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The neural method of sea bottom shape modelling for the spatial maritime information system

A.Stateczny
Department of Navigation
Maritime University of Szczecin, Poland

Abstract

One of the basic problems of the spatial maritime information system is the three -dimensional numerical model of the sea bottom. It means depth interpolation of the sea bottom - in dependencies from geographical coordinates in any analysed point of an area. There exist a lot of classical methods of spatial modelling. In the article the neural method of marking depths in any investigated point of a reservoir and spatial modelling of the shape of the sea bottom is presented. Several types of neural networks were analysed and optimised to find a proper solution. Three of them, Multilayer Perceptron, Generalized Regression Neural Network (GRNN) and Radial Basis Function Network were chosen. The criterion of optimisation was accuracy of depth estimation. Trained neural networks can mark depth for any position in a given rectangular area with satisfactory accuracy. The article presents some results of spatial modelling on the base of depth measurements in Gdańsk port.

1 Introduction

The basic problems in the elaboration of a spatial maritime information system is such elaboration of hydrographical data that it is possible to delimit the depth in any point of the map, especially in a regular net of coordinates. The problem of modelling of the shape of the sea bottom - for the needs of a three-dimensional chart has been analysed in the recent years many times. In [6] there was presented a classical method of marking by a [?] numerical model of the sea bottom. This method assured a comparatively high exactitude of the obtained model, because the obtained model passed all measuring points. The utilization of the classical

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system of spatial information to solve the problem of fashioning bottoms was introduced in [3].
Works [2 and 1] determine the effect of the first tests of use one of the methods of artificial intelligence, which are artificial neural networks to modelling of shape of sea bottom. In those works there were presented the results of using multilayer perceptron learned by different methods. The following step in the research to find optimum methods of modelling was wide investigation and optimisation of the radial net [9] the usefulness of which was shown in [2 and 1].
In this article some results of the latest researches made to find the optimum neural method are presented.

During hydrographical works data were gathered by synchronous registration of geographical coordinates ϕ,λ obtained most often by means of GPS system in difference version and depths h. During planning hydrographical works future courses have been planned. in the form of regular profiles. In practice, at sea, it is not possible to realize of planned trajectory. The appointed coordinates will not be found in the nodes of a regular net. The real profiles taken in Gdańsk port are introduced on figure 1.

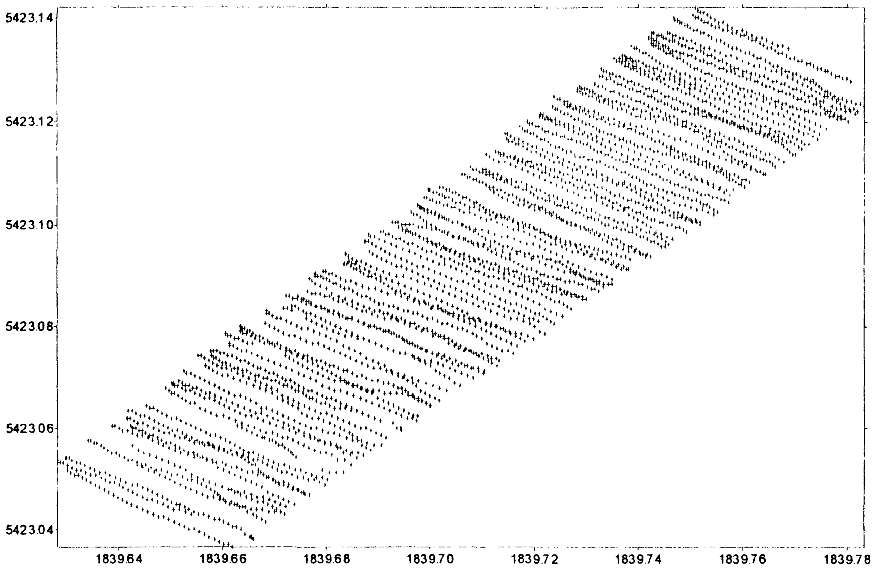

Figure 1: Real data taken in Gdańsk harbour.

2 Neural methods for the sea bottom shape modelling

Artificial 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 network. The first and basic neuron model defined as early as in 1943 by McCulloch and Pitts is the nerve cell, the function

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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 [4] [8]:

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

where:
x_j ($j = 1,2, \dots, N$) represent input signals,
W_{ij} – respective weight coefficients.
f is activation (transfer) function

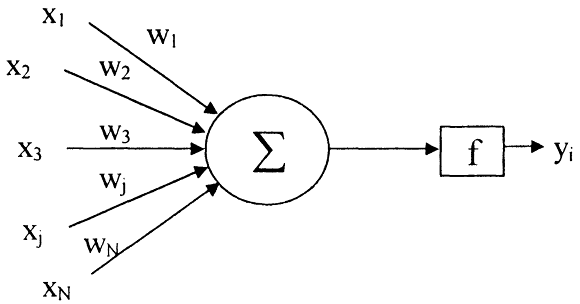

Figure 2: Neuron diagram [10]

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

During research there was examined the possibility to apply the following neural algorithms for sea bottom shape modelling:

- Multilayer perceptron
- Kohonen networks
- Hamming recurrent networks
- Radial Basis Function Networks (RBF)
- Probabilistic networks
- Neurofuzzy networks
- Generalized Regression Neural Networks (GRNN)

Three of them are shortly described in this article.

2.1 Multilayer perceptron (MLP)

This is perhaps the most popular network architecture in use today, discussed at length in most neural network handbooks ([4],[5],[7],[8],[10]).
Multilayer perceptron (MLP) consists of minimum three layers. There are input, output and hidden layers. MLP may have a lot of hidden layers; however, one or two is adequate for virtually all problems.
Each layer in MLP consists of the identical neurons with a linear activation (transfer) function (i.e., they perform a weighted sum of their inputs), or a (usually) non-linear activation function. The standard activation function for the perceptron is the logistic (sigmoid) transfer function. A good alternative is the hyperbolic function (tanh), which is a symmetric version of the logistic function. This can produce better performance than the logistic function in many cases. If the perceptron is being used in regression problems, performance can sometimes be improved by changing the units in the output layer to linear activation function. This allows extrapolation beyond the training data in addition to interpolation. MLP should be taught by a special algorithm. Conjugation of the gradient descent, Levenberg-Marquardt, back propagation, quick propagation and other can teach multi-layer perceptron.
These networks are relatively compact, and widely applicable; however, the training process can be protracted, and they are prone to meaningless extrapolation if given highly novel data.

2.2 Radial Basis Function Network (RBF)

Radial basis function networks (RBF) have an input layer, a hidden layer of radial units and an output layer of linear units.
The radial layer has exponential activation functions; the output layer linear activation functions.
It is sometimes useful to alter the output layer activation function to logistic, and to use the conjugation of gradient descent training, as linear optimization is more prone to error and extrapolation. Conjugate gradient descent can also be used on a linear output layer, although it is slower than pseudo-inverse training in this case.
Radial-basis function networks are trained in three stages:
1. Center-assignment. The centers stored in the radial hidden layer are optimized first using unsupervised training techniques. Centers can be assigned by a number of algorithms: by sampling, K-means or Kohonen training. These algorithms place centers to reflect clustering.
2. Deviation assignment. The spread of the data is reflected in the radial deviations (stored in the threshold). Deviations can by assigned by a number of algorithms (explicit, isotropic, K-nearest neighbor).
3. Linear optimization. Once centers have been assigned, the linear output layer is usually optimized using the pseudo-inverse technique, as this is quick, and guaranteed to minimize the error if the deviations are not too small. However, it

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could be also used to conjugate gradient descent, back propagation, quick propagation or others method of training.
RBF network produce the output signal by the following dependence [8]:

$$y_i = \sum_{i=1}^{P} W_i \cdot f\left(\left\| x_i - t_i \right\|\right) \tag{2}$$

where:
p – number of radial neurons,
W_i – represent weight coefficients of linear neuron.
f is radial activation (transfer) function
t_i is the center of radial function
The most popular radial function is Gauss function:

$$f(\rho) = Exp(-\frac{\rho^2}{2\sigma^2}), \tag{3}$$

where:

$$\rho = \left\| x_i - t_i \right\|, \tag{4}$$

σ - shape parameter, $\sigma > 0$.

Other radial functions are:

$$f(\rho) = \frac{1}{\sqrt{\rho^2 + \sigma^2}}, \tag{5}$$

or

$$f(\rho) = \sqrt{\rho^2 + \sigma^2}. \tag{6}$$

Radial basis function networks train relatively quickly and do not extrapolate too far from known data; however, they tend to be larger than multi-layer perceptron and therefore execute more slowly.

2.3 Generalized Regression Neural Network

Regression networks (often called generalized regression neural networks, or GRNNs, in the literature) have exactly four layers: input, a layer of radial centers, a layer of regression neuron, and output.
The radial layer units represent the centers of clusters of known training data. A clustering algorithm such as sub-sampling, K-means or Kohonen training must train this layer. The layer is typically large, but not necessarily as large as the number of training cases.

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The regression layer must have exactly one neuron more than the output layer. The regression layer contains linear neurons. There are two types of neurons: type A neuron calculates the conditional regression for each output variable, with the single type B unit calculating the probability density.
The output layer performs a specialized function: each neuron simply divides the output of the associated type A neuron by that of the type B neuron, in the previous layer.
RBF network produce the output signal by the following dependence:

$$y_i = \frac{\sum_{i=1}^{p} w_i \cdot f(x_i)}{\sum_{i=1}^{p} f(x_i)} \tag{7}$$

where:
p – number of radial neurons,
W_i – represent weight coefficients of linear neuron.
f is radial activation (transfer) function (usually (3), see figure 3)

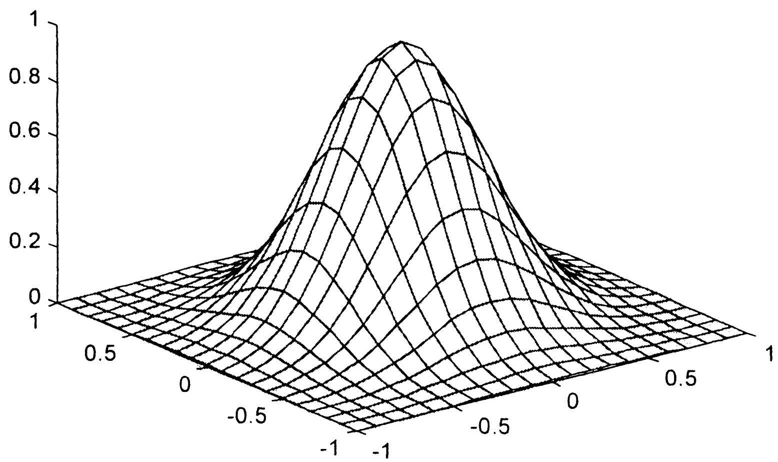

Figure 3: Gauss transfer function (3).

GRNNs train extremely rapidly, but tend to be very large, and hence execute slowly.

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3 Results of numerical experiments

The gathered data presented in the form of trios ϕ, λ, h should be divided into training data and testing data. It was accepted, that 10% of at random well-chosen measuring - trios would become as a testing set. All remaining measurements were used in the learning set. Data measuring was to filter to aim and detect and remove big errors. All data were standardized to section <0, 1>. On individual drawings presented results presented obtained with the utilization of each networks.

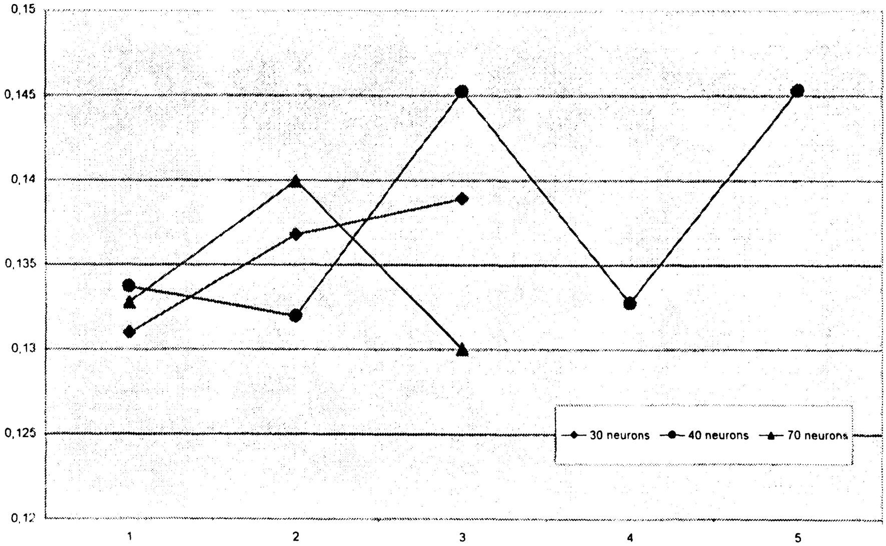

Figure 4: Mean error produced by MLP dependence on the number of neurons in hidden layer during several works.

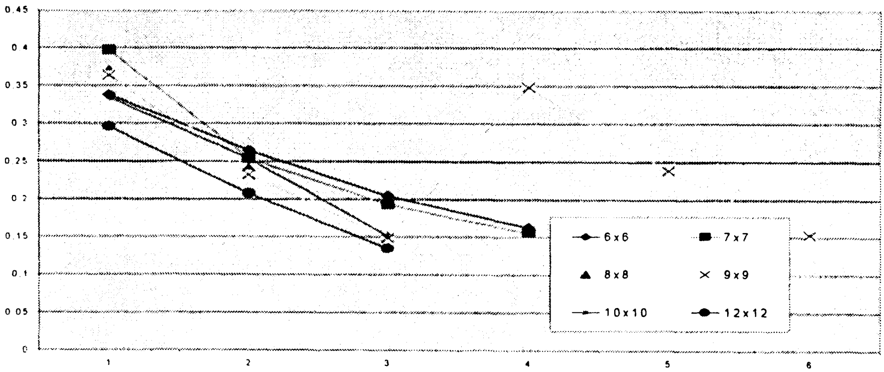

Figure 5: Mean error produced by RBF network dependence on shape parameter.

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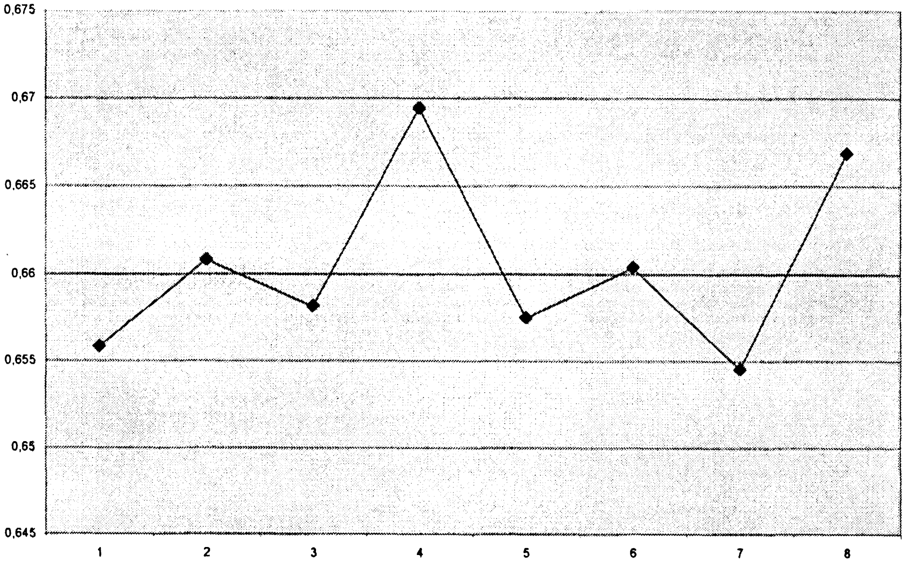

Figure 6: Mean error produced by optimised GRNN during several works.

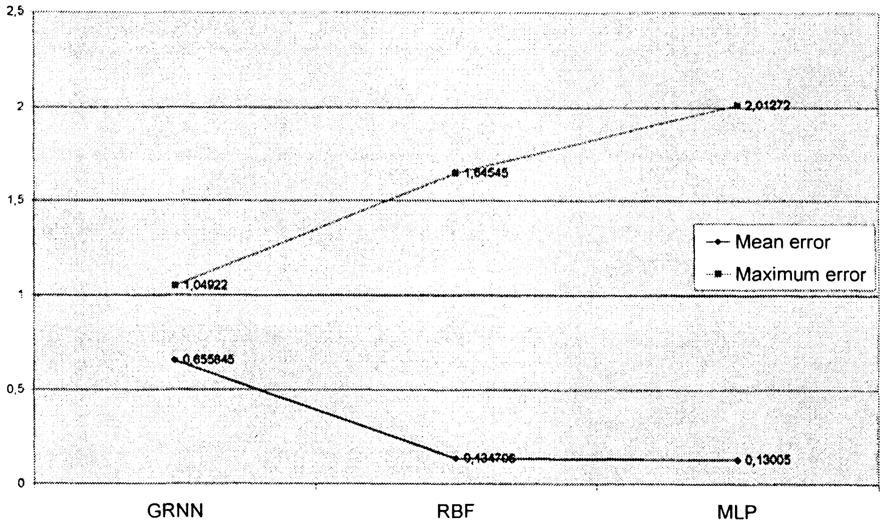

Figure 7: Comparison of the best results produced by chosen neural networks

4 Conclusions

In the article results of researches to find the optimal method of modelling the sea bottom shape are presented. Every analysed neural network produced satisfactory results. MLP produce the least mean error but had produced the biggest maximum error. GRNN made the least maximum error and the worst average error. RBF networks produced errors between results of other networks. All of the introduced networks could be recommended to model the sea shape bottom and could be chosen according to needs.

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