

SHIP'S HYDROACOUSTICS SIGNATURES CLASSIFICATION

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(received June 15, 2008; accepted November 3, 2008)

The paper presents the technique of artificial neural networks used as classifier of hydroacoustics signatures generated by moving ship. The main task of proposed solution is to classify the objects which made the underwater noises. During the complex ships' measurements on Polish Navy Test and Evaluation Acoustic Range hydroacoustics noises generated by moving ship were acquired. Basing on these results the classifier of coustic signatures using Kohonen neural network was worked out. To check the correctness of the classifier performance the research in which the number of right classification for presented and not presented before hydroacoustics signatures were made. Some results of research were presented in this paper.

Keywords: self-organizing map, Kohonen's neural networks, hydroacousitcs 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 and based on a training set of previously labeled items [4].

Formally, the problem can be stated as follows: given training data $\{(x_1, y_1), \dots, (x_n, y_n)\}$ produce a classifier $h: X \rightarrow Y$ which maps an object $x \in X$ to its classification label $y \in Y$.

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 the same frequencies. 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 where measurements take place, the water parameters such as salinity, temperature and presence of organic and non organic pollutants.

Acoustic signatures have the great significance because its range of propagation is the widest of all physics field of ship. 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.

2. Classification method

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 [1–3].

The network is created from a 2D lattice of nodes, each of which is fully connected to the input layer. One of the most interesting aspects is that 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 [3]:

- 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.

There are many methods to determine the distance [4] but the most popular Euclidean distance is given as:

$$d(x, w_i) = \|x - w_i\| = \sqrt{\sum_{j=0}^N (x_j - w_{ij})^2}, \quad (1)$$

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:

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

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:

$$w_{ij}(t+1) = w_{ij}(t) + \Theta(t)\eta(t)(x_j(t) - w_{ij}(t)), \quad (3)$$

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:

$$\eta(t) = \eta_0 \exp\left(-\frac{t}{\lambda}\right), \quad t = 0, 1, 2, \dots \quad (4)$$

In Eq. (3), 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:

$$\Theta(t) = \exp\left(-\frac{\text{dist}}{2\sigma^2(t)}\right), \quad t = 0, 1, 2, \dots, \quad (5)$$

where dist is the distance a node is from the BMU, σ is the width of the neighborhood function as calculated by Eq. (2).

3. The results of research

During research the ten ships were measured on the Polish Navy Test and Evaluation Acoustic Ranges. Ships No. 1 and 2 were minesweeper project 206FM, ship No. 3 was

minesweeper project 207DM, ships Nos. 4, 5 and 6 were minesweeper project 207M, ship No. 7 was racket corvette project 1241RE, ship No. 8 was salvage ship project 570, ship No. 9 and 10 was racket kutter project 205.

The recordings were carried out by means of the array of hydrophones which were strung in a line along the bottom at depth 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. The ship under test was running at a constant speed and course during cross over hydrophones.

The best solutions to detect a ship are the discrete components in the low frequency part of the ship's noise spectrum. As input vector for classifier was used spectrum with band from 5 Hz to 200 Hz because there are no components discrete lines at frequencies range grater than 200 Hz in the modern submarines and surface warships.

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.

After about 50 000 cycles of neural network learning, was obtained the map of memberships for every presented ship as it is shown in Fig. 1. All areas activated by signals generated by considered class of 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. Table 1 shows number of correct classification of presented data relatively to the class of ship. The number of correct answer is presented as percent of all answers. After this part of researches the new ship No. 11 which was rocket corvette project 1241.1MP was presented. In few first presentations it was classified as ship No. 7 what was comprehensible because ship No. 7 is the oldest version

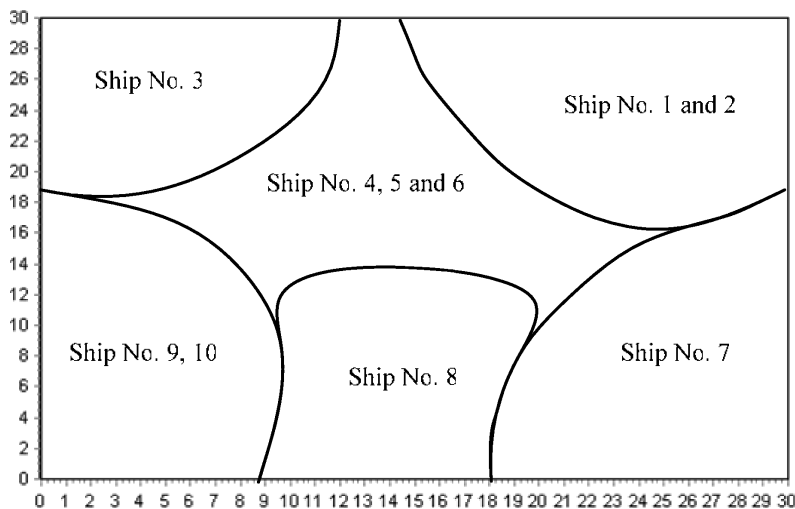


Fig. 1. The map of partition for area of activation for researched ships.

Table 1. The number of correct classifications.

Data	Ship no.									
	1	2	3	4	5	6	7	8	9	10
presented before	91.4%	92.5%	93.4%	90.9%	93.7%	94.6%	94.9%	91.2%	92.5%	94.4%
not presented before	75.2%	76.3%	76.7%	75.2%	75.9%	77.7%	76.6%	71.5%	76.0%	73.0%

of this vessel. Next the new group was created, which was separated from the area activated before by ship No. 7. The new map of partition for area of activation looks like is presented in Fig. 2.

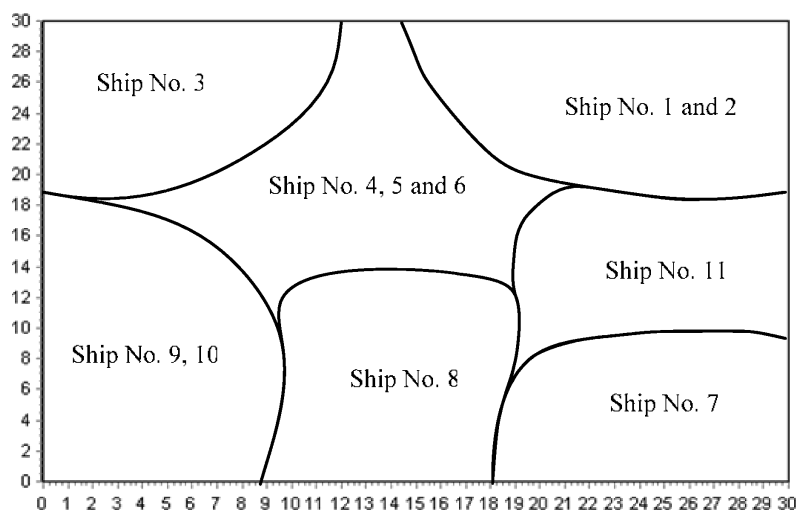


Fig. 2. The new map of partition for area of activation for researched ships after introducing new ship.

4. 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%). 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 class of ship. 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.

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. In this time there are some results about using Mel-Frequency Cepstral Coefficient as method of creating some kind of indexes for hydroacoustics signals [5].

References

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