

# Selected method of artificial intelligence in modelling safe movement of ships

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## Abstract

The main goal in this paper is presented using one of the methods of artificial intelligence, especially neural networks, for determination of the coefficients of state equations of a ship's safe motion in a horizontal plane. The recurrent optimization network is used to identify parameters of the ship's dynamics. A structure and the operating principle of the network and results of computer simulation of a ship's motion along a desired trajectory are presented in this paper as simulation trials using the MATLAB program.

*Keywords: safe motion, neural network.*

## 1 Introduction

The main problem of ship exploitation in sea movement is assuring the right level of navigational safety to a ship. In order to increase the reliability level of sea traffic and the development of its steering, standards have been created [3, 5]. The structure of an automatic safe system of steering a ship must always include an accurate mathematical model of a ship. Many theoretical and practical works have been focused on problems of mathematical modelling and methods of parametric identification were developed especially for safe motion of ships. These methods were very efficient for both linear static and dynamic objects. Recently, an increasing interest has been observed in combining artificial intelligence tools with classical control techniques. Hence neural networks are used to mathematical model a ship's dynamic. One of the most important tasks during designing of safe automatic control systems is defining an accurate mathematical model of the ship. The results of much research allows one to model both the linear static and dynamic objects. However, a ship as an



automatic control object is a non-linear object. Non-linear object models are complicated and very difficult to model mathematically. We have difficulties with modelling and we can define an accurate mathematical model of a ship only by approximate classical methods. In this case, to model non-linear objects neural networks are often used. The attractiveness of use of the neural networks in modelling is the approximation of any curve and the ability to tune the structure to be based on experimental and other data.

## 2 Mathematical ship's model

Linear equations of ship's motion applied for the control object can be formulated as follows [3]:

$$\dot{x}(t) = Ax(t) + Bu(t) + C(x, t) \quad (1)$$

where:  $u(t)$  – control vector,

$x(t)$  – state vector,

$A$  – state matrix,

$B$  – input matrix,

$C(x, t)$  – forced vector influenced on controlled object.

The expression, eqn. (1), in discrete form can be written as below:

$$X[(k+1)T] = \Phi(T)X(kT) + G(T)u(kT) + N(T)C(x, t) \quad (2)$$

where:  $\Phi(T)$  – basic matrix,

$X(kT)$  – state vector,

$u(kT)$  – control signal,

and these values are defined as:

$$\Phi(T) = I + AT + A^2 \frac{T^2}{2!} + A^3 \frac{T^3}{3!} + \dots + A^n \frac{T^n}{n!} \quad (3)$$

where:  $I$  – identity matrix,

$$G(T) = IBT + AB \frac{T^2}{2!} + A^2 B \frac{T^3}{3!} + \dots + A^n B \frac{T^{n+1}}{(n+1)!}, \quad (4)$$

$$N(T) = IT + A \frac{T^2}{2!} + A^2 \frac{T^3}{3!} + \dots + A^n \frac{T^{n+1}}{(n+1)!}, \quad (5)$$

The vector of control signal  $u(kT)$  must take factors into consideration as the physical limit of maxima values of stern plane saturation and stern angle speed,

$$|u(kT)| \leq 30^\circ. \quad (6)$$



### 3 Neural network for modelling ship's dynamics

The main task of the neural network in this paper is calculating the values of matrices  $\Phi(T)$  and  $G(T)$ , and in such a way that the neural model of ships will behave as real ships described by eqn. (1). The identification of the ship's model is made by minimizing the energetic function  $F(\phi, g)$  which is defined for this model as [4]:

$$F(\phi, g) = 0.5 \varepsilon^T \varepsilon$$

$$F(\phi, g) = \varepsilon_1^2 + \varepsilon_2^2 + \varepsilon_3^2 + \varepsilon_4^2 + \varepsilon_5^2 + \varepsilon_6^2 + \varepsilon_7^2 \quad (7)$$

The total error  $\varepsilon$  is the difference between values of the state vectors  $x_o$  - generated by the analytical model and the state vector  $x_m$  - generated by the neural model, for every step of each iteration:

$$\varepsilon = x_o x_m = [\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4, \varepsilon_5, \varepsilon_6, \varepsilon_7]^T \quad (8)$$

After substitution of eqn. (2) and (8) the energetic function  $F(\phi, g)$  can be written as:

$$F(\phi, g) = 0.5 (x_o - \phi x - g u)^T (x_o - \phi x - g u) \quad (9)$$

A gradient method is used to minimize this function. After calculating the partial derivative of  $F(\phi, g)$  by  $\phi$  and  $g$ , and equaling them to zero we receive the mathematical prescription which is a rule of teaching the neural network:

$$\begin{aligned} \phi_{ij} [(k+1)T] &= \phi_{ij}(kT) - U \varepsilon_i x_j(kT) \\ g_{ij} [(k+1)T] &= g_{ij}(kT) - U \varepsilon_i u(kT) \end{aligned} \quad (10)$$

where:  $U$  is the coefficient of teaching and  $0 < U < 1$ .

This coefficient was defined experimentally. The eqn. (10) describes the method of modification of values of coefficients  $\phi_{ij}$  and  $g_i$  that guarantee the minimisation of the energetic function in every step of the iteration. Such a method ensures that parameters of the neural model will approach to the parameters of the identified object.

In fig. 2 the elements of Hopfield's recurrent neural network are presented. The basic elements are: block of data selection, block of preliminary solution, block of improvement of solution, block of comparison vector and block of parameters modification. A block of data selection is the analysis of state vectors and this eliminates the vectors which are restricted, because these vectors have false information which does not permit precise identification of matrix  $\Phi$ ,  $G$ .

Block of preliminary solution calculates values of  $\phi$ ,  $g$  of the neural model's approximation. It is realised by analytic solution of matrix equations based on selected status vectors from the block of data selection. Receive in this way the neural model is improved.



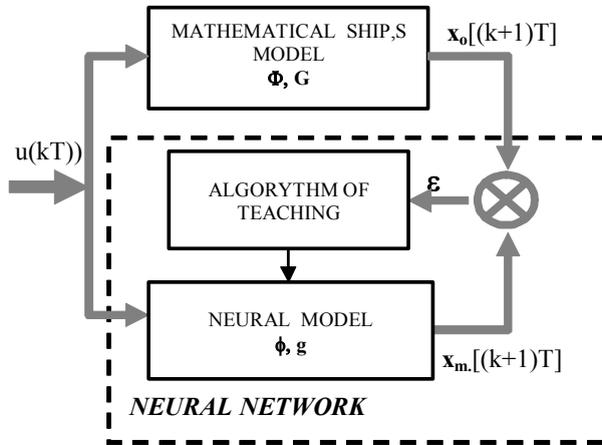


Figure 1: The teaching of neural network for a ship’s movement.

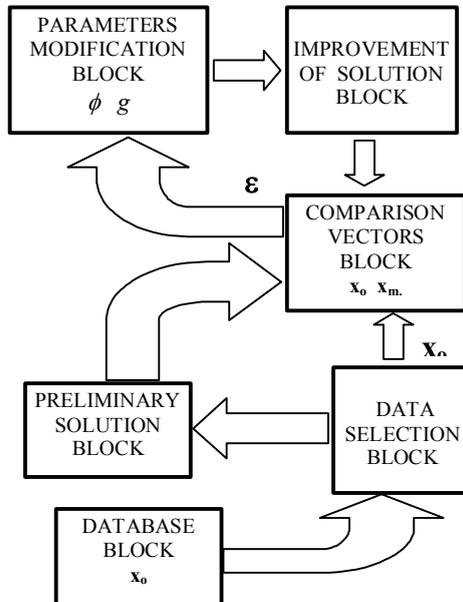


Figure 2: Hopfield’s recurrent network.

Block of improvement of solution consists of 8 neuron which works on loop back. The result operations of this block are new parameters of the status vector  $x_m$ . The parameters are new input data for the neural network for next iteration. In a block of parameters, modification takes effect by importance network  $\phi_{ij}$  and  $g_i$ , according to the rule of teaching. Values of  $\epsilon$  are the basic modification importance.

Block of comparison vectors calculate total error  $\varepsilon$  between the state vectors  $x_o$  - generated by analytical model and state vector  $x_m$  - generated by neural model, for every step to each iteration.

#### 4 Selected results of simulation trials

For a ship described by eqn. (2) many element collections of status vector were generated. Factors of this vector are the input data for neural network. For the purpose of verification of the neural model for a ship performed standard test manoeuvring trials: zig-zag test and spiral test were carried out. The tests were made for a neural model mine-hunter ship of a speed of 17 knots. External disturbances are waves and wind. The results were executed by a personal computer under MATLAB program. On fig. 3 to fig. 4 are presented the results of research of mathematical and the neural model of the ship for zig-zag test without disturbances and on fig. 5 to fig. 6 with disturbances. Solid lines are presented for the real object, and dashed lines – value for neural model.

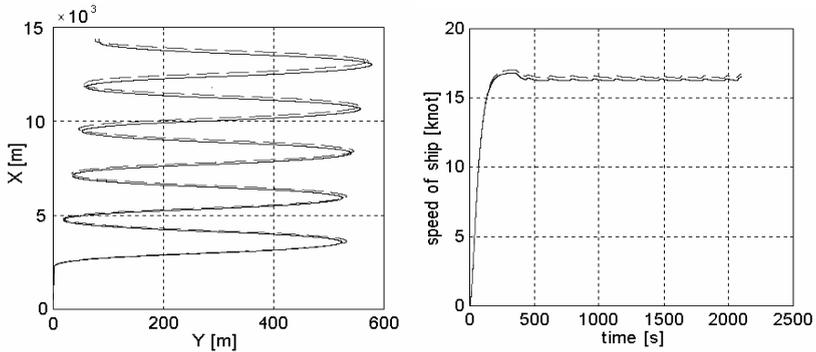


Figure 3: Zig-zag test: left - trajectory of ship and right - speed of ship.

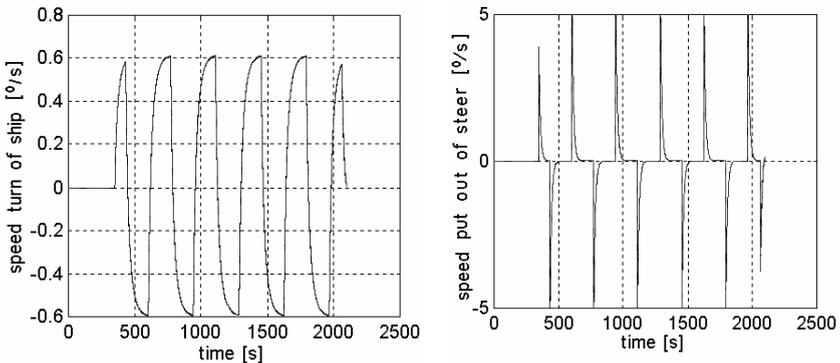


Figure 4: Zig-zag test: left - speed turn of ship and right - speed put out of steer.



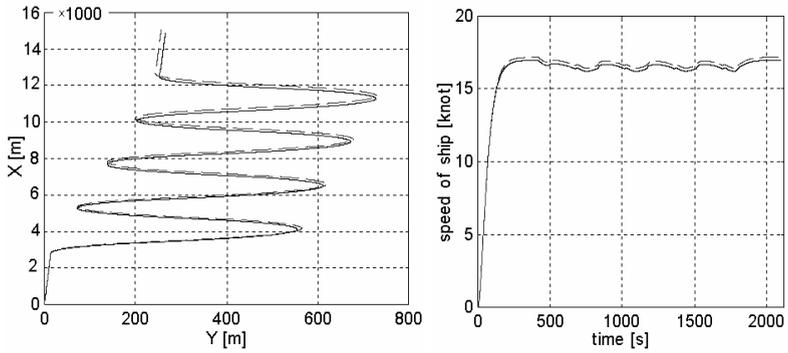


Figure 5: Zig-zag test: left - trajectory of ship and right – speed of ship.

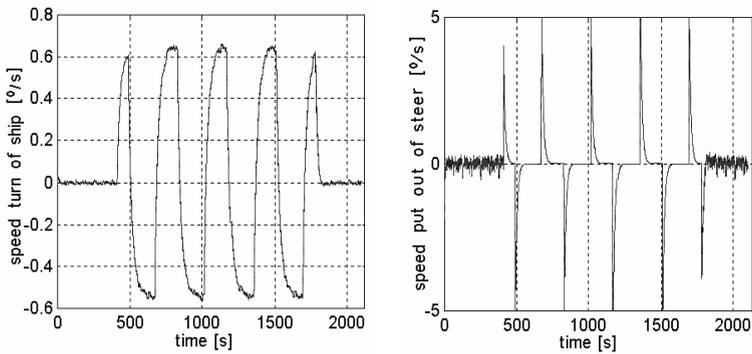


Figure 6: Zig-zag test: left - speed turn of ship and right - speed put out of steer.

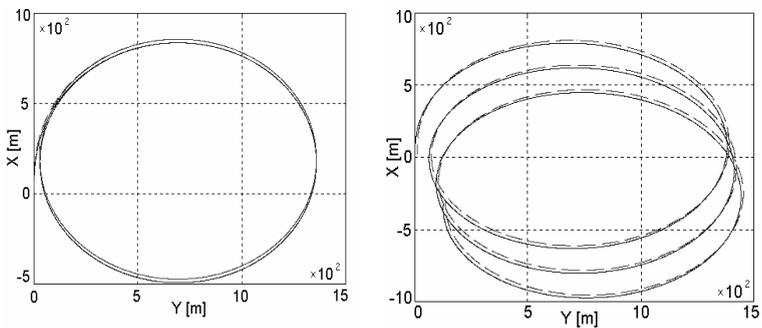


Figure 7: Trajectory for spiral test: left - without disturbances and right - with disturbances.



On fig. 7 trajectory for spiral test are presented. The test made are for a speed of 15 knots and for without disturbance and with disturbance, and with a presented trajectory for the rudder angle of  $30^\circ$ . In this paper we took external disturbance into consideration such as waves and wind. Their influence is shown on simulation trials.

## 5 Conclusion

The examples in this paper show that those neural networks are very attractive for the design of the ship's model. Generally, neural networks permit also to create a non-linear object for example ships and the model is sufficiently accurate. Results of simulation are concerning only the linear model of a ship but are confirmed in this case. Results of simulation show a significant efficiency of the presented neural network for control and modelling of a ship's dynamics. The relative error between state vectors generated by ship and its neural model is smaller than 1%. In the method presented there exists a strong dependence between preciseness neural model and the value coefficient of teaching  $U$ , that's why the important problem is strategy selection and modification value coefficient  $U$  in the iteration process.

## References

- [1] Miller, W.T., Sutton R.S., Werbos P.J.: *Neural Networks for Control*. The MIT Press, Cambridge, MA. 1990
- [2] Narendra, K.S., Parthasarathy, K.: *Identification and control of dynamical systems using neural networks*. IEEE Trans Neural Networks. Vol.1, No.1, 4-27. 1990.
- [3] Garus, J., Malecki, J., Żak, B., *Application of Network Hopfield's for Modelling of Motion Ship*. XIII Native Control Conference, Poland, Opole, Vol.2, 211-214. 1999
- [4] Ossowski, S., *Algorithms depict of Neural Network*, WNT 1996
- [5] Lisowski, J., *Safety of navigation based on game theory – mathematical models of game ship control*, Journal of Shanghai Maritime University, 25(1004), 2004

