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NEURAL ALGORITHM OF FIXING THE SHIP'S POSITION

ABSTRACT Comparative methods of plotting the ship's position based on the radar picture can be applied in coastal regions and narrow passages. The article presents the algorithm of comparative plotting of the ship's position with the application of an artificial intelligence method – artificial neural networks. The results of numerical experiments have been adduced, conducted according to the method worked out.

INTRODUCTION

In the process of plotting the ship's position by comparative methods the radar picture undoubtedly plays a great role. Computer systems of plotting the ship's position are likely to find universal application in coastal sailing, as their basic advantage is that they bind themselves directly to the coast, which is a basic requirement of coastal navigation. An unquestionable advantage of these systems is also their autonomy, i.e. independence of information sources, unlike other positional systems.

The hitherto applied classical methods of analytical comparison of digitally recorded radar pictures and the sea chart are based on complex and time-consuming calculation algorithms requiring the computer's memory. Due to the number of calculations the results obtained are likely to become outdated. The article presents a new approach to the problems of plotting the ship's position by comparative methods and artificial neural networks have been applied for this purpose.

One of the most important features of artificial neural networks is the parallel data transformation. They have found application in many situations. The elements of the network, simple in structure and functioning, when connected into a specific system create enormous possibilities of data transformation. Another advantage of applying neural networks is their considerable resistance to damages and errors. The improper functioning or damage of one neurone does not greatly affect the functioning of the whole network; it does not cause loss of knowledge – it is spread over the whole network.

Recognising pictures is one of the main applications of neural networks. Numerous treatises and technical solutions have arisen concerning this subject. In the matter of picture recognition the ability of the network to function in interference conditions becomes of great importance. Unlike with classic algorithms performing the task of picture recognition, the distorted picture does not require filtration; it is a very important feature of neural networks, especially in the case of radar picture recognition, especially because they have certain interference and noise difficult to filter.

Neural networks can be treated as a certain data structure, which changes in the course of learning, adapting to the kind of problem to be solved. This structure is constituted by single neurones bound into a network; they perform simple arithmetic functions. In effect, the output signal of such a neurone is described by the following dependencies [Tadeusiewicz, 1993]:

$$v = \sum_{i=1}^{m} W_j \cdot u_j \tag{1}$$

$$y = f(v) \tag{2}$$

where: u_j – input signal values;
W_j – weight coefficient values;
m – number of neurone inputs;
$f()$ – activation function;
y – neurone output signal.

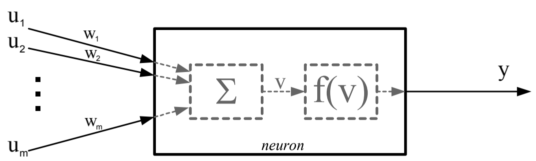

Fig.1. Diagram of an artificial neurone (elaborated on the basis of [Korbicz 1994].

There are a few function types describing the activation block presented in Fig.1. They can be linear, single-transfer, sigmoidal, tangesoidal and other functions. The two last-mentioned activation functions describe in more detail the non-linear characteristic of neurone passage.

THE CONCEPT OF NEURONE METHOD FOR DETERMINATION OF THE SHIP'S POSITION

Authors of applying artificial neural networks in comparative navigation have worked out the concept. It presupposes the use of chart pictures at the stage of teaching the neural networks. A specially constructed teaching sequence (teaching pictures) can be expanded by a few radar pictures, which will cover by their range the water region considered. In this way, the representability drawn into the sequence of the network teaching will be expanded. The stage of network testing commences after successful network teaching. a specially prepared teaching sequence serves this purpose, which incorporates registered radar pictures.

Initial research conducted on the possibility of applying neural networks for comparing radar pictures with a sea chart have proved that it is indispensable to compress beforehand the pictures to a smaller size. The original size of the pictures causes the neural network to have a very expanded structure and the teaching process takes a very long time and does not reach the required results. Besides diminishing the size of the input data of the neural network, the selected compression method should extract the most important features out of the pictures considered.

The most important element of the concept elaborated is the artificial neural network. Its structure and parameters depend on the selected network type. The concept worked out has been tested on a few known types of artificial neural networks. An optimisation of their structure has been carried out.

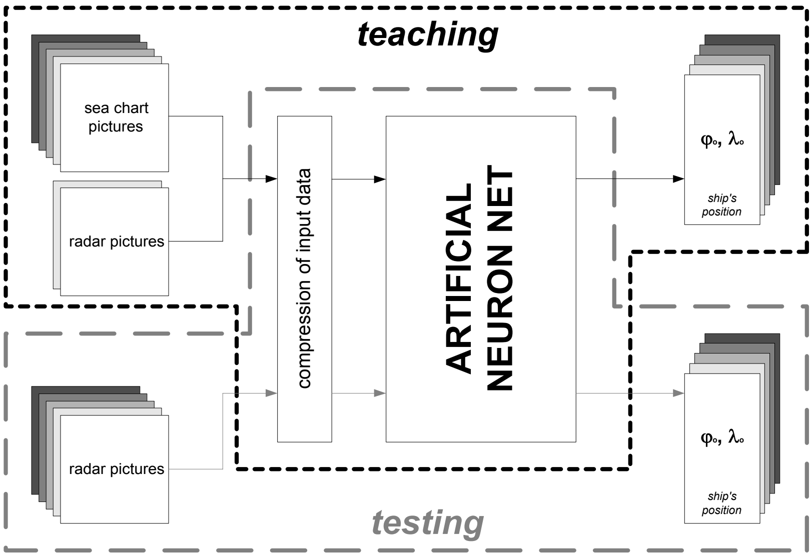

Fig.2. The concept of neurone method of plotting the ship's position by means of comparing the radar picture with the sea chart

The means of joining the neurones among one another and their cooperation have divided the networks into various types. Every of them is bound with a certain method of teaching, that is the selection of neurone weights. The research was conducted for a few types of neural networks. The multi-layer perceptron, the Kohonen network, the radial and neurofuzzy network and the GRNN (General Regression Neural Network) were applied, for which the best results were obtained of adapting the radar pictures to the sea chart.

GRNN NETWORKS

The developed method of plotting the ship's position by comparing the radar picture with the sea chart is based on the network of GRNN type. In the course of simulation research it turned out that it is the best for the process of fitting the two pictures. The observed ship's position in most cases and for various testing sequences was the same as the real position taken from DGPS.

GRNN neural networks function in a similar way to probabilistic networks (PNN). In an analogous way, for every teaching set the value of Gauss function is defined. With every next recognised picture (radar picture) the response level (of the vessel's position) is found on a certain height with relation to the indicated point in space with a progressively decreasing reply in the immediate proximity of this point.

The former layer concealed in the GRNN network contains radial neurones; the latter performs special procedures. The neurones of this layer help calculate the average value of gravity centres, which is a reply of the GRNN system:

$$y = \frac{\sum_{i=1}^{N} W_i \mu_i(u)}{\sum_{i=1}^{N} \mu_i(u)}, \tag{3}$$

where: $\mu_i\ (u)$ - allegiance function (Gauss function);

W_i - the weight corresponding to the value of radial function centres from the concealed GRNN network.

A diagram of the GRNN network is presented by the following figure:

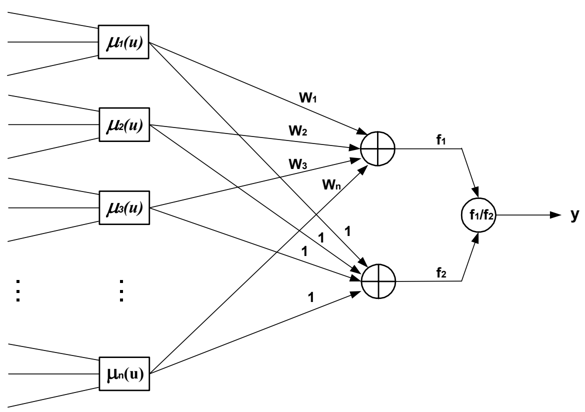

Fig.3. A diagram of the GRNN neural network type

In order to obtain the average from a reply centres of radial neurones, the sum must be divided by the sum of influencing factors. The value is calculated by a single neurone in the second layer. Next, the output layer calculates the division layer; in this way, the concealed layer always possesses one neurone more than the output layer. In GRNN networks, mostly only one layer is calculated, so the second concealed layer usually has two neurones.

Before application, the neural network is subjected to the teaching stage; a specially constructed teaching sequence serves this purpose. The most often used method of teaching neural networks (perceptron, radial network, neurofuzzy network etc.) is the algorithm of backpropagation – the algorithm of supervised type teaching. According to this, the teaching process consists in such equalising of the network weights, that the error generated should be as small as possible. The algorithm minimises the sum of squares of network teaching errors using the methods of most fall. Teaching the network, we seek for the minimum function value described by the function [Osow96]:

$$F = \frac{1}{2} \cdot \sum_{i=1}^{k} \left(y_i - \omega_i \right)^2 \tag{4}$$

where: y_i – the real reply of the network to the enforcement in the form of u_i;
ω_i – the required form of the network response.

A GRNN network learns almost immediately; this process takes a course different from other networks. In the process of its learning the teaching sequences are copied into the network in order to using them in the process of acting (testing) of a proper estimation of replies to new points. The output of the network is calculated taking advantage of the average weighed output for the teaching sequence, which is strictly bound with the distance of the point from the estimated point (adjacent points have most importance in designating the weight).

SIMULATION RESEARCH ON THE NEURAL METHOD

Initial research on applying neural networks for the recognition of radar pictures has shown that the primary structure of registered radar pictures greatly affects the number of input data sets. Pictures in a form like this (half-tone screen) because of their large size are not fit for practical application (no satisfactory results have been obtained concerning teaching the network). And thus, before accessing the building of a suitable teaching sequence, it will be indispensable to select a method of the radar picture compression. It should, on one hand, limit the size of the input vector supplied to the network, and on the other hand, extract the most essential features from the radar and chart pictures.

The next step is to prepare a teaching set, i.e. a sequence of data by means of which the network will learn the proper recognition of the pictures. It must be stated that the construction of such a sequence is a necessary condition for the correct functioning of the neural network. The pictures contained therein should be representative; their spatial layout should in the highest possible degree correspond with the real distribution of input data. The representability of the sequence can be ensured by increasing its length each time the network results are unsatisfactory, or by means of their proper selection with the help of e.g. self-organising networks. The pictures for the teaching sequence were obtained by suitable cutting out of pictures from the part of a sea chart of a size and scale corresponding to the radar picture. In order to ensure the representability of the teaching pictures, registered radar pictures were also included in the composition of the sequence, which completely cover the area of the sea chart fragment.

The last step is the construction of a suitable neural network. For this purpose, advantage was taken of an object-oriented design Westmount program, based on Sun computers.

The following block diagram can present the numerical experiment conducted, which researches particular neural algorithms of picture matching:

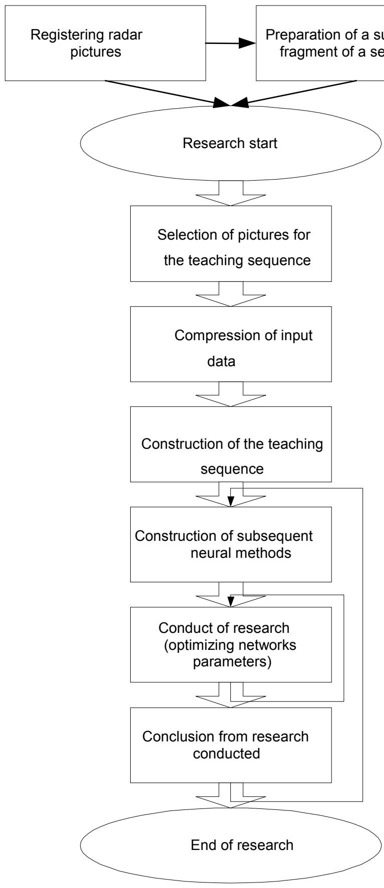

Fig.4. Algorithm of simulation research on neural networks (own work)

PICTURE COMPRESSION

In the course of the research the neural method of picture compression was used, thanks to which the programmed neural networks evinced the capacity to learn; it makes use of Kohonen neural network to decrease the size of the input picture and to emphasise its most important characteristic features.

Kohonen networks usually constitute a single layer of neurones, whereby the input number of each of them is equal to the length of the input vector. They belong to the class of networks learning without supervision, by self-organising which consists in neurone competition in adapting to the presented input patterns.

The input picture is registered as a half-tone screen and recorded in the form of a matrix of a size of 100x100 elements (picture pixels).

Before embarking on the compression, each picture was divided into 100 equal parts; each of them had an equal number of 100 elements. The division of a picture of 100x100 pixels resolution is very simple in this case.

The input of the network gives divided pictures in their primary form. In turn, the network reads one by one each of the 100 pieces of the main picture. The teaching of such networks consists in the neurones competing to be stimulated and to update their weights. The answer of the network is in the number of the winning neurone (the stimulated one), which will constitute the compressed value of the picture fragment read by the network. a diagram of picture compression using the Kohonen network is presented on Fig.5

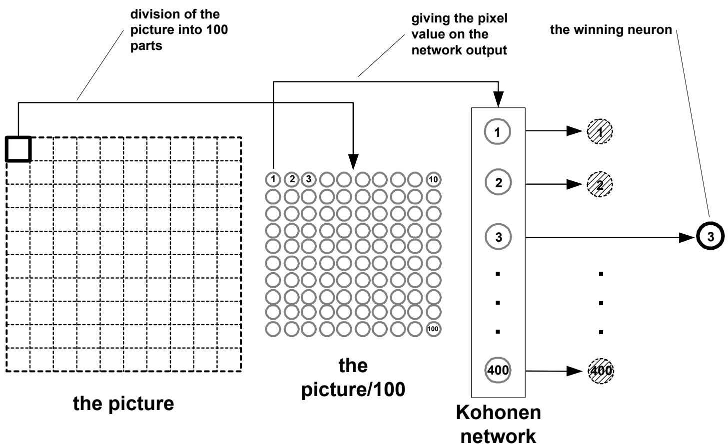

Fig.5. A diagram of particular picture parts compression using the Kohonen network

A network thus constructed divides the space of input pictures into as many areas as many neurones it has. In our case the space has been divided into 400 areas. The neurone number has been chosen experimentally. Networks of various sizes were examined. The best compression results of input picture were obtained for 400 neurones.

As a result of compression functioning the space closest to a given piece of the picture is sought for. Pictures thus compressed are part of the neural network teaching sequence performing the task fitting the pictures.

SELECTION OF THE TEACHING SEQUENCE

The network's functioning quality is defined as measure of its ability to generalise the knowledge gained. It depends on the methods of teaching the network, as well as on what the network is taught by. Thus, a very important factor is the proper selection of the teaching sequence, so as to minimise the generalising error. For this purpose, the teaching sequence has to contain data representing the total range of their changeability.

The representability of data in the teaching sequence is brought about by its lengthening each time the network has been insufficiently taught. Yet, with a limited number of data this is not always possible. In such a case, the teaching data are suitably selected; knowledge of the distribution of available patterns is therefore indispensable. Thanks to Kohonen network's ability to divide input data into groups most similar to one another in terms of the distance among them, are we able to determine roughly their spatial distribution and construct the teaching sequence in such a way that it should contain data from every class defined by Kohonen network. In this way we increase its representability.

In order to put this into practice, it was purposeful to introduce registered radar pictures into the teaching sequence, which would completely cover the considered picture of the map fragment. With a larger number of radar pictures available, whose position at the moment of registration is known, it is possible to teach the network without the participation of sea chart pictures.

Conducted by these principles a suitable teaching sequence was constructed, made up of compressed forms:

- 400 pictures of a sea chart of 100x100 pixels resolution covering the examined area of the sea chart;
- 40 radar pictures of 100x100 pixels resolution to increase the variety of elements inthe teaching sequence.

The radar pictures occurring here did not repeat themselves during testing the correctness of the neural network's functioning.

FIXING THE SHIP'S POSITION USING THE GRNN NETWORK

Comparing research results obtained by classical methods and the elaborated neural methods of comparative navigation we can state that for the teaching and testing sequence selected for the simulation research conducted the best results were reached by applying the neural method functioning based on the GRNN method. The number of correctly matched radar pictures of the testing sequence served for classifying the best method to be selected.

The structure of the elaborated method of plotting the vessel's position on the basis of comparison between the radar picture and the sea chart is presented on Fig.6.

The radar pictures read in turn are subjected to compression by Kohonen network (400 neurones). Input data of 100 elements length are obtained. Next, the GRNN networks read the latitude and longitude of the vessel at the moment when the radar picture is recorded. The GRNN network structure has been established for 440-2-1 neurones in consecutive layers. The neurone number of the input layer corresponds to the size of the teaching sequence (400 chart pictures and 40 radar pictures). The neurones remember the teaching pictures; each of them is consecutively given one picture consisting of 100 elements. The value of σ-shape parameter has been established as equal to 1.

On the basis of analysis of research results obtained it can be stated that these networks are capable of functioning in a different way in the case of radar pictures of different structure (size, resolution, distortions). An optimised structure of GRNN and Kohonen networks is thus characteristic of pictures analysed during our research.

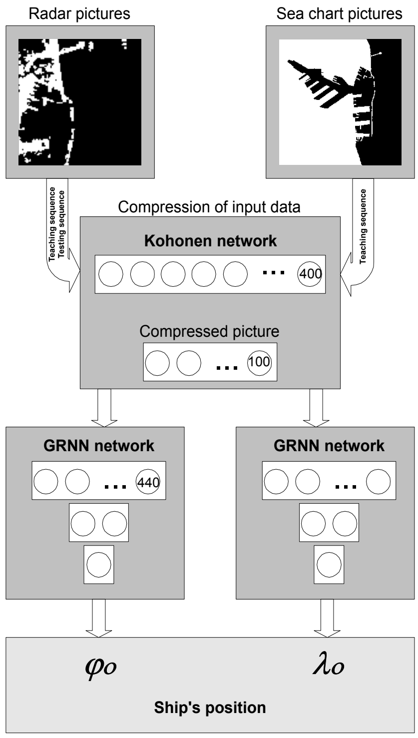

Fig.6. A diagram of the elaborated comparative method of plotting the ship's position

Neural networks of the GRNN type learn almost immediately. The teaching sequence is copied into the network in order to be used later during testing.

The network correspondingly estimates the reply for the new pictures. Result values are strictly bound with the distance of the remembered teaching sequence picture from the estimated picture. Adjacent pictures have most influence on the increase of the weight value.

The GRNN network structure is strictly determined. The first concealed layer contains as many neurones as the number of elements that the input picture consists of. These are radial neurones, which determine the value of the Gauss function $\mu_i(u)$. The second concealed layer is usually constituted by two neurones, which respectively calculate the average value of radial neurone centres.

The research done tested the possibility of using the GRNN network for plotting the position by comparative methods and the accuracy of results obtained. What was also tested was the effect of the *σ*-shape parameter on the quality of the process of matching the pictures (position accuracy) measured by the percentage of radar picture position indications in the function of distance from the true position (recorded in the course of registration of the radar pictures).

It turned out that the application of the GRNN in our case and for a testing sequence matched in this way gave excellent results of picture matching. The value of *σ* was altered in the range from 0.5 to 14.5 stepwise by 0.5. Exemplary results are included in the following table.

Table 1. Results of matching radar pictures with the chart for exemplary values of parameter σ of the GRNN network

GRNN Network									
Parameter **σ**	Number of testing pictures	The number of matched pictures with position removed from the true position							
		0 pixels	1 pixel	2pixels	3 pixels	4 pixels	5 pixels	6 pixels	other
0.5	126	122	2	1	1	0	0	0	0
1.5	126	121	2	2	1	0	0	0	0
3.5	126	76	33	10	5	1	1	0	0
	Picture amount in %	The amount of matched pictures with position removed from the true position [%]							
0.5	100%	96.83%	1.59%	0.79%	0.79%	0%	0%	0%	0%
1.5	100%	96.03%	1.59%	1.59%	0.79%	0%	0%	0%	0%
3.5	100%	60.32%	26.19%	7.94%	3.97%	0.79%	0.79%	0%	0%

For pictures occurring in the testing sequence the matching of almost all pictures with the best accuracy was obtained. The vessel's position obtained as a result of GRNN network action with *σ* equal from 0.5 to 1.5 nearly always pointed to the same pixel of the sea chart picture, in which the true position of the radar picture had been registered. As we know, the size of the picture pixel is bound with the picture's resolution. For radar pictures registered during sea trials and research for the assumed observation range of radar pictures of the teaching and testing sequences, the pixel size was about 40 metres.

Figure 8 presents the compared results of percentage amounts of correctly matched radar pictures with the charts, depending on the value of parameter *σ*. The best matching percentage is presented by graphs for various areas of accuracy of the position obtained.

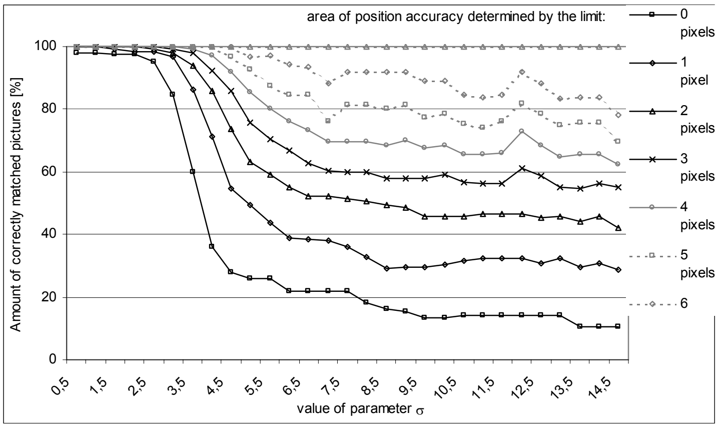

Fig.7. Amount of radar pictures correctly matched by the GRNN network depending on parameter σ

Such a high percentage of accurately plotted positions can be a proof that the constructed teaching sequence was representative in relation to other pictures occurring in the testing sequence. This representativeness was increased by applying the Kohonen network for compressing and preparing the input data. It divided the whole data area into groups of input patterns closest to one another. The values of input vectors were averaged and compressed.

Evidence of good representativeness of the teaching sequence can also be the relatively low value of the sigma parameter. Good results were obtained for σ from the range <0.5, 2.5>. There had been fears that determining this value on a relatively low level (below 0.5) would eliminate the influence of neighbouring weights in the group and the network would start functioning in an unstable way. The above graphs show that the choice of too high value of σ causes broadening of all teaching populations, which in turn leads to wrong classification (Fig.7).

TESTING THE METHOD WITH RESPECT TO INTERFERENCE RESISTANCE

In order to check the generalising ability of the network for a disturbed teaching sequence, random disturbances of radar pictures were generated. Undesirable radar echoes were added or cut out in places where they actually occurred (land, coastline, etc.). a simple generator was constructed which distorted the primary picture from 1% to 20%. The research was conducted for the best GRNN network structure with parameter σ equal to 0.5 to 2.

The graph below illustrates the results obtained from research conducted. It can be noticed that a relatively accurate matching of the pictures was obtained for the whole noise range even in the area limited by three pixels of distance from the true position. In all cases more than 80% of pictures fitted into this area.

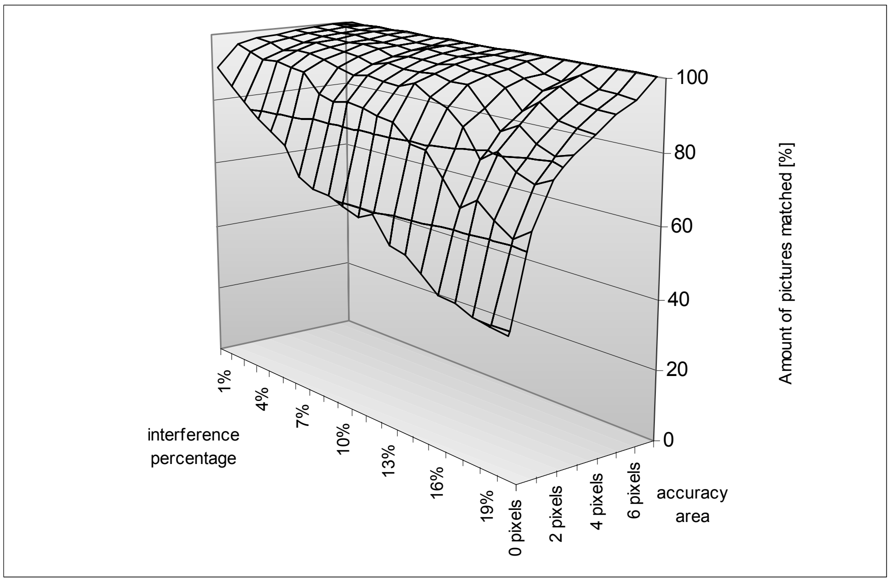

Fig.8. Amount of matched pictures for various accuracy areas depending on disturbance level of the radar picture (GRNN network with σ = 1)

The graph below presents the distribution of average position error committed during attempts to match the disturbed radar pictures with the sea charts. For sigma equal to 0.5, 1 and 1.5 the error is of roughly equal distribution; with higher sigma values its value increases.

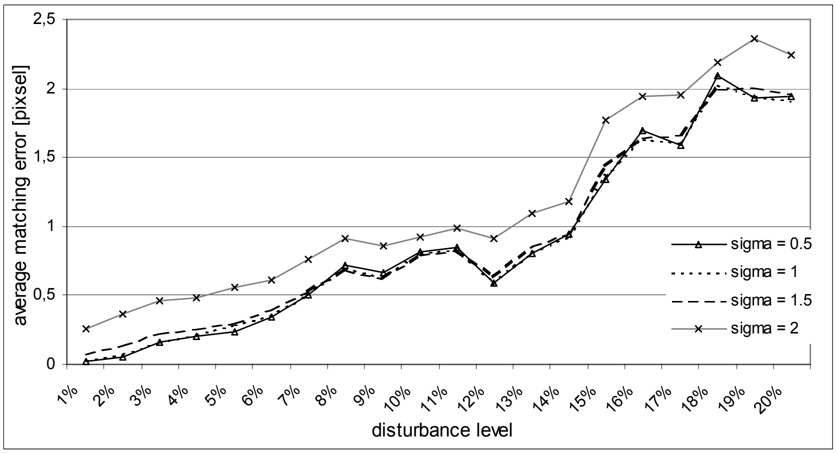

Fig.9. Average error of picture matching by the GRNN network at various disturbance levels of radar pictures

PRINCIPLES OF EVALUATING THE RELIABILITY AND ACCURACY OF THE FIXED POSITION

The confidence level the navigator can place in a designated position is essential matter in navigation. In the case of applying neural methods the position reliability level depends on the selection of the teaching sequence and the successfully conducted teaching process. The pictures for the sequence should be selected in such a way, so as to ensure their highest representativeness. Among other things, increasing its length and introducing radar pictures with interference and distortions can achieve this. In the research use was made of a teaching sequence consisting of 400 sea chart pictures (without disturbances) and 40 radar pictures (partly with disturbances). This ensured the obtainment of very good results in plotting the vessel's position. Using the GRNN network 97% of the tested radar pictures exactly fitted into the chart. The position determined was contained in the pixel area, the centre of which was the true position.

The accuracy of the determined position depends on a lot of factors. The basic effect on the accuracy of the position determined by comparative methods (analytical and neurone) is exerted by the size of the side of the elementary picture surface – the pixel. The range of radar observation and the resolution of pictures recorded affect this size. The range selection depends on the distance from the land. The closer the vessel gets to the coastline, the smaller the range value becomes; thus, the picture pixel size decreases, and the pictures are more accurately matched, and the position becomes more accurate.

The resolution of the registered pictures depends on the technical capacities of the recorder. The pictures compared during research had a size of 100x100 pixels. This resulted from the properties and technical possibilities of radar picture recording by application of a specialised IMAQ 1408 computer card.

The world's known systems of digital transformation and handling of radar pictures, so-called Radar Scan Converters – RSC, can record pictures of 2048 x 2048 resolution. The size of the picture pixel, with assigned observation ranges, would be much smaller. So, it could be supposed that the obtained vessel's position with the application of the neural method would be considerably more accurate. The following errors of the determined position can be expected: from 15 to 20 m for the observation range of 12 nautical miles and below 10m for smaller ranges of radar observation.

The method elaborated ensures an increase in the accuracy of the plotted position the closer the vessel gets to the coastline; this is a requirement set by IMO.

The accuracy evaluation of a potential computer system of position plotting based on the radar picture and examining the statistical characteristics of a particular system during sea trials should make a sea chart.

CONCLUSION

The obtained results of position plotting by means of the GRNN network have proved to be the most accurate among all previously examined methods. It made possible to match about 97% of testing pictures with the chart, with the accuracy of one central pixel. For comparison, when using analytical methods the best results of matching radar pictures with the sea chart and plotting position were obtained by applying the so-called extended decision criterion of plotting the vessel's position. In the first place, it used correlation as the similarity function, and next, a picture matching algorithm based on Gauss function. a matching of about 93% of testing pictures was obtained then, with accuracy up to three picture pixels. The results of picture matching with the application of different methods are presented on Table 2. Only a few best algorithms have been presented for comparison out of all the examined ones.

Table 2. Results of matching radar pictures with the chart for various matching algorithms

Matching radar pictures with the sea chart									
Picture matching algorithm	Number of pictures	Number of matched pictures with position removed from the true position							
		0 pixels	1 pixel	2 pixels	3 pixels	4 pixels	5 pixels	6 pixels	other
Analytic 1 – Tanimoto function	126	24	39	23	12	8	10	4	6
Analytic 1 – algorithm based on Gauss function	126	38	41	33	5	4	2	0	3
Neural – three-layer perceptron (100-35-40-2)	126	111	8	4	2	1	0	0	0
Neural – double GRNN network (440-2-1)	126	122	2	1	1	0	0	0	0
	Picture amount in %	Amount of matched pictures with position removed from the true position [%]							
Analytic 1 – Tanimoto function	100%	19.05%	30.95%	18.25%	9.52%	6.35%	7.94%	3.17%	4.76%
Analytic 1 – algorithm based on Gauss function	100%	30.16%	32.54%	26.19%	3.97%	3.17%	1.59%	0%	2.38%
Neural – three-layer perceptron (100-35-40-2)	100%	88.10%	6.32%	3.17%	1.59%	0%	0%	0%	0.79%
Neural – double GRNN network (440-2-1)	100%	96.83%	1.59%	0.79%	0.79%	0%	0%	0%	0%

An advantage of the method elaborated is the fact that GRNN networks learn almost immediately by reading the teaching sequence onto the input layer. The teaching speed depends on the length of the sequence. The only disadvantage of the GRNN network is that it requires a larger memory store for the teaching sequence; in spite of this, however, networks of this type are faster and provide more accurate results of matching a radar picture with the sea chart than analytical methods do.

A possible system of comparative navigation functioning based on artificial neural networks could find application as an independent, autonomous system of computer vessel position plotting, based on navigational radar. a prototype of such a system for coastal navigation could be undertaken, for ships navigating in narrowed regions or manoeuvring in ports in conditions of limited visibility.

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