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*Andrzej Stateczny*
*Tomasz Praczyk**

Department of Navigation
Maritime University of Szczecin
email: astat@wsm.szczecin.pl

*Institute of Informatics
email: tomekp@mw.mil.pl

# A modified probabilistic method of identifying radio wave sources for the needs of sea navigation

The problems of identification of objects have been strictly bound with sea navigation for a long time. The article presents a method of object identification by means of artificial neural networks. The classification of objects is effected on the basis of a radio signal. A comparison between classical methods and neural methods has been made. The results of research performed have been presented on real data, and a detailed analysis of the probabilistic network and its identification.

## INTRODUCTION

In sea navigation problems of object identification have to be solved very often. Be it enough to mention the identification of celestial bodies in astronavigation, the identification of fixed marking on the basis of comparison with a template included in navigational aids. Commonly known and applied are methods of light identification based their characteristics or rough identification of sea objects emitting fog signals. Another example is provided by identification through a coastal radio station called radio beacon based on a listening watch performed. The method presented in the article will allow to automatically identify both coastal (e.g. radio beacon) and ship radio stations, and on the basis therefrom to identify the coastal object (e.g. radio beacon) or the sea object. This method can find application not only for plotting the ship's position; it can also be applied in sea rescue, by the Cost Guard units or by reconnaissance vessels of the Navy.

Commonly known are numerous conventional algorithms of object identification, which have already proved their great possibilities. They have, however, two basic faults, which very often preclude their practical application. The first of them (on the algorithm part) is the need for conclusions to be made of a set of object features, the determination of which is difficult and labour-consuming. The fault of another group of classical solutions is the need to use a large set of examples of object pictures, which in real conditions is often difficult to fulfil, and besides causes the methods thus construed to be slow.

Another approach to the identification problem is the application of recent years' achievements – methods of artificial intelligence, especially artificial neural networks. Artificial neural networks are currently applied in a variety of ways. Because of the concurrent signal transformation of in neurons they are a promising alternative to the classic computer data transformation. An analysis has been carried out concerning the possibility of using selected models of neural networks for identifying the source of radio waves emission.

The article presents a comparison of selected conventional algorithms with neural algorithms in conditions of limited availability of information, i.e. applying a short teaching sequence. A method based on modified probabilistic network has been presented, which showed the best identification results during research.

## *Conventional identification methods*

### The pattern method

The basis of this method of object identification is the principle, according to which an unknown object $x$ is classified in the $i$-th class if it is contained in the area of $X^i$ pattern, which belongs to this very class. $X^i$ pattern is, as a rule, one of the elements of the teaching sequence. Of course, such an approach to the situation will bring about numerous situations where the identification system will be incapable of determining the affiliation of an unknown pattern to any class of objects, as it is very unlikely, in the case of multidimensional vectors which are pictures of the real objects, there being a lot of interfering factors, for the signals received to completely coincide with the signals already registered in the teaching sequence. For this reason, $X^i$ pattern has been defined as the following sphere [10]:

$$X^i = \left\{x_k^i \in U^i : \rho\left(x, x_k^i\right) \langle \varepsilon_k^i\right\} \tag{1}$$

Briefly speaking, it is a sphere of radius $\varepsilon_k^i$ described on the $k$-th pattern of the teaching sequence belonging to the $i$-th class. Coefficient $\varepsilon$ plays an essential role in this definition. In the simplest case, it is fixed for every pattern from the teaching sequence and experimentally selected. An approach like this, however, lowers the qualities of the algorithm presented. The best solution is to select coefficient $\varepsilon$ individually for every teaching pattern, for example, on the basis of the following rule [10]:

$$\varepsilon_k^i = \frac{1}{2}\left(\min \rho\left(x_q, x_k^i\right) \text{for}\, x_q \notin U^i\right) \tag{2}$$

i.e. determining the radius value for the k-th pattern belonging to the $i$-th category on the level of the smallest distance from the teaching patterns that do not belong in this category.

With an algorithm thus defined a situation may arise where an unknown pattern is found in the area of a number of teaching patterns belonging to various classes, or it remains removed from any teaching picture and from the sphere described thereon. In such a case, the algorithm will provide the answer 'don't know'. That was the reason for working out a modification of the algorithm, the essence of which was: if the picture tested is found within the reach of a number of pictures coming from various classes, the pattern is classified within the category that has the largest number of $X$ patterns, with which the tested pattern coincides. The modification will not, of course, prevent all 'don't know' answers of the algorithm. They will occur in the following situations:

- the unknown pattern is found beyond the reach of all $X$ patterns from the teaching sequence
- the unknown pattern is found within the reach of the same number of $X$ patterns belonging to different categories.

The first case may be interpreted as the classification of the unknown object in an unknown category, the second case, on the other hand, is a critical situation, where the algorithm was unable to provide an unequivocal answer, which class of objects we are dealing with.

The research was performed for both variants concerning value $\varepsilon$. In the first part of the research the quality of the algorithm was examined with identical $\varepsilon$ values for every pattern from the teaching sequence for the following range of variability <200,1500>. The results obtained have been presented below.

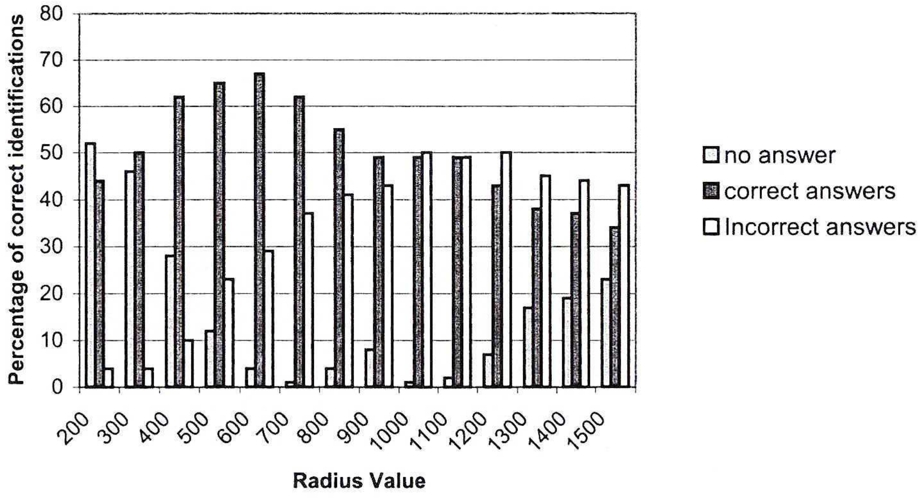


Fig.1. The obtained result of no answer, correct and incorrect object identifications depending on value $\varepsilon$

The best result obtained by this method is 67% of correct identifications for $\varepsilon = 600$. For the same radius value the algorithm obtained 3% of no answers and 30% of incorrect identifications.

The second step in the research on the algorithm was to examine its possibilities when the variable value $\varepsilon$ was individually selected for every pattern of the teaching sequence in accordance with rule (2). With this approach 80% of correct identifications were obtained, 12% of incorrect identifications and 8% of no answers.

*Minimum-distance methods*

Classification by minimum-distance methods is based on the distance of the unknown pattern from those within the teaching sequence. The concept of distance is always bound with metric. Euclidian metric defined by the following formula [10] seems to be most natural:

$$\rho(x_1, x_2) = \sqrt{\sum_{k=1}^{n} \left(x_1^k - x_2^k\right)^2} \tag{3}$$

or the metric determined by the following dependence [10]:

$$\rho(x_1, x_2) = \sqrt{\sum_{k=1}^{n} \left|x_1^k - x_2^k\right|} \tag{4}$$

There are two variants of the minimum-distance method. The first is based on classifying the tested pattern into a category where the closest teaching picture in the sense of the selected metric belongs. Such an approach, however, results in little resistibility of the algorithm to errors of the teaching sequence. This results from the idea assumed in the method of the closest neighbour, which wrongly subordinates every unknown pattern in the neighbourhood of $\varepsilon^{\alpha}$ erroneous teaching pattern. In order to limit this effect a modification of the algorithm called $\alpha NN$ was introduced. The method consists in counting the distance of the unknown pattern from every picture in the teaching sequence according to the metric selected. Next, the teaching sequence is ordered according to increasing distance values From a sequence thus constructed a sub-sequence is created by segregating the first $\alpha$ pictures of the smallest distance from the test pattern, which is next classified into the category most strongly represented in the sub-sequence created.

During research, both variants of the minimum-distance method were tested. For the $\alpha NN$ algorithm, the effect of the $\alpha$ parameter on the end result was examined.

The next-door neighbour algorithm *NN* for both metrics applied, (3) and (4), gave a result of 85% of correct identifications. The results obtained by the $\alpha NN$ method have been presented on the graph below. The first column for the given $\alpha$ value signifies the percentage of correct identifications for metric (3), the second column for metric (4).

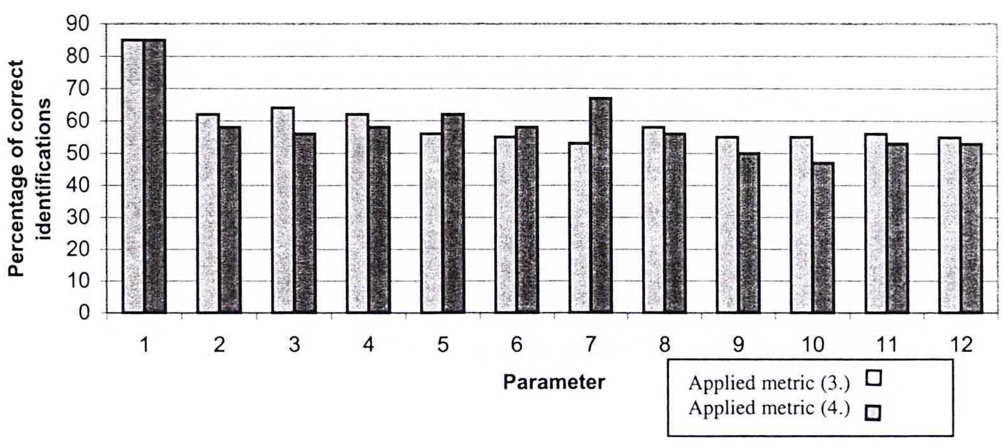


Fig.2. The result of correct identifications depending on $\alpha$ parameter

As the graph shows, the best result was obtained for $\alpha$ = 1–85%, which is of course the same result as in the case of *NN* method, as for $\alpha = 1$ both methods are equivalent to each other.

## *Neural methods*

In research on artificial intelligence two main trends have appeared. The first of them ignores the construction of the human brain concentrating mainly on the functions performed by it. These are expert systems. The other approach, which is getting more and more popular, consists in attempts to copy the structure of our brain, concentrating on its structure, not functions.

Neural networks can be treated as a certain kind of data structure, which changes in the course of the learning process adapting to the kind of problem to be solved. This structure is constituted by single neurons performing simple arithmetic functions bound into a web. The first and basic neuron model defined as early as in 1943 by McCulloch and Pitts is the nerve cell, the function of which consists in the weight sum of neuron entrances, and next subjecting the sum thus obtained to the action of non-linear activation function. In effect, the output signal of such a neuron is defined by the following dependence [5] [9]:

$$y_i = f\left(\sum_{i=1}^{N} W_{ij} x_j\right) \tag{5}$$

where $x_j$ ($j = 1,2, \ldots , N$) represent input signals, and $W_{ij}$ – respective weight coefficients.

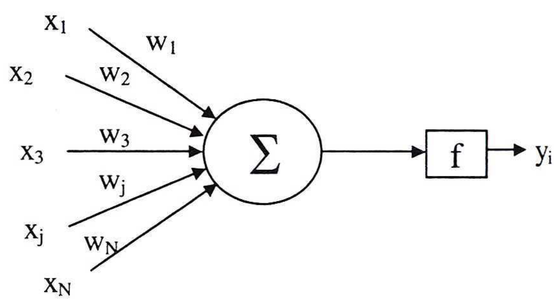


Fig. 3. Neuron diagram [9]

Neural networks are tools of a very wide scope of applications. The most important features proving their enormous advantages and wide possibilities is the parallel transformation of information and their ability to learn and generalise the acquired knowledge.

The basic advantage of the network used in identification tasks is its ability to learn by examples. Having been presented sample object pictures the network is able to create the ability to classify them during the learning process.

During research there was examined the possibility to apply the following neural algorithms for identifying sea objects:

- Multi-layer perceptron
- Kohonen network
- Hamming network
- RBF radial network
- Probabilistic network
- Neurofuzzy network

Spectrums of radio signals were the object pictures. The experiment was carried out for objects belonging to three categories.

Below there have been presented results of applying neural methods for identifying sea objects. The graph presents the percentage number of correctly recognised patterns from the testing sequence containing pictures formerly presented to none of the network works.

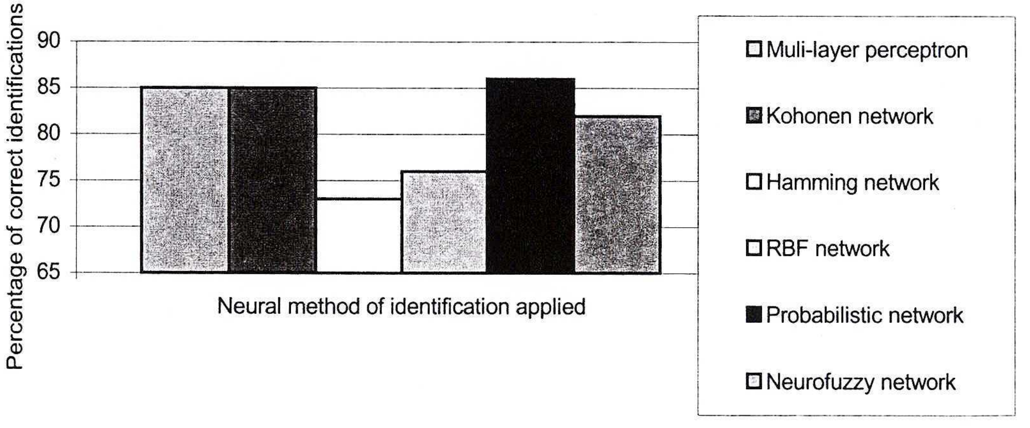


Fig. 4. The application of selected neural algorithms for identifying sea objects

The probabilistic network proved to be the best solution, which obtained 88% of correct identifications in the testing sequence.

## Probabilistic network

One of the categories of neural networks are probabilistic networks based on a statistical algorithm of classification created already tens of years ago. In spite of its great merits known at the time of its creation, its practical application was limited by the state of computer technology. Modern computers make it possible to use it, as they provide enough memory and sufficient speed.

The algorithm basis is the definition of a function describing the degree of affiliation of an unknown object picture with a definite category. That function is the density of probability. Because of the density of function being frequently unknown for a class of objects, its estimator is determined on the basis of pictures from the teaching sequence. The estimator for a single class of objects is a scaled average of weight functions determined for object pictures of that class coming from the teaching sequence. The weight function is characterized by maximum value at the point equal to the teaching picture, which abruptly falls to zero along with the increase of distance between that point and the picture classified. The Gauss is a popular function, for which the density function assumes the following form:

$$g(x) = \frac{1}{(2\pi)^{p/2}\sigma^p n}\sum_{i=0}^{n-1}\exp\left(-\frac{\left\|x - x_i\right\|^2}{2\sigma^2}\right) \tag{6}$$

The classification of the object represented by picture $x$ into the $i$-th category in based on the relationship:

$$h_i c_i g_i(x)\rangle h_j c_j g_j(x) \tag{7}$$

for every $j$ class different from $i$. $H_i$ denotes the apriori affiliation of a picture to the $i$-th class, $c_i$ the cost of incorrect identification of a picture belonging to the $i$-th category; $g_i(x)$ is the function of probability density for the $i$-th category.

Assuming values $c$ and $h$ to be equal for every object class the task of classification consists in comparing the values of decision functions g($x$) and classifying the function into the category, for which the value of the function is largest. Besides, formula (6), assuming value σ to be the same for every class, can be brought to the following form:

$$g(x) = \frac{1}{n}\sum_{i=0}^{n-1}\exp\left[-\left(\frac{d(x, x_j)}{p\sigma}\right)^2\right] \tag{8}$$

where $d$ is the Euclidian distance between vectors $\boldsymbol{x}$ and $\boldsymbol{x}_i$ , $n$ is the distance of the teaching sequence, $p$ is the size of the input vector.

Form (8) of the decision function makes it possible to implement the statistical algorithm of classification in the shape of a multi-layer structure of one-direction flow of the signal from input to output, consisting of elements performing simple arithmetic functions.

During research the possibility was tested of applying probabilistic network for identifying sea objects. Object pictures were spectrums of radio signals. The experiment was carried out for objects belonging to three categories. It was examined how the length of the teaching sequence and parameter $\sigma$ affects the quality of network identification, measured by the percentage of correct classifications of pictures belonging to the testing sequence.

The results show that the network reaches the best results for maximum length of the teaching sequence equal to 24 pictures – 88% of correct identifications. As can be seen on the graph describing the dependence between the length of the teaching sequence and the percentage of correct identifications, it is not linear, which can be due to unequal representation of all data areas in the teaching sequence when it is of smaller length. Besides, it can be noticed that the shorter the teaching sequence, the smaller the $\sigma$ value, for which the results attained by the network are the best.

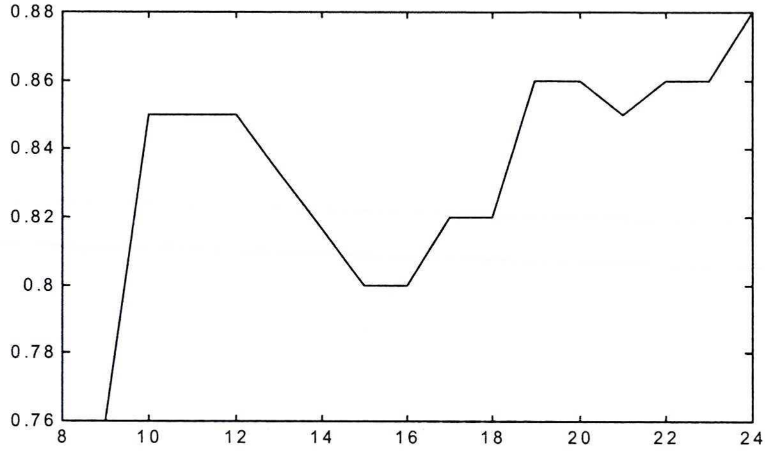


Fig.5. Percentage number of correct identifications depending on the length of the teaching sequence.

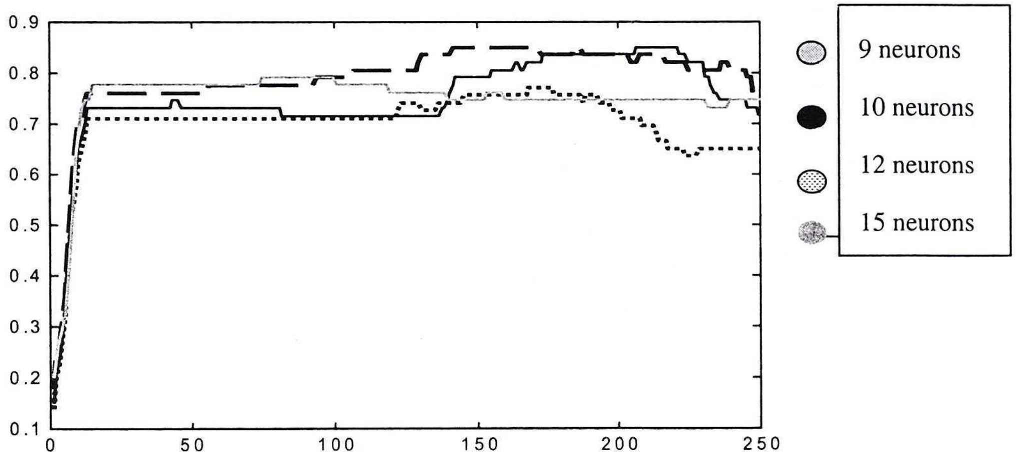


Fig.6. Result of correct identifications for 9, 10, 12 and 15 neurons in the teaching sequence depending on $\sigma$

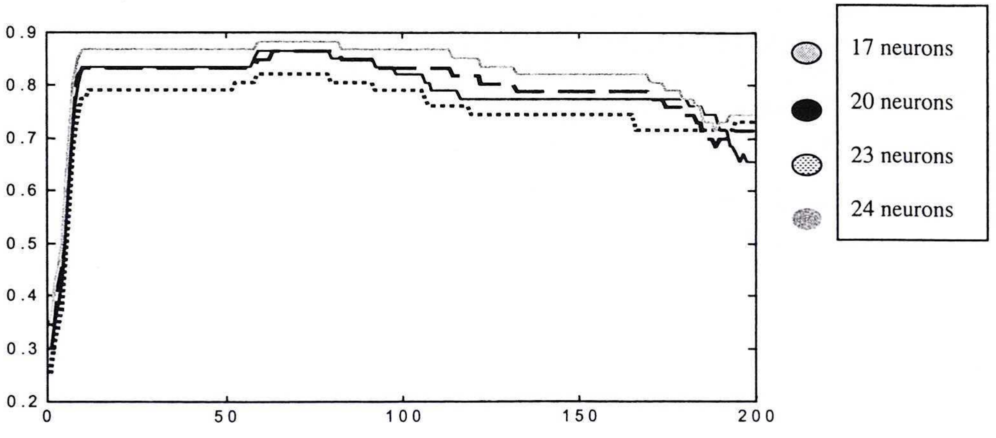


Fig.7. Result of correct identifications for 17, 20, 23 and 24 neurons in the teaching sequence depending on $\sigma$

*A modified probabilistic method of identifying objects*

A demerit of the classical probabilistic solution is its slowness. It is a result of applying in the concluding process all the teaching data remembered in the probabilistic network structure. In the case of applying long teaching sequences, and it is this situation that we have to do with most often, such a solution causes a long replying time of the classical algorithm.

A method of shortening the replying time is replacing the teaching data with their averaged representatives. The averaged patterns can be calculated by means of Kohonen network, taught, for instance, by the adaptive algorithm of vector quantization, using a previously defined teaching sequence. Lest the use of average pictures should impair the ability of the method modified in the scope of object identification, it is necessary to alter the construction of decision function (8). It consists in introducing into (8) an additional parameter $S$, which determines the number of teaching patterns, associated with the average pattern calculated on their basis. The final shape of the decision function for the modified probabilistic method looks as follows:

$$g(x)=\frac{1}{n}\sum_{i=1}^{w} S_i \exp\left[-\left(\frac{\rho(x,x_i)}{\mathrm{p}\sigma}\right)^2\right] \tag{9}$$

where $x_i$ is $i$ – the average pattern.

The decision function thus defined, based on average pictures, attains higher values in places of frequent occurrence of teaching patterns of a given object category. A similar approach was applied in the classical probabilistic network.

*A comparison of conventional algorithms and the modified probabilistic method*

The graph (Fig. 8) presents a comparison of the methods of patterns, minimum-distance algorithms – $NN$ and $\alpha NN$, and also the probabilistic and a new method, which is a

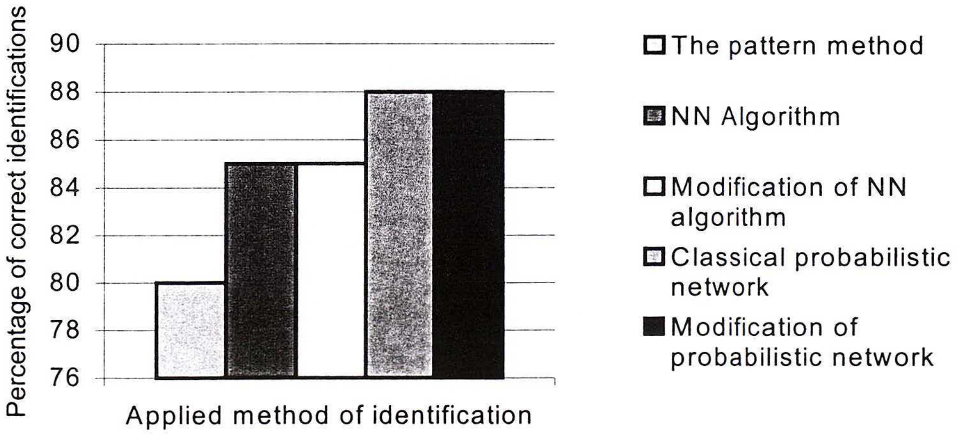


Fig.8. Percentage number of correct identifications of pictures from the testing sequence depending the method applied

modification of it. This modification consists, as formerly mentioned, in using not one decision function per one class of objects, as in the classical algorithm, but a larger number of them, depending on the number of centres selected to represent the teaching data of a defined category of objects. With a solution like that the classification of objects consists in comparing the values of all decision functions and assigning to the unknown pattern the category bound with the decision function of the strongest input signal. Such a modification of the probabilistic network requires less memory on the part of the computer for it being put into practice owing to the teaching pictures being replaced by their less numerous representatives. Besides, a solution like this is faster than the classical one.

The results show the superiority of the probabilistic network and its modification over conventional algorithms. Besides, in the case of the neural solution they showed the possibility of using for the network construction a smaller amount of data than in the case of the classical solution. Thus, we have gained an algorithm which is fast and less demanding in the area of the memory indispensable for it being put into practice, and also gaining results as good as the classical probabilistic network.

## CONCLUSIONS

In the article there has been presented a method of identifying the source of emission of radio waves for the needs of sea navigation. The new method is a modification of the probabilistic network. Conventional and Neural methods have been compared from the angle of their usability for coastal or ship radio identification. Results have been presented of research carried out using registered real signals.

The teaching sequence containing a small number of example pictures as also interference introduced into the pure system caused a lot of differentiation attained by results of neural algorithms. Among methods examined, the best proved to be the probabilistic network, which gained 88% of correct identifications of pictures from the testing sequence, which makes it a perfect tool of sea objects classification. Identical results were obtained by a new method, which is a modification of the probabilistic network. In this method, so-called central points replaced teaching patterns as an element of the classical structure of probabilistic solution. Such an approach preserves the very good qualities of the original shape, simultaneously reaching a higher answering speed, and also requiring less memory to put it into practice.

Conventional algorithms, particularly minimum-distance methods – of next-door neighbor NN and αNN reaching 85% of correct identifications, proved to be solutions that did very well in conditions of real signal. The small number of teaching data did not prevent them from creating a decent level of generalising the acquired knowledge. The result obtained is worse, however, than the results of the probabilistic network and its modification.

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*Andrzej Stateczny*
*Tomasz Praczyk*

**Zmodyfikowana metoda probabilistyczna identyfikacji źródeł fal radiowych dla potrzeb nawigacji morskiej**

S t r e s z c z e n i e

Problematyka identyfikacji obiektów jest od dawna ściśle związana z nawigacją morską. W artykule przedstawiono metodę identyfikacji obiektów za pomocą sztucznych sieci neuronowych. Klasyfikacja obiektów realizowana jest na podstawie sygnału radiowego. Porównano metody klasyczne z metodami neuronowymi. Przedstawiono wyniki przeprowadzonych badań na danych rzeczywistych oraz szczegółową analizę sieci probabilistycznej i jej modyfikacji.

*Анджей Статечны*
*Томаш Прачик*

**Модифицированный метод вероятностной идентификации источников радиоволн для потребностей морской навигации**

Р е з ю м е

Проблема идентификации объектов издавна тесно связана с морской навигацией. В статье представлен метод идентификации объектов при помощи искуственных нейронных сетей. Классификация объектов выполняется на основе радиосигнала. Проведено сравнение классических методов с нейронными методами. Представлены результаты проведенных исследований на действительных данных, а также подровных анализ сети вероятностей и её модификации.