ADAPTIVE NEURAL NETWORK CONTROL OF MECHATRONICS OBJECTS

Egor NEMTSEV*, Yuri ZHUKOV*

*Baltic State Technical University "Voenmeh", 198005, St. Petersburg, 1 Krasnoarmeyskaya 1, Russia

enemtsev@mail.wplus.net, zh_kv@mail.ru

Abstract: This paper presents an adaptive neural network approach to control of mechatronics objects. This approach is applied in adaptive control of DC motor in SISO-system and 3-DOF robot arm actuators in MIMO system. Results of computer simulation and comparison with other control techniques are introduced.

1. INTRODUCTION

Currently there are a lot of approaches to mechatronics objects control. Linear algorithms are very easy to employ, they provide acceptable results in case of using linearized models. Still, implementing such algorithms with unknown control object parameters and variable external disturbances leads to unsatisfactory performance.

So-called "dynamic" control methods based on solving the inverse dynamics problem became widespread. Realizability is the main problem of such algorithms application. Besides, in case of inaccurate control object parameters estimation such approach does not give satisfactory results. Adaptive algorithms provide efficient control in case of parameter and external disturbances uncertainty. However, implementation complexity makes it difficult to use them wide in engineer practice.

The ability of artificial neural networks (ANN) (Hagan and Demuth, 1999; Hunt et al., 1992; Murray et al., 1992; Narendra and Mukhopadhyay, 1997; Omidvar and Elliot, 1997) to represent non-linear systems makes them a powerful tool for dynamic systems modeling and control. Multilayered perceptron networks are capable of performing adaptive controller, identifier and optimizer tasks in control systems. Neural network control algorithms are easy to employ, however some problems of parametric and structural synthesis remain unsolved.

Another considerable shortcoming of ANN is the necessity of initial neural network learning phase. That is unsuitable for control tasks as the uncertainty of initial ANN weights means that during the learning phase controller cannot be turned on.

In this paper a universal ANN-based control algorithm with on-line learning (Omidvar and Elliot, 1997)), which doesn't need the initial learning phase, is investigated. An application of such an algorithm in control of DC motor in SISO-system and 3-DOF robot arm actuators in MIMO system is reviewed.

2. ANN CONTROLLER

Structure of ANN-based control algorithm mentioned above is presented at Fig. 1. As an input controller vector q_d a vector of desired object coordinates is used.

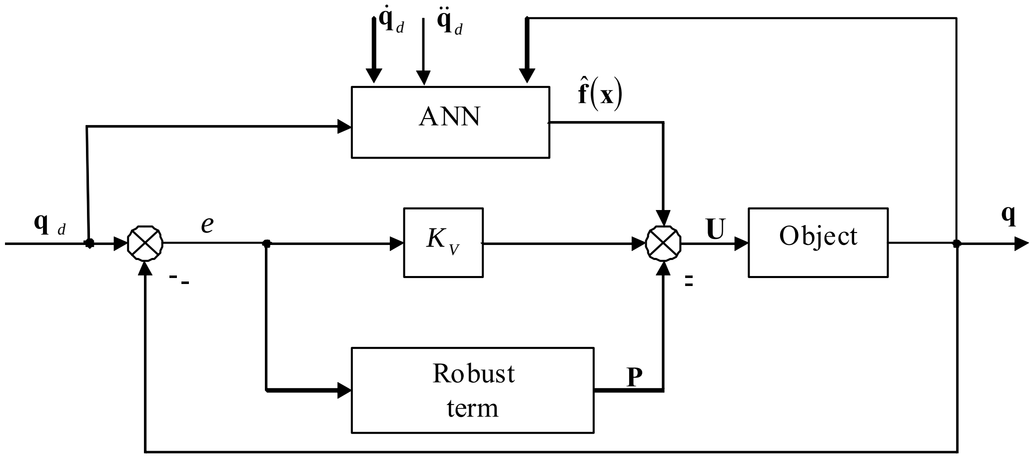

Fig. 1. Neural network controller structure

According to Eq. 1 ANN forms a control signal f(x) with $\hat{\mathbf{W}}, \hat{\mathbf{V}}$ the estimated values of the target ANN weights W (from input to hidden layer), V (from hidden to output layer) and σ(.) – hidden layer sigmoid activation function. These estimates will be provided by the weight tuning algorithm.

$$\hat{f}(\mathbf{x}) = \hat{\mathbf{W}}^T \sigma\left(\hat{\mathbf{V}}^T \mathbf{x}\right). \tag{1}$$

Control vector input U is defined as:

$$\mathbf{U} = \left(\hat{\mathbf{f}}(\mathbf{x}) + \mathbf{K}_V \mathbf{e} - \mathbf{P}\right). \tag{2}$$

With $\hat{\mathbf{f}}(\mathbf{x})$ – neural network functional estimate of nonlinear object function. Controller stability is provided by proportional control block with K_V coefficient matrix. P – robustness providing function.

3. SISO DISCRETE-TIME CONTROL SYSTEM

5 hp DC motor was chosen as a control object for case of SISO discrete-time control system. As the simulation was held in mathematic modeling environment MatLab Simulink, ready to use model of DC motor with given parameters presented in Simulink SimPowerSystems library was used. According to proposed controller structure (Fig. 1) a model of discrete ANN-based control system was implemented in Simulink.

ANN learning occurs on-line every time step according to Eq. 3:

$$\begin{aligned}\hat{\mathbf{V}}(k+1) &= \hat{\mathbf{V}}(k) - \alpha_1 \hat{\varphi}_1(k)\left[\hat{\mathbf{y}}_1(k) + \mathbf{B}_1 \mathbf{K}_v \mathbf{r}(k)\right]^T \\ &\quad - \Gamma \,\|\, \mathbf{I} - \alpha_1 \hat{\varphi}_1(k) \hat{\varphi}_1^T(k) \,\|\, \hat{\mathbf{V}}(k), \\ \hat{\mathbf{W}}(k+1) &= \hat{\mathbf{W}}(k) - \alpha_2 \hat{\varphi}_2(k) \mathbf{r}(k) - \Gamma \,\|\, \mathbf{I} \\ &\quad - \alpha_2 \hat{\varphi}_2(k) \hat{\varphi}_2^T(k) \,\|\, \hat{\mathbf{W}}(k).\end{aligned} \tag{3}$$

With Γ, α_i – scalar design parameters, B_1 – known parameter matrix, $\hat{\varphi}_1(k) = \varphi\left(x\left(k\right)\right)$ – sigmoid activation function, $\hat{\varphi}_2(k) = \varphi\left(\hat{\mathbf{V}}^T(k)\varphi\left(\mathbf{x}(k)\right)\right)$ – output of ANN hidden layer, r(k) – filtered tracking error and $\hat{\mathbf{y}}_1(k) = \hat{\mathbf{V}}^T(k)\hat{\varphi}_1(k)$. As there are no analytic synthesis methods for investigated control algorithm, coefficients were selected empirically during computer simulation.

3.1. Simulation Results

Results of control system simulation in conventional operating regimes presented at Fig. 2, 3. Step variation of torque payload is used to show adaptive abilities of control algorithm. To compare results obtained a PD controller was also created in Simulink. Results, shown at Fig. 2, 3 (left plots for ANN controller, right for PD), obtained with zero initial ANN weights, 50 neurons in hidden layer and 0.01s step time.

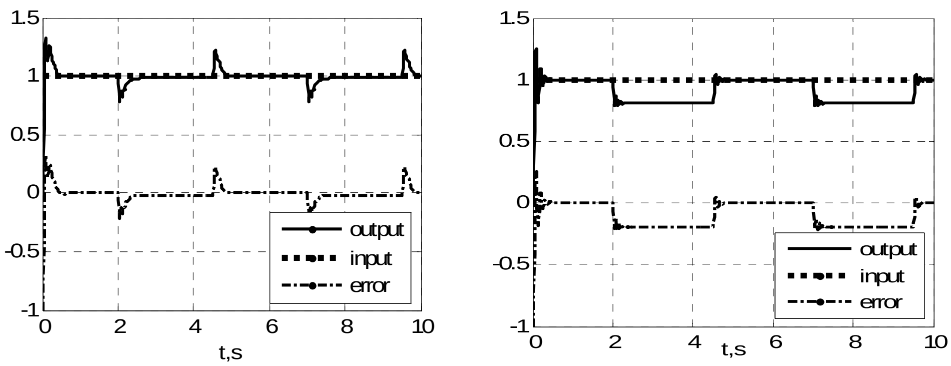

Fig. 2. Step input with variable torque payload simulation results (ANN and PD)

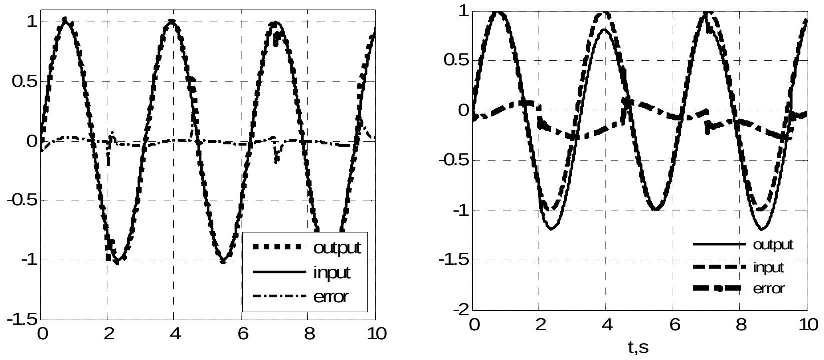

Fig. 3. Sin wave input with variable torque payload simulation results (ANN and PD)

4. MIMO CONTROL SYSTEM

4.1. Control object

PUMA-560 is 6-link anthropomorphic robot. DC motors with independent excitation are used as actuators. Robot links a connected by 5-class joint, so robot location in Cartesian coordinate system is defined by generalized coordinates vector **q**=[q_1, q_2, q_3, q_4, q_5, q_6]^T, with q_i – i-th joint coordinate relative to i-1. With elastic deformation of robot links ignored, according to Lagrange's equation a matrix equation for robot mechanics was derived as:

$$\mathbf{A}(\mathbf{q},\boldsymbol{\xi})\cdot\ddot{\mathbf{q}}+\mathbf{B}(\dot{\mathbf{q}},\mathbf{q},\boldsymbol{\xi})+\mathbf{C}(\mathbf{q},\boldsymbol{\xi})=\boldsymbol{\tau}. \quad (4)$$

With **A** – manipulator matrix, **B -** Coriolis and centrifugal forces vector, **C** – gravity forces vector, $\boldsymbol{\tau}$ - generalized forces vector, $\boldsymbol{\xi}$ – manipulator parameter matrix.

Actuator dynamics is defined in Eq. 5, with R_A – armature resistance, L_A - armature inductance, C_e, C_m – constructive constants, i_A – armature current, U – armature voltage, M - electromagnetic torque.

$$U=R_A i_A + C_e\Omega_M + L_A\frac{di_A}{dt},\quad M=C_m i_A. \quad (5)$$

Motor's instantaneous output torque of i-th link corresponds to generalized forces vector as:

$$\tau_i = g_i M_i - k_i\dot{q}_i. \quad (6)$$

With g_i – reduction gear ratio, k_i – viscous friction coefficient of i-th link.

According to Eq. 4-6, robot and actuators constructional parameters (Soloway and Haley, 1996) in mathematic modeling environment MatLab PUMA-560 robot manipulator dynamic model was developed.

4.2. Adaptive ANN Controller

For MIMO system a continuous case of ANN learning algorithm was used (Eq. 7).

$$\begin{aligned}\dot{\mathbf{W}}&=\mathbf{F}\boldsymbol{\sigma}\cdot\mathbf{e}^{\mathrm{T}}-\mathbf{F}\boldsymbol{\sigma}\cdot\mathbf{V}^{\mathrm{T}}\mathbf{x}\mathbf{e}^{\mathrm{T}}-k\cdot\mathbf{F}\left\|\mathbf{e}\right\|\mathbf{W},\\ \dot{\mathbf{V}}&=\mathbf{G}\mathbf{x}\left(\boldsymbol{\sigma}'^{\mathrm{T}}\cdot\mathbf{W}\mathbf{e}\right)^{\mathrm{T}}-k\cdot\mathbf{G}\left\|\mathbf{e}\right\|\mathbf{V}.\end{aligned} \quad (7)$$

With σ=σ(V^Tx) – hidden layer output, **F, G** – algorithm tuning coefficient positive-definite matrices, k – scalar tuning coefficient, **e** – tracking error.

With $\sigma'(z)=\sigma(z)(1-\sigma(z))$ – expression for sigmoid activation function derivative and **I** – identity matrix define:

$$\boldsymbol{\sigma}'^{\mathrm{T}}\mathbf{W}\mathbf{e}=diag\ \left(\sigma\left(\mathbf{V}^{\mathrm{T}}\mathbf{x}\right)\right)\cdot\left[\mathbf{I}-diag\left(\sigma\left(\mathbf{V}^{\mathrm{T}}\mathbf{x}\right)\right)\right]\mathbf{W}\mathbf{e}. \quad (8)$$

Robust term provides algorithm stability with variation of ANN gains and weights according to:

$$\mathbf{P}=-\mathbf{K}_Z\left(\left\|\mathbf{Z}\right\|_F+\mathbf{Z}_M\right)\cdot\mathbf{e} \quad (9)$$

With $\mathbf{K}_Z$ – tuning positive-definite matrix, $\mathbf{Z}_M$ – maximum value of $\|Z\|_F$ – Frobenius norm of all ANN weights.

$$\mathbf{Z}=\begin{vmatrix}\mathbf{W} & 0\\ 0 & \mathbf{V}\end{vmatrix}. \quad (10)$$

To compare results received, three other controllers were implemented in MatLab.

PD controller was developed according to Eq. 11.

$$\mathbf{U}=\mathbf{k}_P\mathbf{e}+\mathbf{k}_D\dot{\mathbf{e}}. \quad (11)$$

With **U –** control vector, $\mathbf{k}_p$, $\mathbf{k}_D$ **–** constant diagonal matrices, **e**=$\mathbf{q_d}$**–q –** tracking error, $\mathbf{q_d}$ **–** desired joint trajectory.

Dynamic controller is described by Eq. (12), with $\mathbf{q_d}(t),\dot{\mathbf{q}}_\mathbf{d}(t),\ddot{\mathbf{q}}_\mathbf{d}(t)$ **–** desired joint trajectories, velocities and accelerations, **K**, $\mathbf{K}_2$, $\mathbf{K}_1$ **–** diagonal matrices providing algorithm asymptotic stability.

$$\mathbf{U}=\mathbf{K}\begin{pmatrix}\mathbf{A}(\mathbf{q}_d,\boldsymbol{\xi})\cdot\ddot{\mathbf{q}}_d+\mathbf{B}(\dot{\mathbf{q}}_d,\mathbf{q}_d,\boldsymbol{\xi})+\\ \mathbf{C}(\mathbf{q}_d,\boldsymbol{\xi})+\mathbf{A}(\mathbf{q}_d,\boldsymbol{\xi})\left[\mathbf{K}_1\mathbf{e}+\mathbf{K}_2\dot{\mathbf{e}}\right]\end{pmatrix}. \quad (12)$$

Regressive adaptive controller (Narendra and Mukhopadhyay, 1997) with unknown robot parameters estimation function defined as:

$$\mathbf{U}=\mathbf{Y}\cdot\boldsymbol{\psi}+\mathbf{K_a}\mathbf{e},\ \dot{\boldsymbol{\psi}}=\mathbf{F}\mathbf{Y}\mathbf{e}. \quad (13)$$

With **Y –** regression matrix derived from robot dynamic model, $\mathbf{K_a}$, **F –** constant matrices, defining rate of convergence, **Ψ –** unknown robot parameters vector.

4.3. Simulation Results

Results of MIMO control system simulation in different operating regimes presented at Fig. 4-7. As the operating regimes were chosen: step control input q^i_p=c·1(t) for each joint, with c – constant coefficient, 1(t) – step function; equivalent harmonic regime of i-th joint in form of q^i_p=(ω^2_i/ε_i)·sin((ε_i/ω_i)t), with ω_i – joint maximum speed, ε_i – joint maximum acceleration. Results presented for 3-rd joint as its dynamics is the most dependent. Besides, during simulation parameter uncertainty is introduced– variation of robot hand payload at 10-th second.

Transient processes for PD controller are shown at Fig. 5: for dynamic control – at Fig. 6; for adaptive robot hand mass definition regressive algorithm – at Fig. 7. Application of ANN adaptive controller for robot actuators control presented at Fig. 6. At start of simulation initial weights of ANN are zero.

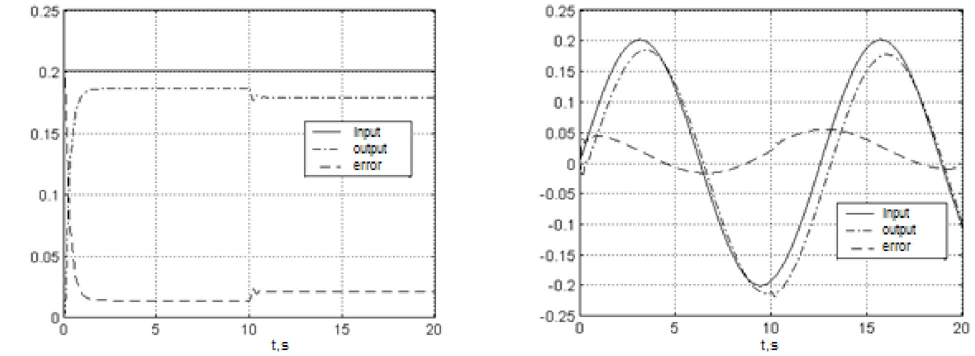

Fig. 4. PD robot control

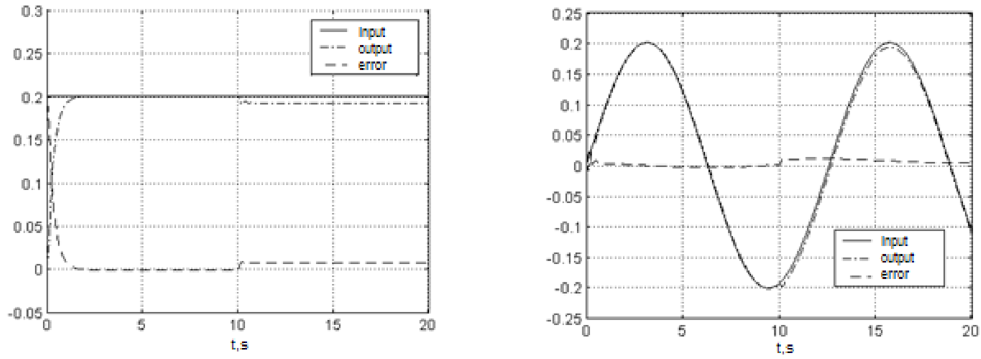

Fig. 5. Dynamic robot control

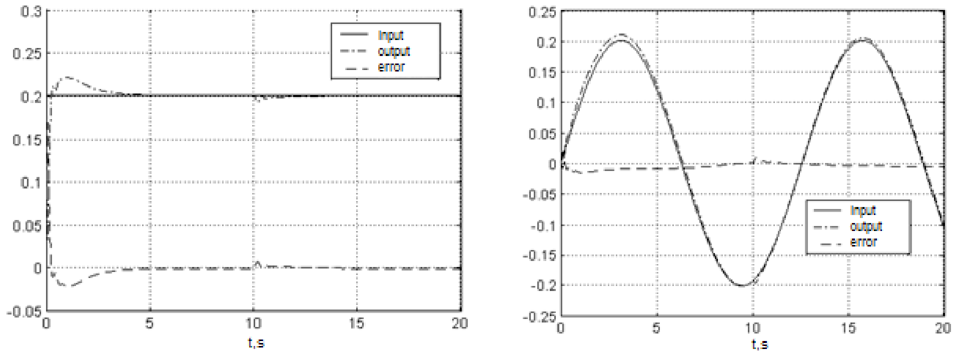

Fig. 6. Adaptive regressive robot control

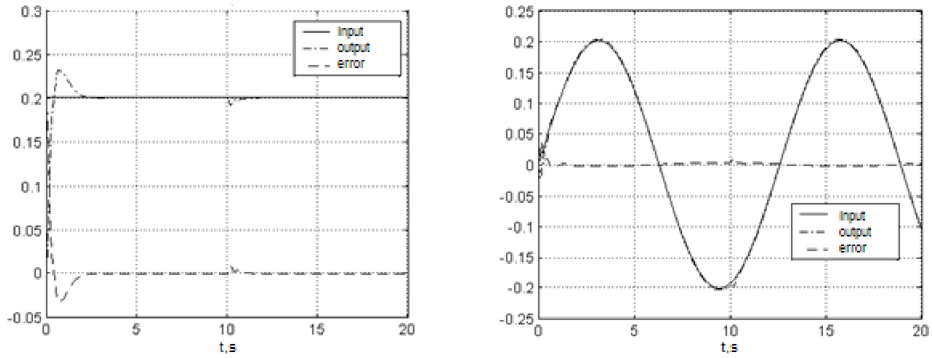

Fig. 7. ANN adaptive robot control

4.4. Results Discussion

Application of neural network controller allows obtaining control performance not worse than with PD, dynamic or adaptive regulators, but in much more heavy conditions of parametric and functional uncertainty. Adaptive neural network controller has some advantages: it can be implemented on a low performance microcontroller; it does not require accurate estimation of control object parameters, therefore neural network weights in initial state may have zero values; it has an ability of real-time on-line network weights tuning.

5. SUMMARY

During this research the following results were obtained:

- application package for estimating capability of using different control techniques in dynamic objects control tasks was created in mathematic modeling environment MatLab Simulink;
- comparative investigation of control algorithms was held;
- algorithm was confirmed to be a promising control method, which can be easily implemented in dynamic systems control tasks in case of parametric and functional uncertainty.

Further ANN algorithms efficiency increasing requires their modification in order receive quasi-optimal structural and parametric synthesis procedures.

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