ARCHIVES OF ACOUSTICS
24, 3, 365–378 (1999)

BOTTOM TYPE IDENTIFICATION USING COMBINED NEURO-FUZZY CLASSIFIER OPERATING ON MULTI-FREQUENCY DATA

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The paper introduces a novel approach to acoustic methods of characterising the bottom type by using a neuro-fuzzy classifier which processes the bottom backscatter data collected with an echosounder on three different operating frequencies. The classifier combining fuzzy logic and artificial neural networks was created using NEFClass system. It constitutes a fuzzy system, which can be viewed as a special 3-layer feed-forward neural network architecture, where the nodes of the second layer represent fuzzy rules. These rules are derived from a set of training data separated into crisp classes. In training and testing stages, apart from using single-frequency data, sets of dual-frequency and triple-frequency data combined together were used in order to enhance the classifier's performance. The results show that combining dual-frequency, or moreover triple-frequency data, clearly improves the generalisation ability of the classifier. The bottom backscattered echoes were acquired from acoustic surveys carried out on Lake Washington using the single-beam digital echosounder working on three frequencies: 38 kHz, 120 kHz and 420 kHz.

1. Introduction

As being non-invasive and faster than other techniques, the hydroacoustic methods of sea-bottom characterisation and identification have gathered a lot of importance in the last two decades and they are still a subject of extensive research. Information retrieved from bottom echo about seabed type is especially useful in hydrography, environmental sciences, marine engineering etc. Among the various acoustic techniques, which have been developed in recent years for characterising and classifying the bottom type, methods of so-called vertical, or normal incidence — utilising backscattered data from a single-beam echosounder — have achieved special attention, due to their simplicity and versatility.

These methods can be roughly categorised as follows:

- measurement of energy ratio in the first and second bottom echo [2, 3];
- comparison of a shape of bottom echo with patterns obtained from backscatter theoretical models [9, 11];
- techniques using wideband (chirp) signals and parametric arrays [1, 4];

- fractal analysis of bottom echo envelope [6];
- analysis of bottom echo using neural networks and cluster analysis [11, 12].

Variety of sediments' types, geomorphologic forms and layer structures make it especially difficult to determine a type of seabed, when an identification process is based only on the acoustic backscatter from the seafloor. The relations between a type of sediment and parameters of the bottom echo sometimes might be ambiguous and vague, and even when found for the explored area they don't necessarily have to be valid when extrapolated on other regions.

Intending to build up a reliable classification system and being aware of the difficulty of the problem, we have commenced with creating a Fuzzy Inference System (FIS) [7]. This system, as based on fuzzy logic, is especially suited when dealing with data with not sufficient information *a priori*, what leads to ambiguous and partial knowledge about the bottom type. Although the achieved results — 62% to 67% of correct classification rate — were promising, the method itself had limitation, which implied turning our interest towards an Adaptive Neuro-Fuzzy Inference System (ANFIS) [5]. Unlike FIS, the neuro-fuzzy system has an ability to adapt itself i.e. to derive shapes of membership functions and fuzzy "*if–then*" rules from a learning data set. This property of ANFIS is especially attractive in situation, when after learning the neuro-fuzzy net must extrapolate its classification abilities to unknown data, even acquired on a region different to the area where the learning data set was collected.

2. Classification methods

In general, the classification problem can be characterised as a function F, assigning a new input $\mathbf{x}_i$ to one of the disjoint classes c_i from the set of all classes C:

$$F : \mathbf{x}_i \to c_i\,, \tag{1}$$

$$F = F(\mathbf{x}_i, \mathbf{w}), \tag{2}$$

where $\mathbf{w}$ — vector of the parameters, $\mathbf{x}_i$ — input vector, $\mathbf{x}_i = [x_1, ..., x_d] \in X$, X — set of all input vectors.

Very often an additional group — "unknown" — is added to the set of classes. An input vector is assigned to this class when it cannot be assigned to any other category.

Most classifiers do not operate on the space X in which the input vector is described, but rather on the space of descriptors $y(X)$, extracted from the input vector, as processing data of lower dimension requires less memory and less computation power. In most situations reduction of the dimensionality of input vectors results in loss of information. Therefore the main goal is to choose such a set of parameters that as much of the relevant information as possible is retained.

For each class c_i a set of representative data, called a *learning set* Z, $Z = \{(y(\mathbf{x}_i), c_i) \in Y \times C\}$ already classified by an observer, is needed. It is used in the learning process, in which the values of parameters of the function F are determined.

The system's ability to classify unknown data is confirmed on an independent data set called a *testing set*.

2.1. *Fuzzy reasoning*

Fuzzy classifiers are based on a notion of the fuzzy logic operating on fuzzy sets, which were introduced by L.A. ZADEH [13] and which offer a formal description of linguistic expressions.

The definition of a fuzzy set is fundamental for the fuzzy logic theory and can be expressed as below [10]:

A fuzzy set μ of X is a function that maps from the space X into the unit interval, i.e.

$$\mu : X \to [0.1].$$

The value of the function $\mu(x)$ denotes the membership degree of x to the fuzzy set μ and is called the membership function. The value zero is used to represent complete non-membership, the value one represents complete membership, while the values in between are used to represent degrees of membership. In practice, the terms: "membership function" and "fuzzy set" get used interchangeably [10].

Fuzzy logic can be viewed as an extension of the binary (Boolean) logic to multivalued logic, which handles the concept of partial truth by operating on fuzzy sets.

The foundation of the fuzzy reasoning lays in the "*if–then*" rules:

$$\begin{aligned} &\textbf{If } \ x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } B_1 \textbf{ Then } y \text{ is } C_1, \\ &\textbf{If } \ x_1 \text{ is } A_2 \text{ OR } x_2 \text{ is } B_2 \textbf{ Then } y \text{ is } C_2 \end{aligned} \tag{3}$$

"x_i is A_i AND x_i is B_i" is an antecedent and "y is C_i" is a consequent of the rule [10].

Usually, especially in the classification systems, a scalar or numeric output value is desired. Therefore, some sort of defuzzifying operation is needed to reduce the output fuzzy set to a single number, which represents a class. From numerous defuzzyfication methods [5] centroid of the set (4) technique was used in the carried-out investigation:

$$y_{COA} = \frac{\int\limits_{\gamma} y\mu_{C'}(y)\,dy}{\int\limits_{\gamma} \mu_{C'}(y)\,dy}, \tag{4}$$

where $\mu_{C'}(y)$ is the combined output membership function.

Classification system, which uses a collection of fuzzy membership functions and fuzzy rules to reason about data, called also the Fuzzy Inference System (FIS) is depicted in form of a block diagram in Fig. 1 and characterisation of its functional blocks is as below:

- **Fuzzyfication** — maps a point from the universe of descriptors to values from 0 to 1 interval using a set of input membership functions.
- **Knowledge base** — contains information about the domains of variables and the fuzzy sets associated with the linguistic terms and a set of "*if–then*" rules.
- **Decision logic** — determines the values of the output variables.
- **Defuzzyfication** — selects a single number to represent the fuzzy output set.

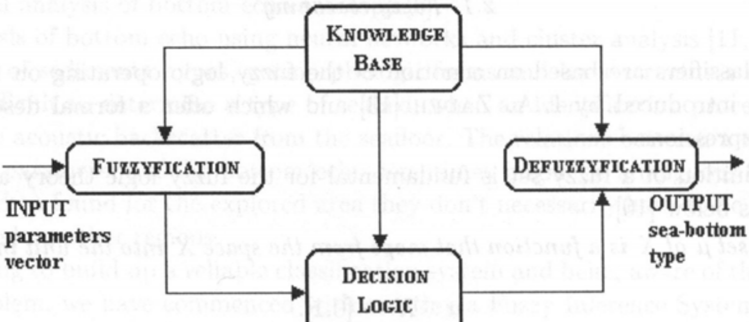


Fig. 1. Architecture of the fuzzy inference system.

2.2. *Neuro-fuzzy classification system — NEFClass*

The Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are derived from the general architecture of FIS system, shown in Fig. 1. By employing artificial neural networks they are able to find optimal membership functions, optimal number and structure of "*if–then*" rules and defuzzyfication method in a given problem [5].

We applied the NEFClass fuzzy inference system [8] to build ANFIS classifier, which can be viewed as a special 3-layer feed-forward neural network architecture. The nodes of the first layer of the net represent input parameters, the nodes of the second layer represent fuzzy rules, and in the output layer one node indicates each class. The fuzzy sets are characterised by fuzzy weights on the connections from the input to the hidden layer. Fuzzy rules are derived from a set of training data separated into crisp classes. A schematic block-diagram of the NEFClass architecture is presented in Fig. 2.

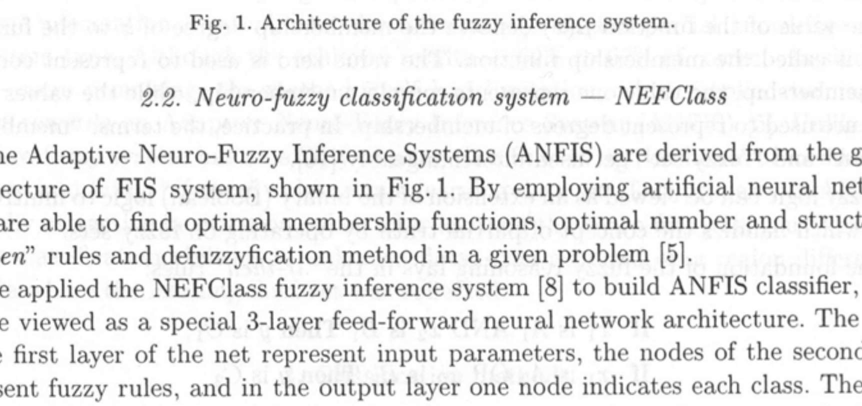


Fig. 2. Architecture of the neuro-fuzzy classification system.

Each connection between the output units and the units of the hidden layer is labelled with a linguistic term like *small, medium, large* etc. Connections coming from the same input unit x_i and having identical labels bear the same weight at all the time.

The task of NEFClass is to learn fuzzy rules and to learn shapes of the membership functions to determine the correct class category of a given unknown input pattern.

The learning algorithm of NEFClass, fully described in [8] can be summarised in the following steps:

1. **Initialization** — For each feature there is an input unit, and for each class there is one output unit designated. For each input unit an initial fuzzy partitioning is specified e.g. a number of equally distributed triangular membership functions is set.

2. **Rule Learning** — The system starts operation without any rules. The rules are inserted during the first run through the training data. A rule is created by finding, for a given input pattern, the combination of fuzzy sets, which gives the highest degree of membership for the respective input feature. If this combination is not identical to the already existing one, a new rule is added. In the second run the rules are evaluated and only the best are kept.

3. **Fuzzy Membership Shape Learning** — When the rule base is created, the learning algorithm adapts the membership functions μ of the antecedents. They are triangles defined by the function (5), where a, b and c are its parameters:

$$\mu:\ R \to [0,1], \qquad \mu(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } x \in [a,b), \\ \dfrac{c-x}{c-b} & \text{if } x \in [b,c], \\ 0 & \text{otherwise.} \end{cases} \tag{5}$$

The back-propagation scheme is used for finding optimal shapes of the membership functions, by adjusting values of a, b and c parameters. The range of each parameter is limited to the space in which parameter x is defined and also depends on how much the membership functions can overlap, which can be set in the NEFClass options. Depending on the output error for each rule unit, a decision is undertaken whether the activation value has to be lower or higher. Each rule unit then changes its membership functions by changing their support (i.e. the base of a membership triangle).

3. Experiment and results

Experimental data was acquired during acoustic surveys using a single-beam digital echosounder DT4000. The echosounder was operating on frequencies of 38 kHz, 120 kHz and 420 kHz with the pulse duration of 0.4 ms. Backscattered bottom echoes sampling rate was 41.66 kHz. The surveys were carried out on Lake Washington. For the experiment only data from an anchored ship was used, as transects were not completely validated due to limited ground truth sampling. To make sure that data collected at different frequencies came from the same regions, so the echoes corresponded to identical types of sediment, the geographical position of the vessel recorded by GPS was checked carefully. Only echoes obtained from the ship anchored in the same location for each bottom type and each frequency were further investigated. The chart of Lake Washington with acoustic sampling sites for each bottom type is presented in Fig. 3.

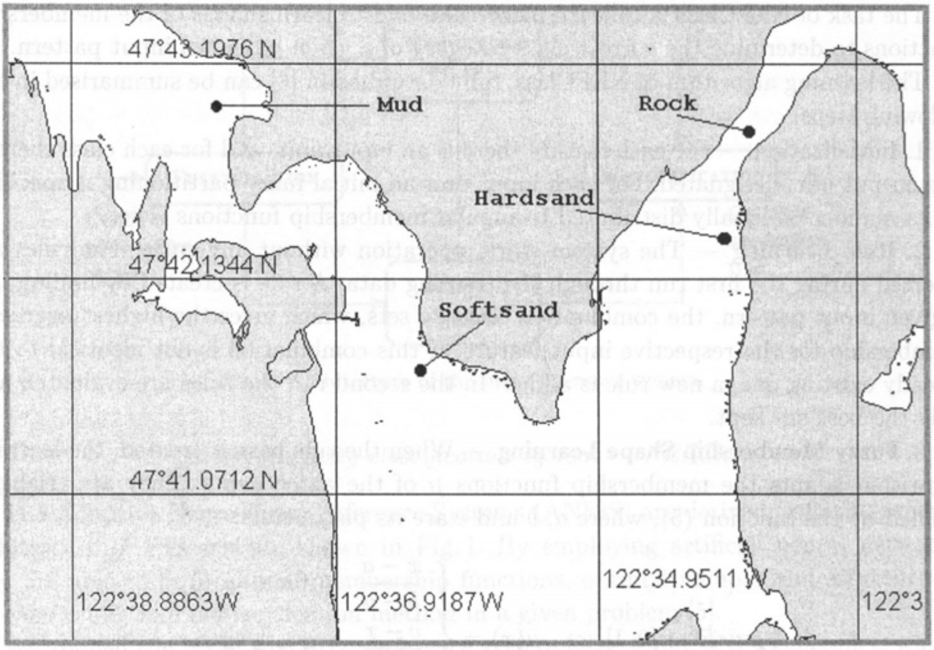


Fig. 3. Chart of Lake Washington with acoustic sampling sites marked.

Three types of classifiers were built. Firstly, two single-frequency classification systems working on 38 kHz or 120 kHz data sets were created. Consequently, these two data sets were combined for a dual-frequency classifying system. The third type of a system — triple-frequency classifier — was based on a set in which also 420 kHz data was combined with the previous two data sets.

3.1. *Parameters extraction*

Development process of each classifier is usually conducted in three steps. Firstly, a set of parameter must be extracted from a digitised echo. It was decided to use three echo parameters, which graphical representation is shown in a screen damp of the Visual Bottom Typer [11] in Fig. 4, and which are listed below:

- Energy of the leading part of the first echo (Bottom Hardness Signature)

$$E_1 = \sum_{i=n_1}^{n_M} a_i^2; \tag{6}$$

- Energy of the falling part of the first echo (Bottom Roughness Signature)

$$E_1' = \sum_{i=n_M}^{n_L} a_i^2; \tag{7}$$

• Amplitude of the secondary echo (Bottom Hardness Signature)

$$A_2 = \max_{i=m_1 \ldots m_L} a_i, \tag{6}$$

where a_i — quantized value of i-th sample of a digitised bottom echo signal, n_1 — number of the first sample in the first echo, n_M — number of the maximal sample in the first echo, n_L — number of the last sample in the first echo, m_1 — number of the first sample in the secondary echo, m_L — number of the last sample in the secondary echo.

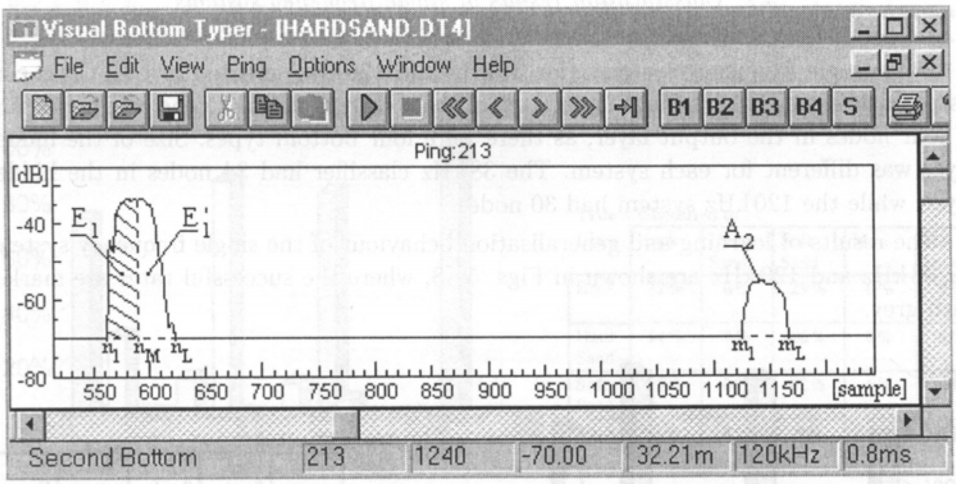


Fig. 4. Graphical interpretation of the parameters extracted from the bottom echo.

The bottom type in each data set was known. Four types of sediments were represented by data collected at 38 kHz and 120 kHz, and these were mud, soft sand, hard sand and rock. For 420 kHz data only three types of bottom data were collected, i.e.: mud, sand and rock.

The second step in creating a classifier is to train the system using the training data set. Then, the generalisation capacity of the systems must be checked on the testing data sets. Therefore, after computing parameters of each echo from all sets of data, they were divided into learning (training) and testing sets. For single-frequency systems, every second echo was chosen from the whole set of data and used for learning. For dual- and triple-frequency systems, the training set consisted of every third echo drawn from the whole set of data. Number of echoes in each of these sets for three operating frequencies is shown in Table 1.

The systems could learn only to some extend i.e. also in the learning phase some misclassifications occurred. Therefore the classification results are presented not only for the generalisation phase but also for the learning one.

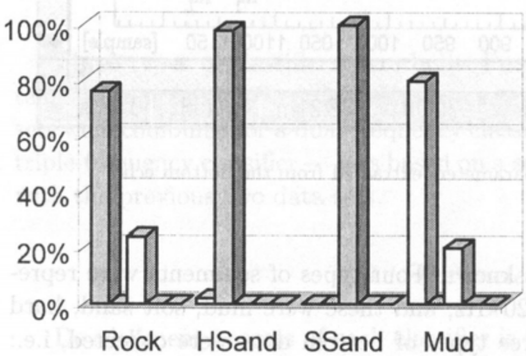
Table 1. Amount of data used in the experiments.

Experiment		Echoes in training set	Echoes in testing set
single-frequency	38 kHz	200	220
single-frequency	120 kHz	395	666
dual-frequency	38 kHz + 120 kHz	200	645
triple-frequency	38 kHz + 120 kHz + 420 kHz	150	445

3.2. Classification results of single frequency systems

Both single frequency-systems (for 38 kHz and 120 kHz) created in NEFClass consisted of three nodes in the first layer, each of them corresponding to one parameter, and of four nodes in the output layer, as there were four bottom types. Size of the hidden layer was different for each system. The 38 kHz classifier had 34 nodes in the hidden layer, while the 120 kHz system had 30 nodes.

The results of learning and generalisation behaviour of the single frequency systems for 38 kHz and 120 kHz are shown in Figs. 5–8, where the successful rates are marked with grey.

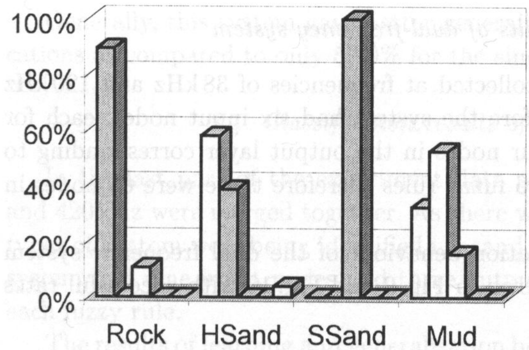


True Class	Classified to: Rock	Hard Sand	Soft Sand	Mud	Not Known
Rock	**76%**	**0%**	**24%**	**0%**	**0%**
Hard Sand	**2%**	**98%**	**0%**	**0%**	**0%**
Soft Sand	**0%**	**0%**	**100%**	**0%**	**0%**
Mud	**80%**	**0%**	**20%**	**0%**	**0%**

Fig. 5. Box diagram and confusion matrix showing the *learning* results of the 38 kHz frequency neuro-fuzzy classifier trained on a set of 200 echoes; percentage of echoes correctly classified in total is **68.5%**.

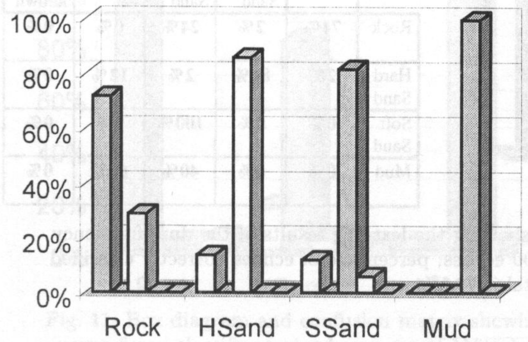
Summarising, although 38 kHz classifier behaved better during training stage, its generalisation behaviour gave low classification ratio of 56.95%. For this frequency the mud type of bottom was entirely misclassified.

More stable results, in the terms of a smaller variance between learning and generalising results, were obtained for the 120 kHz data i.e. the classification ratio during training and testing varied between 63.5% and 60%. Fewer misclassifications were encountered for the soft sand echoes but unfortunately hard sand correct classification rate dropped to zero.



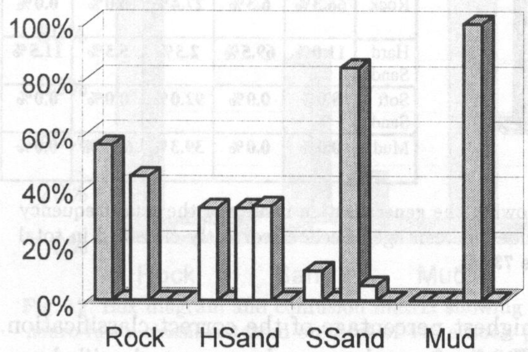
True Class	Classified to: Rock	Hard Sand	Soft Sand	Mud	Not known
Rock	**89.3%**	**0.0%**	**10.7%**	**0.0%**	**0.0%**
Hard Sand	**57.7%**	**38.5%**	**0.0%**	**0.0%**	**3.8%**
Soft Sand	**0.0%**	**0.0%**	**100%**	**0.0%**	**0.0%**
Mud	**32.1%**	**52.4%**	**15.5%**	**0.0%**	**0.0%**

Fig. 6. Box diagram and confusion matrix showing the **generalisation** results of the 38 kHz frequency neuro-fuzzy classifier tested on a set of 220 echoes; percentage of echoes correctly classified in total is **56.95%**.



True Class	Classified to: Rock	Hard Sand	Soft Sand	Mud	Not known
Rock	**72%**	**0%**	**29%**	**0%**	**0%**
Hard Sand	**14%**	**0%**	**86%**	**0%**	**0%**
Soft Sand	**12%**	**0%**	**82%**	**6%**	**0%**
Mud	**0%**	**0%**	**0%**	**100%**	**0%**

Fig. 7. Box diagram and confusion matrix showing the **learning** results of the 120 kHz frequency neuro-fuzzy classifier trained on a set of 395 echoes; percentage of echoes correctly classified in total is **63.5%**.



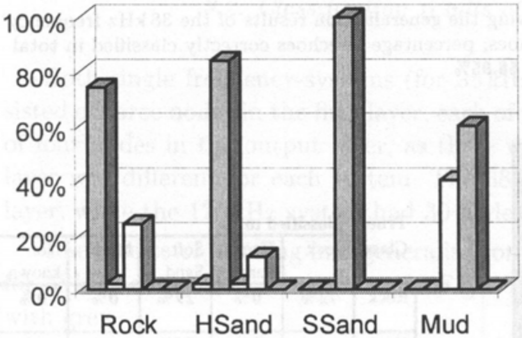
True Class	Classified to: Rock	Hard Sand	Soft Sand	Mud	Not known
Rock	**55.6%**	**0.0%**	**44.4%**	**0.0%**	**0.0%**
Hard Sand	**33.1%**	**0.0%**	**33.1%**	**33.8%**	**0.0%**
Soft Sand	**10.7%**	**0.0%**	**84.0%**	**5.33%**	**0.0%**
Mud	**0.0%**	**0.0%**	**0.0%**	**100%**	**0.0%**

Fig. 8. Box diagram and confusion matrix showing the **generalisation** results of the 120 kHz frequency neuro-fuzzy classifier tested on a set of 666 echoes; percentage of echoes correctly classified in total is **59.9%**.

3.3. Classification results of dual-frequency system

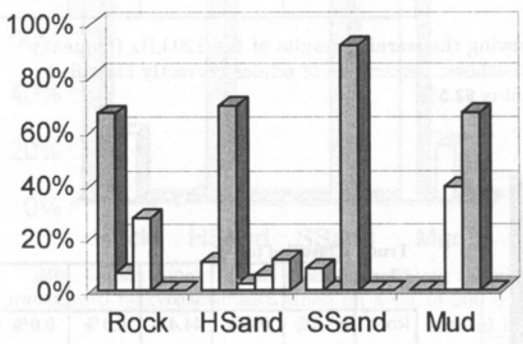
In this part of the experiment data collected at frequencies of 38 kHz and 120 kHz was combined and used together. Therefore the system had six input nodes, each for one parameter of each frequency and four nodes in the output layer corresponding to each bottom type. The system created 66 fuzzy rules therefore there were 66 nodes in the hidden layer.

The results of learning and generalisation behaviour of the dual frequency system for combined 38 kHz and 120 kHz are shown in Fig. 9 and Fig. 10 with successful rates marked with grey.



True Class	Classified to Rock	Hard Sand	Soft Sand	Mud	Not known
Rock	**74%**	**2%**	**24%**	**0%**	**0%**
Hard Sand	**2%**	**84%**	**2%**	**12%**	**0%**
Soft Sand	**0%**	**0%**	**100%**	**0%**	**0%**
Mud	**0%**	**0%**	**40%**	**60%**	**0%**

Fig. 9. Box diagram and confusion matrix showing the **learning** results of the dual-frequency neuro-fuzzy classifier training on a set of 200 echoes; percentage of echoes correctly classified in total is **79.5%**.



True Class	Classified to Rock	Hard Sand	Soft Sand	Mud	Not known
Rock	**66.3%**	**6.3%**	**27.4%**	**0.0%**	**0.0%**
Hard Sand	**11.0%**	**69.5%**	**2.5%**	**5.5%**	**11.5%**
Soft Sand	**8.0%**	**0.0%**	**92.0%**	**0.0%**	**0.0%**
Mud	**0.0%**	**0.0%**	**39.3%**	**66.7%**	**0.0%**

Fig. 10. Box diagram and confusion matrix showing the **generalisation** results of the dual-frequency neuro-fuzzy classifier tested on a set of 645 echoes; percentage of echoes correctly classified in total is **73.6%**.

The soft sand bottom type had the highest percentage of the correct classification. During learning process as much as 100% of soft sand type echoes were classified correctly, while during testing only 8% of soft sand echoes were misclassified.

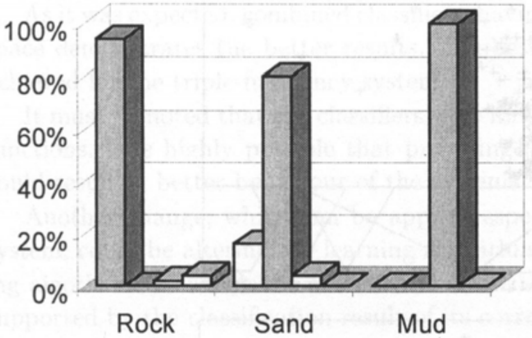
Unfortunately, also about 40% of the mud type echoes were misclassified and categorised to the soft sand type. Also the system was not able to assign over 11% of hard sand echoes to any of the classes.

Generally, this system gave better generalisation results of 73.6% of correct classifications as compared to only 59.9% for the single frequency system.

3.4. Classification results of triple-frequency system

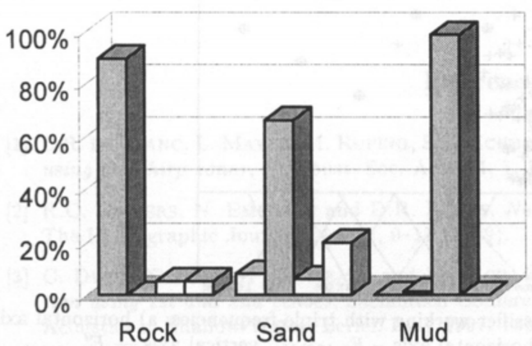
In the last part of the experiment data sets for three frequencies 38 kHz, 120 kHz and 420 kHz were merged together. As there was no data for hard sand type, only three types of bottom were being identified i.e. sand, rock and mud. Therefore the neuro-fuzzy system had nine input nodes and three outputs. 45 hidden nodes were created one for each fuzzy rule.

The results of learning and generalisation behaviour of the triple-frequency system for combined 38 kHz, 120 kHz and 420 kHz are shown in Fig. 11 and Fig. 12 with successful rates marked with grey.



True Class	Classified to Rock	Sand	Soft Sand	Not Known
Rock	**94%**	**0%**	**2%**	**4%**
Sand	**16%**	**80%**	**4%**	**0%**
Mud	**0%**	**0%**	**100%**	**0%**

Fig. 11. Box diagram and confusion matrix showing the **learning** results of the triple-frequency neuro-fuzzy classifier trained on a set of 150 echoes; percentage of echoes correctly classified in total is **91.3%**.



True Class	Classified to Rock	Sand	Mud	Not Known
Rock	**89.5%**	**0.0%**	**5.2%**	**5.3%**
Sand	**8.0%**	**66.0%**	**6.0%**	**20.0%**
Mud	**0.0%**	**1.3%**	**98.7%**	**0.0%**

Fig. 12. Box diagram and confusion matrix showing the **generalisation** results of the triple-frequency neuro-fuzzy classifier tested on a set of 445 echoes; percentage of echoes correctly classified in total is **84%**.

In general, the triple-frequency system gave better generalisation results of 84% of correct classifications as compared to only 59.9% for the single-frequency (120 kHz) system and 73.6% for the dual-frequency one. Unfortunately, the full comparison of these classifiers is not possible as the single- and dual-frequency systems operated on four sediment types and the triple-frequency classifier only on three classes.

In Fig. 13, sample bottom classification results obtained from the triple-frequency ANFIS system are presented. The data is depicted in form of two-dimensional projection, where the membership functions of two different input parameters are also presented on X-axis and Y-axis. The nine-dimensional input vectors, i.e. vectors containing echoes' parameters are projected on the two-dimensional surface and it is clearly seen that they are not easily separable in the 2D space created in such a way.

a)

b)

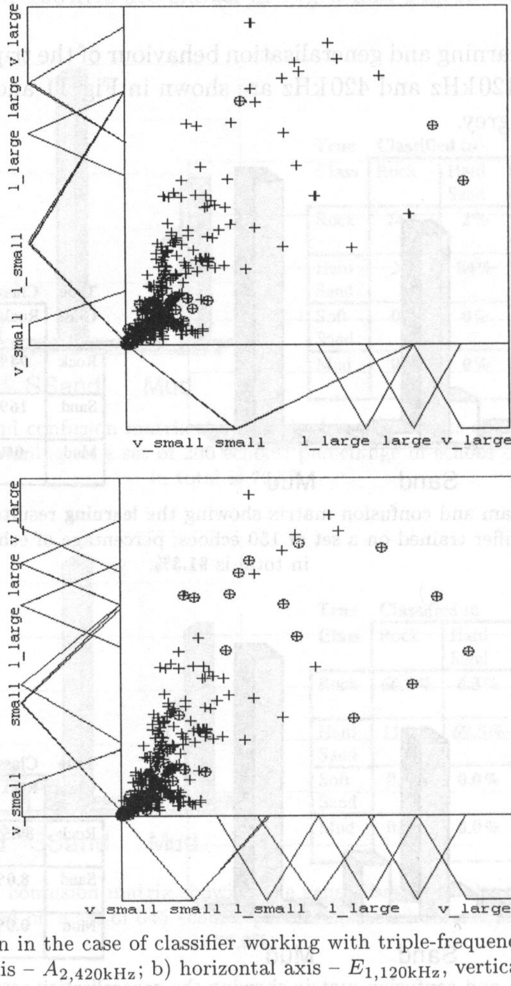


Fig. 13. 2D data projection in the case of classifier working with triple-frequencies: a) horizontal axis — $E_{1,420\mathrm{kHz}}$, vertical axis – $A_{2,420\mathrm{kHz}}$; b) horizontal axis – $E_{1,120\mathrm{kHz}}$, vertical axis — $E'_{1,120\mathrm{kHz}}$.

4. Conclusions

Neuro-fuzzy classifiers have been constructed in NEFClass system and tested on the hydroacoustics data i.e. bottom echoes acquired with a single-beam echosonder at normal incidence. For each digitised echo's envelope a set of parameters was extracted, viz.: E_1 — energy of the leading part of the first echo, E_1' — energy of the falling part of the first echo, A_2 — amplitude of the second echo. These descriptors where used in the further classification process.

The system constitutes an adaptive three-layered neural network in which the hidden layer's nodes represent fuzzy rules and the weights between the input and second layer denote the membership functions of the input features. Depending on data the number and shape of membership functions and fuzzy rules were chosen and optimised in the process of learning.

Three different systems were created and investigated, starting from the single-frequency classifier (operating on 38 kHz or 120 kHz), then extending its function to the combined dual-frequency (38 kHz and 120 kHz) and triple-frequency (38 kHz, 120 kHz and 420 kHz) systems.

As it was expected, combined classifiers, having higher dimension of the input vector's space demonstrates the better results. The best correct classification rate of 84% was achieved for the triple-frequency system.

It must be noted that the classifiers were limited to have only triangular membership functions. It is highly possible that providing more complex shapes or smooth curves could result in better behaviour of the systems.

Another change, which can be applied especially to the combined multi-frequency system, could be altering the learning algorithm to use some kind of a reinforced learning algorithm, in which the classification decision about one frequency input sample is supported by the classification result of its corresponding sample collected on the other frequency.

Currently the authors are working on the multi-staged neural network architecture for a multi-frequency classifier, in which each single-frequency data are sequentially processed by the corresponding stage.

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