17th SYMPOSIUM ON HYDROACOUSTICS

Jurata May 23-26, 2000

INCREMENTAL NEURO-FUZZY CLASSIFIERS OF SEABED USING WAVELET DECOMPOSITION

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The neuro-fuzzy classifier of seabed type from acoustic echoes was investigated in the context of possible reducing the number of input parameters. The incremental architecture of fuzzy neural network classifier (IFNN) was used in the experiment, utilising dual-frequency echo collection. In particular, the wavelet decomposition of these bottom echoes was used to generate input parameters of IFNN. The Principal Component Analysis (PCA) was subsequently applied for redundant parameters reduction.

1. INTRODUCTION

Acoustic methods of bottom characterisation have known advantages, as they are non-invasive and more cost effective than other methods. The methods of so called normal incidence – which use the backscatter data from a single-beam echosounder – have achieved special attention, due to their simplicity and versatility. The various normal incidence methods have their advantages and shortcomings or constraints. In general, the performance of the methods and their generalisation ability increases concurrently with the number of input parameters or dimensionality of the input vector space [1], [2]. This feature is specifically characteristic for the class of artificial intelligence methods, and neuro-fuzzy methods in particular [2].

In such a context, the objective of the paper was to investigate the possibility of reducing the redundant number of input parameters without decreasing the quality of seafloor classification from acoustic echoes. This sort of "feasibility study" was carried out using neuro-fuzzy IFNN structure, that processed the set of data consisting of wavelet coefficients of bottom echoes. The redundancy of the input parameters vector space was reduced by application of the Principal Component Analysis (PCA).

2. INCREMENTAL FUZZY NEURAL NETWORK CLASSIFIER

Classifier implemented in the experiment described in this paper is based on the fundamental structure of the Sugeno fuzzy inference system [3]. The neuro-fuzzy version of this model (ANFIS – artificial neural network fuzzy inference system) is able to derive the optimal shapes of membership functions and number of fuzzy rules from the given data sets. The structure of fuzzy inference subsystem is "hidden" in the neural network, therefore the system adapts its parameters in the learning process.

The ANFIS was implemented in the multistage incremental architecture IFNN, which basic structure is depicted in Fig. 1.

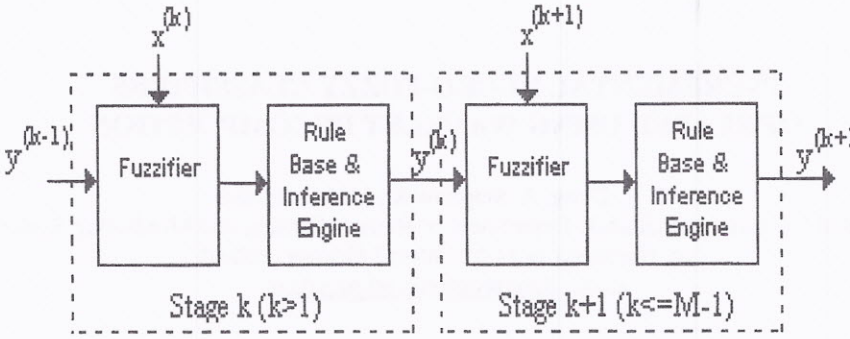


Fig. 1. Basic structure of the Sugeno IFNN adopted for a multistage system

Multistage fuzzy reasoning mechanism was explained in detail in [2].

3. WAVELET ANALYSIS

Wavelet analysis represents particular windowing technique with variable-sized regions, which allows to use the longer time intervals for extracting more precisely low frequency information, and shorter intervals for high frequency information. Mathematically, the continuous wavelet transform (CWT) of signal $x(t)$ is defined similarly to Fourier transform as a projection of a signal x on a family of zero-mean functions derived from an elementary function (mother wavelet) by translations and dilations [4], [5]:

$$C(a,b) = \int_{-\infty}^{\infty} x(t)\psi(a,b,t)dt \ , \tag{1}$$

where: $C(a,b) \equiv C_{a,b}$ – a set of wavelet coefficients;

$\psi(a,b,t) \equiv \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right)$ - wavelet function;

a – the variable representing scale;

b – the variable representing position.

By definition, the wavelet transform is more a time-scale than time-frequency representation. However, for wavelets which are well localised around a non-zero frequency f_0 at a scale $a=1$, a time-frequency interpretation is possible due to the formal identity $f = \frac{f_0}{a}$.

Wavelet Transform demonstrates its usefulness in variety of applications [4] [5]. It seems to be also well suited and attractive tool for recognition of seabed type from acoustic echoes. However, its computation is time consuming, so for actual implementation the Discrete Wavelet Transform (DWT) was used. The discrete version of this transform consists of $\log_2 N$ stages (levels) for a signal containing N samples. In every step, two sets of coefficients are obtained by convolution with a low-pass filter for approximation coefficients and with a high-pass filter for detailed ones, followed by downsampling. In the following step, the same procedure is used for approximation coefficients only. This tree algorithm developed by Mallat [5] can be implemented very efficiently and allows a real-time computation during measurement. The DWT tree algorithm was used for calculation of wavelet coefficients from seabed echoes acquired by the digital echosounder – see section 4.

Sample results of these computations are presented in Fig. 2 in the form of four sets of wavelet coefficients, which were obtained for four bottom types (Fig. 2a). The corresponding echo envelopes for these four bottom types are also shown in Fig. 2b.

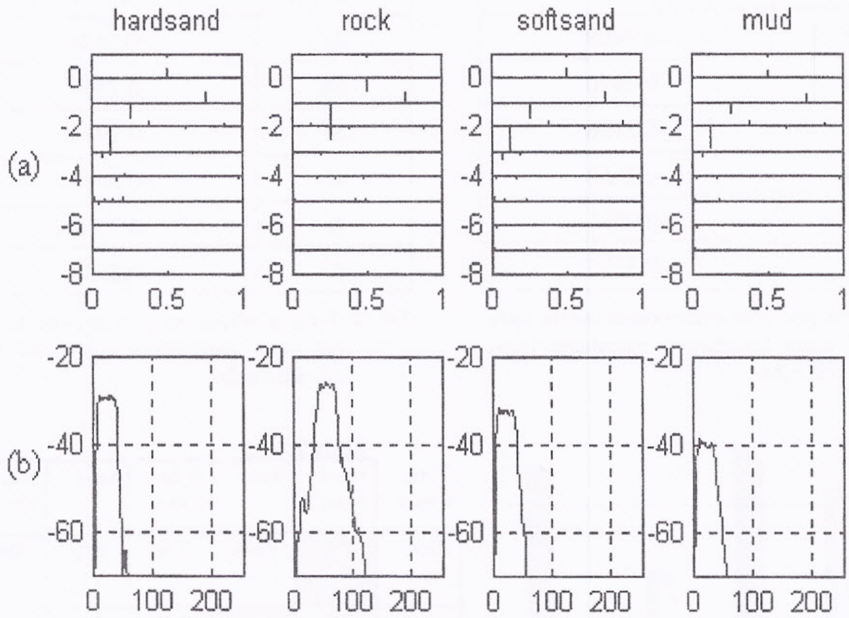


Fig. 2. Discrete Wavelet Transform of bottom echoes collected on 120kHz: a) Wavelet coefficients set; b) Corresponding echo envelopes of four types of bottom

4. PRINCIPAL COMPONENT ANALYSIS OF EXPERIMENTAL DATA

Experimental data was acquired from acoustic surveys carried out in Lake Washington using a single-beam digital echosounder DT4000 with two operating frequencies: 38 kHz and 120 kHz. The sampling rate of backscattered bottom echoes was 41.66 kHz. For the experiment, only the data obtained from the anchored vessel in the same location for each bottom type and each frequency was further investigated in order to assure more reliable grandtruthing information.

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

A set of parameters was extracted from each digitised bottom echo:

1) The sums of the wavelet coefficients of i^{th} level absolute values S_i, where $i = 1, 2, ...,8$;

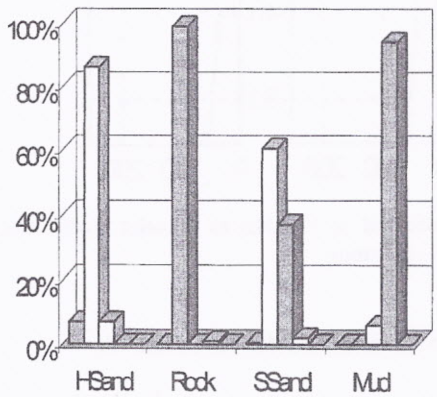
2) The sums of the absolute values of all wavelet coefficients, *S*;
3) First wavelet coefficient of third level, *C*.

Parameter	1st principal component coefficient
S1	0,3326
S2	-0,0382
S3	0,3147
S4	0,1537
S5	-0,2869
S6	-0,2870
S7	-0,2908
S8	-0,2650
S	-0,0581
C	-0,3162

Tab. 1. First principal components coefficients for input parameters calculated from 38 kHz echo

Parameter	1st principal component coefficient
S1	0,2834
S2	-0,3012
S3	0,1952
S4	-0,2775
S5	-0,2426
S6	-0,2558
S7	-0,2916
S8	-0,2388
S	-0,3000
C	-0,2534

Tab. 2. First principal components coefficients for input parameters calculated from 120 kHz echo



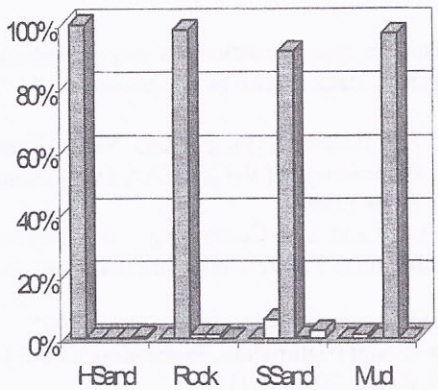
a)

Classified as

True Class	Hard Sand	Rock	Soft Sand	Mud	Not known
Hard Sand	7%	86%	7%	0%	0%
Rock	0%	99%	0%	1%	0%
Soft Sand	0.5%	60.5%	37%	2%	0%
Mud	0%	0%	6%	94%	0%

b)

Fig. 3. Box diagram (a) and confusion matrix (b) of the testing results after the 1st stage of the IFNN system (the sums of the first level wavelet coefficients at 120 kHz); percentage of echoes correctly classified in total is **50.1%**



a)

Classified as

True Class	Hard Sand	Rock	Soft Sand	Mud	Not known
Hard Sand	99.5%	0%	0%	0%	0.5%
Rock	0%	97.9%	1.1%	1.1%	0%
Soft Sand	0%	6%	91%	0.5%	2.5%
Mud	0%	1.3%	0%	96.7%	0%

b)

Fig. 4. Box diagram (a) and confusion matrix (b) of the testing results after the 2nd stage of the IFNN system (the sums of the first level wavelet coefficients at 38 kHz); percentage of echoes correctly classified in total is **96%**

In this way, 10 wavelet coefficients parameters were extracted for each frequency from the echo. In total, 20 parameters were extracted as an input parameters for further analysis. The developed IFNN classifier was trained on a learning set of data and its generalisation ability was checked on testing data. The learning set counted 200 records and testing set had 645 records.

To select, which of mentioned parameters of backscattered echoes from seabed is most useful in the classification process as the input parameter, the PCA was applied [6]. Principal component analysis was carried out using 10 input parameters for each frequency. The results of PCA are presented in Tab. 1 for 38 kHz and in Tab. 2 for 120 kHz. The analysis shows that the sums of the wavelet coefficients of the first level wavelet coefficients have the first principal component of largest value at both frequencies. Therefore, these sums were chosen for further investigation. In the testing process, the percentage of correctly classified echoes obtained was 50.1% after the 1st stage (Fig. 3) and 96% after the 2nd stage (Fig. 4).

5. CONCLUSIONS

The application of a Digital Wavelet Transform of the backscattered echoes for seafloor classification purposes was investigated. The wavelet coefficients obtained from DWT were conbined with six other echo parameters (energy, amplitude, etc.) by means of PCA. The PCA reduced the number of input parameters to only one, viz. sum of the first level wavelet coefficients (for each of two frequencies), that appeared to be sufficient enough for achieving good classification results.

The accuracy of the developed classification schemes based on the time-frequency approach using the wavelet coefficients is better in comparison with time-domain methods that use the echosounder data. This is due to including both temporal as well as spectral characteristics of echo features in the classification procedure.

These results show that introducing the proposed multistage system seams to be a promising solution in seabed classification problems.

REFERENCE

[1] Stepnowski A., Maciołowska J., Dung T. V., Bottom type identification using combined neuro-fuzzy classifier operating on multi-frequency data, Archives of Acoustics, 24, 3, 365-378 (1999).

[2] Dung T. V., Maciołowska J., Stepnowski A., Sea Bottom Typing Using Neuro-Fuzzy Classifier Operating on Multi-Frequency Data, Proceedings of the 2nd EAA International Symposium on Hydroacoustics, Gdańsk-Jurata, 79-84 (1999).

[3] Jang J. S. R., Sun C. T., Mizutani E., Neuro-Fuzzy and Soft Computing – A Computational Approach to Learning and Machine Intelligence, Prentice-Hall International, Inc. 1997.

[4] C. K. Chui ed., Wavelet: A Tutorial in Theory and Applications, Academic Press 1992.

[5] M. Moszyński, Wavelet decomposition in target strength estimation, Proceeding of the 4th European Conference on Underwater Acoustics, Rome, 205-210 (1998).

[6] Simpkin P. G., Collins W. T., Results from the use of broad-band, sub-bottom seismic data with statistically based sediment classification techniques, Proceedings of High Frequency Acoustics in shallow Water, Lerici, Italy, 493-500 (1997).