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THE DECISION TREE SEABED TYPE CLASSIFIER OPERATING ON ACOUSTIC DATA

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A decision tree classifier was developed for sea bottom recognition from acoustic echoes. The acoustic data was acquired by DT4000 echosounder at 200 kHz frequency. The performance of the classifying system was investigated involving various backscattered echo parameters, in particular wavelet coefficients. The results of the decision tree classification were compared with those obtained from the adaptive neuro-fuzzy system (IFNN) involving reduced number of input parameters by the use of Principal Component Analysis (PCA).

INTRODUCTION

In recent years the advanced swath-beam techniques using multibeam sonars [1] have been successfully introduced for imaging and classifying the seabed. However, the conventional methods of normal incidence – utilising bottom backscatter from a single-beam echosounder – are still in use, due to their simplicity and versatility. Among these methods which include: measurement of the first and second echo, its comparison with theoretical models, wideband and parametric techniques, spectral and time-frequency approaches, the application of expert systems and neural networks have been justified its practical usefulness.

The paper proposes a new method of sea bottom classification, which is based on the decision tree algorithm which constructs classification models by revealing and analysing patterns found in seabed echo records.

1. DECISION TREE PRINCIPLES

The decision tree algorithm generates a classifier in the form of a *decision tree* structure, that is either a *leaf*, indicating a class or a *decision node* that specifies some test to be carried out on a single attribute value, with one branch and subtree for each possible outcome of the test.

A decision tree can be used to classify a case by starting at the root of the tree and moving through it until a leaf is encountered. At each nonleaf decision node, the case's outcome for the test at the node is determined and attention shifts to the root of the subtree corresponding to this outcome. When this process finally reaches to a leaf, the class of the case is predicted to be that recorded at the leaf.

If any algorithm can be said to have fundamental importance in this software, it is the process of generating an initial decision tree from a set of training cases. However, the tree-building process is not intended merely to find any such partition, but to build a tree that reveals the structure of the domain and thus has predictive power. Ideally, we would like to choose a test at each stage so that the final tree is simplest. One of the methods for constructing a decision tree from a set T of training cases is *gain criterion*, which is defined as [2]:

$$gain(X) = info(T) - info_X(T)$$

where: $info(T) = -\sum_{j=1}^{k} \frac{freq(c_j, T)}{|T|} \times \log_2\left(\frac{freq(c_j, T)}{|T|}\right)$ - the entropy of the set T,

$$info_X(T) = \sum_{i=1}^{n} \frac{|T_i|}{|T|} \times info(T_i)$$

k – class record, n – number of outcomes belonging to subset T_i, $|T|$ - number of cases in set T, $freq(C_j,S)$ – number of cases in T that belong to class C_j.

The gain criterion prefers the attributes, which have higher gains. Although the gain criterion gave quite good results, it has a serious deficiency, as it generates a strong bias in favour of tests with many outcomes. The bias inherent in the gain criterion can be rectified by a kind of normalisation in which the apparent gain attributable to tests with many outcomes is adjusted. Consider the information content of a message pertaining to a case that indicates not the class to which the case belongs, but the outcome of the test. By analogy with the definition of *info(T)*, we have

$$split\ info(X) = -\sum_{i=1}^{n} \frac{|T_i|}{|T|} \times \log_2\left(\frac{|T_i|}{|T|}\right)$$

This represents the potential information generated by dividing T into n subsets, whereas the information gain measures the information relevant to classification that arises from the same division. Then,

$$gain\ ratio(X) = gain(X) / split\ info(X)$$

expresses the proportion of information generated by the split that is useful, i.e., that appears helpful for classification. The *gain ratio* criterion selects a test to maximise the ratio above, subject to the constraint that the information gain must be large – at least as great as the average gain over all tests examined.

The idea of tree pruning is to remove parts of the tree that do not contribute to classification accuracy on unseen cases, producing something less complex and thus more comprehensible. Decision trees are usually simplified by discarding one or more subtrees and replacing them with leaves; as when building trees, the class associated with a leaf is found by examining the training cases covered by the leaf and choosing the most frequent class.

2. WAVELET ANALYSIS

Wavelet Transform demonstrates its usefulness in variety of applications [3] [4]. It seems to be also well suited and attractive tool for recognition of seabed type from acoustic echoes. The Principal Component Analysis (PCA) shows [5], that the wavelet coefficients demonstrate higher degree of importance in seabed classification performance than the other echo parameters. The particularly useful is the Discrete Wavelet Transform (DWT) which achieve the energy compaction in its first few coefficients [6].The DWT is defined as:

$$C(j,k) = \sum_{n=0}^{N-1} x(n)\psi_{j,k}(n)$$

where: $C(j,k)$ - set of discrete wavelet coefficients; $\psi_{j,k}(n)=2^{-j/2}\psi\left(2^{-j}n-k\right)$ - wavelet filter constructed from wavelet function $\psi(\bullet)$, N - signal length.

The DWT-tree algorithm was used for calculation of discrete wavelet coefficients from seabed echoes using the family of Symlet wavelets [3].

3. EXPERIMENTAL DATA AND RESULTS

Experimental data was acquired from acoustic surveys carried out in the Southern Baltic using a single-beam digital echosounder DT4000. The echosounder was operating on frequency of 200 kHz with the pulse duration of 0.3 ms and transducer 3dB beamwidth 6^{o}. The sampling rate of backscattered bottom echoes was 41.66 kHz. To make sure that data collected came from the same sites, so the echoes corresponded to identical types of sediment, the geographical position of the vessel recorded by GPS was carefully checked. The ground truthing was obtained from a TV camera. Four types of sediments were represented in the collected data and labelled as follows: *type1* for mud, *type2* for fine- and medium-grained sand, *type3* for medium-grained sand and *type4* for gravel, hetero-grained sand and rock.

A set of the following parameters was extracted from each digitised bottom echo: eight first wavelet coefficients C_i; sums of the absolute values of wavelet coefficients of i^{th} level, S_i; energy of the leading part of the echo, E'; energy of the falling part of the echo, E; amplitude of the echo, A; echo duration, T. In this way, nineteen parameters were extracted from each bottom echo record.

The program C4.5 [2] was used to build up the decision trees. C4.5 starts with large sets (learning sets) of cases belonging to known classes. The cases, described by any mixture of nominal and numeric properties, are scrutinised for patterns that allow the classes to be reliably discriminated. These patterns are then expressed as models, in the form of decision trees or sets of *if-then* rules, that can be used to classify new cases, with emphasis on making the models understandable as well as accurate.

Decision tree was trained on a learning set of data and its generalisation ability was checked on testing data set. The learning set counted 182 records and testing set had 1361 records. Sample decision tree scheme is shown in Fig. 1. The classification results are as follows: In the learning process the percentage of correctly classified echoes was 98.35%. In the testing process the percentage of correctly classified echoes was **93.98%**.

As it was shown in the Fig. 2, the decision tree algorithm works satisfactorily and allows achieving good classification results.

For comparison, concurrently to decision tree algorithm, where all input parameters were processed simultaneously, the incremental fuzzy neural network (IFNN) were also investigated [5]. In the IFNN architecture, all input parameters were processed sequentially and their sequence was determined by the PCA. The PCA analysis shows that the fifth wavelet coefficients *C5* and the echo duration *T* have the largest first principal components. On the basis of PCA parameter selection, the sequence of input parameters was as follows: *C5* was connected to the first stage, *T* to the second stage. The final percentage of correctly classified echoes obtained was **94.71%**. As seen from Fig. 3, the performance of IFNN classifier was similar to those obtained from decision tree.

4. CONCLUSIONS

The main objective of authors' investigation was to create an automatic bottom-typing tool using a decision tree algorithm that operates on acoustic data.

The decision tree method uses wavelet coefficients calculated by Digital Wavelet Transform (DWT) from the backscattered echoes received from a single beam echosounders. The wavelet coefficients were combined with several selected echo parameters viz. energy, amplitude, echo duration etc., subsequently analysed by means of decision tree algorithm to create the rules. Results achieved from decision tree algorithm were satisfactory.

These results show that introduced decision tree classification system seams to be a promising tool in seabed classification techniques.

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Decision Tree:
        S3 <= 156.491 :
        |   C1 > 275.79 : type1 (40.0/1.0)
        |   C1 <= 275.79 :
        |   |   A > 7.43533e-005 : type2 (2.0/1.0)
        |   |   A <= 7.43533e-005 :
        |   |   |   C3 <= -242.374 : type2 (62.0/1.0)
        |   |   |   C3 > -242.374 :
        |   |   |   |   C4 <= 111.278 : type2 (3.0)
        |   |   |   |   C4 > 111.278 : type1 (6.0)
        S3 > 156.491 :
        |   S2 <= 193.627 : type4 (22.0)
        |   S2 > 193.627 : type3 (47.0)

Simplified Decision Tree:
        S3 <= 156.491 :
        |   C1 > 275.79 : type1 (40.0/2.6)
        |   C1 <= 275.79 :
        |   |   C3 <= -242.374 : type2 (64.0/3.8)
        |   |   C3 > -242.374 :
        |   |   |   C4 <= 111.278 : type2 (3.0/1.1)
        |   |   |   C4 > 111.278 : type1 (6.0/1.2)
        S3 > 156.491 :
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Fig. 1. Decision tree scheme obtained from C4.5 program.

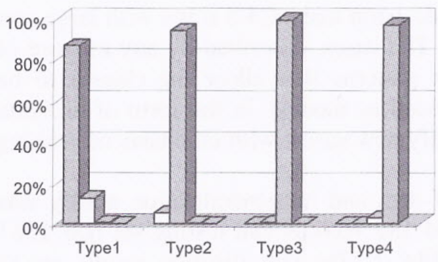

Fig. 2. Box diagram of the testing results of the decision tree; percentage of echoes correctly classified in total is **93.98%**

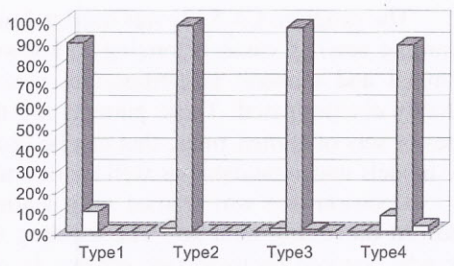

Fig. 3. Box diagram of the testing results after the 2nd stage of the IFNN system; percentage of echoes correctly classified in total is **94.71%**

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