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Ship's Hydroacoustics Signatures Classification Using Neural Networks

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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 labelled items [Stąpor, 2005], [Zak, 2008].

Formally, the problem can be stated as follows: given training data $\{(x_1, y_1), \ldots, (x_n, y_n)\}$ 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 [Szczepaniak, 2004].

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 [Zak, 2008].

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.

2. Ship's hydroacoustics 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 [Gloza & Malinowski, 2001]. 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.

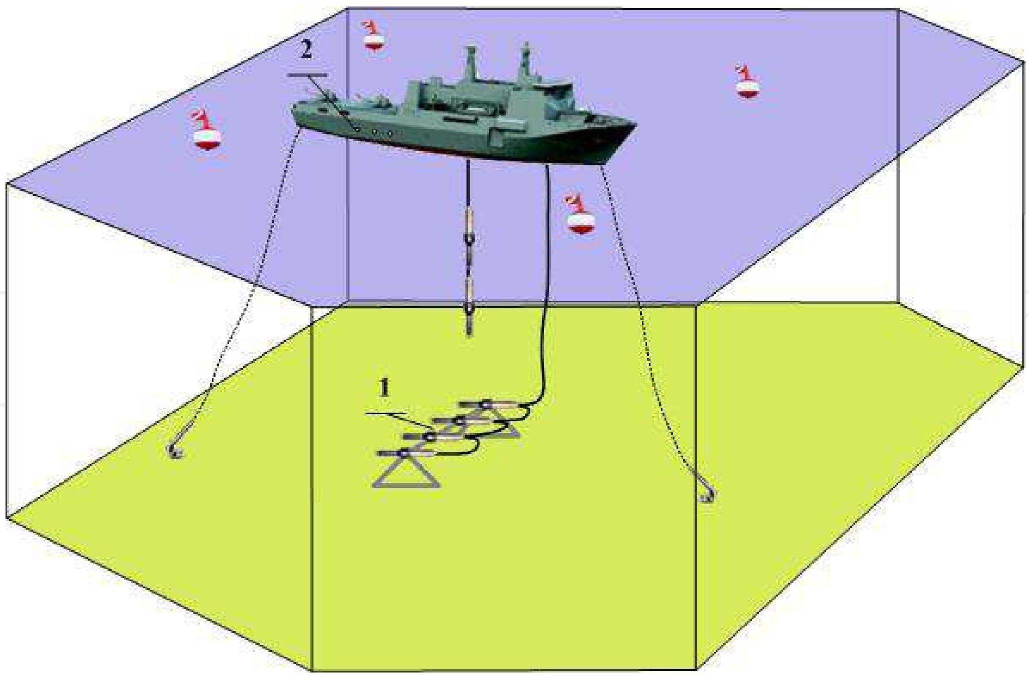


Fig. 1. Schema of hydroacoustics range during measurements using statical method; 1) sensors of acoustic signatures – array of hydrophones, 2) sensors of vibrations – accelerometers

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 [Gloza & Malinowski, 2002]. 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.

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 as follow [Gloza & Malinowski, 2001]:

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

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.

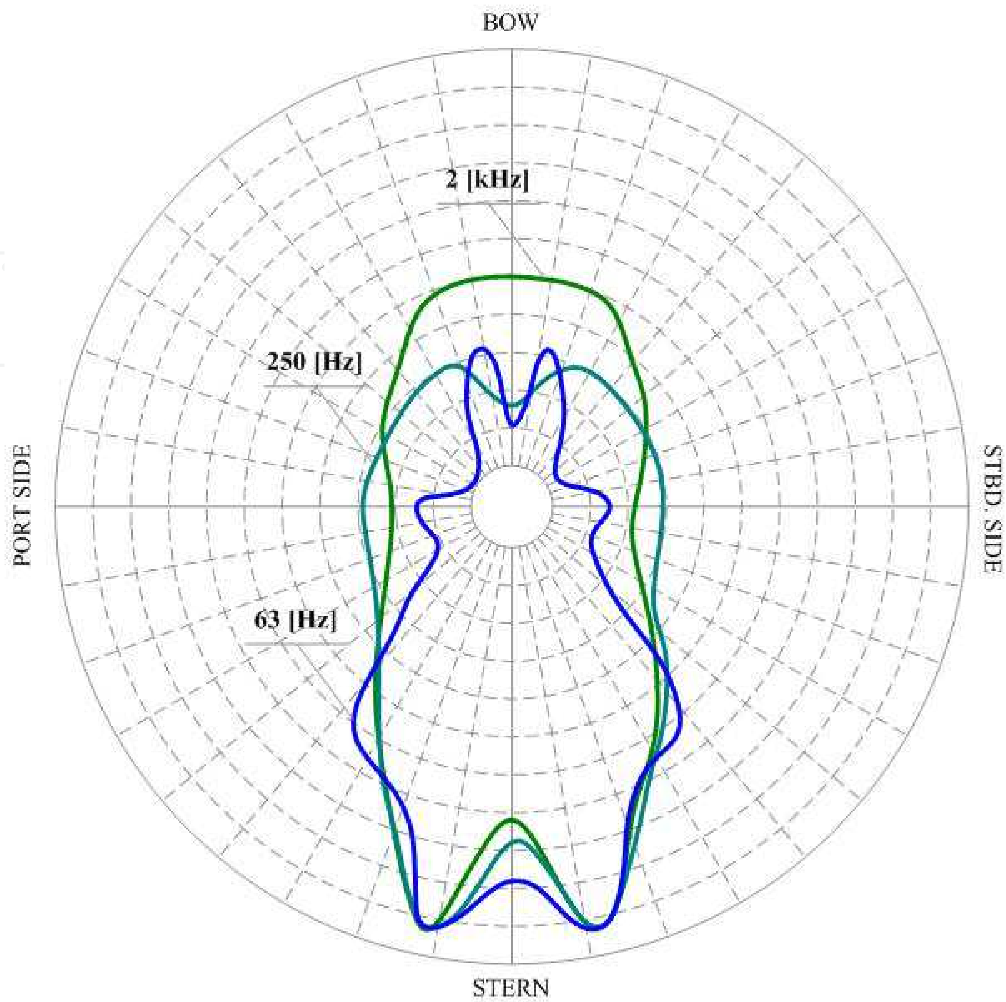


Fig. 2. Equal pressure level contours of noise around a ship

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

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

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.

Frequency [Hz]	Coherency function	Vibration on the hull [μm/s]
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

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

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.

Vibration	Frequency		Harmonics
	Formula	[Hz]	
Unbalanced parts	$f_n = kf_0$	25	50, 75, 100, 125, 150, 175, 200, …
Diesel firing rate	$f_s = \frac{kz_c f_0 s}{4}$	12.5	25, 37.5, 50, 62.5, 75, 87.5, 100,112.5, 125, 137.5, 150, …

Table 2. Basic frequencies and harmonics of vibration

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;

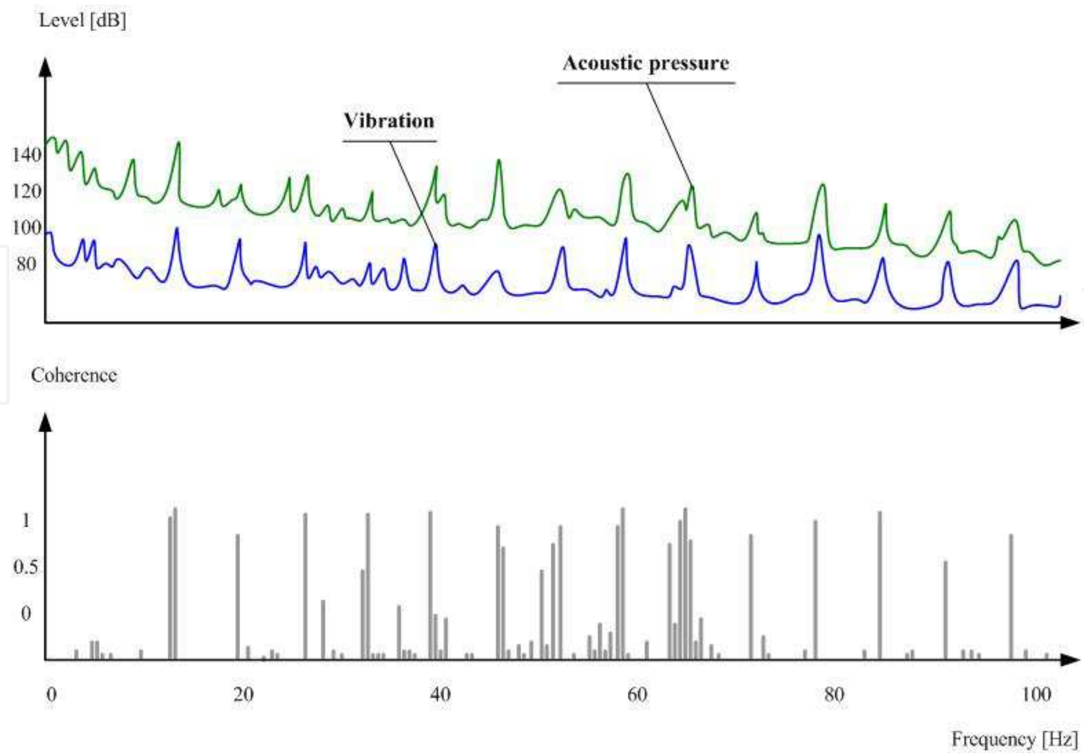


Fig. 3. Narrow-band spectra and coherence function of underwater acoustic pressure and vibration of a stationary ship

Relations between mechanical vibration and hydroacoustics 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.

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	$7.7\ 10^{-2}$

Table 3. The energy transmission coefficient calculated for consecutive frequencies

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 [Urick, 1975], [Gloza & Malinowski, 2002].
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.

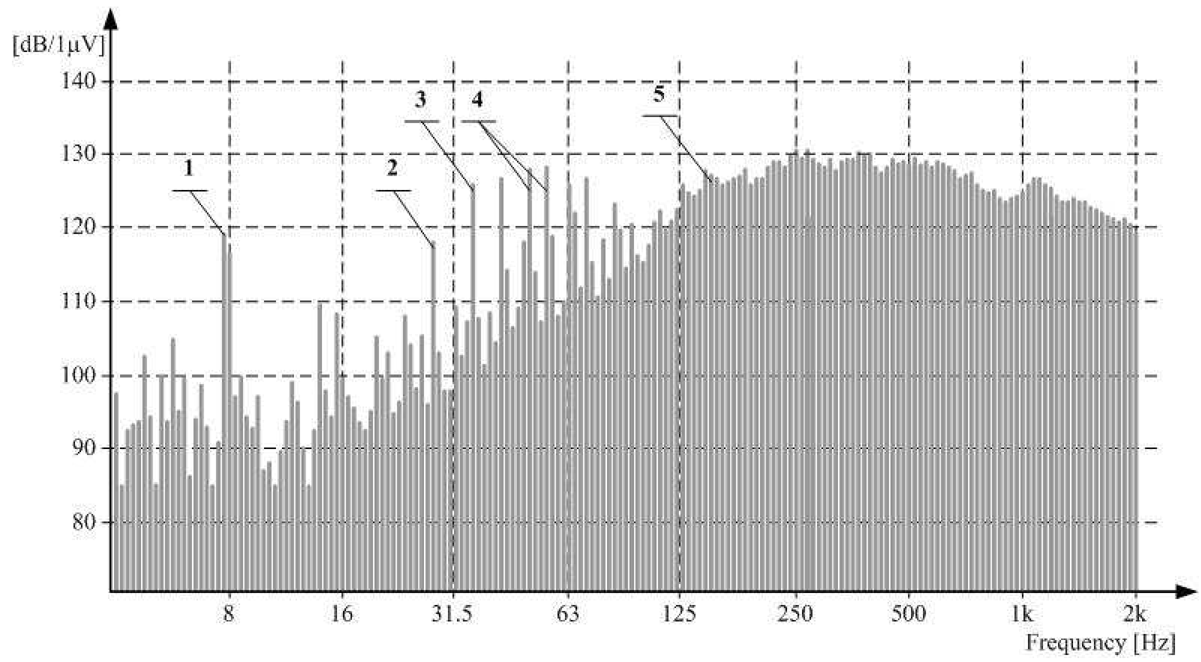


Fig. 4. The underwater noise spectrum or so called "acoustic portrait" of a moving ship; 1) shaft, 2) diesel generator, 3) propeller blades, 4) main engines, 5) propeller

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 [Gloza & Malinowski, 2002].

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.

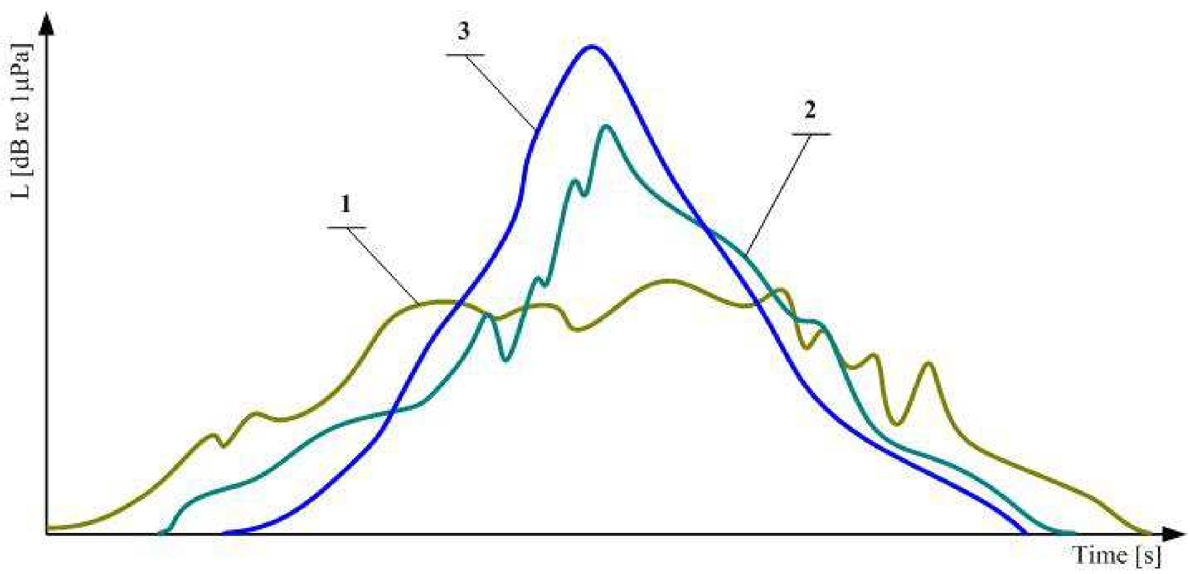


Fig. 5. The sound levels radiated by moving ship with different speeds; 1) 3.8 kn, 2) 8 kn, 3) 11 kn

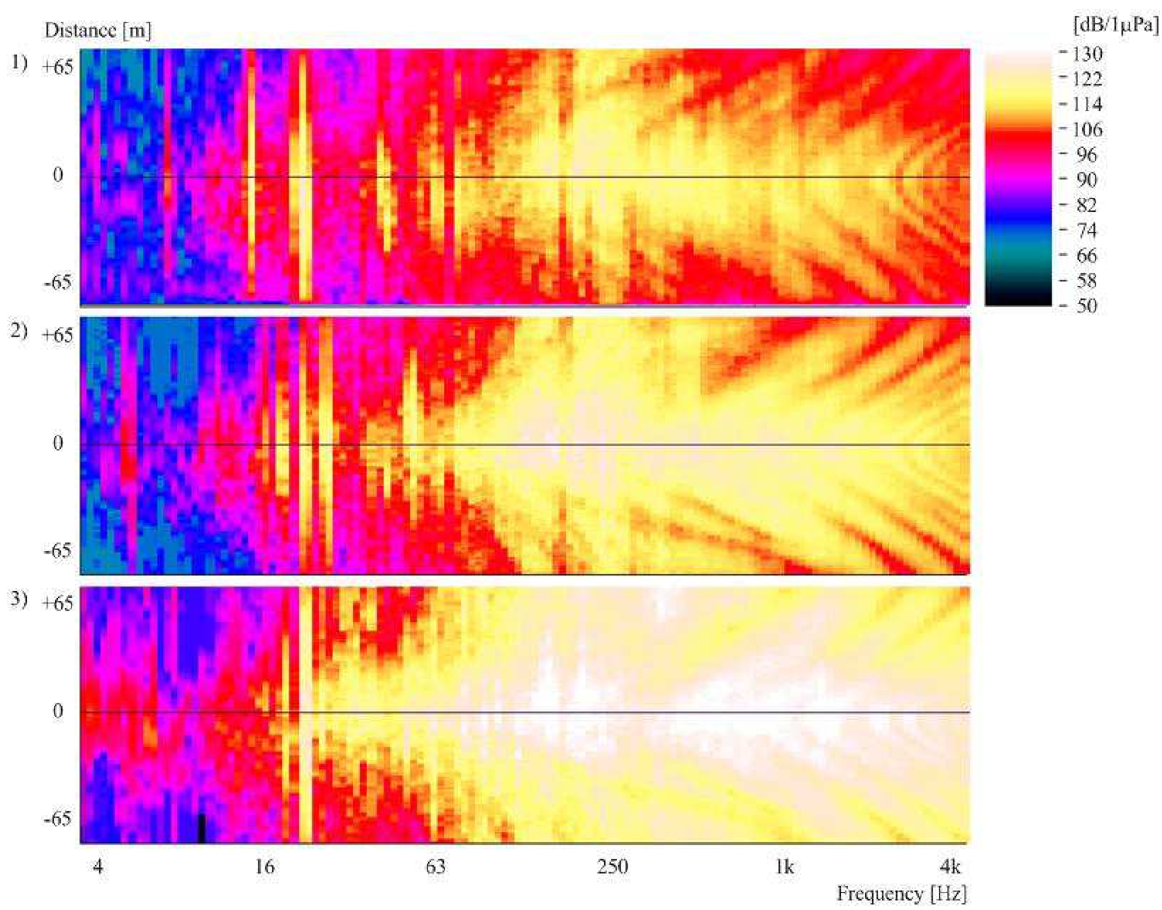


Fig. 6. The spectograms received during ship running over hydrophones with different speeds; 1) 3.8 kn, 2) 8 kn, 3) 11 kn

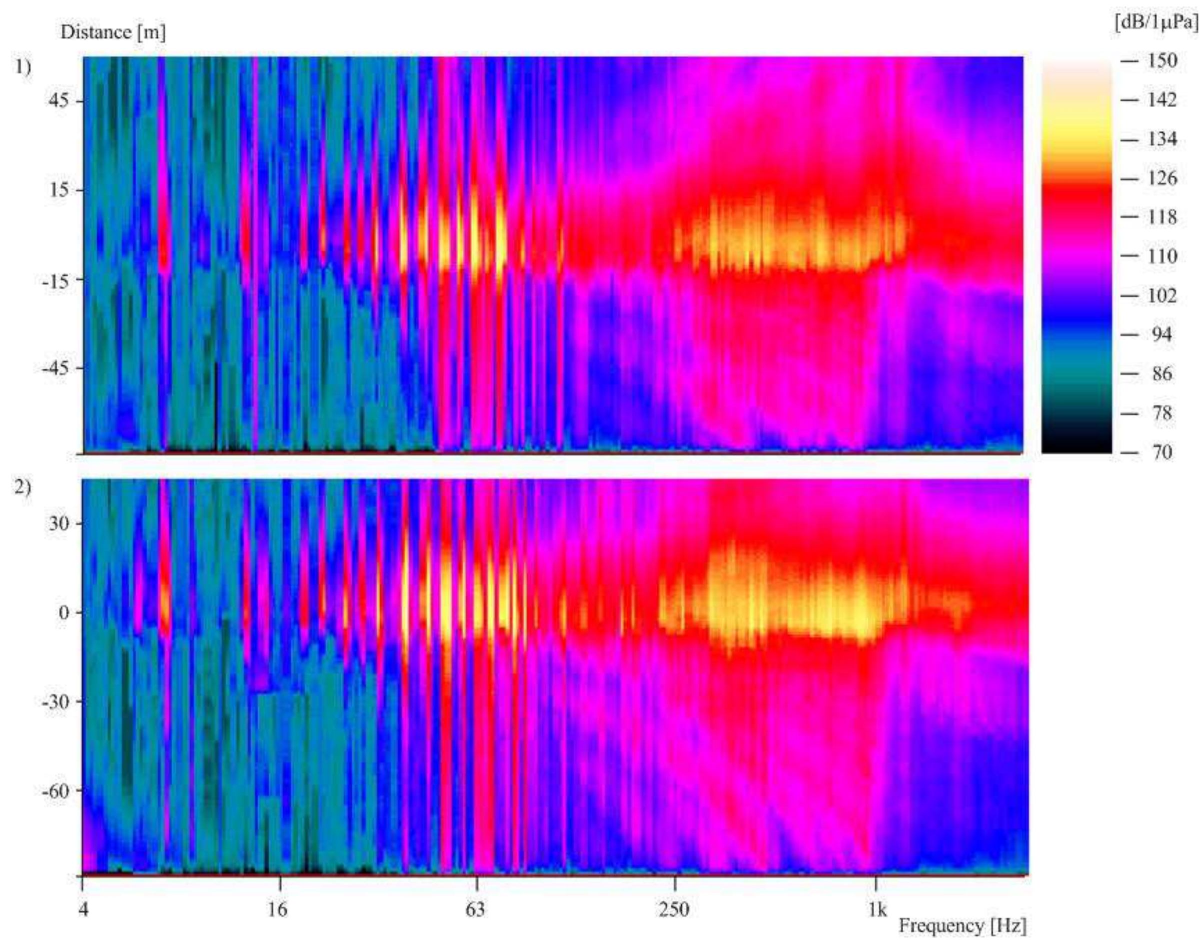


Fig. 7. The spectograms received during ship running over hydrophones in different phase of exploitation; 1) after general renovation, 2) 2 years after general renovation

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.

3. Feature extraction

The purpose of signal feature extraction module is to convert the sound waveform to some type of parametric representation for further analysis and processing. This is often referred as the signal-processing front end. A wide range of possibilities exist for parametrically representing the signals for the sound recognition task, such as Linear Prediction Coding (LPC), Mel-Frequency Cepstrum Coefficients (MFCC) [Zak, 2005], and others. Mel-Frequency Cepstrum Coefficients method will be discussed in this paper.
MFCC's are based on the known variation of the human ear's critical bandwidths with frequency, filters spaced linearly at low frequencies and logarithmically at high frequencies have been used to capture the phonetically important characteristics of speech. This is

expressed in the mel-frequency scale, which is a linear frequency spacing below 1000 [Hz] and a logarithmic spacing above 1000 [Hz].
A block diagram of the structure of an MFCC processor is given on figure 8. As been mentioned previously, the main purpose of the MFCC processor is to mimic the behavior of the human ears. In addition, rather than the speech waveforms themselves, MFFC's are shown to be less susceptible to mentioned variations.
First step of MFCC processor is the frame blocking. In this step the continuous sound is blocked into frames of N samples, with adjacent frames being separated by M where $M < N$. The first frame consists of the first N samples. The second frame begins M samples after the first frame, and overlaps it by $N - M$ samples. Similarly, the next frames are created so this process continues until all the sound is accounted for within one or more frames.

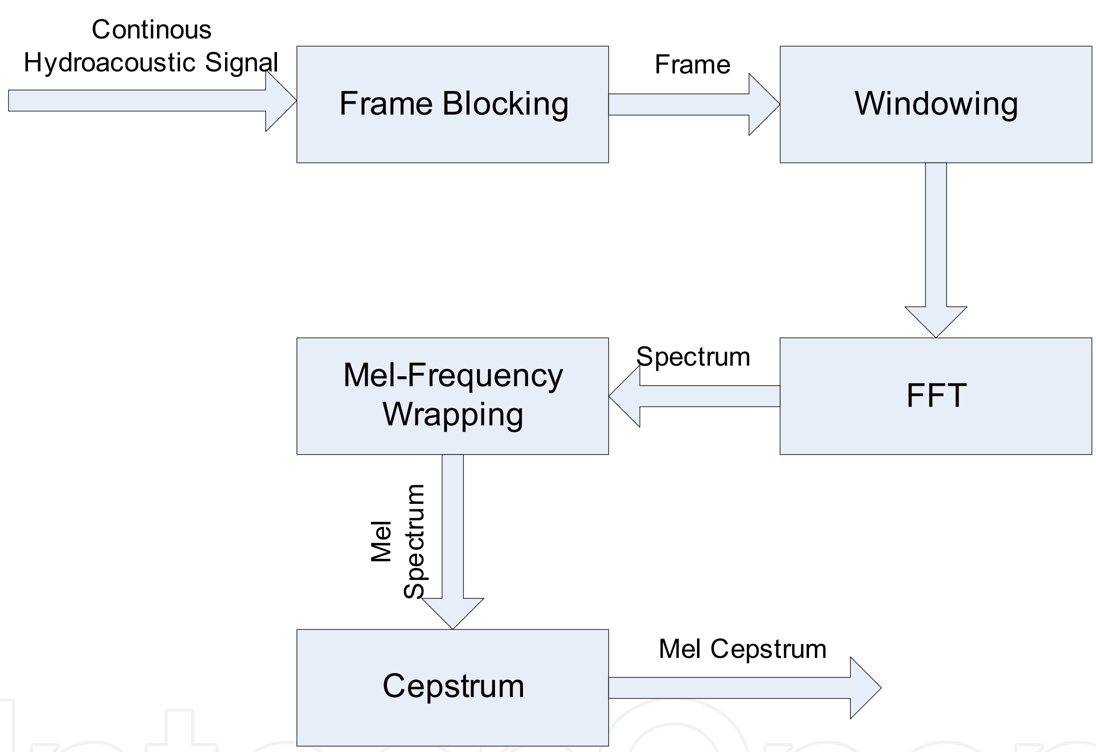


Fig. 8. Block diagram of the MFCC processor

The next step in the processing is to window each individual frame so as to minimize the signal discontinuities at the beginning and end of each frame. The concept here is to minimize the spectral distortion by using the window to taper the signal to zero at the beginning and end of each frame. If we define the window as: $w(n), \quad 0 \le n \le N-1$, where N is the number of samples in each frame, then the result of windowing is the signal:

$$y(n) = x(n)w(n), \quad 0 \le n \le N-1 \tag{7}$$

Typically the Hamming window is used, which has the form [Therrien, 1992]:

$$w(n) = 0.54 - 0.46\cos(\frac{2\pi n}{N-1}), \quad 0 \le n \le N-1 \tag{8}$$

The next processing step is the Fast Fourier Transform, which converts each frame of N samples from the time domain into the frequency domain. The FFT is a fast algorithm to implement the Discrete Fourier Transform (DFT) which is defined on the set of N samples, as follow [Therrien, 1992]:

$$X_n = \sum_{k=0}^{N-1} x_k e^{-2\pi jkn/N}, \quad n = 0,1,2,\ldots,N-1 \tag{9}$$

Next step in MFCC processor is the Mel-frequency Wrapping. As mentioned above, psychophysical studies have shown that human perception of the frequency contents of sounds for speech signals does not follow a linear scale. Thus for each tone with an actual frequency f, measured in [Hz], a subjective pitch is measured on a scale called the "mel" scale. The mel-frequency scale is a linear frequency spacing below 1000 [Hz] and a logarithmic spacing above 1000 [Hz]. As a reference point, the pitch of a 1 [kHz] tone, 40 [dB] above the perceptual hearing threshold, is defined as 1000 mels. Therefore we can use the following approximate formula to compute the mels for a given frequency f in [Hz]:

$$mel(f) = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right) \tag{10}$$

One approach to simulating the subjective spectrum is to use a filter bank, spaced uniformly on the mel scale (figure 9). That filter bank has a triangular bandpass frequency response, and the spacing as well as the bandwidth is determined by a constant mel frequency interval.

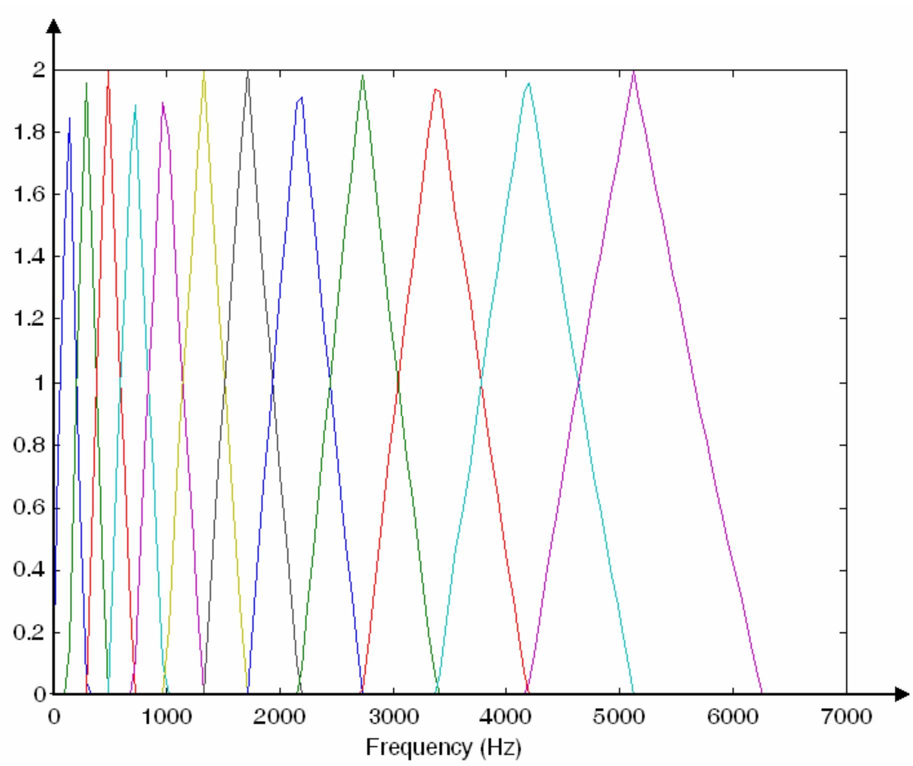


Fig. 9. An example of mel-spaced filterbank

In this final step, we convert the logarithmic mel spectrum back to time. The result is called the mel frequency cepstrum coefficients (MFCC). The cepstral representation of the speech spectrum provides a good representation of the local spectral properties of the signal for the given frame analysis. Because the mel spectrum coefficients, and so their logarithm, are real numbers, we can convert them to the time domain using the Discrete Cosine Transform (DCT). Therefore if we denote those mel power spectrum coefficients that are the result of the last step are $S_k, \quad k = 1,2,\ldots,K$, we can calculate the MFCC's, as [Zak, 2005]:

$$c_n = \sum_{k=1}^{K} \log(S_k)\cos(\frac{n(k-0.5)\pi}{K}), \quad n = 1,2,\ldots,K \tag{11}$$

Note that we exclude the first component, c_0 from the DCT since it represents the mean value of the input signal which carried little speaker specific information.

4. Classification process

4.1 Self organizing maps

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.

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 [Fort, 2006], [Haykin, 1999].

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 10 shows a very small Kohonen network of 4×4 nodes connected to the input layer (shown as rectangle) representing a two dimensional vector.

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 [Kohonen, 2001]:

- Each node's weights are initialized.
- A vector is chosen at random from the set of training data and presented to the lattice.
- 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).
- 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.
- 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.
- 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.

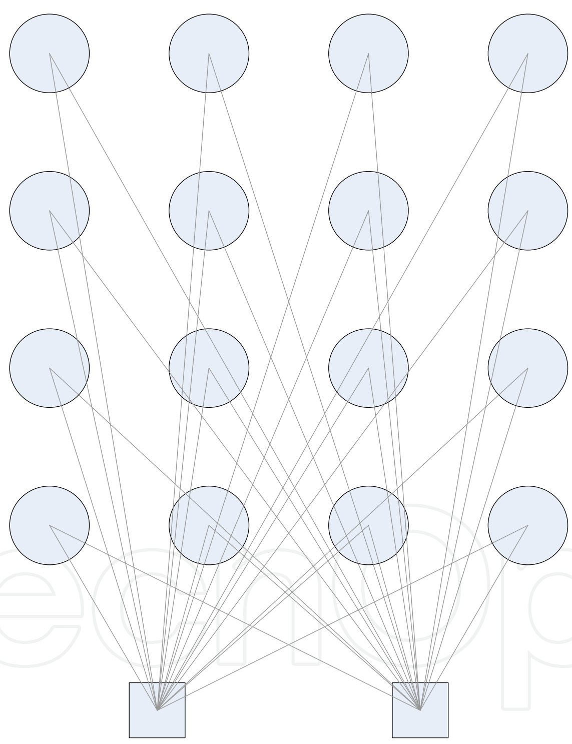


Fig. 10. A simple Kohonen network

There are many methods to determine the distance [Kohonen, 2001] but for our purpose we will use the most popular Euclidean distance which is given by:

$$d(x, w_i) = \|x - w_i\| = \sqrt{\sum_{j=0}^{N} (x_j - w_{ij})^2} \tag{12}$$

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.
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:

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\lambda}\right) \qquad t = 0,1,2,\ldots \tag{13}$$

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:

$$w_{ij}(t+1) = w_{ij}(t) + \theta(t)\eta(t)(x_j(t) - w_{ij}(t)) \tag{14}$$

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:

$$\eta(t) = \eta_0 \exp\left(-\frac{t}{\lambda}\right) \qquad t = 0,1,2,\ldots \tag{15}$$

In equation (14), 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:

$$\theta(t) = \exp\left(-\frac{dist}{2\sigma^2(t)}\right) \qquad t = 0,1,2,\ldots \tag{16}$$

where: $dist$ is the distance a node is from the BMU; σ is the width of the neighborhood function as calculated by equation (13).
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 feedforward networks, what makes possible to speed up the learning process. The following methods of learning with strain can be pointed [Fort, 2006]:

- method of autoassociation:

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

- method of incremental autoassociation:

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)\cdot(x_j(t) - x_j(t-1))(z_j(t) - z_j(t-1)) \tag{18}$$

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

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)(z_j(t) - w_{ij}(t)) \tag{19}$$

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.

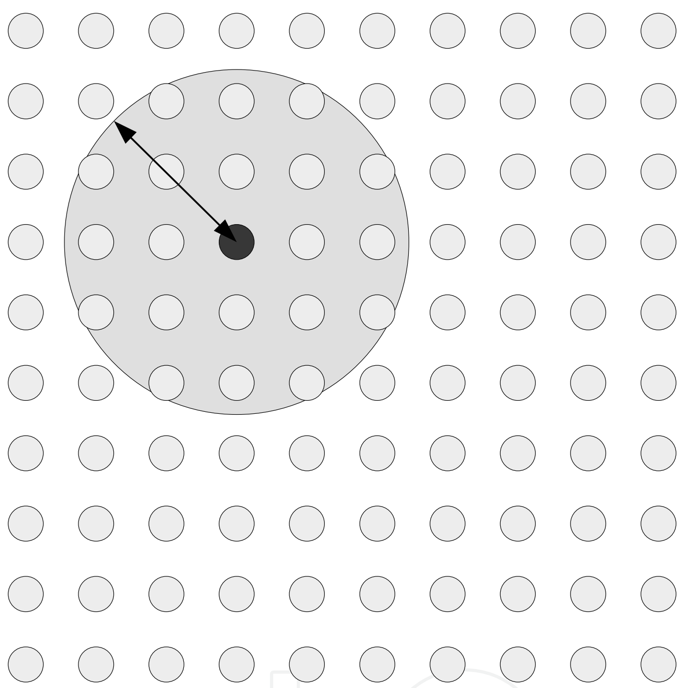


Fig. 11. The BMU's neighborhood

4.2 End-user classification

We must notice that using Kohonen's neural networks in classification as a results gives maps of membership in which each activated region is connected with particular ship. But basing of these results we can't say anything about type of ship because we don't know in which region of membership maps will be particular ship associated. Of course after many cycles of calculations person which is supervising classification will be able to say which type of ship is connected to given region of maps. But on introduction we assume that classification will be made automatically so we use feedforward neural network to connect activated regions in membership maps acquired form Kohonen's network with particular name of type of ship. Let's see how to do this.

Feedforward neural networks are the most popular and most widely used models in many practical applications. Neural networks consist of artificial neurons which are the systems with many inputs and one output. Each neuron performs a weighted summation of the inputs, which then passes a nonlinear activation function, also called the neuron function. Mathematically the functionality of a neuron is described by [Osowski, 1996]:

$$y_i = f\left(\sum_{j=1}^{N} w_{ij} x_j\right) \tag{20}$$

where: y is the output of i-th neuron, w denotes the weight vector, x is the input vector, $f()$ denotes activation function.

The activation functions can be any differential function. Most common is used standard sigmoid function. The variables w for each neuron are the parameters of the network model that can be represented collectively for whole neural network by the parameter vector Θ.

The network is divided into layers. The input layer consists of just the inputs to the network. Then follows a hidden layer or layers, which consists of any number of neurons. The network output is formed by the output layer. Generally, the number of inputs depend on length of input vector and number of neurons in output layer equals the number of outputs of the approximation problem. During creating architecture of feedforward neural network the problem is to determine numbers of hidden layers and number of neurons in each hidden layer. This problem can be solved using Vapnik-Chervonenkins rules [Osowski, 1996].

Given a fully specified network, it can be trained using a set of data containing N input-output pairs (x, z) where x denotes input vector and z desired values of output of neural network. With this data the mean square error (between calculated output of neural network and desired values) is defined by [Osowski, 1996]:

$$E(\Theta) = \frac{1}{N}\sum_{i=1}^{N}\left(y_i(k) - z_i(k)\right)^2 \tag{21}$$

Then, a good estimate for the parameter is one that minimizes the MSE that is:

$$\hat{\Theta} = \arg\min_{\Theta} E(\Theta) \tag{22}$$

The various training algorithms that apply to feedforward networks have one thing in common—they are iterative. They start with an initial parameter vector Θ_0, which is generated using random function. Starting at Θ_0, the training algorithm iteratively decreases the MSE by incrementally updating along the negative gradient of the MSE, as follows [Osowski, 1996]:

$$\Theta(k+1) = \Theta(k) - \eta R \nabla_{\Theta} E(\Theta) \tag{23}$$

where: the matrix R may change the search direction from the negative gradient direction to a more favorable one, η is the learning rate.

The purpose of parameter η is to control the size of the update increment in Θ with each iteration i, while decreasing the value of the MSE.

There are few algorithms of training neural networks for example the most popular are: Backpropagation, Levenberg-Marquardt, Gauss-Newton, Steepest-descent. The basis method is backpropagation algorithm which is similar to the steepest descent algorithm with the difference that the step length η is kept fixed during the training. Hence the backpropagation algorithm is obtained by choosing $R = I$ in the parameter update in (23). The MSE calculated for output layer if propagated back from the output layer through hidden layers to the input layer, and become basis to determine changes of neural network parameters Θ . The training algorithm may be augmented by using a momentum parameter μ . According to this the new algorithm is [Osowski, 1996]:

$$\Theta(k+1) = \Theta(k) - \eta R \nabla_{\Theta} E(\Theta) + \mu(\Theta(k) - \Theta(k-1)) \tag{24}$$

The idea of using momentum is motivated by the need to escape from local minima, which may be effective in certain problems. In general, however, the recommendation is to use one of the other, better, training algorithms and repeat the training a couple of times from different initial parameter initializations.

5. Results of research

5.1 Research conditions

During research the five ships were measured on the Polish Navy Test and Evaluation Acoustic Ranges which schema was presented on figure 1. 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.

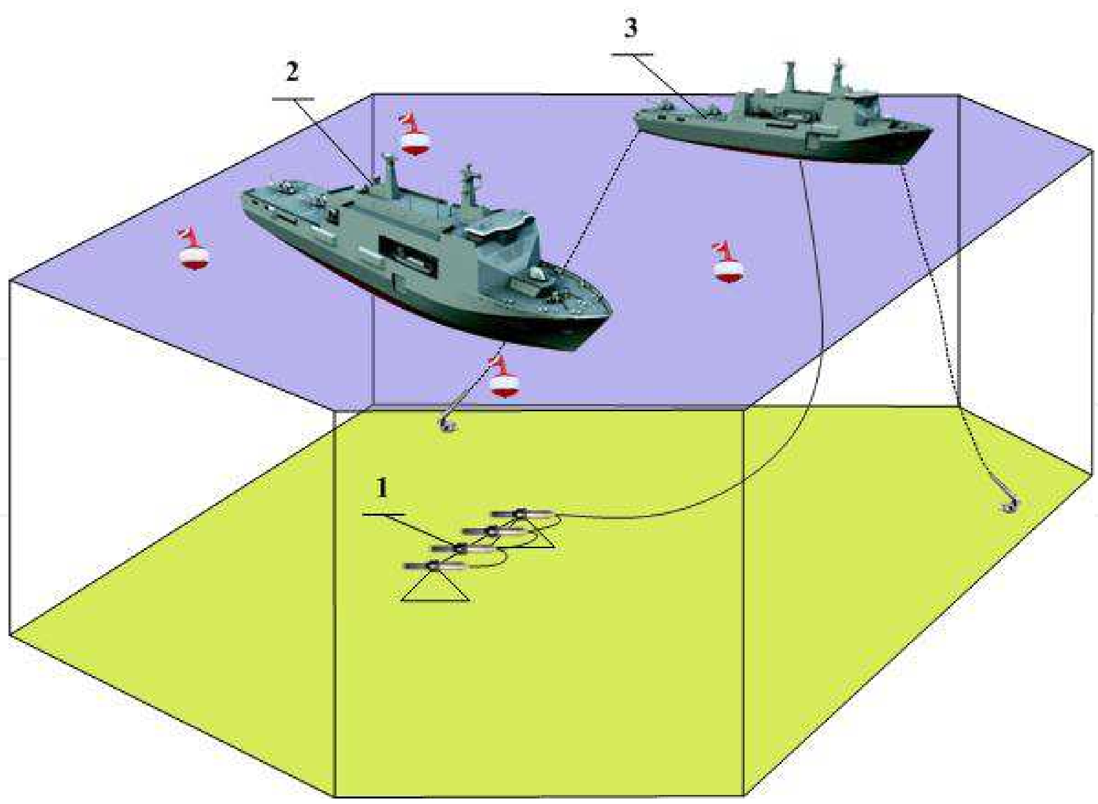


Fig. 12. Schema of hydroacoustic range during measurements; 1) sensors of acoustic signatures – array of hydrophones, 2) measured ship, 3) ship – base with mounted hydroacoustic measuring system

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 than 28 dB.

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

Data from hydrophones were recorded on digital recorder designed by crew of Hydroacoustics Institute 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/ μ Pa, 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.

5.2 Parameters setup

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 greater than 200 Hz in the modern submarines and surface warships. In the Baltic's shallow waters and 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.

5.3 Results

Classification is made by neural classifier in which first layer was Kohonen network which has two dimensional architecture and second layer was feedforward neural network, both described above. Characteristic parameters of used Kohonen network 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.

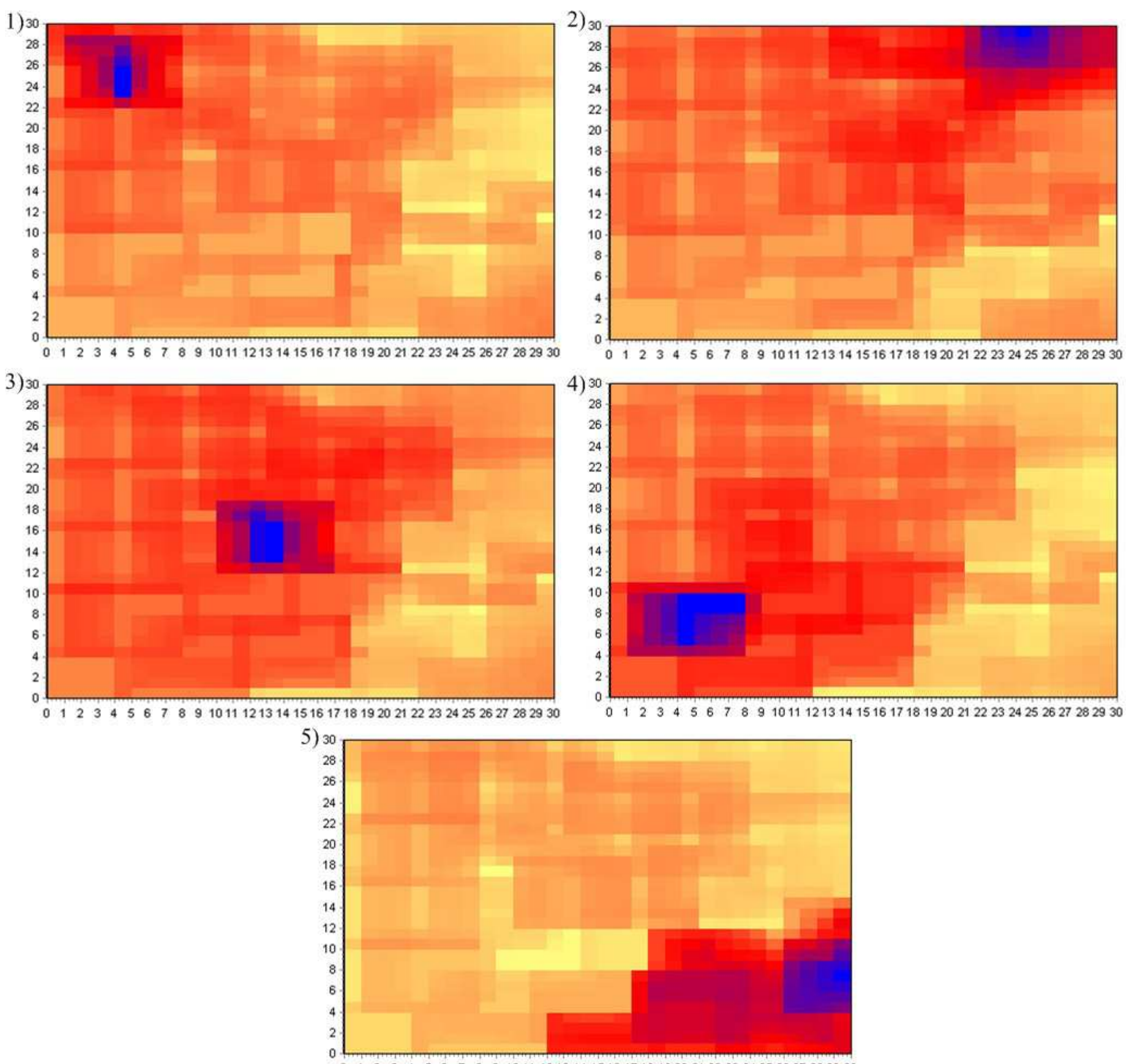


Fig. 13. The results of classifier work out - maps of memberships 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5

As it was said second layer of neural classifier was feedforward neural network which characteristic parameters are: number of layers, number of neuron in each layer, learning rate, momentum rate, methods of learning. In this experiment it seems that using 3 layers feedforward neural network (one input layer, one hidden layer and one output layer). The value of learning rate was set up at 0.3 and momentum rate at 0.65. With this parameters the possibility to classification (number of correct answers, speed of learning and minimum number of neurons) was the best.
After about 35 000 cycles of neural network learning, from the first layer on neural classifier (Kohonen network) was obtained the map of memberships for every presented ship as it is shown on figure 13.
All areas activated by signals generated by considered ships were clearly separated as it was shown on figure 14.

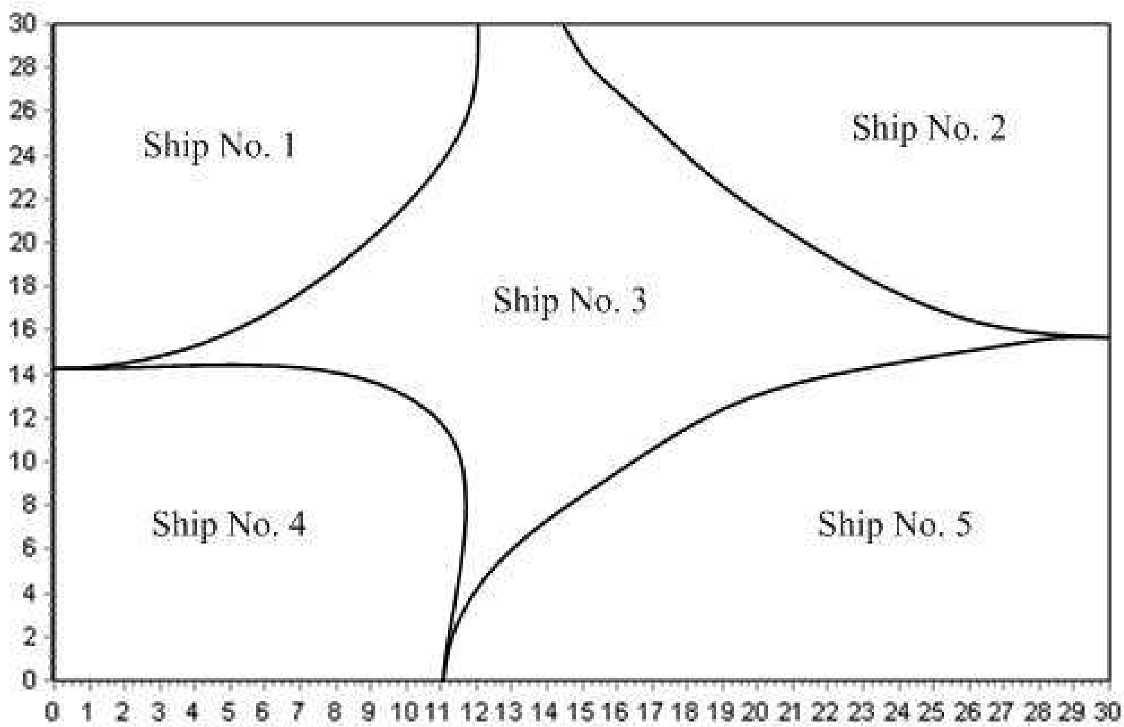


Fig. 14. The map of partition for area of activation for researched ships

Now to assign for each active region of membership maps to the name of ship's class we use the second layer of neural classifier (feedforward network). Using supervised learning we create fully usefulness classifier.
Firstly to check if the classifier works properly we make test on data which were 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 table 3 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.
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 15.

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%

Table 3. The number of correct classifications

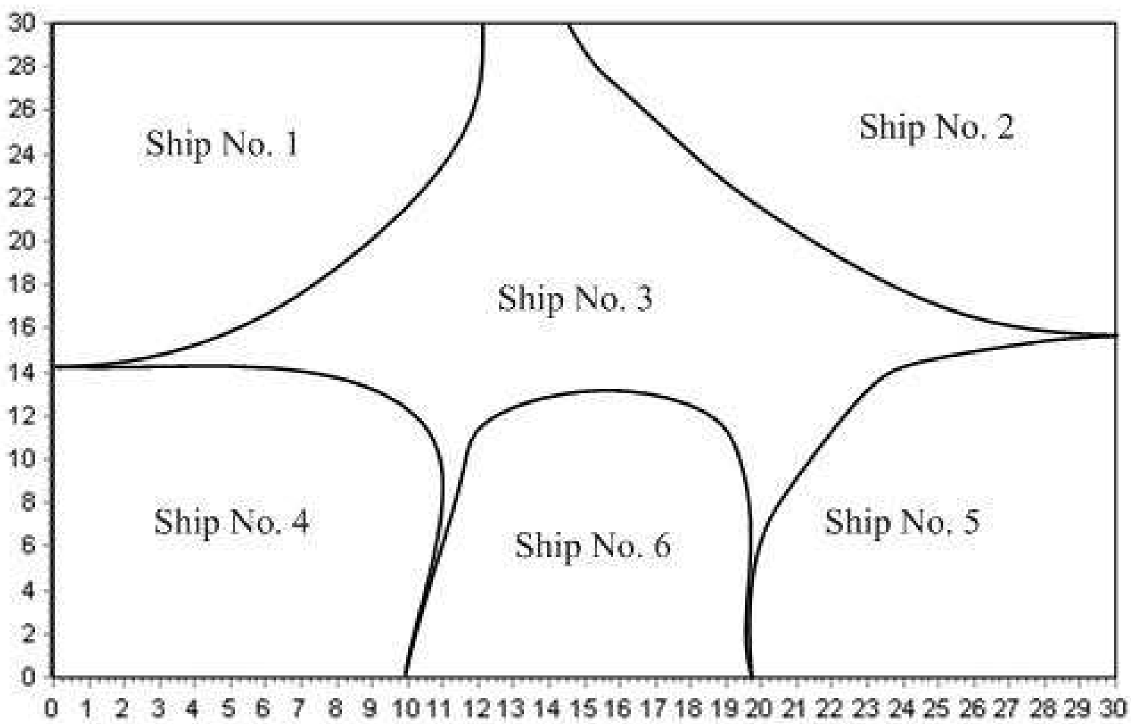


Fig. 15. The new map of partition for area of activation for researched ships after introducing new ship

6. Conclusion

As it is shown on results the used Self-Organizing Map is useful for ships classification based on its hydroacoustics 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 associated with feedforward 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 classifier 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 damaged), sound rates, etc. It doesn't consider the influence of changes of environment on acquired hydroacoustics signals. In next step of research the proper work of this method will be checked for enlarged vector of objects. The hydroacoustics signatures of ships were acquired in different environmental conditions and in different stage of ship operating. Therefore the cases of changing hydroacoustics 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 hydroacoustics signature should be made.

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 hydroacoustics 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.

7. References

Fort J. C., SOM's mathematics, *Neural Networks*, 19: 812–816, 2006

Gloza I., Malinowski S. J., Underwater Noise Radaited by Ships, Their Propulsion and Auxiliary Machinery and Propellers, *Hydroacoustics vol*. 4, pp. 165-168, 2001

Gloza I., Malinowski S. J., Underwater Noise Characteristics of Small Ships, *Acta Acoustica United with Acustica*, vol. 88 pp. 718-721, 2002

Haykin S., *Self-organizing maps, Neural networks - A comprehensive foundation*, 2nd edition, Prentice-Hall, 1999

Kohonen T., *Self-Organizing Maps*, Third, extended edition, Springer, 2001

Osowski S., *Neural Networks*, Publishing House of Warsaw University of Technology, 1996

Stąpor K., *Automatic object classification*, Publishing House EXIT 2005

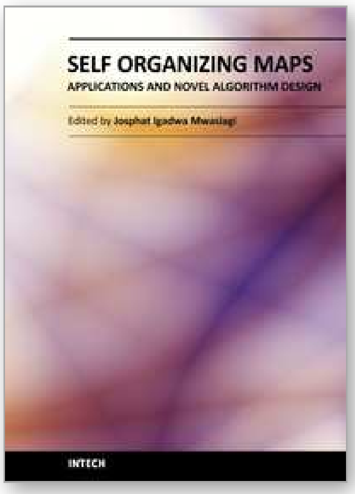
Szczepaniak P. S., *Intelligence Calculations, Fast Transforms and Classification*, Publishing House EXIT, 2004

Therrien Ch. W., *Discrete Random Signals and Statistical Signal Processing*, Prentice Hall International, Inc. 1992

Urick R. J., *Principles of Underwater Sounds*, McGraw-Hill, New York 1975

Zak A., Creating patterns for hydroacoustics signals, *Hydroacoustics* Vol. 8, pp. 265- 270, 2005

Zak A., Neural Classification Of Ships Hydroacoustics Signatures, Proceedings of the 9th European Conference on Underwater Acoustics ECUA 2008, Paris, France 2008, pp. 829-834



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Kohonen Self Organizing Maps (SOM) has found application in practical all fields, especially those which tend to handle high dimensional data. SOM can be used for the clustering of genes in the medical field, the study of multi-media and web based contents and in the transportation industry, just to name a few. Apart from the aforementioned areas this book also covers the study of complex data found in meteorological and remotely sensed images acquired using satellite sensing. Data management and envelopment analysis has also been covered. The application of SOM in mechanical and manufacturing engineering forms another important area of this book. The final section of this book, addresses the design and application of novel variants of SOM algorithms.

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