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Application of neuro-fuzzy network in marine sediment classification from side scan sonar data

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Summary

Remote seabed classification approaches used with the acoustic backscatter measurements offer continuous and rapid coverage of wide area. The backscatter information obtained through side scan sonar survey can be effectively utilized to classify the underlying seafloor sediments in addition to mapping of seafloor features and underwater objects.
The present study deals with exploitation of backscatter data obtained from a side scan sonar for marine sediment classification using artificial neuro-fuzzy information (ANFIS) technique. The variation in backscatter strength as a function of range/grazing angle for different seabed sediments forms the key input to simulate the ANFIS model. The results indicate successful classification with 90 percent of test data, which are not used in training the model.

Introduction

Side Scan Sonar (SSS) is an effective tool in mapping the seafloor topographic features and underwater objects. Any change in topography or geology reflects as variation in tonal intensity of the SSS image. The tonal variation in the image represent level of backscattering strength (BS) which is function of many factors like seabed sediment physical properties, variations in topography and the operational conditions. The contrast in tonal changes corresponding to the lithological variations may not be much appreciated when the transition from one type of sediment to the other is smooth spatially and vice versa. In such cases, it is rather difficult at times to distinguish the changes in the sediment type.

The conventional approaches like clustering techniques and other statistical methods have limitations when use with large amount of data for classification. Soft computing methods such as genetic algorithms, artificial neural networks and fuzzy logic have an edge over the conventional while dealing with non-linear complex data in classification. Artificial intelligence techniques based on soft computing include fuzzy and neural networks, have been highly exploited for solving variety of complex problems in various fields, where the physics involved is not fully known. Recently, a good number of works based on soft computing were reported in hydrocarbon exploration, seismic data processing, subsurface modeling and geophysical well-logging (Nikravesh, 2004; Nikravesh and Aminzadeh, 2001; Van Der Ban, 2000; Banchs and Michelena, 2002; Poulton et al., 1992).

In the present study an attempt is made to exploit the backscatter information for seabed sediment classification using combined approach of artificial neural networks and fuzzy logic, without going much into the theoretical aspects and the scattering process involved. The combined approach is capable of dealing with multidimensional parameters in classification (Satyanarayana and Udaybhaskar, 2009). In the present study, the input information required for training and learning the network is derived from the image data (Satyanarayana and Murty, 1999). The network model found to be very effective and yield reasonably good results in sediment classification.

Side scan sonar data

Here, we have used backscatter data obtained from side scan sonar Model 560 and Model 272TD of EdgeTech make. The data were acquired at operated frequency of 100 kHz in an area where seafloor sediment characteristics known from the sediment samples. The sonar image data (Figure 1) were selected from nine different sediment sample locations, representing mainly 4 types of sediments, namely, sand, silty sand, sandy silt and clayey silt. The detail of the image size and sediment information at the stations are given in Table1.

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Data set	Image size (pixels)	Bottom - type	Composition of the sediment		
			sand (%)	silt (%)	Clay (%)
P10	99x512	Sand	79	18	03
P11	99x512	Silty sand	60	29	11
P18	99x512	Silty sand	60	33	07
P19	99x512	Sand	87	12	01
P24	99x512	Sand	85	08	07
P37	99x512	Sandy silt	25	61	14
P55	99x512	Clayey silt	01	65	34
P64	99x512	Sand	90	09	01
P67	99x512	Sand	97	03	00

Table-1. Image samples and the corresponding seabottom type

The sonar images represent backscatter strength variations along a swath range of 200m on the starboard side. As the images at different locations amounts to large data size, it is required to compress the data representing the image meaningfully for further analysis to use in modeling.

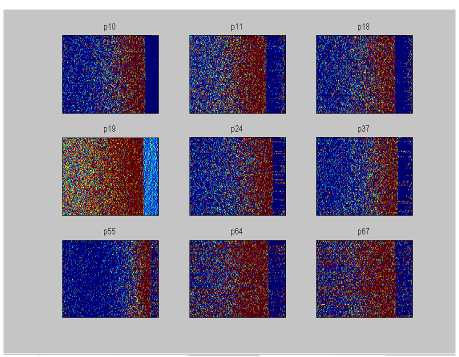

Figure 1 SSS images (starboard side) over different bottom types.

The details of the sediment type at these locations are given Table-I, Each image is represented by 99 scans (pings) and each scan contains 512 pixels for a swath of 200m (Table-I). The pixel values ranges from zero to 255 (grey scale). Since the BS variation along any single scan is more oscillatory and more noisy, we have considered an average of 20 successive scans represented by a single curve corresponding to the particular section of the image. Thus we have over a 180 averaged data sets from the 9 images acquired across four type of sediments. Figure 2 represents the BS variation curves with range. It may observed that the intensity of the BS intensity drastically fall, even close to zero at a very short ranges over the silty sand and clayey-silt bottom compared to sandy bottom. However, for some sediment samples of sand and silt, the BS curves are overlapping each other and show hardly any significant discrepancy and difficult to judge the type of sediment from these curves. It is observed that the pixel histograms indicate mainly two types of distributions namely, Rayliegh type associated with sandy bottom and Poisson type associated with silty sand and clayey silt. Such results are also reported by Chakraborty et al, (2001) from multibeam echosounder data analysis whose operating frequency is relatively low.

The gradient of BS curves corresponding to the different sediments are acoustic representation of their physical characteristics. The percentage of individual constituents of the sediment like sand, silt and clay may slightly influence the gradient of the BS curve. However, sandy bottom can be clearly distinguished from the rest of the sediments by relatively less loss in BS intensity with range. Therefore the significant changes in BS intensity values at short ranges are more representative of their causative sources, ie. at lower grazing angles. Hence it is worth to consider the data at lower grazing angles for characterization or classification studies. We have considered the averaged BS intensity values at four ranges below the half swath coverage ie, 100m out of 200m range and one at 150m range. Representing in terms of range instead grazing angles is more meaningful and avoids the complication of estimation of the same, since side scan sonar data utilized was acquired over a flat seabed, with the towed sensor height kept constant from the bottom.

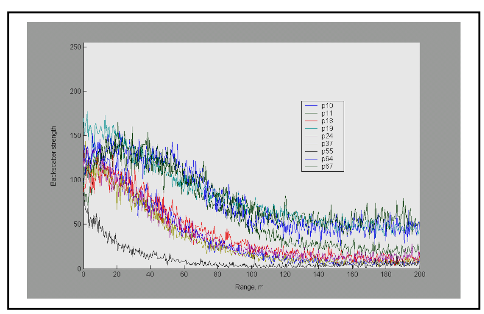

Figure 2. Mean BS variation with range for different images.

Adaptive Nureo- Fuzzy inference system

In the present study an attempt is made to exploit the advantages of Adaptive Neuro-Fuzzy Inference Systems (ANFIS), an approach that combines the rule based fuzzy inference system and artificial neural networks for classification.

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang (1993), is a universal approximator and, as such, is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang et al., 1997). Neuro-fuzzy systems (Jang, 1993, Jang et al 1997) are hybrids of fuzzy systems (Russo, 1999, Zhang and Wang, 1997, Jang, 1993, Jang et al 1997, Pal and Mitra, 1992, Takagi and Sugeno, 1985. Takagi and Hayashi, 1991) and neural networks (Haykin,1994, Hayashi et al 1993, MathWorks 2002). The goal of neuro-fuzzy systems is to combine the learning capability of a neural network with the intuitive representation of knowledge found in a fuzzy system. This may be accomplished by designing a network architecture to mimic a fuzzy system, by incorporating linguistic terms into the computations performed by the network, by means of an explanation mechanism for the network, and so forth. Thus a neuro-fuzzy system is simply a fuzzy inference system trained by a neural network- learning algorithm, which address some of the problems in FIS to derive definite criteria for selection of membership functions, rule base and degree of overlapping. The integrated neuro-fuzzy system combines advantages of both ANN and FIS. ANFIS grasps the learning abilities of ANN to enhance the intelligent system's performance using a priori knowledge. Using a given input/output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least square type of method. This allows the fuzzy systems to learn from the data used in modeling. The mathematical details of the ANFIS are given by Jang (1993).

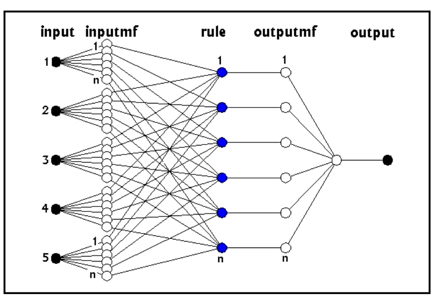

Figure 3. A typical architecture of ANFIS Network

Discussion of Results

Sugeno ANFIS architecture with the fix bell membership function, hybrid method for training and 5-input and 1-output structure is used in the present study (Figure 3). The work is carried out using the Fuzzy logic tool box of Matlab (MathWorks, 2002), on a PC with configuration of dual core Pentium-IV processor, 3GHz speed, 160GB HDD and 1GB RAM.

Now the network has to be trained, so that a particular input leads to a specific target output. Each input data set consists of five averaged BS intensity values selected at 5 specific ranges (grazing angles) namely at 20m, 40m, 60m, 80m and 150m respectively and corresponding sediment type (1 to 4) as desired output. Out of 180 data sets made from data representing all sediments, only 100 data sets were considered for training the ANFIS model and remaining 80 sets used for testing the model.

It is found 70 out 80 test data were successfully classified (~90%) and matching with ground truth. However ten data sets corresponding to sandy-silt and clayey-silt bottom were wrongly classified, because of their overlapping ranges. More sample data for different percentage of their constituents of these sediment types allow to define the membership functions in fuzzy more precisely and help to over come this problem to some extent.

The error in classification may be attributed to other factors like compactness and roughness resulting similar net acoustic response from the seafloor.

Conclusion

Seabed classification from the acoustic backscatter data offer continuous and rapid coverage of wide area. ANFIS is found to be a very effective tool in classification of the seafloor sediments with the backscatter strength obtained from the side scan sonar. The BS variation at short ranges forms the significant input to the network model.

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