different layers inferred from image2 (Fig1b). The validation results with untrained test image data sets acquired from the same sediment layer zones indicate the successful classification of subbottom images. The analysis was carried out using the image processing and neural network toolbox of MATLAB (2009). The details are discussed below.

Subbottom Image data

In the present study, subbottom acoustic image data used were acquired at an offshore location at the depth range of 60m-65m on the continental shelf, using an hull-mounted subbottom profiler of Innomar GbH, with an operational parametric frequencies ranging from 6kHz to 12kHz. With the pinging rate of 2 to 3 per second, provides 1 to 2m station interval along the track at 8 knots of ship speed. Two subbottom images viz., image1 (Fig1.a) and image2 (Fig.1b), acquired at two locations of different environment. The size of the images are 2000x600 pixels each. The reflection data in terms of two way travel time and amplitudes provides information on vertical section of layered subsurface structure. Within the homogeneous sediment layer, the response is uniform and at the boundary, the intensity of reflections are attributed to acoustic impedance contrast and reflectivity. Both the images show a very a strong reflector associated with the water-bottom interface due to strong acoustic impedance contrast. The first image (Fig.1a) is relatively clearer indicating the absence of any subsurface layer. However the image at second location (Fig.1b) indicates clear water-bottom interface to some extent, but the subbottom layers are masked noise, without any distinct demarcation of their interfaces, may be due to local sediment depositional environment and background noise.

Image Processing

Image processing techniques utilise the spatial variability of the image characteristics, have ability to resolve spatial resolution and extraction of features used in qualitative and quantitative analysis. In the present study, it is found to be good in demarcating the boundaries of the sediment layers associated with weak acoustic reflectivity, hidden in the noisy background. Image processing techniques, like segmentation and GLCM are found to be very useful in identification of subbottom structure and extraction of textural features.

Image segmentation

Image segmentation is the process used in identification of the boundaries of different sediment strata /structure and isolation of an image corresponding to structural feature. A number of segmentation techniques (Pham Dzung et al, 2000; Hossein Mobahi et al, 2011) are being used in image processing to both qualitative and quantitative analysis. They exploit the statistical measures and are efficient in extraction of features in spite of minute changes, as they utilise spatial variations. The selection of a particular approach depends on the nature of problem. General approaches to segmentation can be categorised into three classes : pixel based methods, continuity methods and edge based methods. Pixel based methods operate on one element at time, are less powerful and susceptible to noise. Continuity based and edge based approaches search for similarities and differences respectively, have an edge over the first approach.

Continuity based method utilises threshold level adjustment (Batenburg and Sibers, 2009) and Gaussian low pass filtering to get a clear separation of segments. Thresholding, in which, all the pixels having same intensity values, above or below some levels are classified as part of segmentation. Intensity histogram is a prime importance in problems of segmentation and different strategies in thresholding (Sonka et al 1993). Continuity approach looks for similarities or consistency. Though they are effective in segmentation, they lack in edge detection, result in blur at the edge regions merging with structure as they use neighbourhood operations. Though the selection of increase in neighbourhood size improves the power of the method, it is a compromise between identification ability and edge definition.

A Gaussian low pass filter used in continuity method is a sliding neighbourhood operation that takes a weighted average over a region, helps in enhancement of consistent characteristics. Applying a thresholding based on the filtered image histogram, isolated segments can be obtained. Here the ‘range operator’ (the difference between maximum and minimum pixel values in the neighbourhood) was used to distinguish the texture feature.

Texture Analysis

Texture analysis has been extensively used to classify remotely sensed images. Land use classification where homogeneous regions with different types of terrains need to be identified is an important application. Texture classification is an image processing technique by which different regions of an image are identified based on texture properties. This process plays an important role in many industrial, biomedical and remote sensing applications. Different textural feature extraction methods based on statistical and structural methods (Conners, 1980, Weszka, et al., 1976, Haralick et al.,1973 and Caelli, 1988), Gaussian Markov random field (GMRF) and Gibbs distribution texture models (Speis and Healey, 1996, Krishnamachari and Chellappa, 1997) and power spectral methods (Conners, 1980) are in use. Julesz (1975) has investigated that the human texture discrimination in terms of texture statistical properties and observed that the textures in grey-level images are discriminated spontaneously only if they differ in second order moments. Different third-order moments require deliberate cognitive effort, which suggests the importance of. statistics up to the second order (Niemann 1981) in automatic processing.

The most popular second-order statistical features for texture analysis are derived from the so-called co-occurrence matrix (Haralick 1979). Lerski (1993) had demonstrated their potential for effective texture discrimination in biomedical-images.

Haralick et al. (1973) used GCLM features to analyse remotely sensed images in estimation of distance of each individual pixel with reference to other spatially separated along four directions, namely Horizontal (H), Vertical(V), Diagonal1(D1) and Diagnol2 (D2) across the image. Using the statistical properties of GLCM as texture features, they have reported approximately 80% accuracy in classification for a seven-class classification problem.

Co-occurrence matrix will help to provide valuable information about the relative position of the neighbouring pixels in an image. Given an image *I*, of size $N \times N$, the co-occurrence, matrix P can be defined as

$$P(i,j)=\sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1, & \text{if } I(x,y)=i \text{ and } I(x\cdot \\ 0, & \text{otherwise.}\end{cases}$$

Here, the offset (Δx, Δy), is specifying the distance between the pixel-of-interest and its neighbour. The offset (Δx, Δy) parameterization makes the co-occurrence matrix sensitive to rotation.

In the present paper we have used four statistical estimates from each GLCM obtained along four directions across the image, ie., 0^0, 45^0, 90^0 and 135^0 angles. The estimates include correlation, energy, contrast and homogeneity as mentioned below. They are found to be more or less characteristic of the images and used as feature vectors in further classification.

'Contrast' is a measure of intensity contrast between a pixel and its neighbour over the whole image and the contrast is 0 for a constant image.

Contrast= $\sum_{i,j}|\ i-\ j\ |^2 p(i,j)$

'Correlation' is a measure of how correlated a pixel is to its neighbour over the whole image, varies between -1 to 1. Negative sign indicates the negatively correlated .

Correlation = $\sum_{i,j}\frac{(i-i\mu_i)(j-j\mu_j)p(i,j)}{\sigma_i\sigma_j}$

'Energy' is the sum of squared elements in the GLCM, varies from 0 to 1. Energy is one for a constant image.
Energy = $\sum_{i,j} p(i,j)^2$

'Homogeneity' indicates the closeness of the distribution of elements in the GLCM to the GLCM diagonal and value lies between 0 and 1. The value 1 indicates for a diagonal GLCM

Homogeneity = $_{i,j}\frac{p(i,j)}{1+|i-j|}$

SOM neural network

Self Organizing Maps (SOM) are a particular kind of unsupervised artificial neural network also known as Kohonen Network (1990,2001), which means that no human intervention needed during learning and little needs to be known about the characteristics of input data. SOM is a clustering technique that enforces neighbourhood relationship on the resulting cluster centroids. The distinguishing feature of the SOM is that it imposes a topographic (spatial) organisation of centroids (neurons). The neurons in the layer of an SOFM can be arranged in physical positions to a grid, hexagonal or random topology and the link or Euclidean distances between neurons are calculated from their positions with an appropriate distance function.

The SOM is able to detect the inherent features of the problem, also known as Self-organizing feature maps (SOFM), learn to classify input vectors according to how they are grouped in the input space. They differ from competitive layers in that neighbouring neurons in the self-organizing map learn to recognize neighbouring sections of the input space. Thus, self-organizing maps learn both the distribution (as do competitive layers) and topology of the input vectors they are trained on.

Here a self-organizing feature map network identifies a winning neuron *i** using the same procedure as employed by a competitive layer. If the input is very close to weights of a neuron, that will an output 1, signifying it is the winner to represent current input feature vector. The remaining losing neurons will have their output remain at zero. However, instead of updating only the winning neuron, all neurons within a certain neighbourhood $N_{i*}(d)$ of the winning neuron are updated, using the Kohonen rule. $N_{i*}(d)$ are updated weights to all nodes within a topological distances using following update rule

$$w\ q\ =\ 1-\alpha\ w\ q-1\ +\alpha p(q)$$

where α is learning rate, w(q) weights

And the neighbourhood $N_{i*}(d)$ contains the indices for all of the neurons that lie within a radius d of the winning neuron *i**,

$$N_{i*}\ d\ =\{d_{i,j}\le d\}$$

when a input data (**p**), the weights of the winning neuron and its close neighbours move toward **p.** The weights are being updated through learning iteratively and all the input vector data will be assigned to a particular neuron/s representing different class or clusters.

Results and Discussion

(i) Segmentation

The acoustic image shown in Fig. 1a with 2000x600 pixels associated with clear reflector corresponds to the seafloor, indicates absence of any subsurface layer. The image was resized to 600x600 pixels for image segmentation (Fig.2a) and corresponding histogram shown in Fig.2b. The histogram shows more or less Gaussian distribution with maximum intensity levels at 0.5. The image was subjected to low pass Gaussian with range operator as neighbourhood function. Fig.2c and Fig.2d represent the processed image and histogram after filtering. The image indicates the presence of a thin sedimentary layer associated with a weak and blurred acoustic reflector and the corresponding histogram also indicates the skewing of pixels intensity, which can be used for thresholding in isolation the layers. It is found that the inferred upper layer has thickness of about 2.5m with clear bottom interface from image segmentation.

Similar process was applied to the second image (Fig.1b). Figures 3a and 3b show the resized image and its histogram used in segmentation. The processed image shows a strong reflector associated with seafloor (Fig.3c). However, the original image (Fig 1b) or resize image (Fig.3a), masked with strong noisy background, hardly provide any indication on the presence of subsurface reflectors, excepting a strong reflector representing a two sediment layer structure in the beginning, as seen in left side section of the images, and distorted further. The processed image (Fig.3c) clearly shows that the presence of second layer in the side, further splits into three thin sediment layers associated with acoustically weak reflectors. The weak reflectors suggest that low acoustic impedance contrast across the interfaces and also indicates a different depositional environment and compactness. Thus, the segmentation reveals a four layered structure in the right side section the image. Textural analysis was carried, considering the sub images from the different layers to differentiate among them while classification.

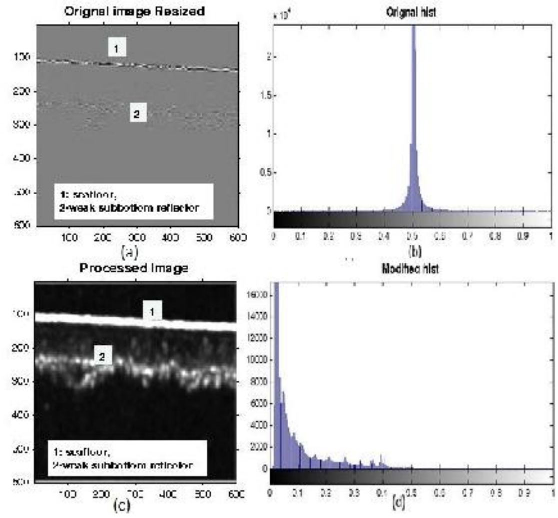

Figure 2. Image1 and its intensity histogram (a,b) : before, (c,d): after, segmentation process.

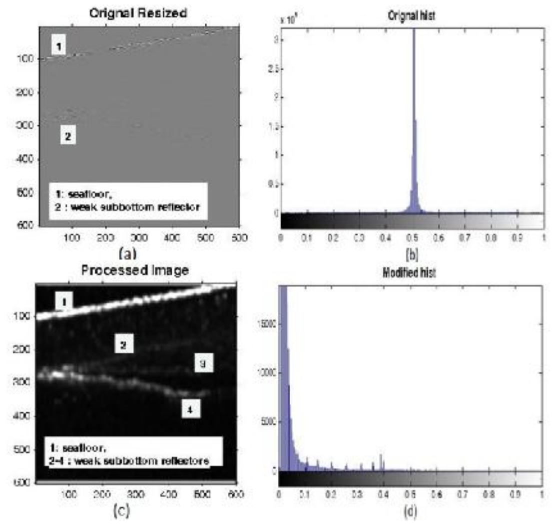

Figure 3. Image2 and its intensity histogram, (a,b): before, (c,d) : after, segmentation process.

(ii) Extraction of textural features

The segmentation process show very clear demarcation of the sediment layer boundaries. The next task is to find out the textural features of the each sediment layer which can be used in classification. For this study, image2 (Fig1b) was considered, which show a four layer structure after the segmentation process. A total of subimages, 64x64 pixel size (Fig. 4) were considered, ie., two samples from each of the four layers for textural analysis and further used in training the network for classification. Grey level co-occurrence matrix of the subimages and their statistical features like contrast, correlation, energy and homogeneity were estimated along horizontal, vertical and right diagonal and left diagonal directions. Thus, a total of 32 (8x4) features from the eight sub-images, form the feature vectors were used in classification**.** Fig.5a shows the sample images from each layer and the corresponding statistical estimates for different angle offsets of GLCM (Fig.5b) obtained are shown**.**

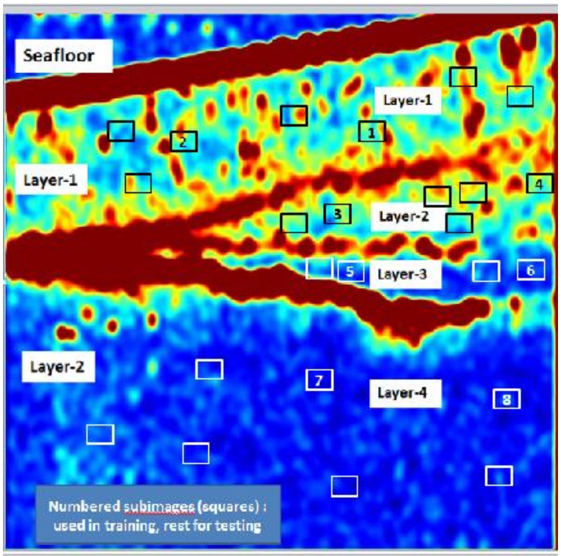

Figure 4. Selection and location of subimages to study textural features, used in training and testing of SOM classification.

(iii) Classification

It is difficult to classify the data from the feature vectors directly, which require an appropriate classification approach. Also the feature vectors of the sub-images representing different layers need to be verified that whether they represent same type of sediment or different from classification. In the absence of any ground truth on sediment type comprising these layers, it was a mere classification based on acoustics. As discussed earlier, Self Organising Map (SOM), an unsupervised neural network approach has ability to classify such data. The feature vectors obtained from GLCM forms the input for SOM.

Though, eight sample images are taken from four different layers, it is expected a maximum of four sediment types, irrespective of the number of neurons selected in the network topology.

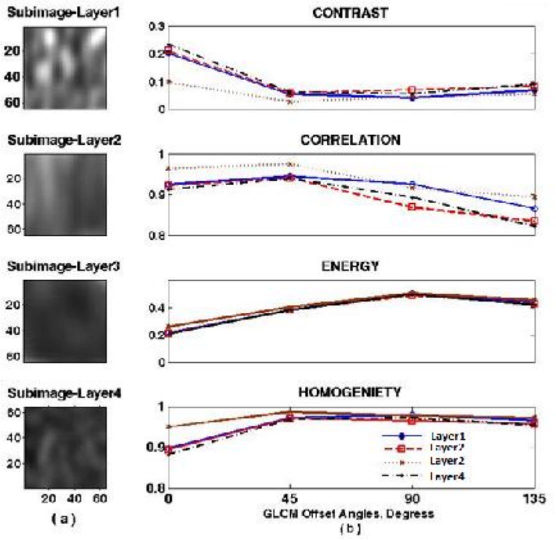

Figure 5. (a) One sample subimage from each of four layers inferred and (b) their textural features

The feature vectors are trained with a one dimensional grid topology consisting of 1x 8 neurons and, Euclidean distance as distance function. The classification results were tested with repeated trials, with different layer dimensions, like 8x1, 16x1. The network classification suggests that the sample images numbered (1,2), (4), (5,6) and (3,7,8) represent four types of sediments corresponding to four different layers. The sample 3 was expected to be in class two, but due to the corresponding subimage overlaps with the interface while sampling, resulted it under class 4. Repeated trials show same grouping irrespective of the neuron layer dimension size indicates the consistency in classification. Further, the SOM network was tested with a few sets of untrained new sample images as shown in Fig.4 (un-numbered squares) representing the four layers show the expected classification. If ground truth is available, LVQ network, is an extension of SOM in supervised learning, the results can be directly represent the actual sediment classification (Satyanarayana et al, 2007).

Conclusion

The image processing utilises the spatial variability of intensity of the images, has capability to deal with noisy acoustic image data, in identifying the boundaries of different substrata and their structure through its segmentation approach. Textural features of the images using grey level co-occurrence matrix and their statistical estimates are characteristic features of the images to differentiate among them, if any spatial changes occur. Unsupervised neural network, such as Self Organised Map (SOM) has capability in classification of the data into different clusters, is a good choice in the absence of ground truth. The present study demonstrates the advantages of the methodology adopted in extraction of the subbottom structure and its classification successfully from a noise subbottom images data.

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