ARTIFICIAL NEURAL NETWORKS FOR INTERPOLATION AND IDENTIFICATION OF UNDERWATER OBJECT FEATURES

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Artificial neural networks can be applied for interpolation of function with multiple variables. Because of concurrent processing of data by neurons, that approach can be seen as hopeful alternative for numerical algorithms. From these reasons, the analysis of capabilities for some models of neural networks has been carried out in the purpose for identification of the underwater object properties. Features of the underwater objects can be recognized by characteristics of a amplitude according to the frequency of measured signals. The feed-forward multi-layer networks with different transfer functions have been applied. Those network models have been trained by some versions of back-propagation algorithm as well as the Levenberg-Marquardt gradient optimization technique. Finally, for determination of the amplitude for the frequency of signal by the two-layer network with the hidden layer of the radial neurons has been proposed.

INTRODUCTION

Artificial neural networks (ANN) are developed for modeling the contour of the sea bed with success [1]. They can be applied for identification of ship sort and the distance between it and the hydro-phone [7]. Moreover, neural models can be employed in statistics, cognitive psychology and artificial intelligence. Neural models designed with emulation of the central nervous system in mind are a subject of theoretical neuroscience, too.

Neural networks or parts of neural networks are used as components in larger systems that combine both adaptive and non-adaptive elements. While the more general approach of such adaptive systems is more suitable for real-world problem solving, it has far less to do with the established artificial intelligence connectionist models. What they do however have in common is the principle of non-linear, distributed, parallel and local processing and adaptation [3].

In this paper, the analysis of capabilities for some models of neural networks has been carried out in the purpose for interpolation and identification of the underwater object features. The gradient optimization algorithm by Levenberg-Marquardt (LMA) provides a numerical solution to the mathematical problem of minimizing a nonlinear function over a space of alternatives. This minimization problem arises especially in least squares curve fitting. LMA interpolates between the Gauss-Newton algorithm and the method of gradient descent. The LMA is more *robust* than the Gauss-Newton algorithm, which means that in many cases it finds a solution even if it starts very far off the final minimum [2]. On the other hand, for well-behaved functions and reasonable starting parameters, the LMA tends to be a bit slower than the Gauss-Newton algorithm. For processing the amplitude for the given value of the frequency of signal two-layer network with the hidden layer of the radial neurons has been proposed.

1. ANN FOR SEA DEPTH DETERMINATION

Artificial neural networks can be used for determination of the sea depth in the positions that did not scanned be an echo-sounder [1]. Let us assume that for the given water region the measurements have been performer and coordinates (ϕ,λ) from the Global Position Systems GPS as well and $d(\phi,\lambda)$ from the synchronized sonar. Echo sounding uses sound pulses directed from the surface or from a submarine vertically down to measure the distance to the bottom by means of sound waves. Distance is measured by multiplying half the time from the signal's outgoing pulse to its return by the speed of sound in the water. *Del Grosso* formulated the relationship between the sound speed and a depth, temperature and salinity of sea water [11]:

$$d = \frac{c - 1448.6 - 4.618T + 0.0523T^2 - 1.25 * (S - 35)}{0.017}, \qquad (1)$$

where

d – depth [m]

c - sound speed [m/s] 4800 ft/s (1500 m/s) in seawater, 4708 ft/s (1435 m/s) in freshwater,

T - temperature [degrees Celsius],

S - salinity [pro mille]

Echo sounding is used to locate the bottom, too. An echo-sounder generates an acoustic pulse directly downwards to the seabed and records the returned echo (Fig. 1). The sound signal is generated by a transducer that emits and indicates the signal. The return time is recorded and converted to a depth measurement by calculating the speed of sound in water. As the speed of sound in water is around 1 500 meters/second, the time interval, measured in milliseconds, between the pulse being transmitted and the echo being received, allows bottom depth and targets to be measured. The value of underwater acoustics to the fishing industry has led to the development of other acoustic instruments that operate in a similar fashion to echo-sounders but, because their function is slightly different from the initial model of the echo-sounder, have been given different terms.

Measurements are supposed to be carried out by uniform way for the sea area. The density of sampling should be greater for the sub-regions outstandingly important or for areas that are explored the first time (Fig. 2). Data of depth are gathering along profiles because of possibilities of the rejection of fault data [4]. We reject data that exceed beyond admissible values and also data with too large changes of depth. Measurements are averaged because of avoiding the sequences of errors. Interferences can be filtered by artificial neural networks, too [6]. An effectiveness of multi-layer neural models is very high according to errors filtering and may be even equal to 40% [12].

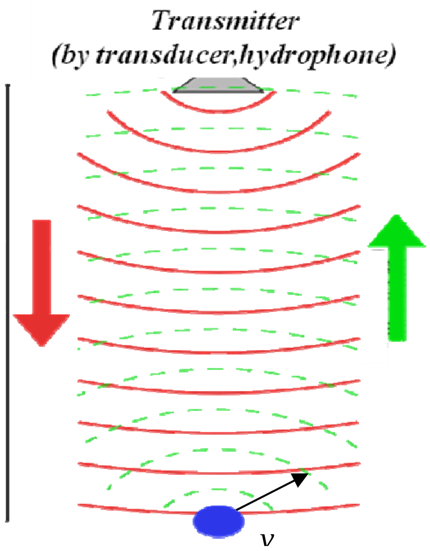

Fig.1 Emitting and indicating of signals by a transducer and a hydrophone

In the designed multi-layer neural networks, there are two input neurons and one output neuron with linear transfer function. Moreover, one or two hidden layer of neurons can be used for interpolation. Hidden neurons have radial transfer functions.

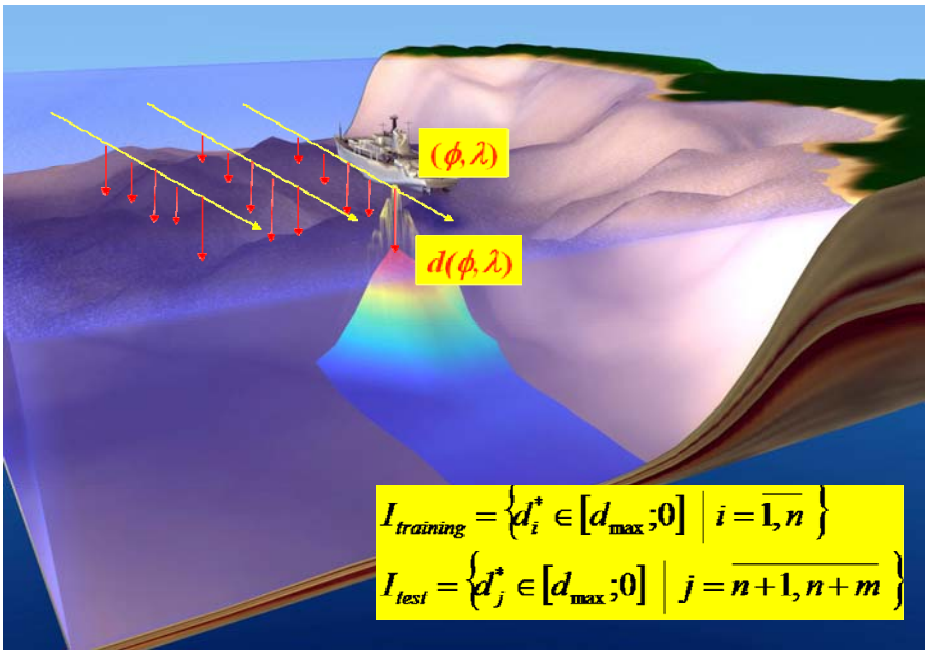

Fig.2 Recording of samples from an active echo-sounder

2. TRAINING RULES FOR NEURAL NETWORKS

Figure 3a shows the process of training the multilayer network by the standard back-propagation algorithm. We can observe the minimization of the root from the sum of squares for errors calculated at the outputs of network. There were 100 samples in the training set. Each triple from a set was randomly chosen and new values of synaptic weights and biases were calculated for the epoch. The global error was reduced to 0.471 after 1000 epochs. However, this results for 100 elements is not very promising because it should be less than 0.02 for the relative error 1%. There were two hidden layers with 5 and 10 neurons, respectively. Although, the numbers of neurons were increased, no improvement can be done. Similar outcomes have been obtained by the model with the hidden layer. In that case, arithmetic error was equal to 8.05% and maximal error - 41.2%. An assigning more time did not cause the improvement In the reasonable rate. So, we studied back-propagation algorithm with momentum and back-propagation algorithm with adaptive rate of learning [5].

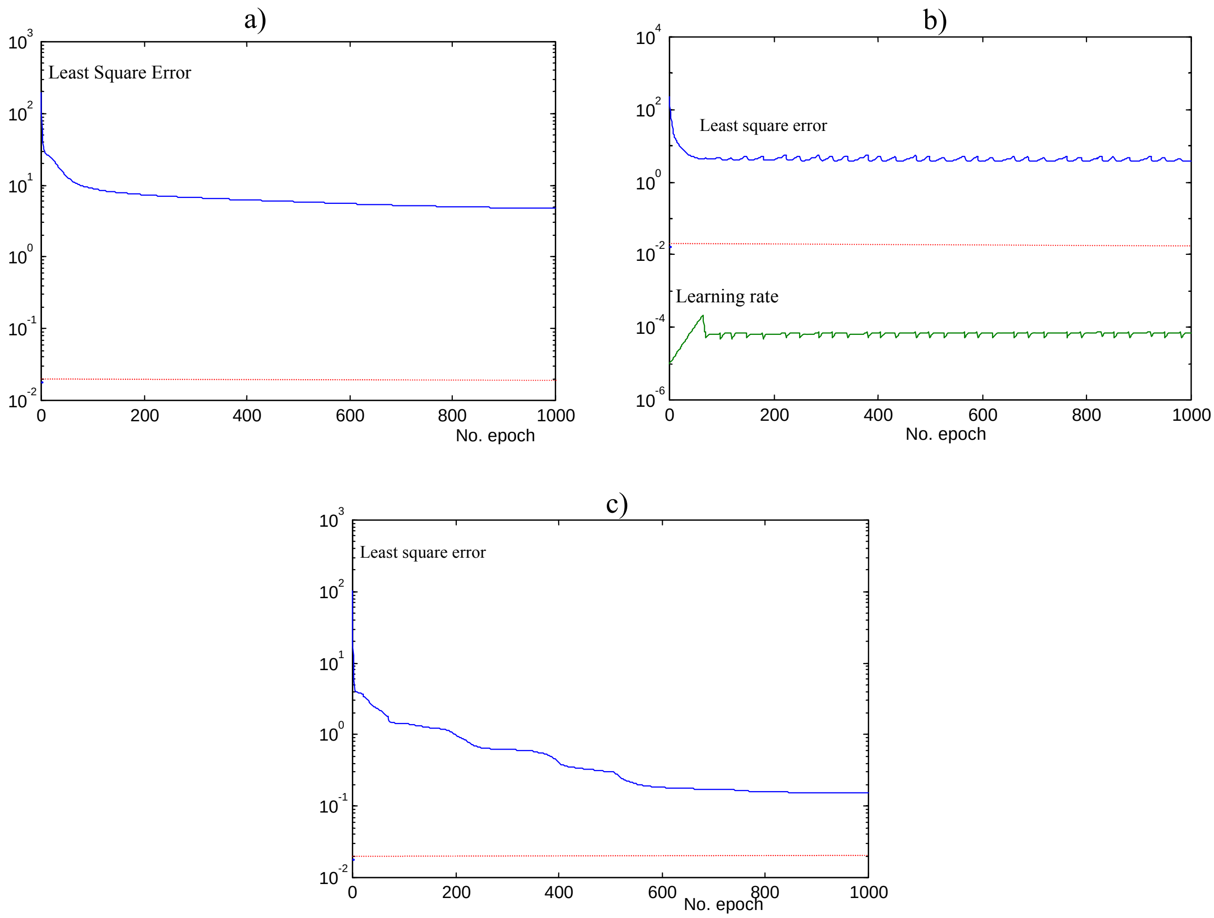

Fig.3 Minimization of the least square terror by:

a) back-propagation algorithm

b) back-propagation algorithm with adaptive learning rate

c) LMA

Biases and weights from two inputs to m hidden neurons are decision variables. So, there are $3m$+2 variables. To avoid the network over-fitting, we assume the number of depth patterns should be greater than $3m+2$. The network can avoid random errors, but it has difficulties with systematic errors from an active echo-sounder and GPS.

Preparing input data is important for the quality of finding the depth map of seabed. Moreover, the rate of learning can be accelerated. Networks that were trained with the normalized data to the period (-1, 1) learned faster and gave better outcomes. Value of the coordinate ϕ is normalized to the value $\bar{\phi}$ that is input data to the network, as follows:

$$\bar{\phi} = \bar{\phi}_{\min} + \frac{\bar{\phi}_{\max} - \bar{\phi}_{\min}}{\phi_{\max} - \phi_{\min}} (\phi_{\max} - \phi_{\min}), \tag{2}$$

where

ϕ^{min}, ϕ^{max}, λ^{min}, λ^{max} – constraints for coordinates of position, $\phi^{min} \le \phi \le \phi^{max}$, $\lambda^{min} \le \phi \le \lambda^{max}$,

d^{max} – maximal depth of water region, $d^{max} \le d \le 0$,

$\bar{\phi}_{\min}$, $\bar{\phi}_{\max}$ - limits of normalization.

Similarly, we can determined $\bar{\lambda}$ and $\bar{d}$. Limits of normalization –1 and 1 are commonly used [9]. However, they can developed for network to values –0,9 and 0,9 because for that period of values sigmoid transfer function there is intense increase functional value with the relatively small value of variable increment.

The training set can include 100, 400 or 900 elements (ϕ,λ,d). In the standard back-propagation algorithm, the rate of training is constant and the best results have been obtained for 0.0001. On the other hand, a learning rate is increased after an epoch for the decrease of the last square error. If the error is not decreased or the decreasing is very small, then the rate factor is decreased because value of error can be in the neighborhood of the local minimum of error function. Figure 3b shows the process of training network by back-propagation algorithm with adaptive rate of learning.

The least square error was decreased from 4.71% to 3.85% and the average error from 8.05% to 6.08%. However the maximal error increased from 41.2% to 42.8%. Back-propagation algorithm with momentum, that can omit a local minimum of an error function, decreased the maximal error to 39.4%.

The Levenberg-Marquardt algorithm is from 10 till 100 times faster than back-propagation ones. Figure 3c shows outcomes obtained during training by this algorithm. After 1000 epochs the least square error was 0.15% and the average error 1.18%. However the maximal error was equal to 10.2% that was unacceptable.

3. CAPABILITES OF RADIAL NEURAL NETWORKS

Radial basis functions (RBF) are powerful techniques for interpolation in multidimensional space [8]. A RBF is a function which has built into a distance criterion with respect to a centre (Figure 4). Radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoid hidden layer transfer characteristic in multi-layer perceptrons. RBF networks have two layers of processing: In the first, input is mapped onto each RBF in the 'hidden' layer. The RBF chosen is usually a Gaussian [10]. In regression problems, the output layer is a linear combination of hidden layer values representing mean predicted output. The interpretation of this output layer value is the same as a regression model in statistics. In classification problems, the output layer is typically a sigmoid function of a linear combination of hidden layer values, representing a posterior probability. Performance in both cases is often improved by shrinkage techniques, known as ridge regression in classical statistics and known to correspond to a prior belief in small parameter values (and therefore smooth output functions) in a Bayesian framework.

Standard multilayer networks develop the stochastic approximation function of two variables transferring the set of input variables $X = \{(\varphi, \lambda) \in R^2 \mid \varphi_{\min} \le \varphi \le \varphi_{\max}, \lambda_{\min} \le \lambda \le \lambda_{\max}\}$ into the set of depth. In the linear or sigmoid neurons, the level of activation u_m is calculated, as follows [9]:

$$u_m = b_m + \sum_{r=1}^{R} p_r w_{rm}, \quad m = \overline{1, M}, \tag{3}$$

where

b_m – value of the mth bias,

p_r – value of the rth input,

w_{rm} – value of the synaptic weight from rth input to the mth neuron of the first layer,

R – number of inputs,

M – number of neurons in the first layer.

In the radial neurons of hidden layer, u_m is multiplication bias by the distance between the vector of inputs p and vector of weights w calculated, as follows [11]:

$$u_m = b_m \sqrt{\sum^{R} (p_r - w_{rm})^2}, \quad m = \overline{1, M}. \tag{4}$$

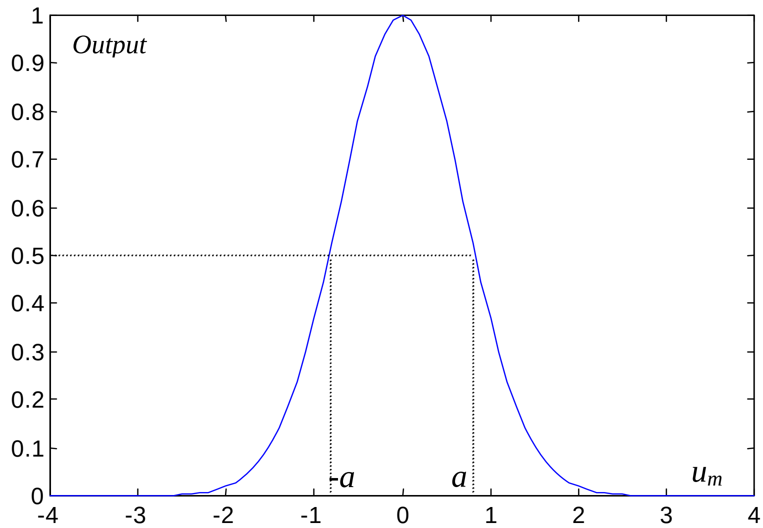

Fig.4 A radial function

If the distance between p and w decreases, then the output from this neuron increases until it obtains value 1 for the p=w. To some extend, a radial neuron is the similarity measure between p and w. A bias scales that distance. If this distance is equal to a/b_m, then output is 0.5. Radial neurons from the hidden layer are connected with the linear output neuron. That approach was the most effective and after 93 epochs the least square error was 10^{-6} %.

Radial networks of networks support modeling of the shape of the seabed with the reasonable precision. Inputs of network are coordinates of position and an output is the depth of water. Time of the depth determination is equal time of few instruction run. There is possibility to present different cut of the depth map.

Patterns to the training set are selected randomly from the measured data carried out during preferred weather conditions. The set of training should not exceed 1000 elements for a sub-region. The plane of water region is supposed to be divided on set of rectangles with the similar size. Common areas with the size 10% of sub-region are required between two neighbors sub-regions. If the distance between input vector and weights decreases in the radial network, then the output from this neuron increases until it obtains value 1. A radial neuron is the similarity measure between these vectors. A bias scales that distance. Radial neurons from the hidden layer are connected with the linear output neuron.

4. IDENTIFICATION OF UNDERWATER OBJECT FEATURES

Vessels consist of many rotational and reciprocating machinery components for their propulsion, navigation and every-day life aboard [7]. So, we can consider principal characteristics of noise radiated by ships such as: waveforms of underwater noise and vibration, sound spectrograms with spectra, and equal pressure contours. These characteristics change themselves with speed of the vessel in a complex manner because ship's service diesel generator (SSDG) creates a series of harmonics which amplitudes and frequencies are independent of ship speed. Moreover, a propeller and main engines radiate a noise that increases with speed of the vessel. What is more, a propeller noise has hybrid forms having features and an origin as machinery (tonals). Finally, there is a hydrodynamic noise with a broad-band character because of irregular flow of water.

Figure 5 presents the hydro-acoustic pressure spectrum and a vibration spectrum made at the same time [7]. Below them, the coherence function between these two signals is shown. The best coherence is if this function is equal to one. It can be seen in some frequencies for example at twenty five Hz.

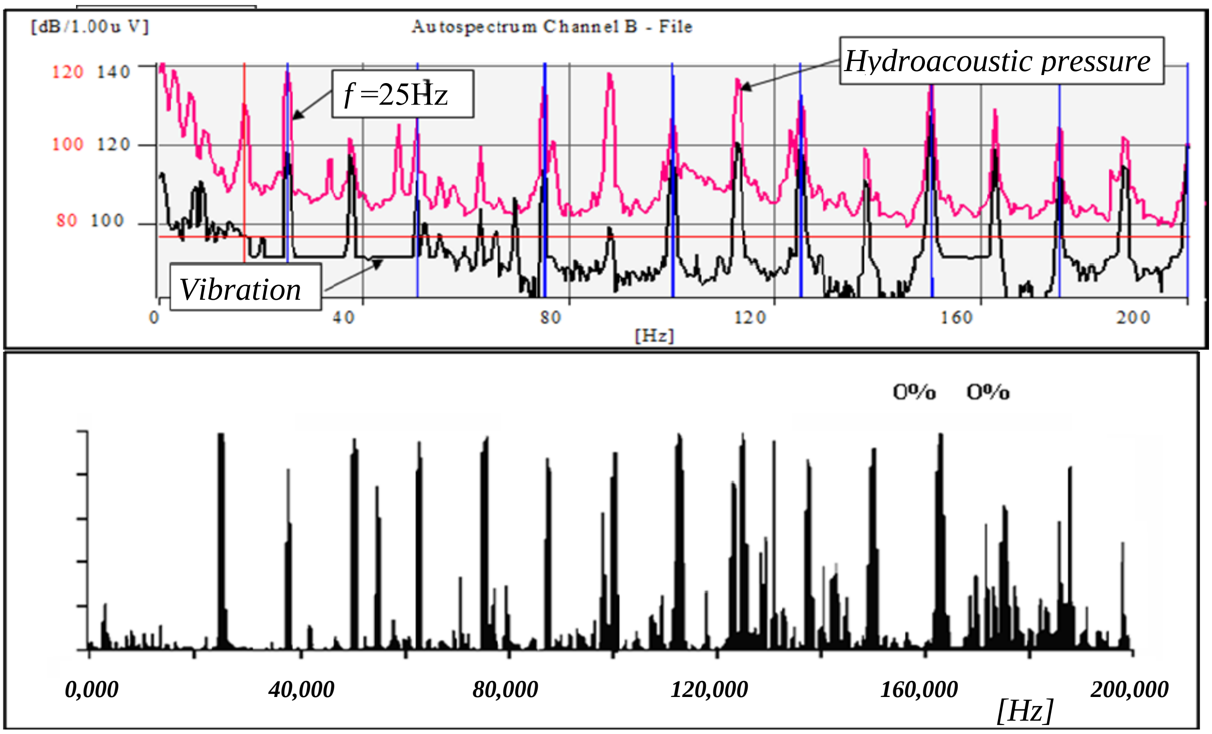

Fig.5 The hydro-acoustic pressure spectrum and a vibration spectrum

Figure 6 presents the sound pressure levels from different elements of vessels [7].

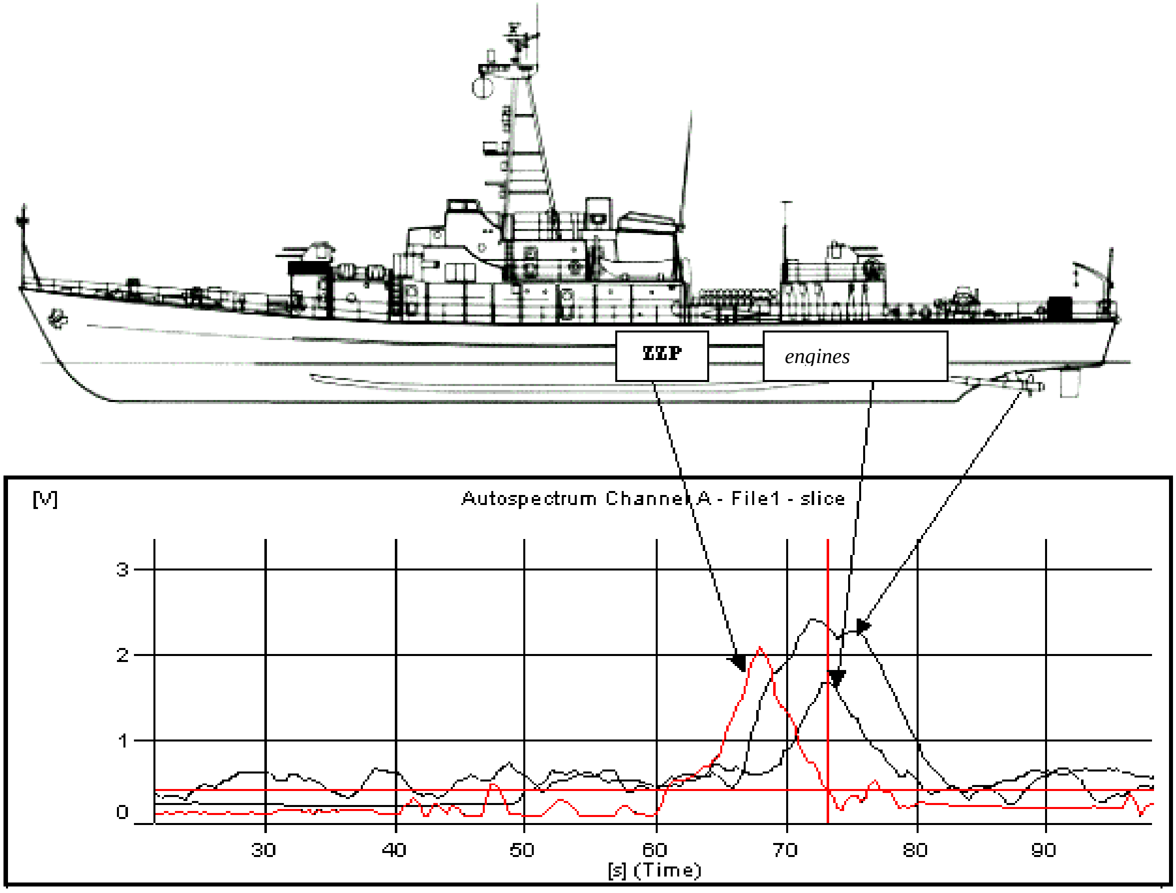

Fig.6 The sound pressure levels from different elements of vessels

In the shallow water, the effective solution to a sound evaluation is the sound intensity. We often measure it instead of sound pressure level which is very changeable. Sound intensity is measured using special type of a probe which consists of from two to four sensors. A sound intensity spectrogram can be prepared. The sound intensity level can be measured in Watts per square meters. We can show the pressure levels for different frequencies: sixty three Hz, two hundred fifty Hz, two kilo Hz. The nosiest place is usually located near the stern. It is possible to present an influence of a hull into the pressure level.

Moreover, there is the effect of screening by the bow of the moving ship. The level is decreasing in the bow direction. In that case, a sound pressure level is changing with ship speeds. Firstly, the quiet noise is from working auxiliary machinery (generators). The ship is going here in a quiet mode because main engines and propellers give less noise than auxiliary machinery. After increasing speed of a vessel, we have the beginning of cavitations from a flow noise and propellers. The main engines give also some noise for higher speed. The main machines may influence into the underwater noise spectrum because of a rotated shaft. It could be if a frequency is about eight Hz. Important frequency influence is from ship's service Diesel generator. It could be about thirty seven Hz. That harmonic is from diesel firing rate connected with cylinder firing cycles. Next tonals are from propeller rotation and from working of the main engines.

The training techniques for hidden neurons with sigmoid activation functions based on several back-propagation algorithms have been tested. We studied standard back-propagation algorithm, back-propagation algorithm with momentum, and back-propagation algorithm with adaptive rate of learning. Furthermore, the Levenberg-Marquardt algorithm has been applied for training the ship identification network. The training set of patterns, preparing input data, training of network, and evaluation of the quality of networks are crucial steps according to methodological approach. Software has been implemented in Matlab language, and numerical experiments have been developed by PC with processor Core2Duo/3 GHz.

If the training set has too many patterns, then the learning time can be too long, as well. On the other hand, sampling of patterns is supposed to be representative for all sub-regions. If there is a rapid whole in the seabed and there in no pattern of it, then model of network is not capable to recognize this whole. It is important to carry out the measurement for different wheatear conditions as well as different perturbations. So, we suggest to consider as much as possible patterns in the learning set for the given time limit of training.

Capability of network over-fitting to the training set is related to the size of that network. The over-fitted network has difficulties with generalization of the knowledge for untrained positions.

5. CONCLUDING REMARKS

The noise of a moving vessel is connected with the way of mounting and vibration of the machines and next transmission in various paths into the water as underwater sound. The knowledge of the levels and structures of underwater noise radiated by ships is important for monitoring the technical state of their mechanisms.

Information about transmission of acoustic energy generated by ships is important for identification of ship's noise sources for example: main engines, auxiliary machinery, hull, shaft, propeller.

Radial networks of networks support an identification process with the reasonable precision. Inputs of network are hydro-acoustic pressure values. Time of the identification is equal time of few computer instruction run. There is possibility to present the distance from the ship and the microphone.

Patterns to the training set are selected randomly from the measured data carried out during preferred speed and ship sorts. The set of training should not exceed 1000 elements for a network. The space of the hydro-acoustic pressure values is supposed to be divided on set of sub-spaces with the similar size. Common areas with the size 10% of sub-region are required between two neighbors sub-regions.

The analysis of capabilities for some models of neural networks has been carried out in the purpose for identification of ship and a distance. The feed-forward multi-layer networks with different transfer functions have been tested. These networks have been trained by back-propagation algorithm and its versions with some improvements. The Levenberg-Marquardt algorithm is from 10 till 100 times faster than back-propagation ones. If the distance between input vector and weights decreases in the radial network, then the output from this neuron increases until it obtains value 1. A radial neuron is the similarity measure between these vectors. A bias scales that distance. Radial neurons from the hidden layer are connected with the linear output neuron.

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