Neural classification of ships hydroacoustic signatures

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The paper presents method of classification of hydroacoustic signatures generated by moving ship. 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. In this paper the hydroacoustic signal 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. Hydroacoutsic signal classification is a difficult task and it is still an active research area. Automatic signal classification works based on the promise 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 paper includes discussion about unique of sound generated by moving ships. To solve problem of hydroacoustic signatures classification the Kohonen networks which belongs to group of self organizing networks where chosen. Hydroacoustic signals were acquired on the Polish Navy Range during the complex ship measurement. At the end the results of classification of underwater noises made by ship were presented.

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 $\{(x_1, y_1), \ldots, (x_n, y_n)\}$ produce a classifier $h : X \rightarrow Y$ which maps an object $x \in X$ to its classification label $y \in Y$. Classification algorithms are very often used in pattern recognition systems [4].

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 [6].

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 principle source of variance is the object himself. Sound signals in training and testing sessions can be greatly different due to many facts such as object sounds change with time, efficiency conditions (e.g. some elements of machinery are damaged), sound rates, etc. There are also other factors, beyond object sounds variability, that present a challenge to signal classification technology. Examples of these are acoustical noise and variations in recording environments and changes of environment itself.

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

2 Self-Organizing Maps

Kohonen 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 [1, 2, 3].

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

A 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.

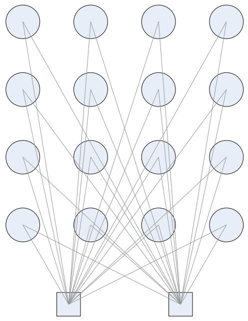

Fig. 1. A simple Kohonen network.

Training occurs in several steps and over many iterations [3]:

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 [5]:

– the most popular Euclidean distance is given as:

$$d(x,w_i) = \|x - w_i\| = \sqrt{\sum_{j=0}^{N}(x_j - w_{ij})^2} \qquad (3)$$

– the scalar product is given as:

$$d(x,w_i) = 1 - xw_i = 1 - \|x\|\|w_i\|\cos(x,w_i) \qquad (4)$$

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

$$d(x,w_i) = \sqrt{\sum_{j=0}^{N}|x_j - w_{ij}|} \qquad (5)$$

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

$$d(x,w_i) = \max_j(|x_j - w_{ij}|) \qquad (6)$$

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 2 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.

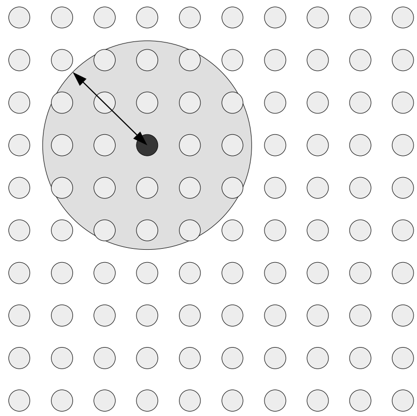

Fig. 2. The BMU's neighborhood.

To do this the exponential decay function can be used as follow:

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\lambda}\right) \quad t = 0,1,2,\ldots \qquad (7)$$

where: σ_0 denotes the width of the lattice at time t_0; denotes a time constant; 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:

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)(x_j(t) - w_{ij}(t)) \qquad (8)$$

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:

$$\eta(t) = \eta_0 \exp\left(-\frac{t}{\lambda}\right) \quad t = 0,1,2,\ldots \qquad (9)$$

In Equation 8, 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:

$$\theta(t) = \exp\left(-\frac{dist}{2\sigma^2(t)}\right) \quad t = 0,1,2,\ldots \qquad (10)$$

where: $dist$ is the distance a node is from the BMU; σ is the width of the neighborhood function as calculated by Equation 7.

3 Results of research

During research the five ships were measured on the Polish Navy Test and Evaluation Acoustic Ranges which schema was presented on figure 3. 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.

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. 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.

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.

Used Kohonen network has two dimensional architecture. 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: 4, beginning learning rate: 0.25 and method to determine the distance: Euclidean distance.

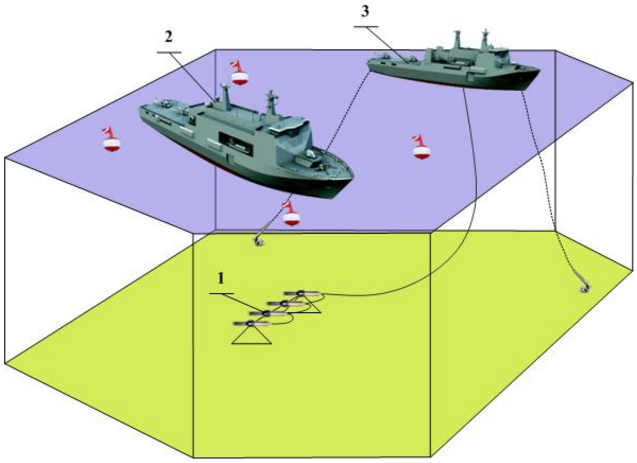

Fig. 3. Schema of hydroacoustic range during measurements; 1) sensors of acoustic signatures – array of hydrophones, 2) measured ship, 3) ship – base with mounted hydroacoustic measuring system.

Data presented as input for Kohonen network were transformed according the method presented in second section. So, Mel-Frequency Cepstral Coefficients calculated from recorded signals become as the input signal for feature matching subsystem it means Self Organizing Maps – Kohonen networks.

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 4. All areas activated by signals generated by considered ships were clearly separated. 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 5.

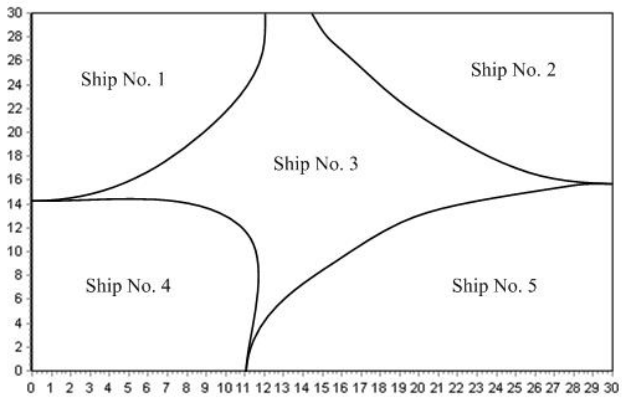

Fig. 4. The map of partition for area of activation for researched ships.

The table 1 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 6. The example results of classification results are presented on figure 7.

Data \ Ship no.	1	2	3	4	5
presented before	85.6%	87.2%	90.1%	89.3%	86.8%
not presented before	72.3%	75.8%	76.8%	71.4%	72.9%

Table 1. The number of correct classifications.

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 85%) 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.

It should be noticed that phase of preparing data it means feature extraction has influence on results of classification. In this paper simples method of Discreet Fourier Transform was used for preparing input data for neural networks. There are some results of using for example method of Mel-Frequency Cepstral Coefficients which may increase number of correct classification [9]. So using other methods of feature extraction should be checked in future research.

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 hydroacoustic signals. Therefore these cases should be investigated in future research. More over in future research the influence of network configuration on the quality of classification should be checked. 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

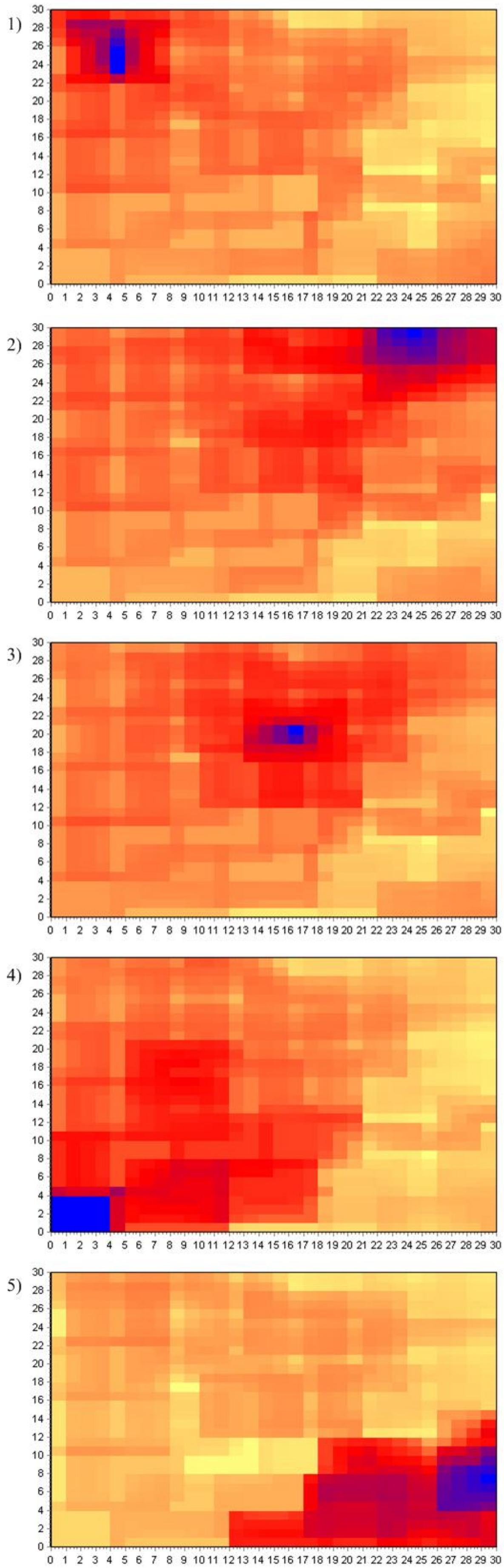

Fig. 5. The results of classifier work out - maps of memberships for data which weren't presented during learning process; 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5.

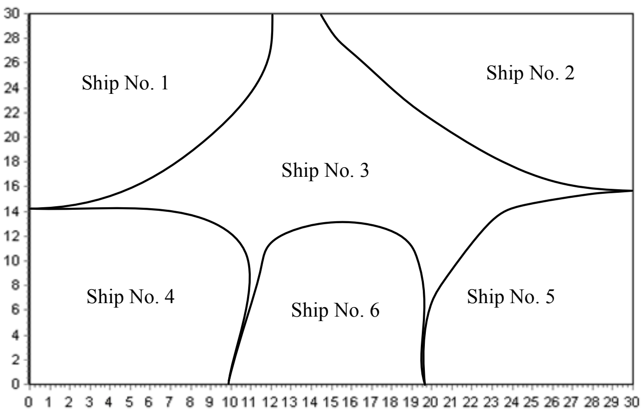

Fig. 6. The new map of partition for area of activation for researched ships after introducing new ship

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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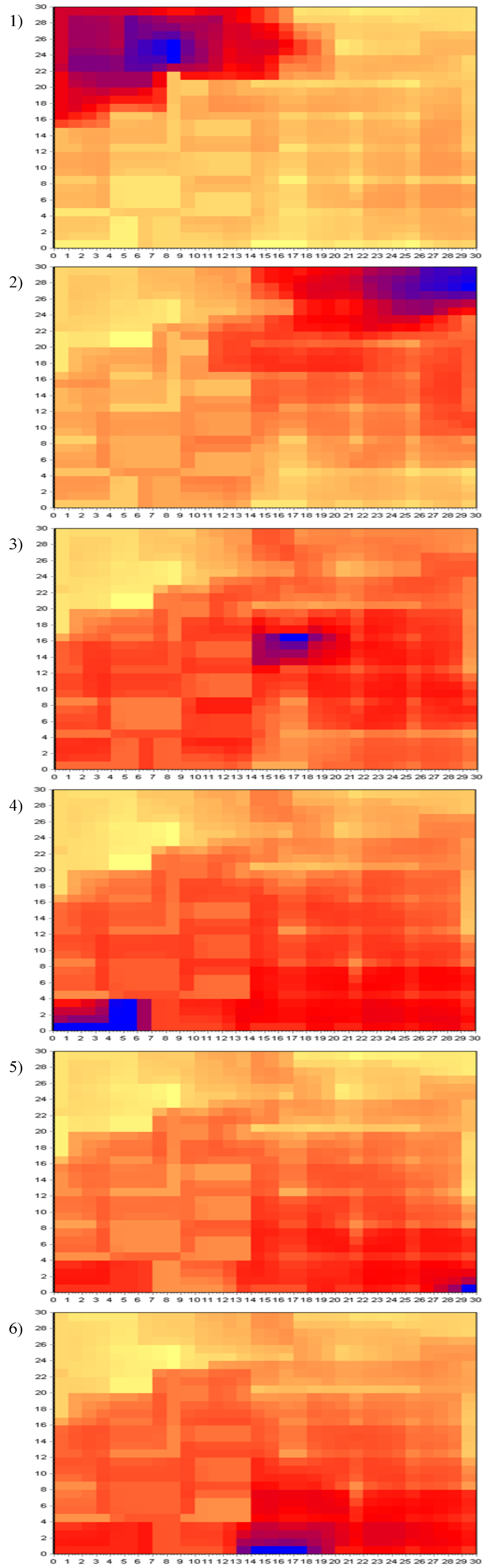

Fig. 7. The results of classifier work out - maps of memberships after adding the new ship; 1) for ship no. 1, 2) for ship no. 2, 3) for ship no. 3, 4) for ship no. 4, 5) for ship no. 5, 6) for ship no. 6.