Combined Method of Neurocontrol for Nonlinear Non-Stationary Object

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Abstract **Problem of finding of optimal turning parameters for neurocontrol of nonlinear non-stationary object in a presence of random disturbances is formulated. Combined method of neurocontrol of nonlinear non-stationary objects with usage of multi-layer perceptron is proposed. The method consists of two stages. In the first stage, a problem of robust neurocontrol is solved by finding the turning parameters for adaptation algorithm on suggested set of object variants. Found turning parameters for adaptation algorithm are used in the second stage – model-free neurocontrol. In this stage it is a finding of optimal turning parameters for algorithm of model free neurocontrol. Regularization method is used to ensure stability of proposed method. Effectiveness and stability of suggested method was verified by the model example. In the presence of random disturbances, neurocontrol was stable and a degree of damping was more than 50%.**

Keywords — Neural Network, Neurocontroller, Control Synthesis

I. INTRODUCTION

Classical control methods based on usage of conventional systems of regulation, such as PID, are not always effective for solving problems of control of complex multi-linked, non-stationary objects essentially with significant nonlinearities [1]. One solution to this problem is the use of neural networks, which are regarded as promising tool for developing intelligent control systems [2-15]. Such control systems that use techniques of neural networks, are called neurocontrol systems [16, 17]. These control systems have an ability to learn with respect to the control object, disturbances of the environment and working conditions. Rapid development of the neurocontrol theory most occured in the 90-ies of XX century [16].

To date neurocontrol methods can be divided into two groups: simple and hybrid neurocontrol.

Hybrid neurocontrol system is a system in which neural network operates in conjunction with conventional controllers. In a series hybrid neurocontrol [16, 17] conventional and neural network based controller are connected in series. The turning coefficients of conventional controller are the outputs from the neural network controller. The input to the neural network provides information about the dynamics of an object and observed disturbances. The advantage of this approach is to simplify the operation of the control system due to elimination of the conventional controller setup procedure while changing an operation mode of an object. The conventional control is transformed into a non-linear control, thus achieving a better quality control of nonlinear dynamic objects. The disadvantage of this approach is the difficulty of ensuring a stability of the control system. In the parallel hybrid neurocontrol the neuroregulators act as a correcting element in a closed loop control [16, 17].

Simple neurocontrol schemes can be divided into the following groups: neurocontrol based on inverse dynamics model of an object; neurocontrol based on direct dynamics model of an object, modeling of regulator, robust control, model-free control.

In case of neurocontrol through inverse dynamics model of an object [6, 9, 16, 17] a control signal is applied to the input of neuroregulators which must be repeated at the output of the control object. Neuroregulator have to be trained for inverse dynamics of an object.

In case of neurocontrol based on the direct model of object dynamics [9, 16, 17], setting the parameters of the control carried out by a neural network model of an object. This model is derived based on neural network training on the existing facility in dynamic modes. The disadvantage of neurocontrol based on direct and inverse models of the dynamics of an object is that this method does not take into account the influence of internal and external random factors.

The simulation method is based on obtaining neural network model of control [8, 16] by learning the dynamics of conventional direct control in the control system. A conventional controller is replaced by a neurocontroller at the end of the process of learning. The advantage of this method is that neurocontroller can be used as a backup in case of failure of the primary conventional controller. This is especially important when the primary regulator is a closed system.

With robust neurocontrol [11, 16] training of neurocontroller is conducted on a variety of object models with different parameter values. Learning is based on the integral criterion, which is the sum of squared errors for the entire set of regulatory models. The disadvantage of this method is that it is impossible to train a neural network with all combinations of changes in the object parameters.

With a model-free neurocontrol [2, 3, 7, 10, 12, 16, 17] neuroregulator is connected to an object through negative feedback. Learning of neurocontroller is produced in direct operation mode of control system. This method can be attributed to the search of adaptive control techniques [18].

In many cases, control objects change their properties during operation. If operating point of an object is changed, the change in configuration of control system is required. Model-free neurocontrol solves this issue. However, at the initial stage of operation it is necessary to determine a structure of a neural network and adjust parameters of an adaptation algorithm, which is impossible in the operation mode of direct control. One method of solving this problem is a combination of model-free and robust neurocontrol.

The optimal structure and tuning parameters of neurocontroller are determined by testing on a set of variants of a control object (stage of robust control). Stage of model-free neurocontrol is carried out during the direct operation mode of the object neurocontrol where there is a continuous search for optimal turning parameters of the control algorithm. The proposed combined method of neurocontrol can be used to control objects with significant nonlinearities and non-stationary parameters.

II. PROBLEM FORMULATION

Consider a scheme of model-free control of nonlinear non-stationary object (Figure 1) like:

$$\frac{d\mathbf{y}(\tau)}{d\tau} = f(\mathbf{a}(\tau),\ \mathbf{u}(\tau),\ \mathbf{z}(\tau)), \qquad (2.1)$$

$$\mathbf{y}(0) = \mathbf{y}_0,$$

$$\mathbf{u}(\tau) \in U,$$

where $\mathbf{y}(\tau) = \{y_1(\tau), y_2(\tau), ..., y_M(\tau)\}$ - object output at time moment τ; $\mathbf{a}(\tau) = \{a_1(\tau), a_2(\tau), ..., a_A(\tau)\}$ - parameters of an object; $\mathbf{u}(\tau) = \{u_1(\tau), u_2(\tau), ..., u_M(\tau)\}$ - control signal; $\mathbf{z}(\tau) = \{z_1(\tau), z_2(\tau), ..., z_M(\tau)\}$ - random disturbance with known correlation function; $\mathbf{y}_0(\tau) = \{y_0^1(\tau), y_0^2(\tau), ..., y_0^M(\tau)\}$ - object output at time moment $\tau = 0$; U - control domain.

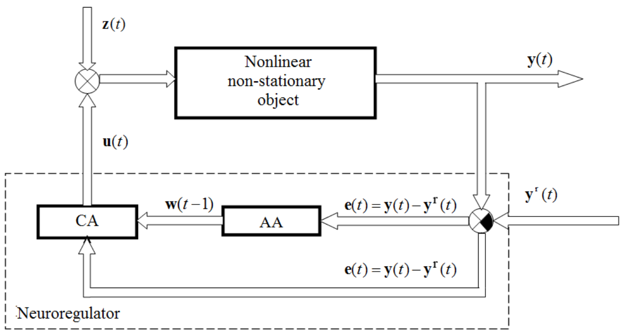

Fig.1. Scheme of model-free control of an object with neuroregulator

The structure and order of mathematical model of object assumed to be known. It is assumed that nonlinear non-stationary object can have R possible implementations, each of which has its own variant of model parameters.

Let t - discrete time, which is relates to continuous time τ as $\tau = t \cdot \Delta\tau$, where $\Delta\tau$ - chosen time step; $t = 0, 1, 2, 3, ..., t_K$, where t_K - the end of a control process. Quality of control at every time moment t is characterized by measured error $\mathbf{e}(t) = \mathbf{y}(t) - \mathbf{y}^r(t)$, where $\mathbf{y}^r(t)$ - reference, the same for all possible R implementations of an object. Under these conditions, the optimal control algorithm (CA) is a sequence of control signals $\{\ \mathbf{u}^*(1), \mathbf{u}^*(2), ..., \mathbf{u}^*(t_K)\ \}$, such that

$$\left\{\mathbf{u}^*(1), \mathbf{u}^*(2), ..., \mathbf{u}^*(t_K)\right\} = \underset{\mathbf{u}(t)\in U}{\operatorname{argmin}} \sum_{t=1}^{t_K}\sum_{m=1}^{M} \mathrm{e}_{\mathrm{m}}^2(t), \qquad (2.2)$$

Equations of CA and algorithm of adaptation (AA) are defined like:

$$\begin{cases} \mathbf{u}(t) = F[\mathbf{e}(t), \mathbf{w}(t-1)] \\ \mathbf{w}(t) = G[\mathbf{w}(t-1), \boldsymbol{\alpha}, \mathbf{e}(t)] \end{cases}, \qquad (2.3)$$

$$t = 1, 2, 3, \dots, t_K,$$

where $\mathbf{w}$ - vector of turning parameters of CA; $\boldsymbol{\alpha}$ - vector of parameters of AA; *F, G* – transcendental functions.

Multi-layer neural network was used for CA. Vector of turning parameters $\mathbf{w}$ of CA is a vector of weight coefficients of neural network, and vector of parameters $\boldsymbol{\alpha}$ of AA is a vector of learning parameters of neural network.

CA computes control signals $\mathbf{u}(\tau)$, as output of neural network according to measured error $\mathbf{e}(t)$ and vector of turning parameters $\mathbf{w}(t-1)$, which stands for weight coefficients of neural network. Current value of vector $\mathbf{w}(t)$ is defined according to the value of this vector on previous time step, measured error $\mathbf{e}(t)$ and value of vector of parameters $\boldsymbol{\alpha}$ of AA. Vector $\boldsymbol{\alpha}$ determines a structure of a network and parameters of learning algorithm of neural network.

III. METHODS

It is suggested to use methods of neurocontrol [19] for solving the formulated problem. A disadvantage of model-free neurocontrol is a long search time for $\mathbf{w}^*(t)$ (2.3) as a result of arbitrary choice of vector $\boldsymbol{\alpha}$ of AA, significant nonlinearity of object and random disturbances [4,5,16,17]. Method of neurocontrol for nonlinear non-stationary objects with usage of multi-layer perceptron is proposed. First stage of the combined method (robust control) is to determine the optimal vector $\boldsymbol{\alpha}$ for AA: for given time interval $t \in [0, t_K]$ and a set of variants of object model: $\{(\mathbf{a}_1(t), \mathbf{z}_1(t)), (\mathbf{a}_2(t), \mathbf{z}_2(t)), ..., (\mathbf{a}_r(t), \mathbf{z}_r(t)), ... (\mathbf{a}_R(t), \mathbf{z}_R(t))\}$

find vector $\boldsymbol{\alpha}^*$, in which optimality criterion reaches minimum, i.e.:

$$\boldsymbol{\alpha}^* = \underset{\boldsymbol{\alpha}\in A}{\operatorname{argmin}} \sum_{r=1}^{R}\sum_{t=0}^{t_k} (\mathbf{y}_r(\mathbf{a}_r(t), \mathbf{z}_r(t), \mathbf{u}_r(t)) - \mathbf{y}^r(t))^2, \qquad (3.1)$$

where A - domain of components of vector $\boldsymbol{\alpha}$; $\mathbf{u}_r$ - control signal, turned by (2.3).

At the second stage of the combined method (model-free control) a system setup is carried out directly in control process of object in a presence of random disturbances $\mathbf{z}(t)$ according to criterion (2.2). Thus, neuroregulator is constantly in process of adjustment during operation of control system. The resulting vector $\boldsymbol{\alpha}^*$ in the first stage remains unchanged, being only a search for the optimum vector $\mathbf{w}^*$.

Thus, the proposed combined method of neurocontrol for nonlinear non-stationary objects takes advantages of robust methods and model-free methods and eliminates their disadvantages.

For the development of CA a MLP neural network was used with a one hidden layer (Figure 2).

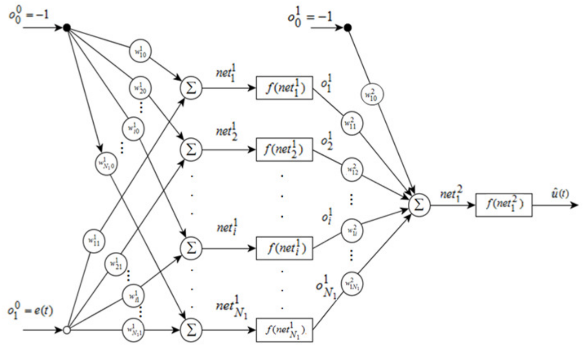

Fig.2. Structure of MLP neural network of neuroregulator with one hidden layer

Every neuron of l-th layer converts input vector o^{l-1} to output vector o^{l} . On every stage the sum of input signals of neuron is computed:

$$net_i^l = \sum_{i=0}^{N_{l-1}} w_{ij}^l o_i^{l-1} , \qquad (3.2)$$

where N_{l-1} - number of neurons in layer $l-1$; w_{ij} - weight coefficient of AA, which characterizes strength of the link between j-th neuron of $l-1$ layer and i-th neuron of l-th layer.

Threshold values of a neurons output are represented as additional neurons with a constant value equal to -1. Further, value of the function (3.2) converts to output value using transfer function:

$$o_i^l = f(net_i^l) .$$

For a transfer function it can be used, respectively, a sigmoid function, hyperbolic tangent and linear function:

$$f(net) = \frac{1}{1+e^{-net}}, \quad f(net) = \frac{e^{net}-e^{-net}}{e^{net}+e^{-net}}, \quad f(net) = net .$$

Task of AA for $t = 1, 2, 3, ..., t_\kappa$ is an adjusting the weight coefficients $\mathbf{w}(t)$ of CA to unknown optimal value $\mathbf{w}^*(t)$ corresponding to condition:

$$\mathbf{w}^*(t) = \underset{\mathbf{w} \in W}{\arg\min}\, E(t) ,$$

$$E(t) = \frac{1}{2}\sum_{m=1}^{M} e_m^2(t) , \qquad (3.3)$$

$$e_m(t) = y_m(t) - y_m^r(t) .$$

Setting of weight coefficients $\mathbf{w}(t)$ is carried out by gradient method according to equation [16,17] (a particular form of the function G in (1.3)):

$$w_{ij}^l(t) = w_{ij}^l(t-1) - \eta \frac{\partial E(\mathbf{w}(t-1))}{\partial w_{ij}^l(t-1)} , \qquad (3.4)$$

where η – step coefficient of gradient method.

Derivative of criterion (3.3) on the weight coefficients w_{ij}^l is determined according to backpropagation rule [5,6,12,16, 17].

As shown in [19], control system with neuroregulator based on (3.4), begins to lose its stability over time due to the accumulation of rounding errors. The problem (3.3) belongs to a class of ill-posed problems. To solve this problem, the regularization method is used [20,21]. To convert ill-posed problem to well-posed, criterion (3.3) was rewritten in the form [22]:

$$\widetilde{\mathrm{E}}(\mathbf{w}(t)) = \mathrm{E}(\mathbf{w}(t)) + \Omega(\mathbf{w}(t)) , \qquad (3.5)$$

where $\Omega(\mathbf{w}(t))$ - uniformly convex function, which is defined as:

$$\Omega(\mathbf{w}(t)) = \frac{1}{2}\lambda \sum_{ijl} (w_{ij}^l)^2 , \qquad (3.6)$$

where λ - coefficient of regularization.

Then according to (3.4)-(3.6) AA is represented as:

$$w_{ij}^l(t) = w_{ij}^l(t-1) - \eta \frac{\partial E(\mathbf{w}(t-1))}{\partial w_{ij}^l(t-1)} - \eta\lambda w_{ij}^l(t-1) .$$

Using the λ parameter will limit the growth of the neural network weights, which will ensure the stability of the control system. Parameter λ is determined experimentally for each specific case.

Parameters of AA are set as vector $\boldsymbol{\alpha} = \{s_1, s_2, N_1, \lambda, \eta\}$, where s_1, s_2 – determine the type of transfer function for neurons in hidden and in output layer respectively; N_1 - number of neurons in a hidden layer.

Parameters s_1, s_2 can have the following values: 1, 2 and 3, where 1 – sigmoid function; 2 – hyperbolic function; 3 – linear function.

The problem of finding the optimal vector $\boldsymbol{\alpha}$ is solved by methods of multivariable optimization.

IV. RESULTS

Model simulation was carried out to verify the proposed combined method. A nonlinear non-stationary object was selected which was represented by differential equation:

$$a_{1,r}\frac{dy(\tau)}{d\tau} + y(\tau) =$$
$$a_{2,r}\left(\frac{1}{1+\exp(-a_{3,r}(\tau)u(\tau-a_{4,r}))} - \frac{1}{2}\right) + z_r(\tau) , \qquad (4.1)$$
$$r = \overline{1,R} ,$$
$$y(0) = 0 ,$$

where τ - continuous time; $a_{1,r}, a_{2,r}, a_{4,r}$ - time constant, coefficient of gain, delay time; $z_r(\tau)$ -random signal with a normal density distribution; R - number of object variants.

Coefficient $a_{3,r}(\tau)$ of equation (4.1) is non-stationary and is defined by:

$$a_{3,r}(\tau) = b_{1,r} + \sin(b_{2,r} \cdot \pi \cdot \tau) ,$$

where $b_{1,r}, b_{2,r}$ - constants of m -th object.

On the first stage of combined method of neurocontrol the 20 variants of object model was defined, specifying different values of coefficients $a_{1,r}, a_{2,r}, a_{4,r}, b_{1,r}, b_{2,r}$ and functions $z_r(\tau): z(\tau) \in [0, Z_r]$ ($r = \overline{1, 20}$) Reference value was the same for all variants of object model.

After that there was a solution of the problem (2.3) by random search method for vector $\boldsymbol{\alpha}^*$. Time step for data processing was $\Delta\tau = 0.1$ s. Optimality criterion for (3.1) reached a minimum at $s_1 = 1;\ s_2 = 1;\ N_1 = 2;\ \lambda = 0{,}01;\ \eta = 0{,}05$. Thus, in the first stage of the control synthesis the optimal vector $\boldsymbol{\alpha}^*$ was founded, that allows to use this result in second stage of combined method – model-free control during usage of object.

In Figure 3 the results of numerical experiment on the model-free neurocontrol system for nonlinear non-stationary object with random disturbances (Figure 4). are shown. Object has the following parameters ($a_1 = 15; a_2 = 1; a_4 = 8; b_1 = 7; b_2 = 0{,}004$). According to Figure 3 and Figure 4 neurocontrol in the presence of random disturbances is stable and a degree of damping Ψ is more than 50 %.

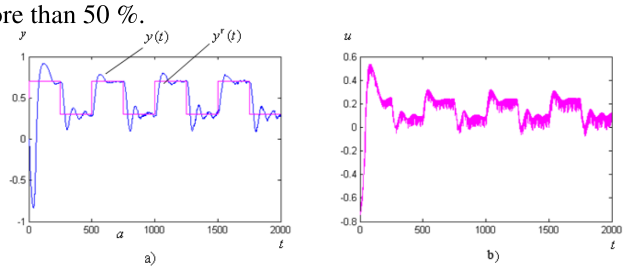

Fig.3. Results of numerical simulation: object output (a); control signal (b)

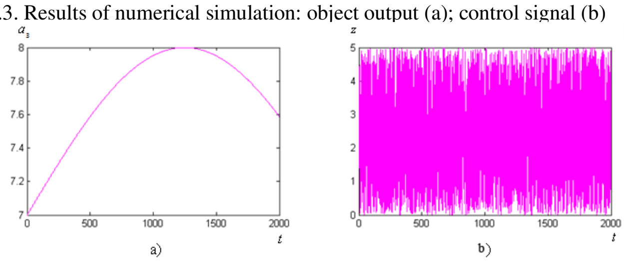

Fig.4. Results of numerical simulation: nonstationary parameter a_3 (a); random disturbance (b)

Sensitivity of the control system to malfunctioning set parameter a_1, a_2, a_4, b_1, b_2 in different implementation of the control object was analyzed. Studies showed that with significant deviation from the nominal parameters of the object the quality of control process is acceptable and process of control is stable.

Attempts to reach acceptable quality of control process using conventional control systems with PID regulator were carried. There were two variant of output: control system was unstable or there was significant discrepancy from the reference.

V. CONCLUSIONS

As shown by a model example, proposed combined method of neurocontrol for nonlinear non-stationary objects using multi-layer perceptron is effective and stable in the presence of random disturbance. Combining robust and model-free neurocontrol can be used in systems with a priori known structure and order of control object. Preliminary determination of parameters of control algorithm on a set of object model variants provides high performance adaptive control during the control process. Neurocontrol process stability is achieved by using the method of regularization.

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