Adaptive Neural Control with Integral-Plus-State Action

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Abstract: *An indirect adaptive neural control with Integral-Plus-State (IPS) action, is proposed. The control scheme contain one identification and state estimation Recurrent Trainable Neural Network. The identified plant parameters and the estimated state vector are used to compute an adaptive IPS control. Two control schemes are proposed, containing one or two integrals in the control law. The good tracking abilities of this adaptive IPS control are confirmed by simulation results, obtained with a mechanical plant with friction model. Copyright © 2002 IFAC.*

Keywords: *Neural Networks, Backpropagation, PID Controllers, Adaptive systems, Reference signal, Feedback Control, Mechanical systems, Friction.*

1. Introduction

Intelligent control using neural networks (NN) has been applied to various control problems, O m a t u et al. [8]. It is known to be effective in many situations, especially when the controlled plant exhibits non-linearity, and the plant parameters are unknown and time varying, especially for mechanical systems. On the other hand, the unavoidable effects of identification and control errors, due to model uncertainties, together with slow load variations, cause a steady-state offset that needs to be removed. In this case, an integral action, added to the control, compensates the plant uncertainties and load effects, and help the system to track the reference signal. Within the context of the servomechanism problem, integral action is a fundamental technique in the control repertoire and the I-PD (or PID) controllers have been the most utilised controllers in the industry, because of their simple structure and robust performance in wide range of operating conditions, C e r v a n t e s and A l v a r e z-R a m i r e z [4]. Here the PD mode is used to speed up response, whereas the PI mode is applied to eliminate the

steady state offset. During the last years, the classical PID scheme has been completed by auto-tuning devices like Neural Networks, H e n s e n et al. [5]; L i m a et al. [7], (Multi-Layer Perceptron, learned by Genetic Algorithms; Radial Basis Functions NN), and Fuzzy Systems, A l m u t a r i and C h o w [1], to adjust on-line its parameters. To resolve some specific control problems in mechanical systems, some extensions to the classical PID scheme, have been added. So, for regulator tasks on mechanical systems that exhibit friction, the PID-controller is combined with mass and friction feedforward, A l m u t a r i and C h o w [1]. The state PD-controller plus gravity compensation terms is widely used in robot manipulators control. However, these linear state feedback controllers could not compensate inertial and corriolis forces and cannot render asymptotic stability for path tracking tasks. To overcome this, in [9] P a r r a and A r i m o t o, a nonlinear PID controller, is proposed. The major disadvantage of these controllers is that they could be applied only for SISO and not for MIMO systems. Also, in a case of high order plants, the PD control term is not sufficient to assure systems stability. The use of RNN for systems control could overcome these problems. B a r u c h et al. [3] have proposed a new RNN and a dynamic Bachpropagation (BP)-like algorithm of its learning, which could resolve identification and control problems in an universal way. The applied indirect adaptive neural control contains one identification and state estimation RNN, which offers a good learning performance.

The aim of the proposed paper is to extend this control scheme with one or two I-control terms, so to obtain an Integral-Plus-State (IPS) indirect, adaptive, trajectory tracking, offset compensation control.

The aim of this paper is to apply the RTNN model in two real-time identification and indirect adaptive IPS control schemes of nonlinear mechanical system with unknown variable parameters and dynamic effects.

2. Recurrent neural network topology and learning

In B a r u c h and F l o r e s [2] ; B a r u c h et al.[3], a discrete-time model of Recurrent Trainable Neural Network (RTNN), and the dynamic Backpropagation (BP) weight updating rule, applied for identification and control purposes, are given. The RTNN model is described by the following equations:

(1) $$X(k + 1) = JX(k) + BU(k),$$

(2) $$X_1(k) = S[X(k)],$$

(3) $$Y(k) = S[CX_1(k)],$$

(4) $$J = \text{block} - \text{diag}(J_i); \; |J_i| < 0,$$

where: $X(.)$ is a N-state vector of the system; $U(.)$ is a M-input vector; $Y(.)$ is a L-output vector; $X_1(.)$ is a N-output vector of the hidden layer; $S(.)$ is a vector-valued activation function with appropriate dimension; J is a weight-state diagonal matrix with elements J_i; B and C are weight input and output matrices with appropriate dimensions. As it can be seen, the given RTNN model is a completely parallel parametric one, so it is useful for identification and control purposes. The controllability and observability of this model is proven in by S o n t a g and S u s s m a n n [11]; S o n t a g and A l b e r t i n e [10]. Parameters of that model are the weight matrices J, B, C and the state vector $X(k)$. The equation (4) is a stability preserving condition. The general *BP* learning algorithm is given as

(5) $$W_{ij}(k + 1) = W_{ij}(k) + \eta \Delta W_{ij}(k) + \alpha \Delta W_{ij}(k - 1)$$

where: W_{ij} (C_{ij}, J_{ij}, B_{ij}) is the *ij*-th weight element of each weight matrix (given in

parenthesis) of the RTNN model to be updated; ΔW_{ij} (ΔC_{ij}, ΔJ_{ij}, ΔB_{ij}) is the weight correction of each corresponding weight matrix; η, α are learning rate parameters. The updates of RTNN model weights are given by:

(6) $$\Delta C_{ij}(k) = [T_j(k) - Y_j(k)] \, S_j'(Y_j(k))Z_i(k),$$

(7) $$\Delta J_{ij}(k) = R_1 X_i(k - 1),$$

(8) $$R_1 = C_i(k) \, [T(k) - Y(k)] \, S_j'(X_{1j}(k)),$$

(9) $$\Delta B_{ij}(k) = R_1 U_i(k),$$

where T is a target vector with dimension L and $[T - Y]$ is an output error vector, also with the same dimension; R_1 is an auxiliary variable; $S'(.)$ is the derivative of the activation function, which for the hyperbolic tangent is, e.g. $S_j'(x) = 1 - x^2$.

3. An indirect adaptive trajectory tracking neural control with IPS-action

Let us suppose that the studied nonlinear plant possesses the following structure:

(10) $$X_p(k + 1) = F(X_p(k),U(k)),$$

(11) $$Y_p(k) = \varphi \, (X_p(k)),$$

where $X_p(k)$, $Y_p(k)$ are plant state and output vector variables; F and φ are smooth, odd, bounded nonlinear functions.

Two control schemes should be considered – with one and with two integrals in the control part.

The block diagram of the first control scheme, containing one integral block is shown on Fig.1. It contains one RTNN, which generates states and parameters, to the control block. The discrete integral term equation of the integral block is written as:

(12) $$V(k + 1) = V(k) + T_0 U(k),$$

where $V(k)$ is a M-vector integral action variable and T_0 is period of discretization. From Fig.1 it is seen that the plant input is the variable $V(k)$. Let us define the measurement vector of the extended system as

(13) $$Y^*(k) = Y_p(k) + V(k) + O(k),$$

where $O(k)$ is a L-vector offset. Linearizing the activation functions of the learned identification RTNN model (eqns. (1) to (3)), the following linear local plant model approximation, could be obtained:

(14) $$X(k + 1) = JX(k) + BU(k),$$

(15) $$Y(k) = CX(k).$$

Based on this local linear plant model (whose parameters are identified by RTNN learning), the extended system model equation, with discrete-time integral term, could be derived:

(16) $$X^e(k + 1) = J^e X^e(k) + B^e U(k),$$

(17) $$Y(k)= C^e X^e(k),$$

where $X^e(k)$ is a $(N + M)$-state vector; J^e, B^e, C^e are weight matrices with dimensions $(N + M)$ x $(N + M)$, $(N + M)$ x M, $Lx(N + M)$, respectively, given by:

(18) $$X^e(k)=\begin{bmatrix} X(k) \\ V(k) \end{bmatrix}, \quad J^e =\begin{bmatrix} J & B \\ 0 & I \end{bmatrix},$$
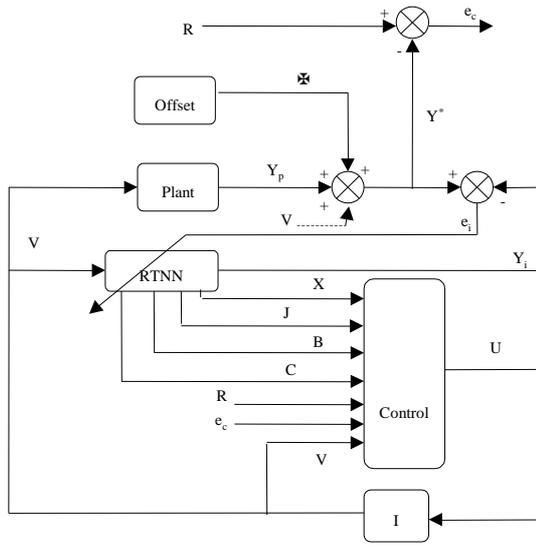
Fig. 1. Block-diagram of an indirect adaptive trajectory tracking control system with single IPS action (one integral block)

$$(19) \qquad B^e = \begin{bmatrix} 0 \\ T_0 \end{bmatrix}, \quad C^e = \begin{bmatrix} C & I \end{bmatrix}.$$

Applying on the extended system, the same design procedure, given by B a r u c h and F l o r e s [2], the following indirect adaptive control law, is obtained:

$$(20) \qquad U(k) = [CB + T_0]^{-1}[-CJX(k) - V(k) + R(k+1) + \sum_i \gamma_i E_i(k)],$$

$$(21) \qquad E(k) = R(k) - Y^*(k),$$

where $E(k)$ is a L-error vector; $R(k)$ – is a L-systems reference vector.

The block-diagram of second control system, containing two integral blocks, is shown on Fig.2. It contains one RTNN, which generates states and parameters to the control block and two successive integral blocks. The output of the second integral block is input of the plant. The discrete integral term equation of the second integral block is written as

$$(22) \qquad Z(k+1) = Z(k) + T_0 V(k),$$

where $Z(k)$ is a M-vector variable of the second integral action. Let us define the measurement vector of the extended system as:

$$(23) \qquad Y^*(k) = Y_p(k) + V(k) + Z(k) + O(k).$$

So, in a similar manner, we could write the equations of the extended system with two integral actions as:

$$(24) \qquad X^{ee}(k+1) = J^{ee}X^{ee}(k) + B^{ee}U(k),$$

$$(25) \qquad Y^{ee}(k) = C^{ee}X^{ee}(k),$$

where $X^{ee}(k)$ is a $(N+2M)$-state vector; J^{ee}, B^{ee}, C^{ee} are weight matrices with dimensions $(N+2M)$ x $(N+2M)$, $(N+2M)$ x M, L x $(N+2M)$, respectively, given by:

$$(26) \qquad X^{ee}(k) = \begin{bmatrix} X(k) \\ Z(k) \\ V(k) \end{bmatrix}, \quad J^{ee} = \begin{bmatrix} J & B & 0 \\ 0 & I & T_0 I \\ 0 & 0 & I \end{bmatrix},$$

4 0

Fig. 2. Block-diagram of an indirect adaptive trajectory tracking control system with double IPS action (two successive integral blocks)
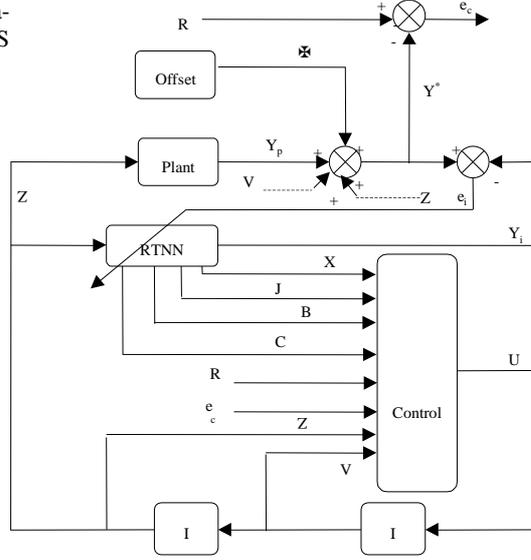
$$(27) \qquad B^{ee} = \begin{bmatrix} 0 \\ 0 \\ T_0 I \end{bmatrix}, \quad C^{ee} = \begin{bmatrix} C & I & I \end{bmatrix}.$$

The control law is given by the following equation:

$$(28) \qquad U(k) = T_0^{-1}[-CX(k) - (CB + I)Z(k) - (T_0 + I)V(k) + R(k + 1) + \sum_i \gamma_i E_i(k)].$$

The following part of the paper gives simulation results with a mechanical plant model with friction.

4. Simulation results

Let us consider a 1-DOF mechanical system with friction, whose general model (L e e and K i m [6]), is given by the equation

$$(29) \qquad m\ddot{q} + fr(\dot{q}, t) + v(t) = k_0 u(t),$$

where m is the mass, $q(t)$ is the relative displacement; $\omega(t) = dq(t)/dt$ is the velocity, $fr(\omega, t)$ is the friction force, $u(t)$ is the control force, k_0 is the system gain, and $v(t)$ is a bounded external load disturbance, with unknown upper bound d, as it is:

$$(30) \qquad |v| \le d \; ; \; t > 0 .$$

The equations, describing the behaviour of the friction force, (L e e and K i m [6]), are given as:

$$(31) \qquad fr(\omega, t) = F_{slip}(\omega)\lambda(\omega) + F_{stick}(u)[1 - \lambda(\omega)] ,$$

$$(32) \qquad \lambda(\omega) = \begin{cases} 1 & |\omega| > \alpha \\ 0 & |\omega| \le \alpha \end{cases} ,$$

4 1

$$(33) \qquad F_{stick}(u) = \begin{cases} F_s^+ & u \ge F_s^+ > 0 \\ u & F_s^- < u < F_s^- \\ F_s^- & u \le F_s^- < 0 \end{cases},$$

$$(34) \qquad F_{slip}(\omega) = F_d^+ \mu(\omega) + F_d^- \mu(-\omega),$$

$$(35) \qquad \mu(\omega) = \begin{cases} 1, & \omega > 0 \\ 0, & \omega \le 0 \end{cases},$$

$$(36) \qquad F_d^+(\omega) = F_s^+ - \Delta F^+ \left[1 - e^{-\left(\omega/\omega_{cr}^+\right)} \right] + \beta^+ \omega,$$

$$(37) \qquad F_d^-(\omega) = F_s^- - \Delta F^- \left[1 - e^{-\left(\omega/\omega_{cr}^-\right)} \right] + \beta^- \omega.$$

The friction model have the following friction parameters [6]: $\alpha = 0.001$ m/s; $F_s^+ = 4.2$ N ; $F_s^- = -4.0$ N; $\Delta F^+ = 1.8$ N; $\Delta F^- = -1.7$ N; $\omega_{cr} = 0.1$ m/s; $\beta = 0.5$ N.s/m. Let us also consider that the measurements are taken with period of discretization $T_0 = 0.1$ s, the system gain is $k_0 = 8$, the mass is $m = 1$ kg, and the load disturbance depends on the position and the velocity ($v(t) = d_1 q(t) + d_2 v(t)$; $d_1 = 0.25$; $d_2 = -0.7$). So the discrete-time model of the 1-DOF mass mechanical system with friction, is obtained in the form:

$$(38) \qquad X_1(k+1) = X_2(k),$$

$$(39) \qquad X_2(k+1) = -0.025X_1(k) - 0.3X_2(k) + 0.8U(k) - 0.1F_r(k),$$

$$(40) \qquad \Omega(k) = X_2(k) - X_1(k),$$

$$(41) \qquad Y(k) = 0.1X_1(k),$$

where: $X_1(k)$, $X_2(k)$ are system states; $\Omega(k)$ is system velocity and $Y(k)$ is system position; k is a discrete time variable and the friction force $F_r(k)$ is governed by the equations (31) to (37) with given values of friction parameters. A second order reference model, introduced in the control laws (20) and (28), has the form:

$$(42) \qquad R(k+2) = -0.9R(k+1) - 0.2R(k+1) + r(k),$$

$$(43) \qquad E(k+2) = -0.9E(k+1) - 0.2E(k),$$

where $E(k)$ is the systems error, defined by (21) and $r(k)$ is a reference model input signal, given by:

$$(44) \qquad r(k) = sat(3\sin(2\pi k)).$$

The graphical simulation results with length of 12 s, are given in the Appendix. The results, obtained using the first control scheme (Fig.1), are given on Fig. A1, A2 of the Appendix and that – by the second scheme (Fig.2) – are given on Fig. A4, A5, respectively. Results, obtained by control scheme without integral terms, are given on Fig. A3 and Fig. A6. The graphics, shown on Fig. A1, a – f, give simulation results, using the first scheme of control system with one integral block and constant offset signal with magnitude of 40%, corrupting the systems output signal. The first graphics (Fig. A1, a) compare the reference signal with the plant output. The second graphics compare the plant output with the output of the identification RTNN (Fig. A1, b). The

third graphics represents the control signal (Fig. A1, c). The fourth graphics represents the mean squared error of control (MSE%) which rapidly decreases to small value (Fig. A1, d). The fifth graphics represents the MSE% of identification, which rapidly decreases to small value (Fig. A1, e). The last graphics represents the three states of the system issued by the identification RTNN (architecture 1, 3, 1, $\eta = 0.01$, $\alpha = 0.001$) and used to compute the IPS control action (Fig. A1, f). Similar results, obtained with the second control scheme (Fig. 2) where the plant output is corrupted by 40% linear (triangular) load disturbance, are given on Fig. A4, a – f. For sake of comparison, on Fig. A2 a, b, c, are shown the graphical results, corresponding to that – given in Fig. A1, a, b, d, but for an offset of 100%. Also the same comparative results, obtained with the second control scheme (Fig. 2), where the plant output is corrupted by 100% linear (triangular) load disturbance, are shown on Fig. A5, a, b, c .Some significant differences are seen only in the first half-period of the systems identification, which show that both systems are practically insensitive of correspondent change of the magnitude of the load disturbance. Results, obtained with a control system without integral blocks and 10% of constant offset, are shown on Fig. A3, a, b, c and results obtained with the same system, but corrupted by 10% linear offset are shown on Fig. A5, a, b, c. As it could be seen, the system without integral action is sensitive to constant and linear load disturbances, especially in the first two periods of change of the reference signal. It is seen also that both schemes of indirect adaptive control with IPS action eliminate the effect of the friction on the output signal (see Fig. A1, a., Fig. A2, a. and Fig. A4, a, Fig. A5, a., respectively). This is due to the good performance of the identification RTNN, which identifies successfully the friction (Fig. A1, b and Fig. A2, b). Something more, both schemes of adaptive IPS control are able to overcome some imperfections in systems identification, as it could be seen from the graphics (see Fig. A1, a, b; Fig. A2, a, b and Fig. A4, a, b; Fig. A5, a, b, respectively). The on-line simulation results, for both control schemes, show an overshoot of the MSE% due to improper identification in the beginning (see Fig. A1, e; Fig. A4, e, respectively) but this MSE% rapidly decreased.

5. Conclusions

A comparative study of various control systems with *I*-action, is done. The paper propose to use two indirect adaptive feedback control schemes with Integral-Plus-State action, applied for 1-DOF mechanical system with friction. The control scheme contains one RTNN model, one or two integral blocks and a computation block of the IPS control law. The RTNN is plant parameters identificator and state estimator. The good tracking abilities of this adaptive IPS control, for both control schemes, is confirmed by comparative simulation results. The results show that the first control scheme could compensate constant offsets, the friction force and some identification errors. The second control scheme could do more, compensating linear offsets.
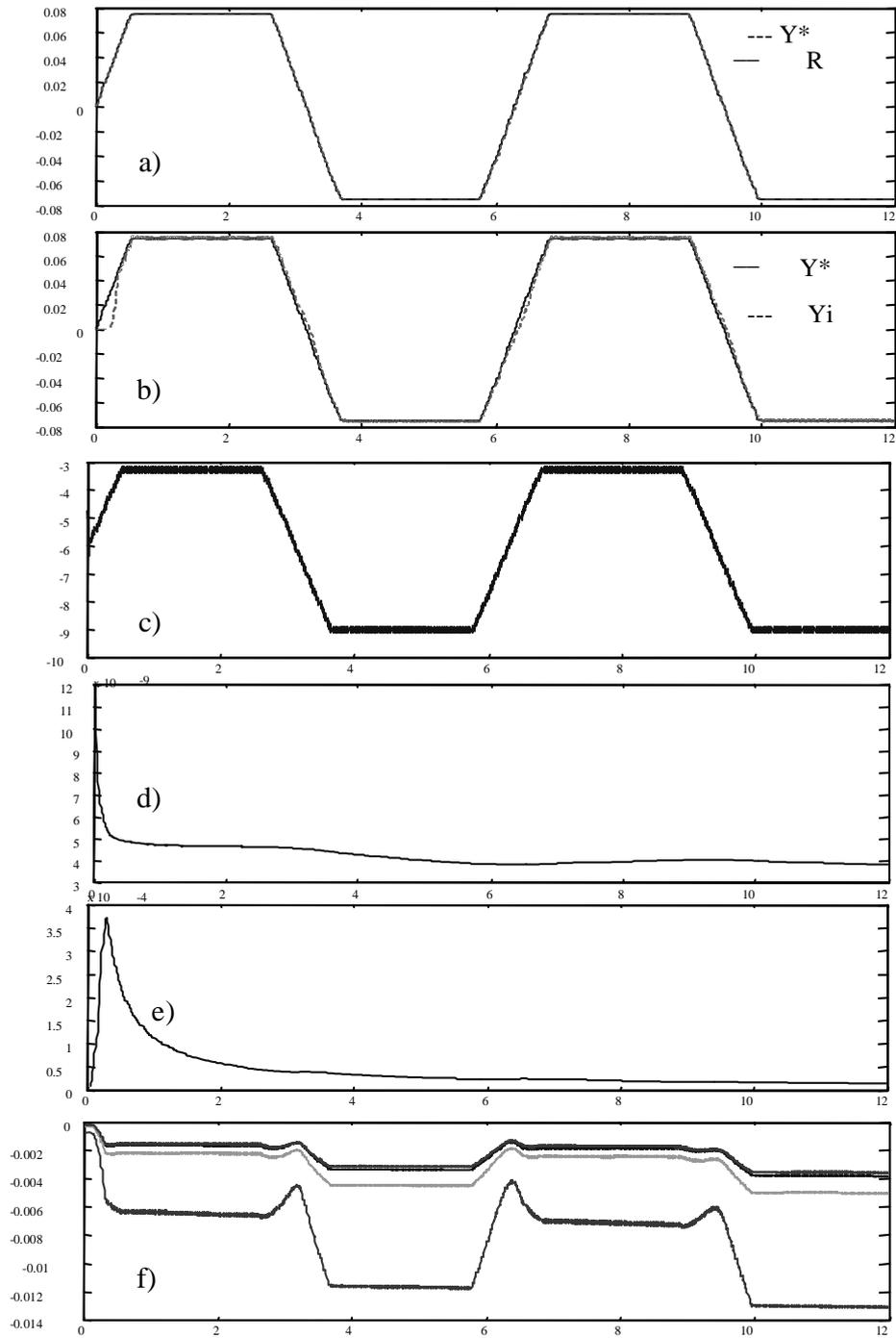
Appendix

Fig. A1. A single integral indirect adaptive trajectory tracking control with 40% constant offset:
a) comparison between the plant output and the reference signal; b) comparison between the output of
the plant and the output of the RTNN; c) control signal; d) mean squared error of control (MSE%);
e) mean squared error of identification (MSE%); f) systems state variable estimated by RTNN
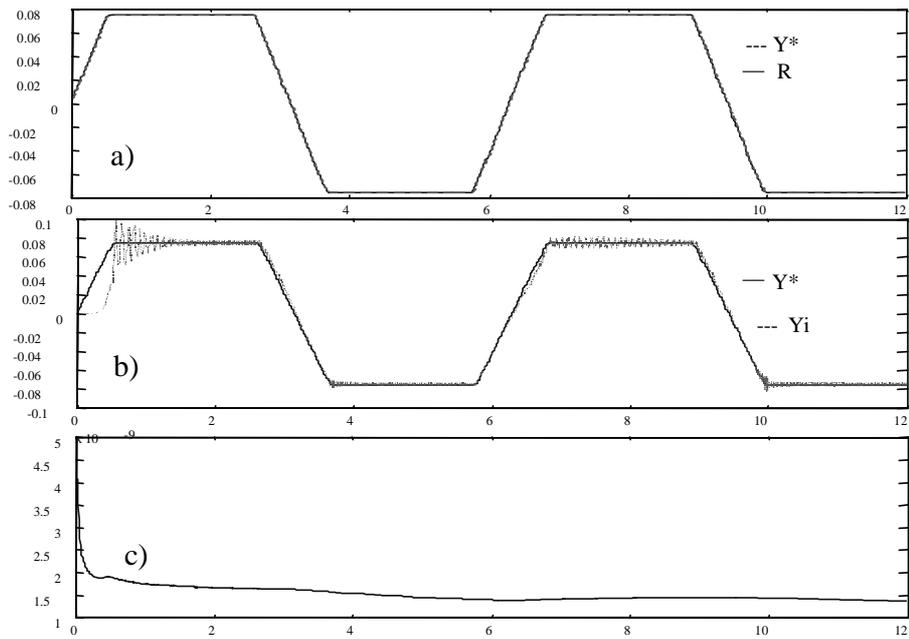
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Fig.A2. A single integral indirect adaptive trajectory tracking control with 100% constant offset: a) comparison between the plant output and the reference signal; b) comparison between the output of the plant and the output of the RTNN; c) mean squared error of control (MSE%)
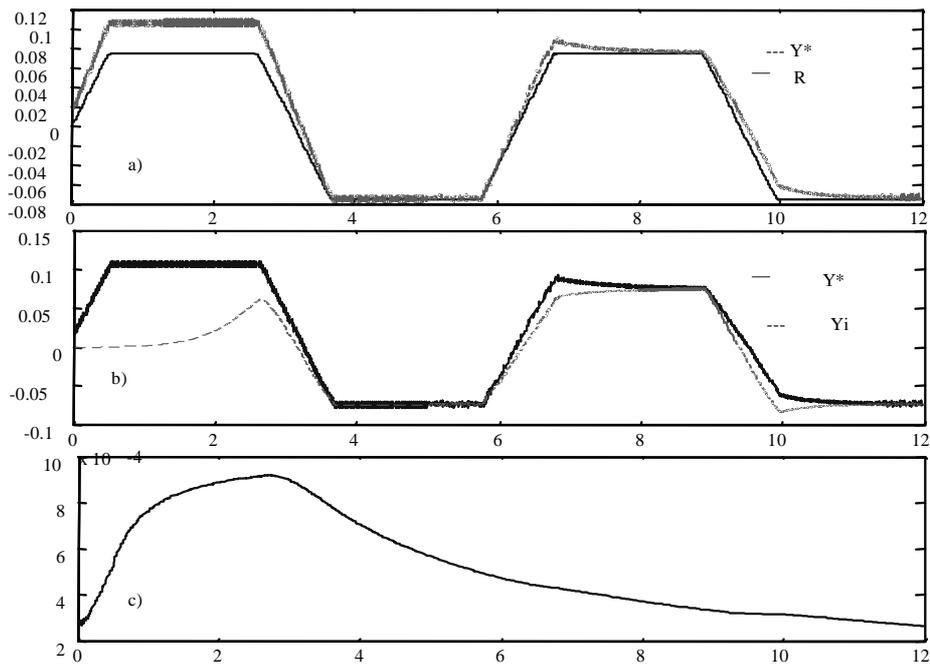

Fig. A3 . An indirect adaptive trajectory tracking control without integral and 10% constant offset: a) comparison between the plant output and the reference signal; b) comparison between the output of the plant and the output of the RTNN; c) mean squared error of control (MSE%)
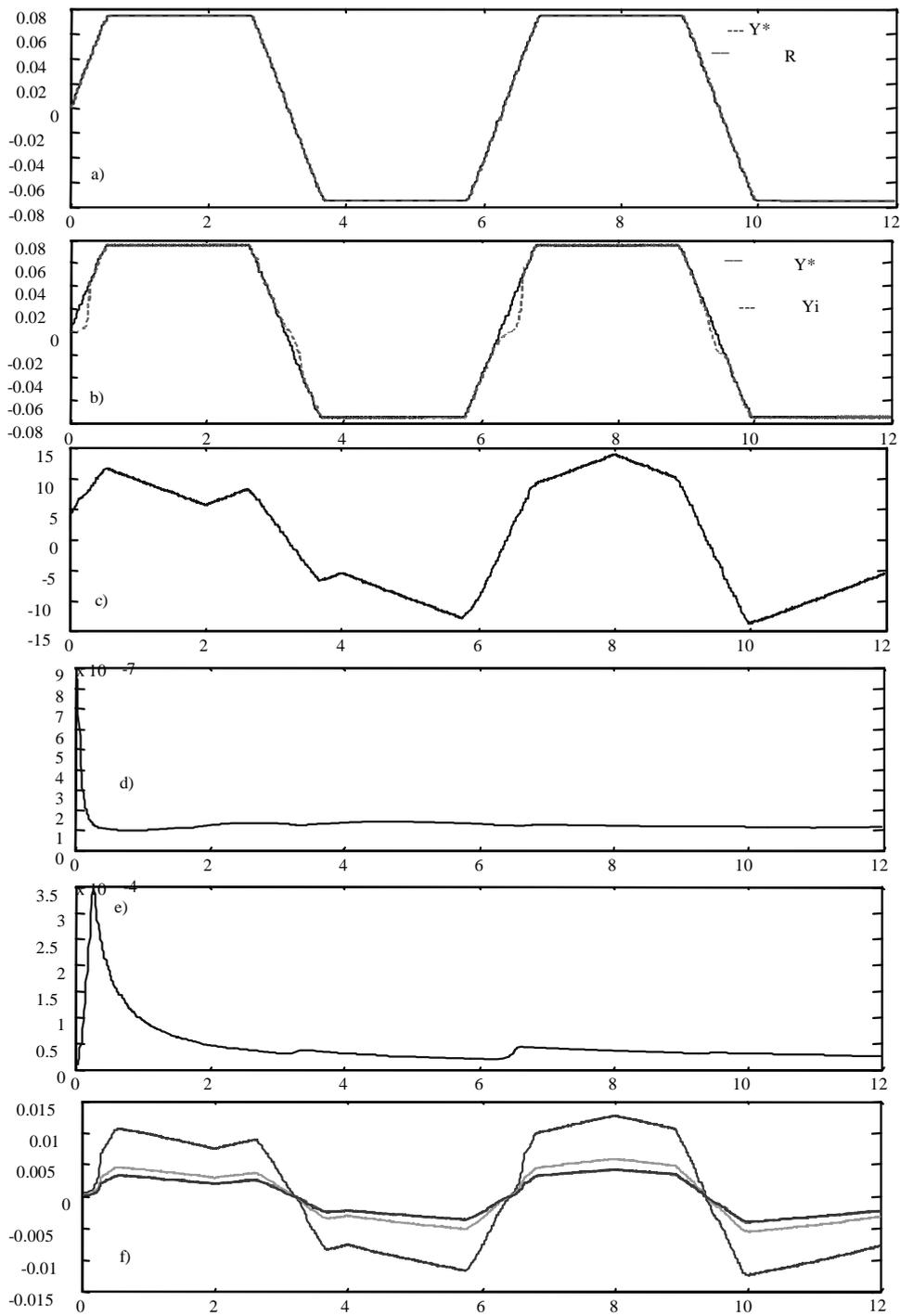
Fig. A4. A double integral indirect adaptive trajectory tracking control with 40% linear(triangular) offset: a) comparison between the plant output and the reference signal; b) comparison between the output of the plant and the output of the RTNN; c) control signal; d) mean squared error of control (MSE%); e) mean squared error of identification (MSE%); f) systems state variable estimated by RTNN
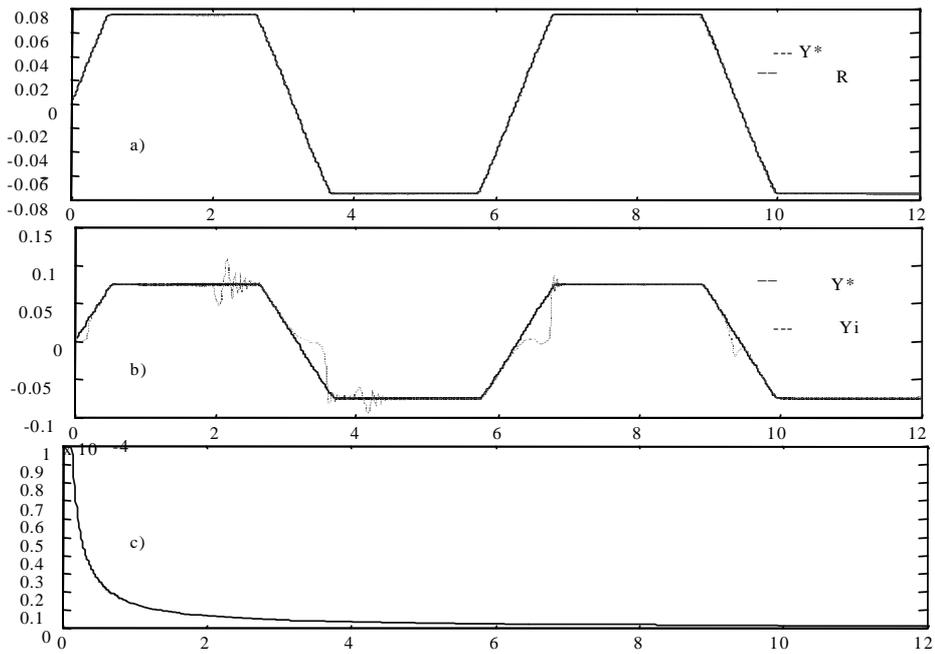
Fig. A5. A double integral indirect adaptive trajectory tracking control with 100% linear (triangular) offset: a) comparison between the plant output and the reference signal; b) comparison between the output of the plant and the output of the RTNN; c) mean squared error of control (MSE%)
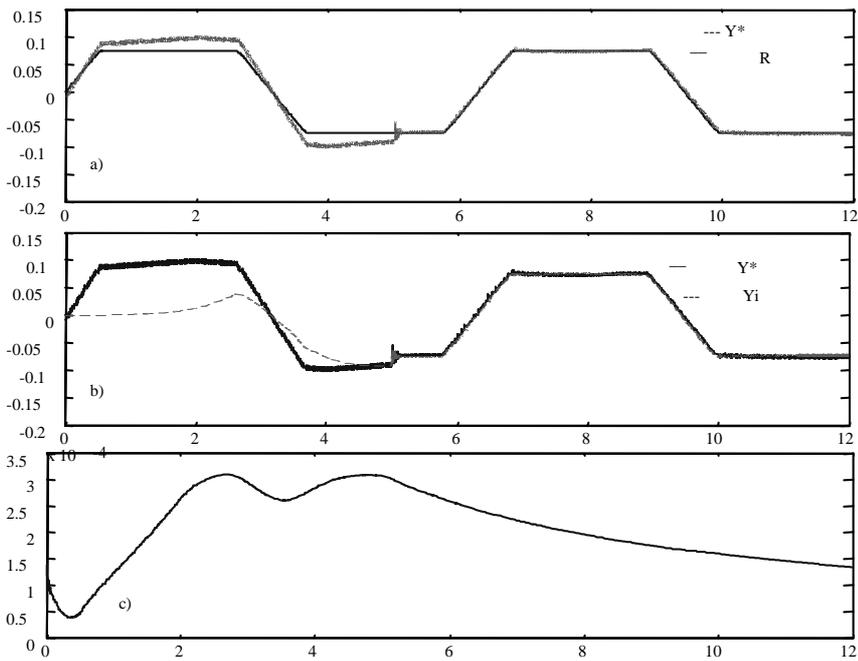

Fig. A6. An indirect adaptive trajectory tracking control without integral and 10% linear (triangular) offset: a) comparison between the plant output and the reference signal; b) comparison between the output of the plant and the output of the RTNN; c) mean squared error of control (MSE%)

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Адаптивно невронно управление от типа „интеграл – състояние" (IPS)

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(Р е з ю м е)

Предлага се индиректно адаптивно невронно управление чрез въздействие от вида интеграл – състояние (IPS). Схемата на управление съдържа рекурентна невронна мрежа за идентификация и определяне на състоянието. Идентифицираните параметри на обекта и полученият вектор на състоянието се използват при изчисляване на адаптивното управление IPS. Предложени са две управляващи схеми, съдържащи един или два интеграла в закона за управление. Добрите възможности на следене на това адаптивно IPS управление се потвърждават от симулационните резултати, получени върху механичен обект с фрикционен модел.