Neurocontrol methods in the context of development of technical solutions for transition to unmanned navigation

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Abstract. The paper considers the features and prospects of using neurocontrol methods in the context of development of technical solutions for transition to unmanned merchant vessels. The paper suggests a non-iterative training based artificial neural network (ANN), which is based on the principles of “direct inverse control” to control the speed and motion of unmanned surface vessels. The model is identified, and the structure of an artificial neural network and the diagram of the automatic control system (ACS) of an unmanned vessel (UV) are considered on the example of an electric propulsion vessel. A series of computational experiments is carried out to obtain a sufficiently complete training sample, and the control law is presented. The principle of the control system for an unmanned vessel is considered based on a neural network. At the next stage of the study, focus is on the synthesis of the optimal control system for UV navigation. The problem of the fastest motion of a third-order control object from one point (with any initial speed) to another (at the end point the vessel stops and the speed is zero) is considered. Based on the results of a series of experiments with the UV model, the controller parameters that provide the best indicators of control quality were set in the MATLAB Simulink environment.

1. Introduction

The leading maritime countries of the world are engaged in the creation of unmanned vessels. This is mainly due to a wide application of these technical systems at relatively low operating costs. The application areas of unmanned vessels can be security activities related to natural resources, water areas and facilities; monitoring of underwater/surface conditions; search and rescue operations; environmental safety and environmental protection; anti-terrorist measures and others. This ensures the safety of the service personnel and significantly reduces its number while increasing the efficiency of the targeted use of unmanned vessels in the interests of the maritime and defense sectors [1].

At present, requirements for the control systems of unmanned vessels imply the increased accuracy due to automation. With an increase in the speed of motion, maneuvering characteristics, requirements for the reliability and efficiency of the works performed, the improvement of such systems by developing new control algorithms is especially relevant.

At the same time, it should be noted that this task is complicated due to the fact that it can be solved only for linear systems. However, the motion of an unmanned vessel is described by a system of nonlinear differential equations; therefore, it is impossible to construct an optimal controller using traditional methods and approaches, since significant uncertainties do not allow obtaining the corresponding transfer function of the control object.

The use of the ANN apparatus – neurocontrol – opens up wide opportunities for improving the efficiency of UV control systems. It is known that one of the most accurate, including for marine vessels, are regulators with the forecast function. They calculate the optimal sequence of control
signals to ensure the maximum proximity of the actual operation modes of the vessel technical equipment (TE) and the motion trajectory of the output coordinates [2].

Thus, with regard to the above, the topic of the paper is of significant scientific and practical interest.

Advanced marine robotics requires the development of theoretical, design, production, and organizational aspects. A number of domestic and foreign authors, such as Moshnyakov D.A., Pushkarev I.I., Chernyakhovich S.E., Castaman, Nicola, Solovey, Li, Shaowei, have devoted their works to this issue.

Various options for solving the problem of optimal speed control were proposed by A.V. Bazylev, V.Ya. Bychkov, S.V. Perevezentsev, and V.I. Plushaev.

Bondarenko V.A., Pavlova V.A., Kim Jonghoek, and Tan Guoge performed the comparative analysis of various types of neural networks and regulators that can be used in UV control systems.

In practice, despite the available theoretical studies and proposals, the synthesis of control systems based on neural modeling arises a number of difficulties. This is due to the fact that a training sample requires a series of complex experiments with UV motion, which is practically impossible due to the lack of statistical data on their operation. In addition, studies often include only the aspect of vessel maneuvering in terms of navigation, and the problem of optimal control of the power system (PS) remains unsolved.

With regard to the above, the paper aims to consider the features and prospects of using neurocontrol methods in the context of developing technical solutions for transition to unmanned navigation.

2. Materials and methods

Thus, UV ACS is created based on the principles of “direct inverse control”, which require a non-iterative training based ANN. According to these principles, an inverse (reverse) model of the control object is created, which is placed in the ACS direct channel. The desired value of the object’s output coordinate, as well as the necessary variables of its state, are fed to the input of the inverse model. Based on these data, the inverse model calculates the control action that is applied to the control object and provides the desired value of the output coordinate.

As previously noted, UV as a control object is nonlinear, since the object PS-SUDNO is a stochastic system. In the work by M. Pourzanjani, G. Roberts, the nonlinearity problem is solved by breaking the inverse model into two sequential parts for further implementation based on two corresponding neural networks [3, 4, 5, 6, 7].

In this study, this experience is employed.

3. Results

The first step is to identify the model. The standard model used to represent a general discrete nonlinear system is the nonlinear autoregressive moving average model (Nonlinear ARMA or NARMA):

\[ y(k + d) = N[y(k), y(k-1), ..., y(k-n+1), u(k), u(k-1), ..., u(k-n+1)] \]

where \( u(k) \) is the system input; \( y(k) \) is the output.

During identification, the neural network is trained to approximate the nonlinear function \( N \) [3]. In our case, it is necessary that the system output follows a certain trajectory \( y(k + d) = y_r(k + d) \), thus, the next step is to develop a nonlinear controller in the form:

\[ u(k) = G[y(k), y(k-1), ..., y(k-n+1), y_r(k+d), u(k-1), ..., u(k-m+1)] \]

The problem with using this controller is that a dynamic backpropagation algorithm must be used to train the neural network to reproduce the function \( G \) in order to minimize the root mean square error. This can take much time. One of the solutions to this problem is to use an approximated model to represent the system. In this case, the controller takes the form:
\[ y'(k + d) = f[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)] \\
+ g[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)] \cdot u(k) \]

This model is presented in paired form, where the next controller signal \( u(k) \) is not within the nonlinearity. The advantage of this form is that it can be solved with respect to the control input for the system to follow a given trajectory \( y(k + d) = y_r(k + d) \). As a result, the controller takes the form:

\[ u(k) = \frac{y_r(k + d) - f[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)]}{g[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)]} \]

Figure 1 shows the structure of the corresponding neural network.

![Neural Network Diagram](image)

**Figure 1.** Structure of the neural network of UV ACS

With regard to the above, the controller takes the form:

\[ u(k + 1) = \frac{y_r(k + d) - f[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)]}{g[y(k), y(k - 1), ..., y(k - n + 1), u(k - 1), ..., u(k - m + 1)]} \]

This controller is suitable for implementation at \( d \geq 2 \). Figure 2 presents a block diagram of the control system.
With regard to the available studies and experiments, it is advisable to choose four parameters as input variables for ANN: the actual speed of UV motion, the angular frequency of rotation of the propeller and its time derivative; the calculated acceleration that ensures the transition from the actual speed to the desired one. ANN output is the only variable – the signal switching time (in seconds) from the beginning of the transition.

Considering the use of this system in practice, focus on the control of the speed of UV motion. When considering an electric propulsion vessel, the optimal control of changes from one speed to another (maneuvering) is provided by supplying a control signal to the object, which consists of three intervals. These are the maximum positive value $u_{\text{max}}$ (maximum value of the power supply voltage of the propeller motor) within the time interval $0$ to $t_1$, the maximum negative value $-u_{\text{max}}$ from the moment $t_1$ to $t_2$, and the new set value of the supply voltage $U_{\text{set}}$ corresponding to the new speed value in the steady state. Thus, in the process of control, it is necessary to determine three values: $t_1$, $t_2$ and $U_{\text{set}}$. When prototyping and considering a scale model, the determination of $U_{\text{set}}$ involves a series of experiments when a certain value of the control signal is supplied to the UV propulsion unit, and it accelerates to a certain stable speed. Application for full-scale objects requires the formation of a certain statistical base inherent in this type of vessels.

The series of computational experiments shows that this allows a fairly complete training sample. To do this, it is necessary to carry out three experiments and change the supply voltage according to the laws shown in Figure 3. In this case, the speed, acceleration and frequency of the propeller change over the entire possible range.
Consider in more detail the features of determining the switching time \( t_1 \) and \( t_2 \). Modeling has shown that the transition from some initial speed \( V_0 \) to any other \( V_1 \) depends only on the value \( t_1 \), since the second switching (time \( t_2 \)) must be carried out at the time when the transient process ends, that is, the acceleration is zero and there is no need to calculate it.

The following technique can be used to determine \( t_1 \). Form a table of data for approximation. The UV accelerates to a certain value of the initial speed \( V_0 \) and goes into a steady state. Then, for a certain period of time \( t_1 \), \( u_{\text{max}} \) is supplied, then \( -u_{\text{max}} \) is supplied until the transient process ends (zero acceleration), and the final speed \( V_1 \) is measured. This experiment is repeated for different combinations of \( V_0 \) and \( t_1 \) values. Thus, a set of vectors \((V_0, t_1, V_i)\) is obtained that characterizes the dependence of the final speed on the initial speed and switching time. This dependence can be approximated in the opposite form to obtain the required function \( t_1 = f(V_0, V_1) \).

The cases of increasing and decreasing the speed must be considered separately, since the combined surface is rather difficult to approximate. For the transition to more complex stochastic processes, which affect the PS-SUDNO, it is necessary to use all the ANN positive characteristics in combination with the fragmentation of the disturbing effects according to the principle of self-similarity of the Mandelbrot set.

Figure 4 shows the experimental points at the increased speed, which form a table for approximation, as well as an approximating surface. As can be seen in Figure 4, the approximation accuracy is satisfactory.

![Figure 4. Dependence of the acceleration interval on the initial and final speed values](image)

The control system based on the neural network functions as follows.

The corresponding network layer (which corresponds to acceleration or deceleration) receives data on the UV current speed and its final speed that must be achieved. The network output indicates the signal switching time (in seconds) from the beginning of the transient process. Thus, the regulator only needs to switch the control signal from \( u_{\text{max}} \) to \( -u_{\text{max}} \) at a certain time point. The moment when the acceleration is equal to zero (the end of the transient process) is monitored, and the signal \( U_{\text{set}} \) is given, while UV switches to the mode of stable motion at a new speed.

After that, it seems appropriate to focus on the synthesis of the optimal control system for UV motion. The task is to move as quickly as possible from one point (with any initial speed) to another (at the end point UV must stop, the speed is zero). In this case, the control object is of the third order, so there are three switching moments. The third switching (no control) occurs at the moment when the acceleration and speed are equal to zero. The second switching determines the duration when the maximum negative value of the control is supplied to the object to bring the UV speed to zero as
quickly as possible. Obviously, this depends only on the UV speed before the start of braking. It can be determined through a series of experiments (or by mathematical modeling of motion in MATLAB).

Based on the results of a series of experiments with the UV model in the MATLAB Simulink environment, the values of the controller parameters that provide the best control quality indicators were set (Table 1).

| Parameter                                | Value  |
|------------------------------------------|--------|
| Number of hidden layers of the neural network | 30     |
| Sampling interval                        | 0.1 sec|
| Number of delays for the input signal    | 1      |
| Number of delays for the output signal   | 3      |
| Number of training data points           | 20000  |

As a result, the value of the root-mean-square error is $7.3 \times 10^{11}$, and the maximum absolute value of the error according to the test data is 0.001 m/sec, which makes up 0.25% of the maximum speed and can be assumed acceptable.

4. Conclusion

Based on the above, non-iterative training based artificial neural networks make it possible to create effective automatic control systems for complex nonlinear systems such as PS-SUDNO, which are subject to stochastic processes, including unmanned vessels. At the same time, the control system provides the fastest possible rectilinear motion of a vessel at any distance regardless its initial speed.

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