Prediction of the trajectory of the tracking object based on adaptive controller

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Abstract. A method for controlling an object that monitors another object is considered. The mathematical formulation of the problem of predicting the trajectory of motion is given. The solution is based on training an adaptive neurosemantic controller. The semantic units of the management process are defined. To highlight the prediction trajectories, the auto-structuring method is used. The results can be used to solve a number of practical problems of autonomous intelligent control in the face of uncertainty. The experiments showed that if there is a pattern (lack of randomness in the behavior of the tracking object), the adaptive controller can determine the behavior of the tracking object and has the ability to predict its movement over a finite number of training steps. It is noted that the implementation of semantic neural network technologies is adapted to the specifics of digital circuitry due to the structure of neurons and the mechanisms of learning.

1. Introduction
Adaptive controllers are systems that can increase control efficiency in difficult conditions of uncertainty, noise and other factors of the external or internal environment. Biomorphism is an approach to the development of control systems based on the principles of biological organization and functions [1], developed as part of the scientific direction of bionic. The structure of synaptic connections of artificial neurons of the network that underlies the neural network implementation of the control system is one of the key factors on which the reliability and quality of control and the degree of its adaptability depend. This paper describes the application of the neurosemantic approach to solving the problem of predicting the trajectory of the tracking object. The controller and its operating principles are described in [2-6].

2. Related works
The following groups of biomorphic neural network algorithms can be distinguished: groups of self-organizing decision rules [7], neuroevolutionary algorithms [8], growth algorithms of bionic neural structures [2-6,9,10]. Earlier, we developed an information system for computer-aided design of neural networks [9] with the ability to automatically generate code in the Verilog language.

A characteristic feature of the neurosemantic approach [2-6] for the synthesis of a neural network control system is the ability to learn from precedents, which distinguishes this approach from classical
neural networks with continuous activation functions. The absence of floating point calculations makes it possible for the neurosemantic method to work effectively within the framework of the reinforcement learning concept [12].

It should be noted that neurosemantic auto-structuring is algorithmically similar to the methods of dynamic synthesis of cortical networks based on spike and impulse neurons [11].

3. Material and methods. Formulation of the problem

Consider the control object A, which monitors the tracking object B (Fig. 1). Let S be the state parameters of the object A and its control; ∆S - parameters S in the scope of the object A; m is the number of variants of the parameter X∈∆S, X0 is the first value of the parameter of the object A; Xn∈{X1, X2, X3, ..., Xm}; Fn - parameter control of object A; Fn∈{F1, F2, ..., Fm}.

The internal state of the control object A is determined by the state vector X, which is determined by the position of the object and is satisfactory if not a single value Xn of this trajectory goes beyond the range B of the visibility ∆S on the sensors of object A. The transition space of the internal states of object A is characterized by a deterministic function f(X). For tracking At the nth control step, the control vector Fn is selected. In this study, we did not take into account the movement of object A, although in the general case this is possible based on the described method. There is such an effect of Fn on the control object A, where the following position Xn+1 = Xn + Fn of the tracking object B on the sensors of the control object is in the range of ∆S.

The control process consists in turning the control object through an angle from the set F so that the tracking object remains in the scope ∆S. The control problem is reduced to the choice at each step of the control of the action vector Fn on the object A, which is in the state Xn. At the same time, it is necessary that the controller learns to hold the tracking object in the field of visibility ∆S for the least number of training attempts J.

We define the trajectory of the control object A as a chain of transitions of the form: (X0) → (X1, F1) → (X2, F2) → ... → (Xn+1). We assume that a trajectory of length L = m2 is satisfactory if not a single value Xn of this trajectory goes beyond visibility. The controller learned when all the trajectories stored in the controller memory do not go out of visibility and have a length of m2. Formally, the statement of the problem statement is as follows:

\[ X_{n+1} = f(X_n) + F_n \]  \hspace{1cm} (1)

where n is the number of steps of satisfactory control in the j-th attempt; Xn is the state parameter of object A (the position of tracking object B on the sensors of control object A), f (Xn) is the function of moving the tracking object B in the visibility area of the control object.

In this paper, we consider a control object with seven sensors m = 7 with a total viewing angle of 180°. The viewing width of each sensor is ~ 25.7°, the set ∆S = {-77°, -51.5°, -25.7°, 0°, 25.7°, 51.5°, ...}.
77°}. We assume that the highest point is the central sensor - 0°. Then the field of view is encoded from -90° (left line of sight) to 90° (right line of sight).

4. Results and discussion.

We define \( Q: Q \cap \Delta S = \emptyset \) as the set of “abnormal states”. It follows from equation (1) that the control process is reduced to determining all pairs \((X_n, F_n)\) of states of the control object and its control parameters that belong to \( Q \). The problem of choosing \( F_n \) for the current \( X_n \) can be solved by enumeration in the state space. This space was divided into two subspaces: the pairs \((X_n, F_n)\) that belong to \( \Delta S \) and the pairs \((X_n, F_n)\) that belong to \( Q \) (do not belong to \( \Delta S \)). To find the elements of the set of abnormal states \( Q \) at which \( X_{n+1} \notin \Delta S \) (going out of visibility), the last pair \((X_n, F_n)\) of the trajectory is selected and the controller forbids the choice of the regulator \( F_n \), with the current state of the object \( X_n \).

![Figure 2. Training schedule of the neurosemantic controller, Abscissa axis (J) serial numbers of attempts to satisfactory control. The ordinate axis (L) is the number of steps of satisfactory control (trajectory length) in the j-th attempt.](image)

An exhaustive search of all possible pairs of elements of two sets \( X \) and \( F \) for the least number of learning attempts \( J \), which coincides with the number of trajectories that end beyond the limits of visibility, gives a fully trained controller for stable control of object \( A \). In figure 2 shows the controller training schedule, where it can be seen that the controller learned to satisfactorily control the object in the test control problem for 47 learning attempts (trajectories \( J \)), the resulting length \( L \) of trajectories reached the target \( m^2 = 49 \).

The ability to detect characteristic repetitions in the data stream in real-time is a useful property of neurosemantics [2] [3] [5]. This property avoids exhaustive search in the learning process due to reinforced learning mechanisms. Applying the neurosemantic approach to the task, characteristic repeating sections of the trajectories were identified. The alphabet for constructing a neurosemantic structure is a pair \((X_n, F_n)\).

During the operation of the controller, a neurosemantic structure was formed and trained in which neurons (N-elements) were assigned sections of trajectories of different lengths \( 1 \leq m^2 \). Those N-elements, the number of activations of which are more than one, encode the prediction trajectories. The obtained neurosemantic graph in the first layer has N-elements that reflect the exhaustive search of pairs of the current state \((X_n, F_n)\) and the next one \((X_{n+1}, F_{n+1})\). The heuristic is that the longer the repeating trajectory and the more inputs of the corresponding N-element are activated, the higher the likelihood of correctly predicting the next position of the tracking object. To derive the predicted value from the neurosemantic network, the N-element anticipation method was used [3].
During the experiments, various behaviors of the tracking object were modeled. Depending on the behavior of the tracking object, the quality of the prediction varied. During the cyclic behavior of the tracking object, an increase in the quality of the forecast with each cycle was recorded (Figure 3a). In figure 3b shows the dynamics of the chance of correct prediction in the case when the behavior of the tracking object consists of repeated maneuvers. In both cases, the adaptive controller was fully trained to predict the position of tracking object B on the sensors of object A. In the case of chaotic behavior of the tracking object, the prediction of its behavior was impossible (Figure 3c).

5. Conclusion

The paper poses and solves the problem of predicting the trajectory of a tracking object based on an adaptive controller and presents the results of neurosemantic modeling. To highlight the trajectories of prediction, you can use the method of neurosemantic auto-structuring. The experiments showed that in the presence of regularity and the absence of randomness in the behavior of the tracking object, the neurosemantic adaptive controller is able to determine the behavior of the tracking object and has the ability to predict its movement in a finite number of steps.

The lack of numerical methods of multi-parameter optimization for training and synthesis of neural network structures compares this approach favorably in terms of the speed of the method. Moreover, the implementation of semantic neural network technologies is well suited to the specifics of digital circuitry due to the principles of the work of semantic neurons and the mechanisms of their learning. Neurosemantic models using hardware solutions require further research.

The results can be used to solve practical problems of autonomous intelligent control in the face of uncertainty. Also, the results of the study are useful in the selection and design of hardware-digital architecture of intelligent machines, neural network algorithms and platforms for the development of adaptive control systems.

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