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Sea Bottom Typing Using Neuro-Fuzzy Classifier Operating on Multi-Frequency Data

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A hybrid neuro-fuzzy classifier was development for sea-bottom identification from acoustic echoes. A multistage ANFIS structure was constructed and tested on data collected on 38kHz and 120kHz echosounder's frequencies. In multistage systems available data is processed in stages. The decisions about assigning a bottom echo, represented by digitised echo envelope's parameters, to one of the classes is made hierarchically. Firstly, an approximate decision is made based only on one set of input variables. The decision is then fine-tuned by considering more and more factors, it is in following stages next parameters are taken under account until the final decision, corresponding to the output class, is made. The proposed approach not only gives better classification results, as compared to parallel ANFIS system, but also it demands less computation-power.

1. Introduction

The non-invasive and fast hydroacoustic methods for bottom typing have been the subject of extensive research in the last decades. Creating an automatic method for bottom identification based on analysis of echoes' envelopes is one of the main tendencies in the subject of bottom-typing. Neural networks, which have proven to be a very useful tool in many applications of identification and classification problems [3], as after training on the given set of data they are able to generalise to an unknown data, has been used also in bottom typing applications [4]. Also, as hydroacoustic data is often ambiguous and partially available, fuzzy logic seams to be a perfect complementary tool when dealing with it. That is why the authors have been investigating advantages of these methods by creating different types of neural networks and fuzzy classifiers and checking them on collected data. As the first attempt to use fuzzy logic in the sea-bottom classification process the Fuzzy Inference Systems (FIS) architecture was used [2], [6]. The achieved results (62-67% of correct decision rate) were promising but the method has limitations. Therefore the Adaptive Neuro-Fuzzy Inference System (ANFIS) was chosen for further investigation, as its main advantage is a possibility to adapt itself to a given set of data. Firstly, a single frequency data has been classified with the result of about 70% of correct classification rate [5]. In another approach multi-frequency data was combined to check how the information acquired on different operating frequencies could reinforce the classification process. The classification results of this method were of 84% [7].

In the paper a novel multistage multi-frequency fuzzy neural network model is described and the results of numerous test are discussed. Parameters extracted from the echoes collected on different operating frequencies were processed sequentially i.e. classification result of a preceding layer influenced the decision made by the successive one.

2. Sugeno Adaptive Neuro-Fuzzy Inference System's Model

The adaptive neuro-fuzzy inference system (ANFIS) based on the general architecture of fuzzy inference system [3] is able to derive from the given data sets optimal shapes of membership functions and number of fuzzy rules.

Classifiers investigated in this experiment are based on the fundamental structure of the Sugeno fuzzy inference system [3]. In the neuro-fuzzy version of this model its structure is "hidden" in the neural network, therefore the system adapts its parameters in the learning process.

An example of two input Sugeno ANFIS model structure is depicted in Fig. 1. The role of each consecutive system's layer is as follows:

Layer 1. Nodes in this layer are adaptive with a node function:

$$O_{1,i} = \mu_{A_i}(x_1), i = 1,2$$
$$O_{1,i} = \mu_{B_{i-2}}(x_2),\ i = 3,4 \quad (1)$$

where x_1 and x_2 are the inputs and A_i and B_{i-2} are linguistic labels associated with each node. $O_{1,i}$ specifies the degree to which the given input x_1 (or x_2) satisfies $A = A_1, A_2, B_1, B_2$. The triangular-shape membership functions are adopted for A, where $\{a, b, c\}$ is the set of *premise parameters*:

$$\mu_A(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } x \in [a,b) \\ \dfrac{c-x}{c-b} & \text{if } x \in [b,c] \\ 0 & \textit{otherwise.} \end{cases} \quad (2)$$

Layer 2. Nodes in this layer are fixed and their outputs are the product of all incoming signals and represent the firing strength of a rule:

$$O_{2,k} = w_i = \mu_{A_i}(x_1)\mu_{B_i}(x_2)\ \ i,j = 1,2 \quad (3)$$

Layer 3. This layer's nodes are adaptive with a node function:

$$O_{3,i} = w_i f_i = w_i(p_i x_1 + q_i x_2 + r_i) \quad (4)$$

where w_i is a firing strength for node i and $\{p_i, q_i, r_i\}$ are so called *consequent parameters* of this node. The last node in this layer computes a sum of all rules' firing strengths.

Layer 4. Nodes in this layer are fixed and compute the sum of all incoming signals:

$$O_{4,1} = \sum_i w_i f_i \quad (5)$$

Layer 5. A single node in this layer calculates the output signal according to the relation:

$$O_{5,1} = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (6)$$

The characteristic future of Sugeno ANFIS model is that the output is calculated as a combination of the firing strengths of the consequence i.e. the process of defuzzyfication is not needed as the output value is represented by a crisp number, not a fuzzy set. In the multistage systems it leads to additional computations as the intermediate results of one stage, expressed as crisp values, must be firstly fuzzified before passing them to the next classifier's stage.

3. Data and Experiment

Experimental data was acquired during acoustic surveys in the Lake Washington using a single-beam digital echosounder DT4000, operating on frequencies of 38kHz and 120kHz. The pulse duration was 0.4 ms and sampling rate was 41.66kHz.

Four types of sediments were represented in the collected data - mud, soft sand, hard sand and rock.

A set of parameters was extracted from a digitised echo (Fig.2): 1) Energy of the leading part of the first echo (*Bottom Roughness Signature*), referred to as E1; 2) Amplitude of the second echo (*Bottom Hardness Signature*), referred to as A2. In this way for each pair of echoes (one collected on the frequency of 38kHz, the other – on 120kHz) four parameters were retrieved and they will be referred to as 38kHz(E1), 38kHz(A2), 120kHz(E1) and 120kHz(A2).

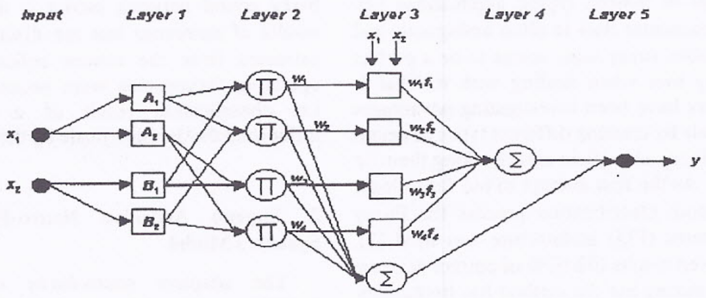

Fig. 1. ANFIS architecture for a two-input fist-order Sugeno fuzzy model.

Two types of Sugeno ANFIS classifiers were constructed using MATLAB [1] neuro-fuzzy toolbox and checked on available data. The first of them had a parallel structure, the other was a multistage classifier.

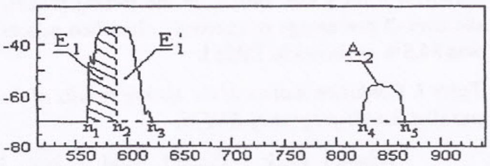

Fig. 2. Graphical interpretation of the parameters extracted from the bottom echo.

All classifiers were trained on a training (learning) set and their generalisation capacity was check on testing data. The learning set counted 200 records and testing set had 645 records.

3.1 Parallel (single stage) Fuzzy Neural Network Structure

For comparison a parallel (single stage) system based on the Sugeno structure was built, as shown in Fig. 3. This kind of ANFIS structure we investigated extensively in [7] and [5] by the authors. In the quoted experiment NEFClass classification system was used, here for uniformity, the system was re-built using MATLAB Neuro-fuzzy Toolbox. It consisted of 4 input nodes, as there were four parameters (38kHz - E1 and A2 and 120kHz - E1 and A2) as these parameters were fed into the system simultaneously, and one output node, corresponding to an output class. The system had 256 rules and (256*5)=1280 consequent parameters.

3.2 Serial (multistage) Fuzzy Neural Network Structure

Creating a multistage classifier was the main objective of the experiment.

The basic multistage ANFIS structure is depicted in Fig. 4. The input variables have been divided into *M* sets and each of them is fed to an individual reasoning stage (module) which corresponds to a single-stage ANFIS introduced in chapter 2.1. Therefore there are totally *M* single-stage ANFIS models involved in a serial manner and the fuzzy inference is carried out stage by stage [2].

$y^{(k)}$ $(k<M)$ is the intermediate variable which represents the output from stage k as well as the input to stage $k+1$. This kind o procedure can be compared to the mechanism of human reasoning. It is quite common that we consider some factors (input variables) first and made an approximate decision, corresponding to the intermediate variables here. The decision is then fine-tuned by considering more and more factors until the final decision, corresponding to the output variable, is made.

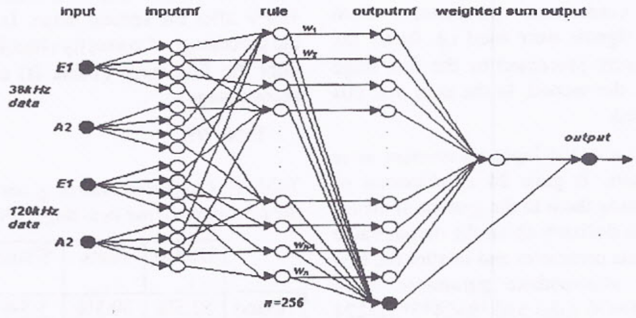

Fig. 3. Structure of a parallel ANFIS.

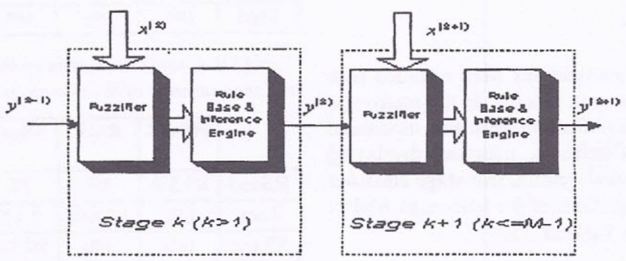

Fig. 4. Basic structure of the Sugano ANFIS adopted for a multistage system.

As this model is based on Sugano ANFIS model, the j^{th} fuzzy rule in stage $k>1$ has the following form:

$$Rule_j^{(k)} : If\,(x_1^{(k)}\ is\ A_{1,j}^{(k)} \cdots x_{n_k}^{(k)}\ is\ A_{n_k,j}^{(k)})\ and\ (y^{(k-1)}\ is\ B_j^{(k-1)}) \tag{7}$$
$$THEN\ y^{(k)} = c_{n_k+1,j}^{(k)} y^{(k-1)} + \sum_{i=1}^{n_k} c_{i,j}^{(k)} x_i^{(k)} + c_{0,j}^{(k)}$$

where:

- $x_i^{(k)}$: i^{th} input variable in stage k.
- $A_{i,j}^{(k)}$: fuzzy term of the i^{th} input variable appearing in the j^{th} rule of stage k.
- n_k : number of input variables used in stage k.
- $y^{(k)}$: single output variable in stage k.
- $B_j^{(k-1)}$: fuzzy term of $y^{(k-1)}$ in j^{th} rule of stage k.
- $c_{i,j}^{(k)}$: consequent parameters in stage k, corresponding to the parameters p_i, q_i and r_i in the equation (4).

Two types of multistage ANFIS were built: two-stage ($k = 2$) and four-stage ($k = 4$) classifiers.

In the case of $k = 2$ the input parameters were divided into two sets. The first stage was fed with E1 and A2 parameters of one frequency and the second stage was fed with the other two parameters. In both stages (16+96)=112 rules were constructed and (16*3+96*4)=432 consequent parameters. Both sequences of input signals were tried i.e. firstly the 38kHz parameters were processed by the first stage and then 120kHz in the second. In the next trial this sequence was inverted.

In the case of $k = 4$, the input parameters were divided into four sets. It gave 24 combination of sequence of introducing them to the system. It means that in each stage the decision about the output value was based only on one parameter and in after the first stage also on the intermediate parameter. Each system had (4+24*3)=76 rules and (8+24*3*3)=224 consequent parameters.

4. Results

The results of classifications were recorded both in the learning and testing process. In the multistage systems results of classification were also monitored after each stage. Confusion matrixes displaying behaviour of the parallel system, two-stage classifier and four different variations of the four-stage ANFIS systems are shown in Tables I ÷ XI.

4.1 Parallel ANFIS

In this single stage classifier all four parameters were processed simultaneously.

In the learning process the percentage of correctly classified echoes was **100%**. In the testing process the overall percentage of correctly classified echoes was **84.5%** as shown in Table I.

Table I. Confusion matrix of the testing results of the parallel double-frequency ANFIS.

	HSand	Rock	SSand	Mud	Not Known
HSand	72%	8.5%	2%	3.5%	14%
Rock	13.7%	68.4%	4.2%	2.1%	11.6%
SSand	0%	2.5%	95.5%	2%	0%
Mud	0%	0%	0%	96.7%	3.3%

4.2 Two-stage ANFIS

Two classifiers of that type were built. In the first classifiers 38kHz parameters were processed first and the result of this stage and the 120kHz parameters were then used in the second stage. The percentage of finally classified echoes was 77.2%. In the second system the sequence of processed parameters was inverted i.e. in the first stage - 120kHz (E1 and A2) parameters were processed and in the second stage 38kHz (E1 and A2).

In the learning process the percentage of correctly classified echoes was 78% after the first stage and **100%** after the second stage. In the testing process the percentage of correctly classified echoes was 66% after the first stage (Table II) and **89.2%** after the second stage (

Table *III*).

Table II. Confusion matrix of the testing results after the first stage of the two-stage ANFIS.

	HSand	Rock	SSand	Mud	Not Known
HSand	52.5%	39.5%	5.5%	0.5%	2%
Rock	21.1%	70.5%	6.3%	0%	2.1%
SSand	4%	37%	52%	5%	2%
Mud	0%	0%	0%	100%	0%

Table III. Confusion matrix of the testing results after the second stage of the two-stage ANFIS.

	HSand	Rock	SSand	Mud	Not Known
HSand	83.5%	3%	2%	1.5%	10%
Rock	0%	88.4%	2.1%	0%	9.5%
SSand	0%	1%	89.5%	0%	9.5%
Mud	0%	0%	0%	96.7%	3.3%

4.3 Four-stage ANFIS I

Inputs: first stage - 38kHz(A2), second - 120kHz (A2), third - 38kHz(E1) and fourth - 120kHz(E1).

In the learning process the percentage of correctly classified echoes was 38.5% after the first stage, 87.5% after the second, 97% after the third and 98.5% after the last stage.

In the testing process the percentage of correctly classified echoes was 40.6% after the first stage (Table V), 81.4% after the second (Table VI), 89.3% after the third (Table VII) and **87.3%** after the last stage (Table VIII).

Table V. Confusion matrix of the testing results after the first stage (38kHz A2) of the system I.

	HSand	Rock	SSand	Mud	Not Known
HSand	3.5%	87.5%	6%	0%	3%
Rock	0%	57.9%	42.1%	0%	0%
SSand	0%	0%	100%	0%	0%
Mud	0%	78%	22%	0%	0%

Table VI. Confusion matrix of the testing results after the second stage (120kHz A2) of the system I.

	HSand	Rock	SSand	Mud	Not Known
HSand	60%	31%	1.5%	0.5%	7%
Rock	26.3%	66.3%	7.4%	0%	0%
SSand	0%	3%	96%	1%	0%
Mud	0%	0%	0%	100%	0%

Table VII. Confusion matrix of the testing results after the third stage (38kHz E1) of the system I.

	HSand	Rock	SSand	Mud	Not Known
HSand	73%	19%	0%	0.5%	8%
Rock	9.5%	88.4%	1.1%	0%	1%
SSand	0%	1%	98%	1%	0%
Mud	0%	0%	0%	100%	0%

Table VIII. Confusion matrix of the testing results after the last stage (120kHz E1) of the system I.

	HSand	Rock	SSand	Mud	Not Known
HSand	65%	26%	0%	0%	9%
Rock	6.3%	91.5%	1.1%	0%	1%
SSand	0.5%	0.5%	98%	0%	1%
Mud	0%	0%	0%	100%	0%

4.4 Four-stage ANFIS II

Input signals: first stage - 38kHz(E1), second - 38kHz(A2), third - 120kHz(A2) and fourth - 120kHz (E1).

In the learning process the percentage of correctly classified echoes was 58.5% after the first stage, 73% after the second, 95.5% after the third and **96%** after the last stage.

In the testing process the percentage of correctly classified echoes was 58.5% after the first stage, 72.7% after the second, 84.3% after the third and **84.7%** after the last stage (Table IX).

Table IX. Confusion matrix of the testing results after the last stage (120kHz E1) of the system II.

	HSand	Rock	SSand	Mud	Not Known
HSand	70.5%	19%	1.5%	0%	9%
Rock	6.3%	90.5%	2.1%	0%	1.1%
SSand	0.5%	9.5%	89.5%	0.5%	0%
Mud	0%	0%	0%	93.3%	6.7%

4.5 Four-stage ANFIS III

Input signals: first stage - 120kHz(E1), second - 38kHz(A2), third - 38kHz(E1) and fourth - 120kHz (A2).

In the learning process the percentage of correctly classified echoes was 58% after the first stage, 99.5% after the second, **100%** after the third and the last stage.

In the testing process the percentage of correctly classified echoes was 52.3% after the first stage, 95.7% after the second, **95.8%** after the third and the last stage (Table X).

Table X. Confusion matrix of the testing results after the third (38kHz E1) and the last stage (120kHz A2) of the system III.

	HSand	Rock	SSand	Mud	Not Known
HSand	87.5%	9.5%	0%	1%	2%
Rock	1.1%	97.9%	0%	0%	1%
SSand	0%	0%	100%	0%	0%
Mud	0%	0%	0%	100%	0%

4.6 Four-stage ANFIS IV

Input signals: first stage - 120kHz(E1), second - 38kHz(E1), third - 38kHz(A2) and fourth - 120kHz (A2).

In the learning process the percentage of correctly classified echoes was 58% after the first stage, 94% after the second, **100%** after the third and the last stages.

In the testing process the percentage of correctly classified echoes was 52.5% after the first stage, 89.2% after the second, **95.7%** after the third and the last stages (Table XI).

Table XI. Confusion matrix of the testing results after the third (38kHz A2) and the last stage (120kHz A2) of the system V.

	HSand	Rock	SSand	Mud	Not Known
HSand	90.5%	4.5%	0%	0%	5%
Rock	0%	99%	0%	0%	1%
SSand	0%	3%	96%	0%	1%
Mud	0%	0%	0%	100%	0%

5. Conclusions

The main objective of this part of the authors' investigation to create an automatic bottom-typing tool for was to create a sequential i.e. multistage classification system.

Double frequency data was available and four parameters (two for each frequency) were extracted from the digitised echoes' envelopes and used as the input parameter of the classifiers. Acoustical echoes of four types of sediments were present in the collected data.

Two versions of sequential systems were built. In the two-stage systems the correct classification rate was up to 89%, in four-stage systems this value varied between 85% to 95% depending on the processing sequence of parameters. For comparison parallel ANFIS was also created and its generalisation behaviour did not exceed 85%.

These results show that introduced multistage solution seams to be a promising solution in sea-bed classification problems. Not only it gives better results but also reduces required computation power. In the parallel structure there were 256 rules created and 12480 parameters had to be tuned. For comparison, in the two-layer multistage classifier there were 112 rules and only 434 parameters, and in the four-layer one only 76 rules were created and only 224 parameters had to be adjusted. Even this amount can be reduced, as the main improvement of the classification results is observed after the second or third layer and a parameter processed in the fourth layer doesn't enhance the results a lot. Therefore it might be possible to eliminated one stage, but this will be investigated further.

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