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Synergetic synthesis of a neural network controller for an adaptive control of a nonlinear dynamic plant

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ABSTRACT

The paper considered issues the development of a self-organizing controller (SC) based on a neuro-fuzzy network that can approximate a nonlinear function with arbitrary accuracy. The SC in the form of neuro-fuzzy networks, possesses the nonlinear property that allows for an increased range of control over the plant, which imparts adaptive properties to the control systems. To reduce the dimensionality of the plant, it is proposed to split the model of the system into sub models with smaller dimensionality, due to which the duration of training of the neuro-fuzzy network is reduced and asymptotic stability is ensured as a whole. The proposed approach is also applicable to multidimensional control systems of the nonlinear dynamic plants. The simulation results showed that the synthesized SC provides good tracking characteristics, the tracking efficiency is no more than 10%, which meets the requirement of the control system.

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1. INTRODUCTION

The majority of the actual operating technological plants are characterized by complex nonlinear dynamic properties and the presence of interference of a random nature, which significantly complicates the application of typical linear adaptive control algorithms for controlling similar plants [1], [2]. In the presence of an accurate mathematical model of the controlled plant, methods based on the application of the principles of adaptive control with a reference model have proven themselves to be effective [3], [4]. In classical systems of adaptive control with a reference model, the detailed mathematical model of the plant must be known, and its structure and parameters of the system do not change in the process of functioning [5], [6]. In the adaptive systems, a construction application the identification approach [7], [8] arises, related to increased computing costs, since in this case there is a necessity to promptly process a large amount of information, which significantly complicates the solution of the task. The linear self-organizing controller (SC) is widely used in industry and has proven itself well in the steady-state operating mode of the plant, that is, around the nominal mode [9], [10]. The application of a SC with a linear control law under such conditions better adapts to changes in parameters and dynamic properties of the control plant [11], [12]. At the same time, industrial plants are characterized by the nonlinear properties, several types of uncertainties and load changes [13], [14], which result in deterioration in the performance of the linear SC and require the use of the nonlinear law of the control. To overcome the difficulties associated with the presence of nonlinearity, it becomes necessary to use neural networks to approximate the nonlinear functions [15], [16].

It is known that neural networks have the properties of approximating any arbitrary nonlinear function, and they can be successfully applied to develop direct adaptive control of the nonlinear systems [17], [18]. In [19], an indirect adaptive control based on neural networks for controlling dynamic plants is presented. In the work [20], the application of SC for direct neural control for a class of structurally uncertain nonlinear plants is proposed. It should be noted that in conventional self-setting controllers, it is necessary to reconfigure their parameters each time the operating point changes, which leads to low performance in controlling the nonlinear plants [21]–[23].

The aim of the work is to develop a method for synthesizing nonlinear dynamic plants based on the hybrid application of a neuro-fuzzy network with a synergetic approach, allowing one to determine the weight coefficients of the neuro-fuzzy network in real time and establish local stability of a closed-loop system. The SC built based on the neuro-fuzzy network can provide opportunities self-learn, related once for specific operating points, and it also allows you to proceed equally from one local model to another.

2. METHOD

Let the dynamics of the control system be described by a system of equations:

$$\dot{x}_1 = f_1(x_1, x_2), \dot{x}_2 = f_2(x_1, x_2, x_3),$$

$$\dot{x}_n = f_n(x_1, x_2, \dots, x_n, u), y = h(x), u = u(y),$$

where x_i is the vector of state variables, f_i is the smooth continuous function, u is a signal of the control, y is the vector of measured variables, $h(x)$ is the differentiable function. The purpose of the control is a function of the macro variable $\psi(y)$, which represents and determines the desired diversity in the space of the system output coordinates. The condition for choosing the macro variable $\psi(y)$ is to ensure the asymptotic stability of the system under study.

To solve this issue, it is necessary to synthesize a law of control $u(y)$ that will bring the system trajectories to the vicinity of the desired variety and stabilize it from that vicinity [24]. It should be noted that qualitative information about the process is presented in the form of a function $f_i(\cdot)$, and the state vector is not available for measurements. We will select a nonlinear law of control based on the method of analytical design of aggregated controllers (ADAC), which allows for the minimization of the objective function:

$$J = \int_0^\infty F\left(\psi^2, \left(\frac{d\psi}{dt}\right)^2, \dots, \left(\frac{d^m\psi}{dt^m}\right)^2, T_1^2, \dots, T_m^2\right) dt$$

where ψ_s is an objective function, $F(\cdot)$ and parameters of T_s characterized the nature of the system and determined the dynamics of its movement by a macro variable. Based on the formulation of the issue and the desired type of transient process, the type of function F is selected. By definition of the ADAC method, the desired motion of the system of the nth order can be presented as a certain function

$$\sum_{i=1}^{n} T_i \frac{d^n\psi}{dt^n} + \psi = 0.$$

Ensuring the stability of the system and giving its desired nature is implemented by choosing the coefficients T_i. To obtain an analytical view of the control law, we differentiate the functional by time:

$$\dot{\psi} = \frac{\partial\psi}{\partial t} + \sum_{i=1}^{n} \frac{\partial\psi}{\partial y}\frac{\partial y}{\partial x_i}\dot{x}_i = \frac{\partial\psi}{\partial t} + \sum_{i=1}^{n} \frac{\partial\psi}{\partial y}\frac{\partial y}{\partial x_i} f_i(\cdot) = \frac{\partial\psi}{\partial t} + F_1\left(x_1, x_2, \dots, x_n, \frac{\partial\psi}{\partial t}\right)$$

$$\ddot{\psi} = \frac{\partial\dot{\psi}}{\partial t} = \frac{\partial\dot{\psi}}{\partial t} + \sum_{i=1}^{n} \frac{\partial\dot{\psi}}{\partial x_i}\dot{x}_i = \frac{\partial^2\psi}{\partial t^2} + \sum_{i=1}^{n} \frac{\partial F_1}{\partial x_i} x_i = \frac{\partial^2\psi}{\partial t^2} + \sum_{i=1}^{n} \frac{\partial F_1}{\partial x_i} f_i(\cdot) = \frac{\partial^2\psi}{\partial t^2} + F_2(x_1, x_2, \dots, x_n)$$

$$\dots$$

$$\frac{d^n\psi}{dt^n} = \frac{d}{dt}\left[\frac{d^{n-1}\psi}{dt^{n-1}}\right] = \frac{\partial^n\psi}{\partial t^n} + \sum_{i=1}^{n} \frac{\partial\frac{d^{n-1}\psi}{dt^{n-1}}}{\partial x_i}\dot{x}_i = = \frac{\partial^n\psi}{\partial t^n} + \sum_{i=1}^{n} \frac{\partial F_{n-1}(\cdot)}{\partial x_i} f_i(x_1, x_2, \dots, x_n) = \frac{\partial^n\psi}{\partial t^n} + F_n(x_1, x_2, \dots, x_n, u)$$

To obtain the control law in analytical form, we expand the derivatives of the function ψ. The main disadvantage of this approach to obtaining the control law is the possibility of measuring the system state vector, *i.e.* the system must be fully observable. Let us consider the case when some of the variables are not available for measurement, *i.e.* unobservable. To restore unmeasured coordinates, we use the inverse function h_k^{-1}, which can be determined based on the measured output variables.

To restore the unobserved variables, we take derivatives of the measured variables:

$$x_{k+1} = f_k^{-1}(x_1, \dots, x_k, \dot{x}_k),$$
$$x_{k+2} = f_{k+1}^{-1}(x_1, \dots, x_k, x_{k+1}, \dot{x}_{k+1}) = f_{k+1}^{-1}(x_1, \dots, x_k, f_k^{-1}(x_1, \dots, x_k, \dot{x}_k), \dot{x}_{k+1}). \quad (1)$$

Let's differentiate the expressions x_{k+1}. We get

$$\dot{x}_{k+1} = \frac{d}{dt}\left(f_k^{-1}(\cdot)\right) = \sum_{i=1}^{k} \frac{\partial f_k^{-1}}{\partial x_i}\dot{x}_i + \frac{\partial f_k^{-1}}{\partial \dot{x}_k}\ddot{x}_k = D_{k+1}(x_1, \dots, x_k, \dot{x}_k, \ddot{x}_k).$$

The resulting expression is the basis for calculating the control law in analytical form, *i.e.* this expression allows using not only the measured variables but also the numerical values of the derivatives of the coordinates (from of the variables). Let the dynamics of some nonlinear system be represented in (2):

$$x(k+1) = f(x(k), u(k), k), \quad (2)$$

where $x(k)$ is the vector of system state variables, $u(k)$ is the vector of control, f is some nonlinear function, k is the number of tacts.

To solve the task of synthesizing a synergetic controller, it is initially necessary to select macro variables that are a function of the system's state variables:

$$\Psi = \Psi(x(k), k). \quad (3)$$

The purpose of control is to ensure asymptotic stability of the system at $\Psi = 0$. The dynamics of a macro variable are characterized by the speed and trajectory of convergence to an invariant diverse (attractor) [25]. In this case, T_s is represented as:

$$T\left[\frac{\Psi(k+1) - \Psi(k)}{T_s}\right] + \Psi(k) = 0, \quad (4)$$

here T is characterizes the rate of convergence of a function (variable). Taking this into account, we rewrite (4) in the following form:

$$T\left(\frac{T}{T_s - T}\right) \cdot \frac{T}{T_s} \cdot \Psi(k+1) + \Psi(k) = 0. \quad (5)$$

The discrete form of writing (1) is:

$$\begin{cases} x_1(k+1) = x_2(k), \\ x_2(k+1) = x_3(k), \\ \vdots \\ x_{n-1}(k+1) = x_n(k), \\ x_n(k+1) = f\big(x(k)\big) + u(k) + d(k), \\ y(k) = x_1(k) \end{cases} \quad (6)$$

where $f\big(x(k)\big)$ - the nonlinear function, $x(k) = [x_1(k), x_2(k), \dots, x_n(k)]^T \in R^n$ - the vector of measured variables of the system's states, $u(k)$ and $y(k)$ - input and output of the system, and $d(k)$ - external disturbance.

The control error signals are defined as follows:

$$e_1(k) = x_1(k) - y_d(k),$$
$$\vdots$$
$$e_2(k) = x_2(k) - y_d(k+1),$$
$$e_n(k) = x_n(k) - y_d(k+n-1),$$

where $y_d(k)$ - a reference trajectory. Let's define a macro variable as follows form:

$$\Psi(k) = K_1 e_1(k) + e_2(k) = \sum_{i=1}^{n-1} K_i e_1(k) + e_n(k), \quad (7)$$

$$\Psi(k+1) = K_1 e_1(k+1) + e_2(k+1) \quad (8)$$

where K_1 - the adjustable parameter of the control

$$e_1(k+1) = x_1(k+1) - y_d(k+1) \quad (9)$$

$$e_2(k+1) = x_2(k+1) - y_d(k) \quad (10)$$

$$\Psi(k+1) = K_1 x_1(k+1) - K_1 y_d(k+1) + x_2(k+1) - y_d(k) \quad (11)$$

$$\Psi(k+1) = K_1 x_2(k) - K_1 y_d(k+1) + f\big(x(k)\big) + u(k) + d(k) - y_d(k) \quad (12)$$

Designating $\alpha = \frac{T}{T_s}\left(\frac{T}{T_s - T}\right)$ and и consolidating (11) and (4) we get

$$\alpha\big[K_1 x_2(k) - K_1 y_d(k+1) + f\big(x(k)\big) + u(k) + d(k) - y_d(k)\big] + \Psi(k) = 0 \quad (13)$$

In this case,

$$\alpha = \frac{T}{T_s}\left(\frac{T}{T_s - T}\right). \quad (14)$$

Then the synergetic control law has the form:

$$u(k) = f\big(X(k)\big) - K_1 x_2(k) + K_1 y_d(k) + y_d(k) - d(k) - \frac{1}{\alpha}\Psi(k). \quad (15)$$

If the nonlinear function $f\big(x(k)\big)$ is known, the law of synergetic control is easily obtained. When the nonlinear function $f\big(x(k)\big)$ is unknown, it is more convenient and simpler to use an adaptive synergetic fuzzy controller using a neuro-fuzzy network. The generalized structure, synthesized synergetic control system with a neuro-fuzzy controller, is shown in Figure 1. The neuro-fuzzy network includes indications of the order of one-dimensional basis functions $y(k)$, the number of basis functions and the weights of neurons determined by the gradient method. The input of this network receives a sequence of reference signals $|y(k) \ldots y(k - nr + 1),\ r(k) \ldots r(k - n_r + 1)|$. The output of the network is a linear combination of the weights and the fuzzified input. Designing the neuro-fuzzy network involves choosing basis functions, ranges of input and output variables, and the number of neurons.

The network output $u(k)$ is determined by the centre of gravity method.

$$u(t) = a^T(x)\theta, \quad (16)$$

where *x(к)* represents the input vector;

$$x(t) = \big|y(k), \ldots, y\big(k - n_y + 1\big), r(k), \ldots, r(k - n_r + 1)\big|, \quad (17)$$

$\theta\big[\theta_1 \ldots \theta_2 \ldots \theta_p\big]^T$ - the neural network weighting coefficients, p – is the number of the weighting coefficients.

The multivariate basis function is a transformed input vector:

$$a_i(x) = \prod_{l=1}^{n} \mu_{A_l^i}\big(x_l(k)\big), \quad for\ i = 1,2, \ldots, p \quad (18)$$

where $n = n_y + n_r$ - the number of input parameters of the state vector $x(k)$. These properties are also applicable to multivariate basis functions:

$$u(k) = \sum_{i=1}^{p} \theta_i a_i(x) = \sum_{i=1}^{p} \theta_i \prod_{l=1}^{n} \mu_{A_l^i}\big(x_l(k)\big). \quad (19)$$

Training a neuro-fuzzy network involves determining the setting parameters of the neural network weights. The weight coefficients of the fuzzy network are adjusted during the training process using the back distribution method:

$$\theta_i(k+1) = \theta_i(k) - g\frac{\partial J}{\partial \theta_i} = \theta_i(k) - ge\frac{\partial J}{\partial \theta_i}, \quad for\ i = 1,2,\dots,p \tag{20}$$

$$\frac{\partial e}{\partial \theta_i} = \frac{\partial y}{\partial \theta_i} = \frac{\partial y}{\partial \theta_u}\frac{\partial u}{\partial \theta_i} = \frac{\partial J}{\partial \theta_i}a_i(x). \tag{21}$$

We will decompose neuro – fuzzy controllers into two parts: static nonlinear and adaptive linear parts, which are trained in the same way as neural networks. The nonlinear property of the control plant and the neuro, fuzzy controller makes it difficult to ensure global stability of the closed, loop control system. The disadvantages of the analytical solution include the need for a task with the characteristics of the control plant.

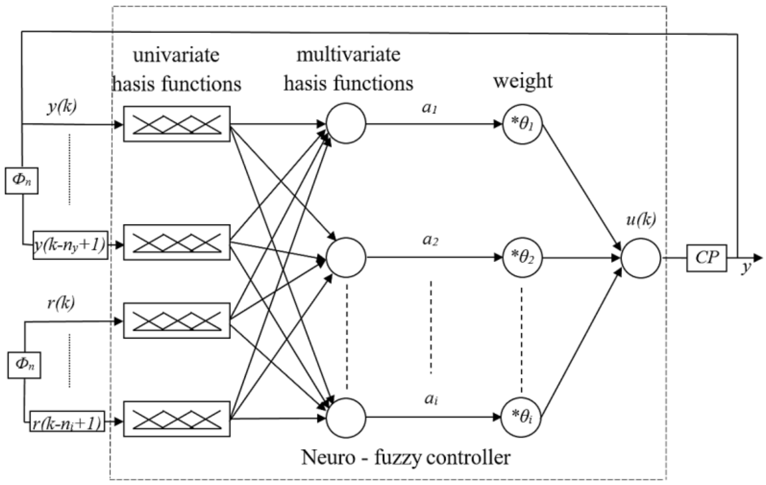

Figure 1. Generalized structure of a neuro-fuzzy network

3. RESULTS AND DISCUSSION.

The dynamics of a nonlinear system is represented as (22):

$$\begin{cases} x_1(k+1) = x_2(k), \\ x_2(k+1) = f\big(x(k)\big) + (K/T)u(k) + d(k), \\ y(k) = x_1(k) \end{cases} \tag{22}$$

where $f\big(x(k)\big) = -\lfloor a_1x_2 + a_2x_2^3(k)\rfloor/T$ - the nonlinear function. $y_d(k) = sin(k\pi/20)$ - the trajectory of external disturbance. Initial conditions:

$$d(k) = \begin{cases} 0, & if\ \ k \le 500 \\ 0.1\ tanh(0.5k), & if\ \ k > 500 \end{cases}$$

We select membership functions in the form $\mu(x_i) = e^{\left(-0.5\left(x_i+6-2(j+1)\right)^2\right)}$, $j = 1,\dots,5$ for states of the system x_i, $i = 1,2$; step of the discretization $T_s = 0.02\ s$.

Let us conduct a simulation experiment, the results of which are presented in Figure 2. It is clear from the graph that a certain law of synergetic control provides good tracking qualities. Herewith, the proposed adaptive synergetic controller $u(k)$ has limitations, see in Figure 3. Comparison of the obtained result with the results of the authors [26]–[28] shows that the proposed method for synthesizing a nonlinear self-organizing controller provides better efficiency. The limitation of the proposed approach is the dependence of the quality of the neural network on the number of training samples. In the future, it is necessary to consider the possibilities of using a state observer in the case when not all states of the system are available for measurement to develop the control system for the nonlinear dynamic plant.

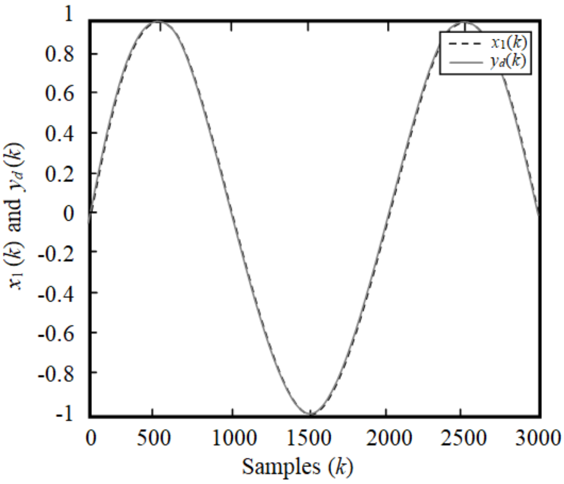

Figure 2. The reference characteristic of the transient process

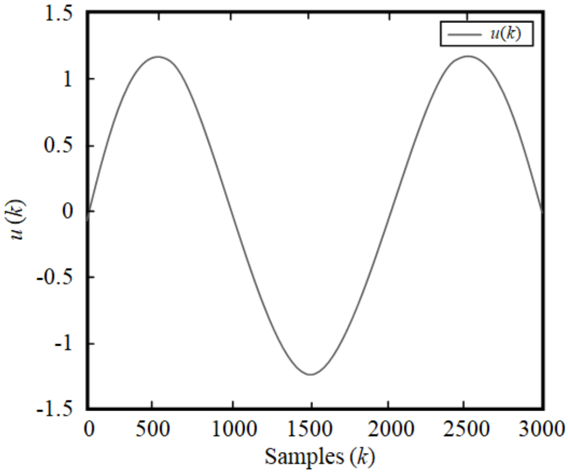

Figure 3. The results of the tracking

4. CONCLUSION

The paper considered the issues of studying the synergetic adaptive control law for a class of nonlinear systems with discrete time. The stability analysis of the adaptive synergetic control system is based on the application of Lyapunov theory. The synthesized adaptive synergetic self – organizing controller takes into account the nonlinear nature of the plant and allows its parameters to adapt to changes in the environment. The controller synthesis is carried out by a hybrid application of methods of the synergetic control theory and fuzzy systems. The proposed method of the synergetic control guarantees the reliability and asymptotic stability of the control system and makes it possible to use the nonlinear control laws. To overcome the difficulties associated with the uncertainty of the state function of plans, the use of the Mamdani neural network model is proposed. The sigmoid function is used as a membership function, which is distinguished by its simplicity of implementation, with the possibility of differentiating input variables. The obtained control law has an analytical dependence, which significantly increases the possibilities of its implementation on industrial controllers.

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