Ships Classification Basing On Acoustic Signatures

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Abstract: - The paper presents the technique of artificial neural networks used as classifier of hydroacoustic signatures generated by moving ship. The main task of proposed solution is to classify the objects which made the underwater noises. Firstly, the measurements were carried out dynamically by running ship past stationary hydrophones, mounted on tripods 1 m above the sea bottom. Secondly to identify the source of noise the level of vibration were measured on board by accelerometers, which were installed on important components of machinery. On the base of this measurement there was determined the sound pressure level, noise spectra and spectograms, transmission of acoustic energy via the hull into water. More over it was checked by using coherence function that components of underwater noise has its origin in vibrations of ship's mechanisms. Basing on this research it was possible to create the hydroacoustic signature or so called "acoustic portrait" of moving ship. Next during the complex ships' measurements on Polish Navy Test and Evaluation Acoustic Range hydroacoustic noises generated by moving ship were acquired. Basing on these results the classifier of acoustic signatures using artificial neural network was worked out. From the technique of artificial neural networks the Kohonen networks which belongs to group of self organizing networks where chosen to solve the research problem of classification. The choice was caused by some advantages of mentioned kind of neural networks like: they are ideal for finding relationships amongst complex sets of data, they have possibility to self expand the set of answers for new input vectors. To check the correctness of classifier work the research in which the number of right classification for presented and not presented before hydroacoustic signatures were made. Some results of research were presented on this paper. Described method actually is extended and its application is provided as assistant subsystem for hydrolocations systems of Polish Naval ships.

Key-Words: - Self-Organizing Map, Kohonen's neural networks, Hydroacousitc signatures, Classification.

1 Introduction

Classification is a procedure in which individual items are placed into groups based on quantitative information on one or more characteristics inherent in the items (referred to as traits, variables, characters, etc) and based on a training set of previously labeled items [7, 8].

Formally, the problem can be stated as follows: given training data $\{(x_1, y_1), \dots, (x_n, y_n)\}$ produce a classifier $h: X \to Y$ which maps an object $x \in X$ to its classification label $y \in Y$. Classification algorithms are very often used in pattern recognition systems [5].

While there are many methods for classification, they are solving one of three related mathematical problems. The first is to find a map of a feature space (which is typically a multi-dimensional vector space) to a set of labels. This is equivalent to partitioning the feature space into regions, then assigning a label to each region. Such algorithms (e.g., the nearest neighbor algorithm) typically do not yield confidence or class probabilities, unless post-processing is applied. Another set of algorithms to solve this problem first apply unsupervised clustering to the feature space, then attempt to label each of the clusters or regions [7].

The second problem is to consider classification as an estimation problem, where the goal is to estimate a function of the form:

$$P(class|\vec{x}) = f(\vec{x};\vec{\theta}) \tag{1}$$

where:

$\vec{x}$ is the feature vector input;

$f(\cdot)$ is the function typically parameterized by some parameters $\vec{\theta}$.

In the Bayesian approach to this problem, instead of choosing a single parameter vector $\vec{\theta}$, the result is integrated over all possible thetas, with the thetas weighted by how likely they are given the training data D:

$$P(class|\vec{x}) = \int f(\vec{x};\vec{\theta}) P(\vec{\theta}|D) d\vec{\theta} \tag{2}$$

The third problem is related to the second, but the problem is to estimate the class-conditional probabilities $P(\vec{x}|class)$ and then use Bayes' rule to produce the class probability as in the second problem.

The most widely used classifiers are the Neural Network (Multi-layer Perceptron, Self Organizing Maps), Support Vector Machines, k-Nearest Neighbours, Gaussian Mixture Model, Gaussian, Naive Bayes, Decision Tree and RBF classifiers.

In this paper the hydroacoustics signals classification is understood as the process of automatically recognition what kind of object is generating acoustics signals on the basis of individual information included in generated sounds. Hydroacoustics signal classification is a difficult task and it is still an active research area. Automatic signal classification works based on the premise that sounds emitted by object to the environment are unique for that object. However this task has been challenged by the highly variant of input signals. The ship own noise is combined with technical environmental noise coming from remote shipping, ship-building industry ashore or port works. There exists also the noise of natural origin: waves, winds or rainfalls. Additional obstruction in the process of spectral component identification can be the fact that various ship's equipment may be the source of hydroacoustical waves of similar or same frequencies. The propeller is the dominant source of the hydroacoustical waves at higher vessel speeds. It generates the driving force that is balanced by the resistance force of the hull. It also stimulates the vibrations of the hull's plating and all elements mounted on it. It should be noticed that, sounds signals in training and testing sessions can be greatly different due to above mentioned facts and because of object sounds change with time, efficiency conditions (e.g. some elements of machinery are damaged), sound rates, etc. There are also other factors that present a challenge to signal classification technology. Examples of these are variations of environment conditions such as depth and kind of bottom of area were measured take place, the water parameters such as salinity, temperature and presence of organic and non organic pollutions.

Acoustic signatures have the great significance because its range of propagation is the widest of all physics field of ship. Controlling and classification of acoustic signature of vessels is now a major consideration for researchers, naval architects and operators. The advent of new generations of acoustic intelligence torpedoes and depth mines has forced to a great effort, which is devoted to classify objects using signatures generated by surface ships and submarines. It has been done in order to increase the battle possibility of submarine armament. Its main objectives are to recognize the ship and only attack this one which belongs to opponent.

In the paper the Kohonen Neural Networks were discussed as hydroacoustic signals, generated by moving ship, classifier.

2 Ship's Hydroacoustic Signatures

2.1 Transmission of acoustic energy

People, who has spent time aboard a ship known that vibration and related with them noise is a major problem there. First off all it should be proved that underwater radiated noise has its origin in vibration of ships mechanism [2]. This can be done by simultaneous measurements of underwater noise and vibrations and then comparison of results using coherence function. Such result are gain over during research on stationary hydroacoustic range where a measured vessel is anchored between buoys which determine the area of range (see figure 1). In this form of measurements the array of hydrophones is positioned one meter above the sea bottom and under the hall of the ship. Accelerometers are installed inside important rooms of ship (engine and auxiliary rooms) to measure vibration. The points of positioning the accelerometers are such chosen to have adequate measurements of transmission vibration energy into water as sound energy. Mostly this points are the places of foundation of main engines, auxiliary engines or set of current generator.

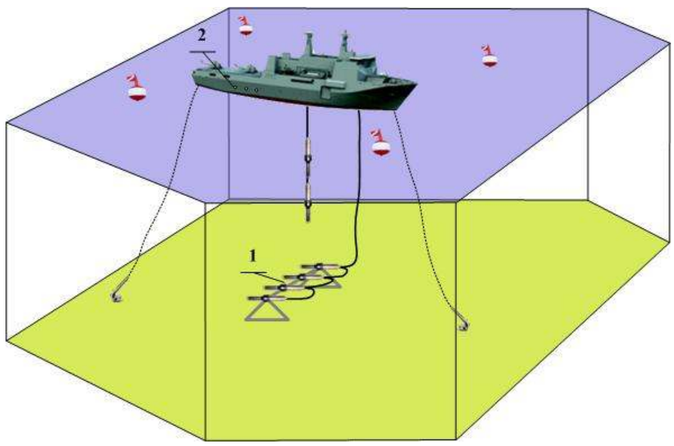

Fig. 1. Schema of hydroacoustic range during measurements using statical method; 1) sensors of acoustic signatures – array of hydrophones, 2) sensors of vibrations – accelerometers.

The directional radiation from the vessel is injected into the water medium, where not only the source but also refraction and boundaries influence the acoustic propagation. At long ranges, the low frequency noise originates mainly from a very narrow sector [11]. The ambient noise due to long – range shipping indicates that shipping noise constitutes a 20 to 30 dB elevation of the ambient noise levels in the low frequencies. What more the level of noise radiated to the sea environment in the all frequencies is increasing due to both the increased number of vessels at the sea and the increased engine power of the modern ships. Ship noise does not transmit acoustic energy uniformly in all directions, but has a characteristic directional pattern in the horizontal plane around the radiating ship as it is shown on figure 2. More noise is radiated in the aft direction, because of the working propellers and because the hull is screening in the forward direction and the wake at the rear.

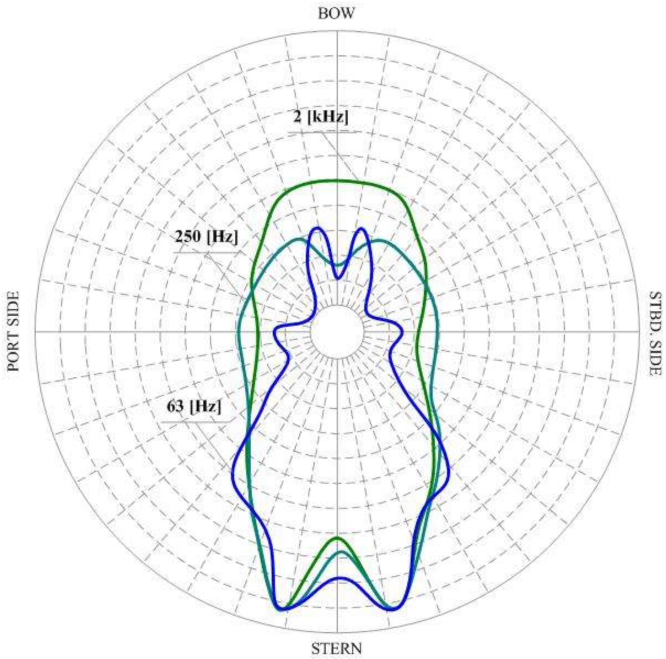

Fig. 2. Equal pressure level contours of noise around a ship

It have to be determined how much total acoustic power is radiated by a running ship and how it compares with the power used by the vessel for propulsion through the water. This can be done by measuring vibration aboard the ship (inside the engine room) and compare it into the underwater sound. The similarities between the vibration signals of chosen elements within the hull and of the ship and the underwater acoustical pressure in the water are represented by the coherence function. For two signals of pressure $p(t)$ and vibration $v(t)$ the coherence function is described ass follow [3]:

$$\gamma_{pv}^2(f) = \frac{\left|G_{pv}(f)\right|^2}{G_p(f)G_v(f)} \tag{3}$$

where:

G_p and G_v denote the corresponding spectral densities of signals $p(t)$, $v(t)$ respectively;

G_{pv} denotes the cross spectral density.

Coherence function is a real function accepting arguments from the range of:

$$O \le \gamma_{pv}^2(f) \le 1 \tag{4}$$

Therefore, the zero value occurs for signals that do not have the cause association and the one value for signals coming from the same source. Using the dependence (3) the coherence function between the signals can be determined. The components in the coherence spectrum determined this way reflect qualitative correlations associated with particular frequencies coming from a working piece of equipment.

Coherence coefficient function is convenient in this kind of research because it allows to determine the similarity between the spectra of particular signals. In the table 1 it can be seen a series of discrete components for which the coherence values are maximum that means from 0.8 to 1. The interpretation of the underwater noise of a vessel was conducted by analyzing the spectra of consecutively powered up machines and comparing them with the corresponding underwater noise. In the first phase the measurements of vibration velocities and aggregate noise (primary engines not working) were carried out. Then, the measurements were continued for the left, right and both main engines.

Table 1. Vibration and coherence function of hydroacoustic pressure and vibration.

Frequency [Hz]	Coherency function	Vibration on the hull
16.5	0.8	13
25	1	80
37.5	0.8	69
50	1	42
62.5	0.9	8.4
75	1	72
87.5	1	64
100	0.8	23
112.5	1	55
125	1	28
150	1	66
162.5	1	35
175	0.7	69
200	0.9	19

The comparison of vibrations velocities registered at the ship's hull and at the fundament of the power generators with the underwater noise were presented in table 2. Analogically, the research was conducted for the ship's main engine. The results of narrow-band spectral levels and the coherence function were shown on figure 3.

Table 2. Basic frequencies and harmonics of vibration.

Vibration	Frequency		Harmonics
	Formula	[Hz]	
Unbalanced parts	$f_n = kf_0$	25	50, 75, 100, 125, 150, 175, 200, …
Diesel firing rate	$f_s = \frac{kz_c f_o s}{4}$	12.5	25, 37.5, 50, 62.5, 75, 87.5, 100,112.5, 125, 137.5, 150, …

where:
$k = 1, 2, \ldots$ is the number of next harmonics;
f_0 is the main frequency;
s is the coefficient of stroke (equal 0.5 for four stroke engines);
z_c is the number of cylinder;

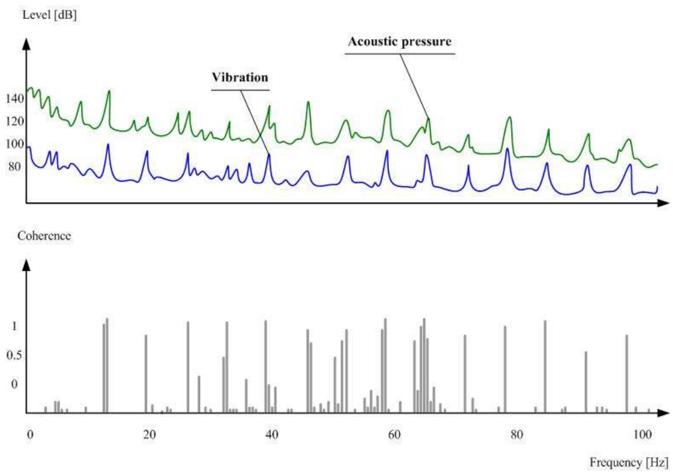

Fig. 3. Narrow-band spectra and coherence function of underwater acoustic pressure and vibration of a stationary ship

Relations between mechanical vibration and hydroacoustic field of a ship is presented by transmission coefficient of the mechanical vibration α :

$$\alpha = \frac{L_{1m,1Hz}}{\rho\, cv} \tag{5}$$

where:
$L_{1m,1Hz}$ is sound pressure level relative to 1μPa at 1 m for 1 Hz;
ρ is fluid density for sea water;
v is vibration velocity;
c is propagation velocity of sound wave.

$$L_{1m,1Hz} = L + 20\log R - 10\log \Delta f \tag{6}$$

where:
L is acoustic pressure level under ship (dB re μPa);
R is the distance between a ship and a sensor (m);
Δf is the width of an applied filter (Hz).

The results of the acoustic levels, vibration speeds and coefficient α are shown in table 3.

Table 3. The energy transmission coefficient calculated for consecutive frequencies

f (Hz)	L (Pa)	v (m/s)	α
12.5	3.14	0.001	2.2 10^{-3}
25	6.3	0.00032	1.4 10^{-2}
37.5	14.1	0.00028	3.4 10^{-2}
75	56.2	0.0005	7.7 10^{-2}

The proportionality factor ρc is the acoustic resistance (specific impedance) of the fluid and for sea water is 1.5 10^5 g/cm^2 s.
Though radiated sound is frequently expressed in spectrum levels, that is, in 1 Hz bands (shown in $L_{1m,1Hz}$), frequency analyses are more conveniently made in wider bands so the results are reduced to a band of 1 Hz. The results are reduced to a band of 1 Hz by applying a bandwidth reduction factor equal to 10 log of the bandwidth used. The distance in this case is the horizontal distance, while the actual source-to-receiver range, the radial distance, was used for these measurements. Therefore here should be calculated as 20 log range (spherical) spreading loss applies in the acoustic field at all frequencies.

2.2 Sources of ship noise and its deviations

Several sources of noise radiation from a ship exist. They have the characteristic frequency bands and are mainly dependent on speed. Among the main sources of ship noises are:

– propeller,
– machinery,
– hydrodynamic processes.

The sources of ship underwater sounds are diverse and a given source changes its sound output with ship speed. Therefore ship noises are variable complex and sound components are distributed through the entire frequency range.
The main source is the hull, which transmits the vibrations of the machinery into the water. The propellers also radiates high level of noise because of hydrodynamic streams and cavitations.

Machinery noise originates as mechanical vibrations of many devices inside a moving vessel. They create underwater noise in the following ways:

– rotating unbalanced shafts,
– repetitive discontinuities,
– explosions in cylinders,
– cavitation and turbulence in the fluid flow in pumps, pipes and valves,
– mechanical friction in bearings.

The first three of these sources radiate sounds of a discrete spectrum in which the noise is dominated by tonal components at the basic frequencies and their harmonics [11].

The harmonic structure of radiated noise is complex, and even a discrete component generated by a single source of noise is irregular and variable. With changing conditions of the ship it can be observed variations of level and frequencies.

There are various paths of sound transmission such as the mounting of the main engine or diesel generator, which connect the vibrating parts to the hull. Radiation at discrete components, caused by low frequency hull vibrations, excited by the machinery is easily detected. In the noise reduction control, it must be reduced as much as possible.

One of the methods of identification of underwater noises generated by moving ship is by investigation of its spectrum. Basing on the conducted analysis it is possible to isolate discrete components in the spectra associated with the work of mechanisms and equipment on board along with the broad band spectrum reflecting the work of the cavitating propeller, turbulent flow in piping and ventilators or bearing frictions.

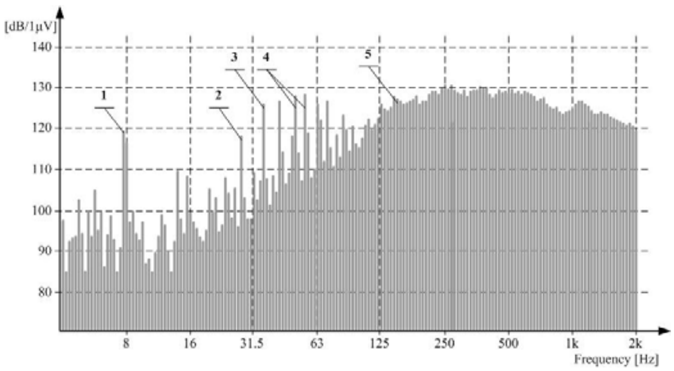

Fig. 4. The underwater noise spectrum or so called "acoustic portrait" of a moving ship; 1) shaft, 2) diesel generator, 3) propeller blades, 4) main engines, 5) propeller.

Figure 4 shows a keel aspect narrow-band power spectrum in 0.5 Hz bands of a typical ship going with the speed of 3.8 knots. The radiated noise data show high-level tonal components which are from the ship's service diesel generator, main engine firing rate and blade rate. A ship's service diesel generator creates a series of harmonics which amplitudes and frequencies are independent of ship speed. Propellers generate cavitation especially at high speeds of a vessel (above 8 kn) which creates noise having a continuous spectrum. The cavitation is production and collapse of cavities and bubbles produced by the propeller action. Cavitation noise consists of a large number of random small bursts formed by bubble collapse. As it was mentioned earlier cavitation noise has a continuous spectrum. At the higher speed of the vessel the propeller noise increases and the main energy shifts to lower frequencies [10].

The sound level spectrum constitutes a mixture of the continuous and discrete lines. The former are characterized by a maximum in the area from 50 to 200 Hz, which is a typical feature in ship noise spectra. At frequencies greater than 200 Hz, sound pressure level (SPL) falls by 6 dB, when the frequency is doubled. It means that SPL is inversely proportional to the square of the frequency. The discrete components are the most visible in a ship's spectra since they are detected even at low speeds (shown on figure 4). Moreover these discrete components of noise spectra are called "acoustic portrait", which is unique for each ship. This acoustic portrait is used to reveal the location and to identify the source of noise.

It can't be forgot that hydroacoustic signatures of ship is mainly generated by phenomena of vibrations of vessel working machinery. Therefore changing the speed of moving ship cause, first of all, the changes in sound volume which is described by sound pressure levels (shown on figure 5) what has the essential influence on the range of sound propagation.

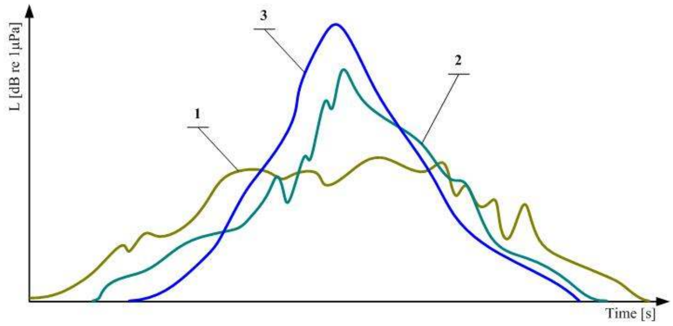

Fig. 5. The sound levels radiated by moving ship with different speeds; 1) 3.8 kn, 2) 8 kn, 3) 11 kn.

But not only the sound level radiated by moving ship change with speed but also the distribution on frequency in hydroacoustic signature of ship is changing (shown on figure 6).

Hydroacoustic signatures changes also with time (shown on figure 7). After few years of exploitation the conditions of mechanical elements of ship's mechanism aren't the same as after general renovation. Elements like bearings, pistons and other movable elements are using up. So it has influence on vibrations and the same the distribution of frequency in hydroacoustic signatures.

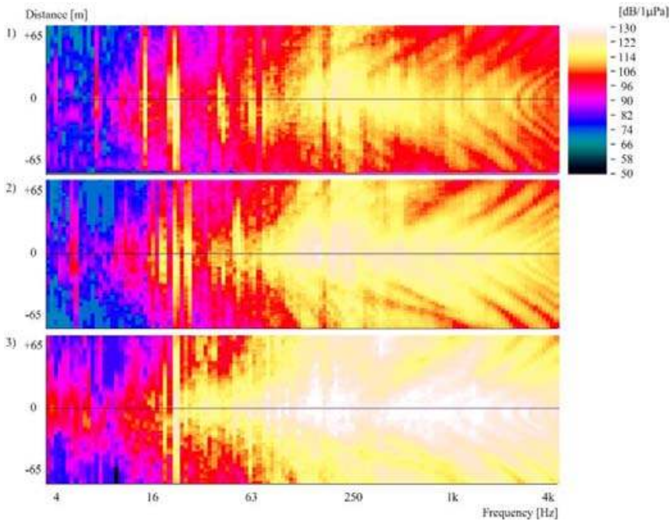

Fig. 6. The spectograms received during ship running over hydrophones with different speeds; 1) 3.8 kn, 2) 8 kn, 3) 11 kn.

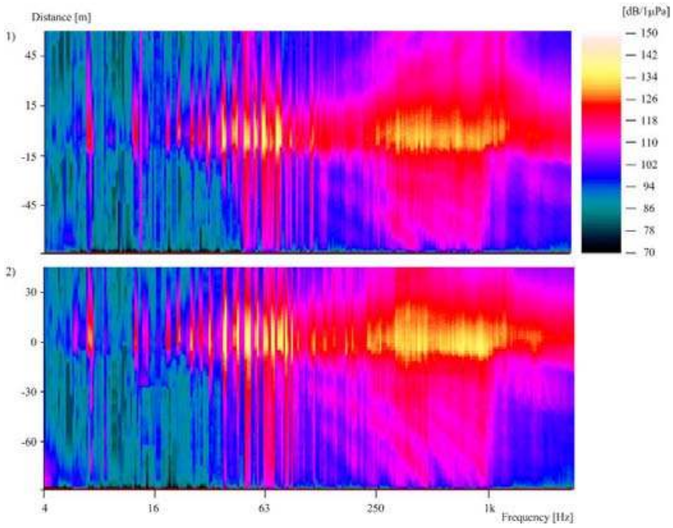

Fig. 7. The spectograms received during ship running over hydrophones in different phase of exploitation; 1) after general renovation, 2) 2 years after general renovation.

3 Classification Method

3.1 Literature review

In literature there is no description of method of classification hydracoustic signatures. It is caused because very narrow group of scientists are interesting in this kind of problem. Most of these scientists are related with military scientific center because this problem from military point of view is very important, so their research works are mostly confidential. Therefore as method of classification of hydroacoustic signatures are used mostly general methods of classification like minimal-distance classifier, feature correlation, decision tree, Bayesian method or radial basis function classifiers. Another group establish methods such as hidden Markov's model where classification is bring to problem of determine the model of signal.

Because of similarity of hydroacoustic to acoustic there exists some basis to use methods of speech recognition as method of hydroacoustic signature's classification. To solve problems of speech recognition or widely acoustic signal recognition with successful are used linear predictive coding method or artificial neural networks.

3.2 Kohonen Neural Network

Kohonen neural network, also known as The Self-Organizing Map (SOM) is a computational method for the visualization and analysis of high-dimensional data, especially experimentally acquired information [2, 4, 5].

One of the most interesting aspects of SOMs is that they learn to classify data without supervision. With this approach an input vector is presented to the network and the output is compared with the target vector. If they differ, the weights of the network are altered slightly to reduce the error in the output. This is repeated many times and with many sets of vector pairs until the network gives the desired output. Training a SOM however, requires no target vector.

For the purposes of this paper the two dimensional SOM will be discussed. The network is created from a 2D lattice of 'nodes', each of which is fully connected to the input layer. Figure 8 shows a very small Kohonen network of 4×4 nodes connected to the input layer (shown as rectangle) representing a two dimensional vector.

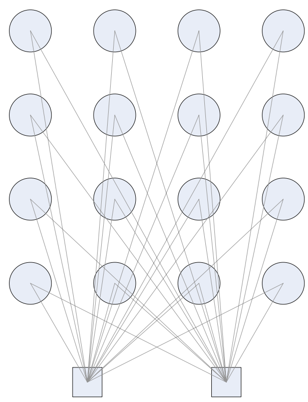

Fig. 8. A simple Kohonen network.

SOM does not need a target output to be specified unlike many other types of network. Instead, where the node weights match the input vector, that area of the lattice is selectively optimized to more closely resemble the data for the class the input vector is a member of. From an initial distribution of random weights, and over many

iterations, the SOM eventually settles into a map of stable zones. Each zone is effectively a feature classifier, so the graphical output can be treated as a type of feature map of the input space.
Training occurs in several steps and over many iterations [5]:

1) Each node's weights are initialized.
2) A vector is chosen at random from the set of training data and presented to the lattice.
3) Every node is examined to calculate which one's weights are most like the input vector. The winning node is commonly known as the Best Matching Unit (BMU).
4) The radius of the neighborhood of the BMU is now calculated. This is a value that starts large, typically set to the 'radius' of the lattice, but diminishes each time-step. Any nodes found within this radius are deemed to be inside the BMU's neighborhood.
5) Each neighboring node's (the nodes found in step 4) weights are adjusted to make them more like the input vector. The closer a node is to the BMU, the more its weights get altered.
6) Repeat step 2 for N iterations.

To determine the best matching unit, one method is to iterate through all the nodes and calculate the distance between each node's weight vector and the current input vector. The node with a weight vector closest to the input vector is tagged as the BMU.
There are many methods to determine the distance for example [7]:

– the most popular Euclidean distance is given as:

$$d(x,w_i)=\|x-w_i\|=\sqrt{\sum_{j=0}^{N}(x_j-w_{ij})^2} \tag{7}$$

– the scalar product is given as:

$$d(x,w_i)=1-xw_i=1-\|x\|\|w_i\|\cos(x,w_i) \tag{8}$$

– the measure according to norm L1 (Manhattan) is given as:

$$d(x,w_i)=\sqrt{\sum_{j=0}^{N}|x_j-w_{ij}|} \tag{9}$$

– the measure according to norm L can be written as:

$$d(x,w_i)=\max_j(|x_j-w_{ij}|) \tag{10}$$

where:
x is the current input vector;
w is the node's weight vector.

Each iteration, after the BMU has been determined, the next step is to calculate which of the other nodes are within the BMU's neighborhood. All these nodes will have their weight vectors altered in the next step. Figure 9 shows an example of the size of a typical neighborhood close to the commencement of training.
A unique feature of the Kohonen learning algorithm is that the area of the neighborhood shrinks over time. This is accomplished by making the radius of the neighborhood shrink over time.
To do this the exponential decay function can be used as follow:

$$\sigma(t)=\sigma_0\exp\left(-\frac{t}{\lambda}\right) \quad t=0,1,2,\ldots \tag{11}$$

where:
σ_0 denotes the width of the lattice at time t_0;
λ denotes a time constant;
t is the current time-step (iteration of the loop).

Every node within the BMU's neighborhood (including the BMU) has its weight vector adjusted according to the following equation:

$$w_{ij}(t+1)=w_{ij}(t)+\Theta(t)\eta(t)(x_j(t)-w_{ij}(t)) \tag{12}$$

where:
t represents the time-step;
η is a small variable called the learning rate, which decreases with time.

The decay of the learning rate is calculated each iteration using the following equation:

$$\eta(t)=\eta_0\exp\left(-\frac{t}{\lambda}\right) \quad t=0,1,2,\ldots \tag{13}$$

In equation 12, not only does the learning rate have to decay over time, but also, the effect of learning should be proportional to the distance a node is from the BMU. Indeed, at the edges of the BMUs neighborhood, the learning process should have barely any effect at all. Ideally, the amount of learning should fade over distance similar to the Gaussian decay according to the formula:

$$\theta(t)=\exp\left(-\frac{dist}{2\sigma^2(t)}\right) \quad t=0,1,2,\ldots \tag{14}$$

where:
$dist$ is the distance a node is from the BMU;
σ is the width of the neighborhood function as calculated by equation (11).

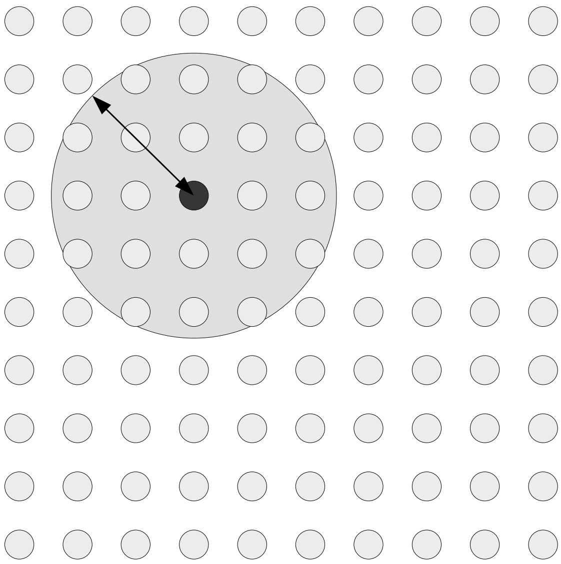

Fig. 9. The BMU's neighborhood.

Another method of learning Kohonen's neural networks is learning with strain. The learning with strain is special modification of concurrent learning. This learning method allows to use Kohonen's network in cases when the vectors of desired output signals of neural networks z_j are known. This learning method has the character of straining the correct answers of network despite of what network want to do. This method needn't to calculate the values of errors made by neural network as it has place in classic feed forward networks, what makes possible to speed up the learning process. The following methods of learning with strain can be pointed:

– method of autoassociation:

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)(x_j(t)z_j(t)) \tag{15}$$

– method of incremental autoassociation:

$$\begin{aligned} w_{ij}(t+1) &= w_{ij}(t) + \Theta(t)\eta(t)\cdot \\ &\cdot(x_j(t) - x_j(t-1))(z_j(t) - z_j(t-1)) \end{aligned} \tag{16}$$

– method of bringing nearer the weight's vector to the desired output vector:

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)(z_j(t) - w_{ij}(t)) \tag{17}$$

Each time the choice of presented above method must be done basing on usefulness in concrete task. It must be noticed that because of lack of general theory in this case there are necessary the experiments and research leaning on empirical investigations.

4 The Results of Research

4.1 The measurements

During research the five ships were measured on the Polish Navy Test and Evaluation Acoustic Ranges which schema was presented on figure 10. Ships No. 1 was minesweeper project 206FM, ship No. 2 was minesweeper project 207D, ship No. 3 was salvage ship project 570, ship No. 4 was minesweeper project 207P, and ship No. 5 was racket corvette project 1241RE.

The recordings were carried out by means of the array of hydrophones. Several hydrophones were strung in a line along the bottom in shallow water. The depth was about 10 m. During the ship measurements, the average see wave height was less than 1 m and wind speeds less than 5 m/s, so the ambient noise level was low. At the time of the measurements the sound velocity profile was typical for the summer. This curve was smooth with gradually decreasing gradient without mixed layers. The ship under test was running at a constant speed and course during cross over hydrophones. The array of hydrophones was mounted about 1 m above sea bottom on tripod. The bottom-mounted hydrophones range is very useful for measuring the noise of surface ships. What more when they are used bottom-fixed hydrophones the irrelevant low-frequency wave-induced noise is also eliminated. Throughout this measurement, the signal-to-noise ratio for the spectrum data was greater then 28 dB.

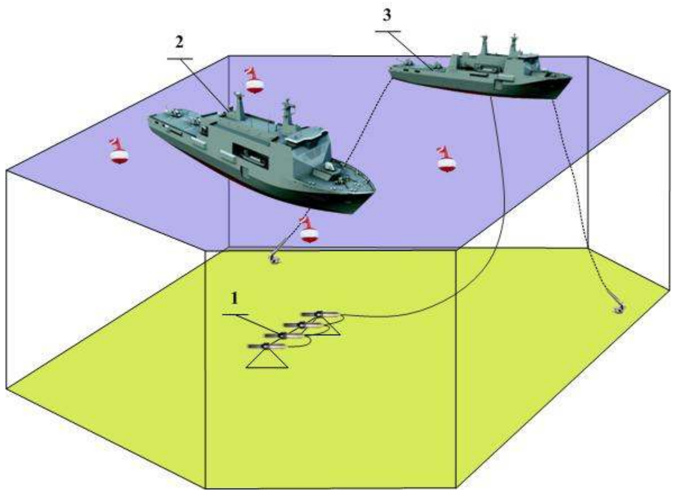

Fig. 10. Schema of hydroacoustic range during measurements; 1) sensors of acoustic signatures – array of hydrophones, 2) measured ship, 3) ship – base with mounted hydroacoustic measuring system.

All of investigated ships were measured at the similar hydrological and metrological conditions. Every ship was measured with few, various speed of crossing.

Data form hydrophones were recorded on digital recorder designed by crew of Radiolocation and Hydrolocation Department of Polish Naval Academy.

This system has possibility to simultaneous recording in 16 channels with resolution of 16 bits and sampling frequency up to 250 kHz per channel. Digital recorder has possibility to make in real time transformation and analysis of acquired data. More over it is possible to create own programs for special use. As a sensors of acoustic field of moving ship were used hydrophones produced by Reson model TC4032. This hydrophones has omnidirectional characteristic in horizontal directivity so they were positioned parallel to the plane of sea bottom. Other parameters which cause that these sensors are proper to acquire data for classification systems are: high sensitivity equal -170 dB re 1V/μPa, preamplifier gain of 10 dB and broad usable frequency range from 5 Hz to 120 kHz. Mentioned above digital recorder has possibility to direct connections of hydrophones TC4032.

4.2 Preparing data for classification

The best solutions to detect a ship are the discrete components in the low frequency part of the ship's noise spectrum and that only narrow band filters can be used. This must be done because there are no components discrete lines at frequencies range grater than 200 Hz in the modern submarines and surface warships. In the Baltic's shallow waters an the conditions under which the measurements were made, the area of optimal frequencies for the propagation of sound lies in the band from several Hz up to 5 kHz.

Recorded during research signals were sampled on digital recorder with frequency of 250 kHz. From the theoretical point of view (Shanon-Kotielnikow Law) it is enough for used sensors which has the upper band of frequency equal 120 kHz. From the practical point of view it is advisable to have 10 samples per period of highest frequency of analyzed signals. In this case we have usable band of signals up to 25 kHz. In research we need signal of band frequency from 5 Hz (because of used hydrophones) up to 200 Hz (because of existence of discrete lines in spectrum). So used measured system is suitable for this research.

To cut off signals above 200 Hz it can be used some digital or analog filters. In other hands using filters may cause to raise the noise-to-signal ratio. Therefore in research we do not use filters but after calculation of spectrum we will use only data which are above 5 Hz and below 200 Hz. To calculate the spectrum of recorded signals Discrete Fourier Transformation DFT was used. Discrete Fourier transform is one of the specific forms of Fourier analysis. DFT requires an input function that is discrete and whose non-zero values have a limited (finite) duration. Such inputs are often created by sampling a continuous signal like in this case hydroacoustic signal. The DFT is described as discrete series of $X(m)$ in frequency domain as follow:

$$X(m) = \sum_{n=0}^{N-1} x(n) e^{-j2\pi nm/N} \tag{18}$$

where:

$x(n)$ is discrete series of sampled values in time domain of continuous variable $x(t)$.

The values of frequency of N succeeding points on frequency axis, in which the strips of DFT are calculated, are described as follow:

$$f_{analysis}(m) = \frac{mf_s}{N} \tag{19}$$

where:

f_s denotes frequency of sampling of input signal.

The Discrete Fourier Transformation was used because the recorded signals are archived in discrete form (after sampling) and because used recorder has digital architecture so discrete form is much more easily to be calculated. To obtain suitable frequency resolution of calculated DFT Fourier transform was calculated for time windows of 1 second length. More over to minimize to influence of leakage of DFT the chosen fragment of signal is multiplying with Hanning window before DFT calculations. Hanning window, named also as window of upraised cosinus, window of Hann or von Hann is described by following equation:

$$w(n) = 0.5 - 0.5\cos(2\pi n/N) \quad for \quad n = 0, 1, \ldots, N-1 \tag{20}$$

The beginning of time windows were chosen randomly from the whole recorded signals, so in this way the effect of distance change of ship from sensors were simulated. After Discrete Fourier Transformation and before creating vector which will be presented as input for Kohonen network the result was normalized according to the follow equation [10]:

$$x(n) = \frac{x(n)}{\sqrt{\sum_{i=0}^{N-1} x^2(i)}} \quad for \quad n = 0, 1, \ldots, N-1 \tag{21}$$

Used Kohonen network has two dimensional architecture. Its characteristic parameters are: number of neurons, beginning size of area of the neighborhood, beginning learning rate and methods to determine the distance between neuron weights and input vectors. Because there is no theory about beginning setup of mentioned above neural network's parameters there were made few experimental research. For this case because of speed of learning, possibilities to classify data and possibilities to generalize the knowledge it seems that follows values are the best: number of neurons: 30x30 neurons map, beginning size of area of neighborhood: 3, beginning learning rate: 0.35 and method to determine the distance: Euclidean distance.

4.3 Results of research

After about 35 000 cycles of neural network learning, was obtained the map of memberships for every presented ship as it is shown on figure 11. All areas activated by signals generated by considered ships were clearly separated. The example results of classifier work out after learning process was presented on figure 12. These results were received for data which where presented during neural network learning process. To find out if the building classifier is properly configured and learned some data which weren't presented before were calculated. The example results were presented on figure 13.

The table 4 shows number of correct classification of presented data relatively to the type of ship. The number of correct answer is presented as percent of all answers. The research was made for data which were presented during learning process and data which weren't presented before.

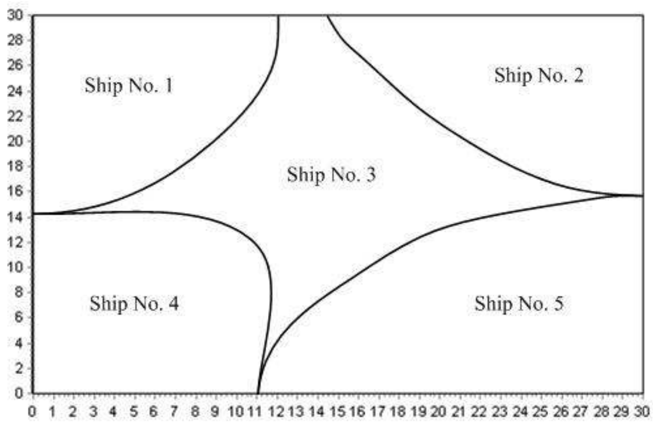

Fig. 11. The map of partition for area of activation for researched ships

Table 4. The number of correct classifications.

Ship no. / Data	1	2	3	4	5
presented before	94.5%	96.0%	92.3%	95.3%	92.8%
not presented before	72.1%	69.4%	75.8%	73.5%	77.2%

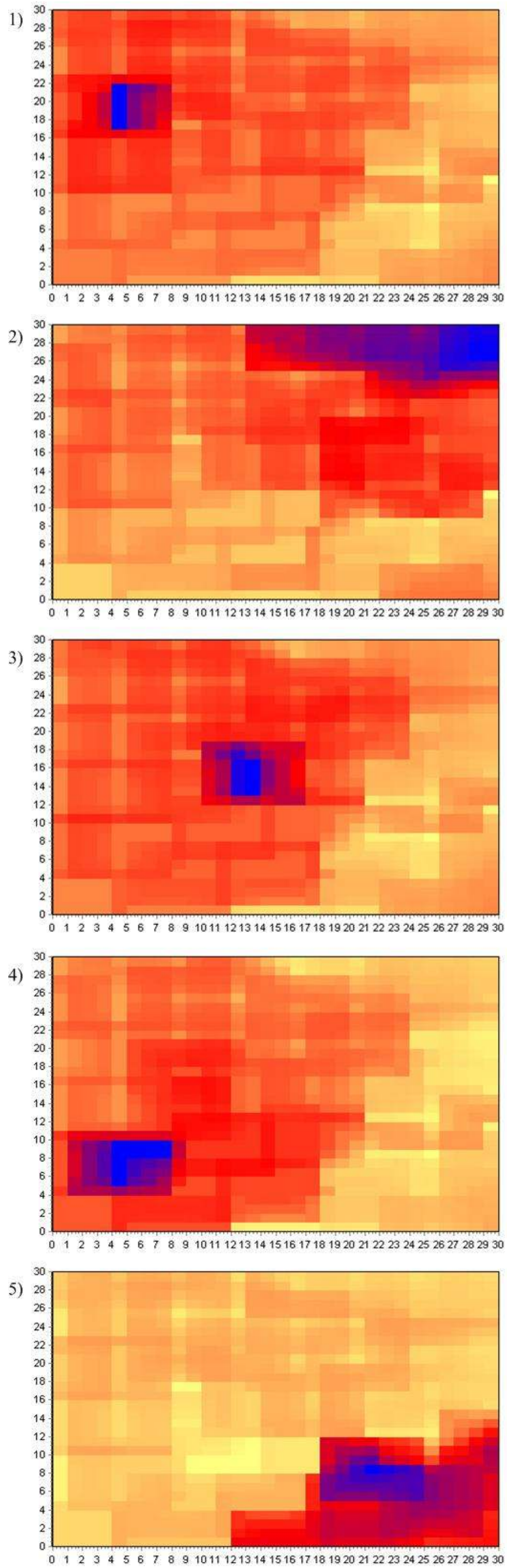

Fig. 12. The results of classifier work out - maps of memberships for data which were presented during learning process; 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5.

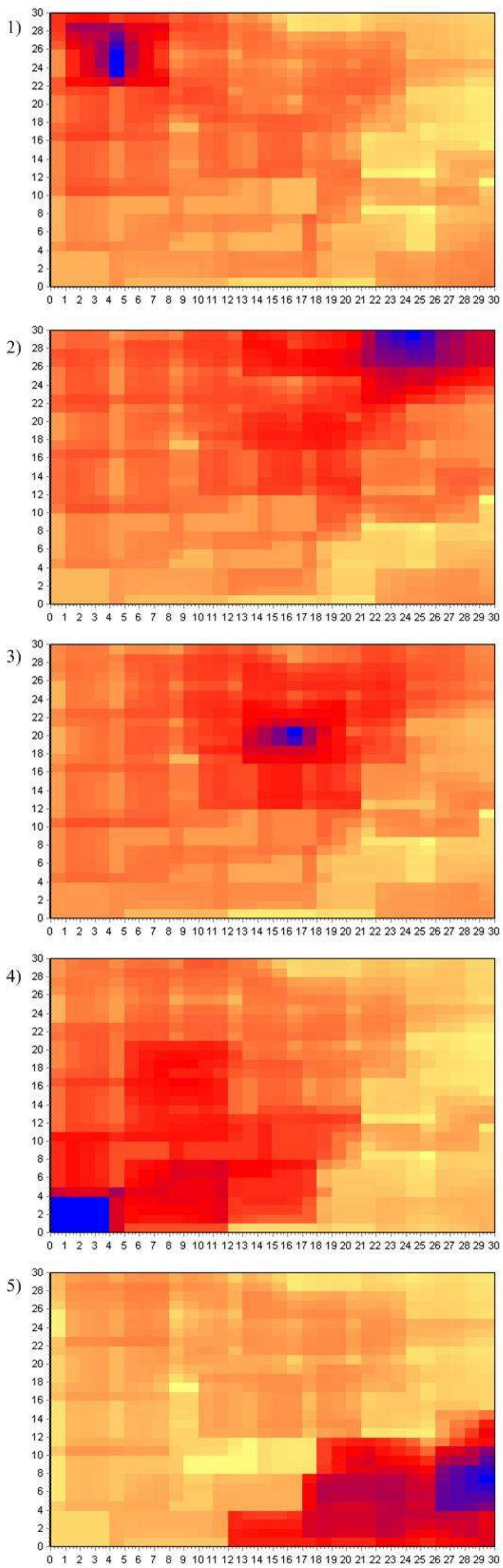

Fig. 13. The results of classifier work out - maps of memberships for data which weren't presented during learning process; 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5.

After this part of researches the new ship No. 6 which was rocket corvette project 1241.1MP was presented. In few first presentations it was classified as ship No. 5 what was comprehensible because ship No. 5 is the oldest version of this vessel. Next the new group was created, which was separated from the area activated before by ship No. 5. The new map of partition for area of activation looks like is presented on figure 14. The example results of classification results are presented on figure 15.

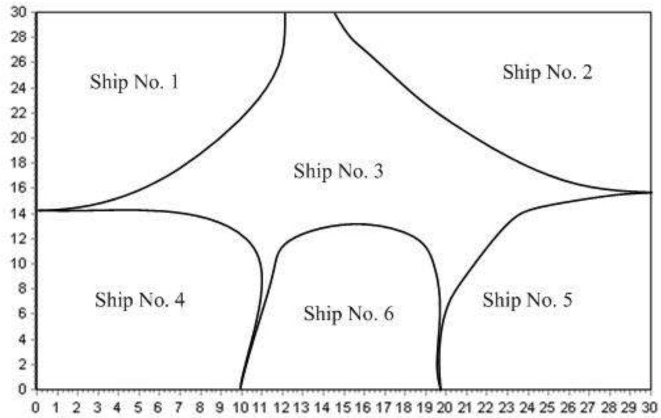

Fig. 14. The new map of partition for area of activation for researched ships after introducing new ship

5 Conclusion

As it is shown on results the used Self-Organizing Map is useful for ships classification based on its hydroacoustic signature. Classification of signals that were used during learning process, characterize the high number of correct answer (above 90%) what was expected. This result means that used Kohonen network has been correctly configured and learned. Presentation of signals that weren't used during learning process, gives lowest value of percent of correct answer than in previous case but this results is very high too (about 70 % of correct classification). This means that neural network has good ability to generalize the knowledge. More over after presentation of new ship which weren't taking into account during creating classifier, the Kohonen networks was able to create new group dividing the group which belongs to the similar type of ship. After few cycles used neural networks expand its output vector or in other words map of membership about new area of activation. This means that used Kohonen networks has possibility to develop its own knowledge so it cause that presented method of classification is very flexible and is able to adaptation to changing conditions.

Presented case is quite simple because it not take into account that object sounds change with time, efficiency conditions (e.g. some elements of machinery are

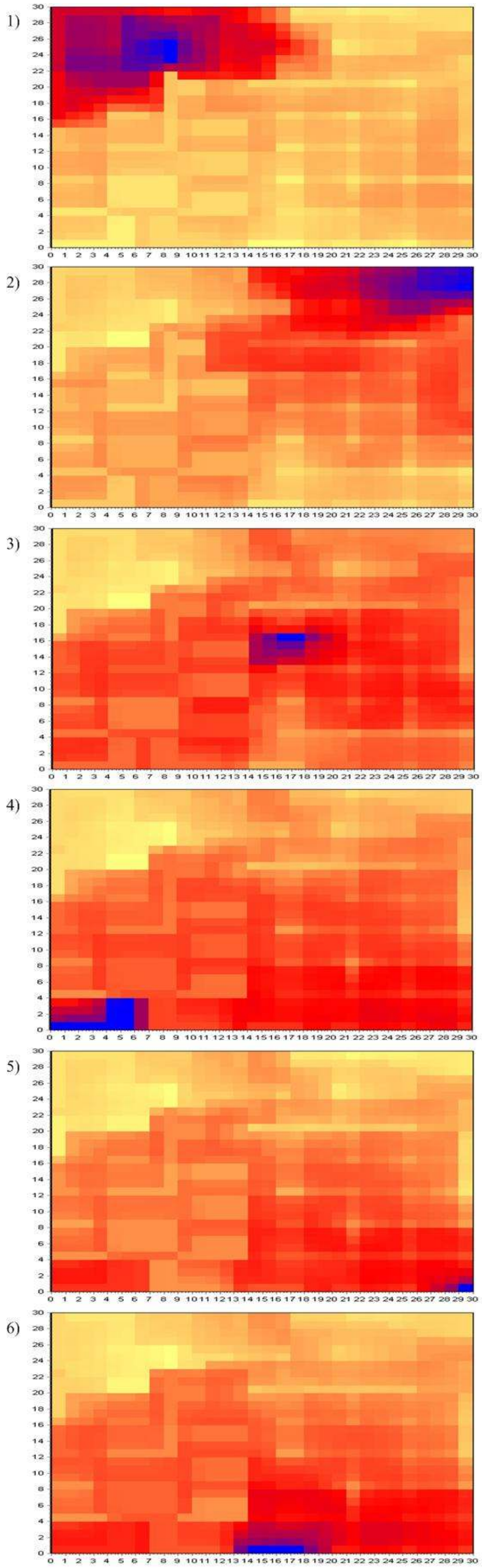

Fig. 15. The results of classifier work out - maps of memberships after adding the new ship; 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5, 6) for ship no. 6.

damaged), sound rates, etc. It doesn't consider the influence of changes of environment on acquired hydroacoustic signals. In next step of research the proper work of this method will be checked for enlarged vector of objects. In few weeks we should have results of using Kohonen Networks to classify the ships which number exceed fifty. The hydroacoustic signatures of ships were acquired in different environmental conditions and in different stage of ship operating. Therefore the cases of changing hydroacoustic signatures which were mentioned before should be investigated too.

In future research the influence of network configuration on the quality of classification should be checked. More over some consideration about feature extracting from hydroacoustic signature should be made. In this time we have got some results about using Mel-Frequency Cepstral Coefficient as method of creating some kind of indexes for hydroacoustic signals [12].

Described method after successful research mentioned above and after preparation for work in real time will be extended and its application is provided as assistant subsystem for passive hydrolocations systems of Polish Naval ships.

The aim of presented method is to classify and recognize ships basing on its acoustic signatures. This method can found application in intelligence submarine weapon and in hydrolocation systems. In other hand it is important to deform and cheat the similar system of our opponents by changing the "acoustic portrait" of own ships. From the point of ship's passive defense view it is desirable to minimize the range of acoustic signatures propagation. Noise isolation systems for vessels employ a wide range of techniques, especially double-elastic devices in the case of diesel generators and main engines. Also, rotating machinery and moving parts should be dynamically-balanced to reduce the noise. In addition, the equipment should be mounted in special acoustically insulated housings (special kind of containers). One of the method to change the hydroacoustic signatures is to pump the air under the hull of ship. It cause the offset of generated by moving ship frequency into the direction of high frequency, the same the range of propagation become smaller.

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