NEURAL NETWORKS FOR PARAMETER IDENTIFICATION OF SERVO-DRIVES OF THE FLYING DEVICE

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Abstract: One of advanced trends of the current airborne control systems modernization is the development of the servos control systems (regulators) on the basis of achievements in the field of artificial intelligence and new information technology.

Keywords: Intelligent control, Linear system, Nonlinear system, Identification, Kalman filters, Neural networks.

1. MATHEMATICAL DESCRIPTION OF THE CONTROL OBJECT

A smart servo control system provides the adaptation mode under conditions of uncertainty regarding the fluctuation and parametric disturbances and loads (Figure 1). The same motor as a control object has not only different parameters, but also a different structure at different laws of external disturbance change. Hence, to ensure the given control quality in the whole scope of parameters and laws of the external moments change in a regulator it is required to change not only adjustment, but also the regulator control law (structure).

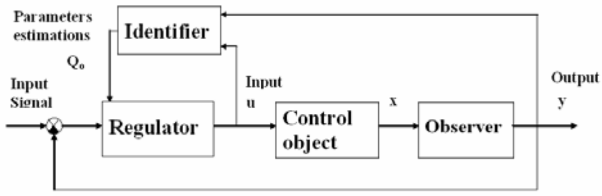


Fig.1. The control system

Generally the control object can be described by the following system of the nonlinear differential equations:

$$\dot{\mathbf{x}} = \mathbf{f}[\mathbf{x}, \mathbf{u}, t] + \mathbf{G}[\mathbf{x}, t]\mathbf{w}\,; \qquad (1)$$
$$\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{u}, t) + \nu\,,$$

where $\mathbf{u}$ is a vector of control actions; $\mathbf{y}$ is a vector of observable signals; $\mathbf{x}$ is an extended state vector including parameters of dynamic objects; $\mathbf{w}$ is a vector of shaping noise of intensity $\psi_\mathbf{w}$; ν is a vector of measurement noise of intensity ψ_ν; $\mathbf{G}[\mathbf{x}, t]$ is a matrix of coefficients.

Generally the linear control object with one input and one output can be presented in the form of the following equation:

$$y[n] + a_1\, y[n-1] + \ldots + a_{n_a}\, y[n-n_a] = b_0 u[n] + \ldots + b_{n_b} u[n-n_b] + c_0\, e[n] + \ldots + c_{n_c} e[n-n_c], \qquad (2)$$

where $y[n]$ is an output signal; $u[n]$ is an input signal; $e[n]$ is a model error; $a_1 \ldots a_{n_a}$, $b_0 \ldots b_{n_b}$, $c_0 \ldots c_{n_c}$ are parameters of model; n is number of the digital process step.

2. IDENTIFICATION METHODS

The smart servo control system comprises: a multi-purpose control device – a classifier of the control object state and a control shaper. The classifier of the control object state and the control shaper can be realized on the basis of both traditional technologies and modern approaches: expert or neuronet systems equipment.

2.1. Invariant immersion method

The continuous algorithm of invariant immersion for a simultaneous estimation of state and parameters of dynamic objects (1) has the following form (Sage and Melsa, 1974):

$$\dot{\mathbf{x}}_o = \mathbf{f}[\mathbf{x}_o, \mathbf{u}, t] + \mathbf{P}\frac{\partial \mathbf{h}^T(\mathbf{x}_o, \mathbf{u}, t)}{\partial \mathbf{x}_o}\boldsymbol{\psi}_v^{-1}\{\mathbf{y} - \mathbf{h}(\mathbf{x}_o, \mathbf{u}, t)\};$$

$$\begin{aligned}\dot{\mathbf{P}} &= \mathbf{G}[\mathbf{x}_o, t]\psi_w \mathbf{G}^T[\mathbf{x}_o, t] + \mathbf{P}\frac{\partial \mathbf{f}^T[\mathbf{x}_o, \mathbf{u}, t]}{\partial \mathbf{x}_o} + \\ &+ \mathbf{P}\frac{\partial \mathbf{f}[\mathbf{x}_o, \mathbf{u}, t]}{\partial \mathbf{x}_o} + \\ &+ \mathbf{P}\frac{\partial}{\partial \mathbf{x}_o}\left[\frac{\partial \mathbf{h}^T(\mathbf{x}_o, \mathbf{u}, t)}{\partial \mathbf{x}_o}\psi_v^{-1}\{\mathbf{y} - \mathbf{h}(\mathbf{x}_o, \mathbf{u}, t)\}\right]\mathbf{P},\end{aligned} \tag{3}$$

where $\mathbf{x}_o$ is an estimation of the extended state vector; $\mathbf{P}$ is a correlation matrix of the filtering errors.

The algorithm of invariant immersion for a simultaneous estimation of state (y) and parameters ($K, \omega = 1/T$) of the dynamic object in the form of aperiodic link is defined by the following vectors and matrixes (Ponyatsky, 2007):

$$x_o = |y_o \quad K_o \quad \omega_o|^T; \mathbf{h}(\mathbf{x}, \mathbf{u}, t) = \mathbf{H}\,\mathbf{x};$$

$$\mathbf{H} = |1 \quad 0 \quad 0|; \qquad \mathbf{y} = y; \qquad \mathbf{v} = v_1; \qquad \boldsymbol{\psi}_\mathbf{v} = \psi_v;$$

$$\mathbf{w} = |w_1 \quad w_2 \quad w_3|^T;$$

$$\mathbf{G}[\mathbf{x}_o, t] = \begin{vmatrix} K_{ro}\omega_{ro} & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{vmatrix}; \ \boldsymbol{\psi}_\mathbf{w} = \begin{vmatrix} \psi_{w1} & 0 & 0 \\ 0 & \psi_{w2} & 0 \\ 0 & 0 & \psi_{w3} \end{vmatrix};$$

$$\mathbf{f} = \begin{vmatrix} -y_o\omega_{ro} + K_{ro}\omega_{ro}u \\ 0 \\ 0 \end{vmatrix};$$

$$\frac{\partial \mathbf{f}}{\partial \mathbf{x}_o} = \begin{vmatrix} -\omega_{ro} & \omega_{ro}u & -y_o + K_{ro}u \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{vmatrix}.$$

The identification equations will have the following form (Figure 2):

$$\dot{y}_o = -y_o\omega_{ro} + K_{ro}\omega_{ro}u + P_{11}(y - y_o)/\psi_V;$$

$$\dot{K}_o = P_{12}(y - y_o)/\psi_V; \tag{4}$$

$$\dot{\omega}_o = P_{13}(y - y_o)/\psi_V,$$

where $K_{ro} = K_o + K_{pr}; \omega_{ro} = \omega_o + \omega_{pr};$ K_{pr}, ω_{pr} – program values of parameters.

The equation for variance of error:

$$\begin{aligned}\dot{p}_{11} &= -p_{11}^2\psi_v^{-1} + 2(-P_{11}\omega_{ro} + P_{12}\omega_{ro}u + \\ &\quad + P_{13}(-y_o + K_{ro}u)) + K_{ro}^2\omega_{ro}^2\psi_{w1}; \\ \dot{p}_{12} &= -p_{11}p_{12}\psi_v^{-1} - p_{12}\omega_{ro} + p_{22}\omega_{ro}u + \\ &\quad + p_{23}(-y_o + K_{ro}u); \\ \dot{p}_{13} &= -p_{11}p_{13}\psi_v^{-1} - p_{13}\omega_{ro} + \\ &\quad + p_{23}\omega_{ro}u + p_{33}(-y_o + K_{ro}u); \\ \dot{p}_{22} &= -p_{12}^2\psi_v^{-1} + \psi_{w2}; \\ \dot{p}_{23} &= -p_{12}P_{13}\psi_v^{-1}; \\ \dot{p}_{33} &= -p_{13}^2\psi_v^{-1} + \psi_{w3}.\end{aligned} \tag{5}$$

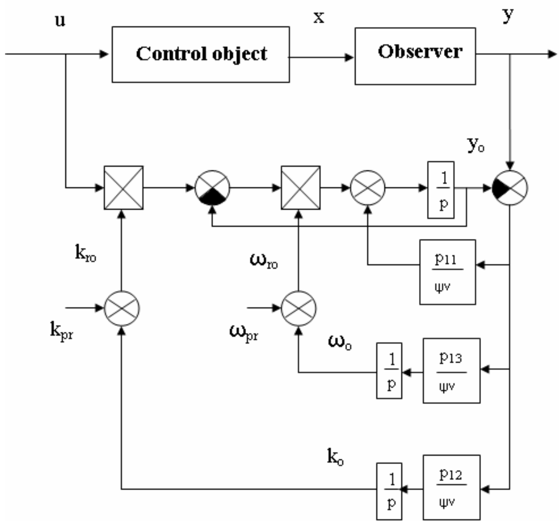


Fig.2. The algorithm of invariant immersion for the control object identification as aperiodic link

The offered algorithm of identification based on a method of invariant immersion, allows to directly receive state estimations and values of time-dependent parameters of nonlinear dynamic object.

2.2. Kalman filtration

Well-known methods of parametric identification, such as the least-squares method, filtering Kalman, mean the representation of required structure of dynamic object in the form of the difference equation. Then the input model (a linear regression) is used as initial data for development of the identification algorithm (Ponyatsky, 2004a):

$$\mathbf{Q}[n+1] = \mathbf{F}[n+1/n]\mathbf{Q}[n] + \mathbf{\upsilon}[n];$$

$$\mathbf{Y}[n] = \varphi^T[n]\mathbf{Q}[n] + \omega[n],$$

where

$\mathbf{Q}[n] = |\mathbf{A}_1 \vdots \ldots \vdots \mathbf{A}_{n_a} \vdots \mathbf{B}_0 \vdots \ldots \vdots \mathbf{B}_{n_b} \vdots \mathbf{C}_0 \vdots \ldots \vdots \mathbf{C}_{n_c}|^T$ is a parameter matrix (dimension $n_M \times p$, $n_M = n_a \times p + (n_b + 1) \times q + (n_c + 1) \times \ell$);

$\mathbf{A}_1 \ldots \mathbf{A}_{n_a}$ is a matrix (dimension $p \times p$);

$\mathbf{B}_0 \ldots \mathbf{B}_{n_b}$ is a matrix (dimension $p \times q$);

$\mathbf{C}_0 \ldots \mathbf{C}_{n_c}$ is a matrix (dimension $p \times \ell$); $\mathbf{Y}[n]$ is a signal of the dynamic object output (dimension $p \times 1$); $\mathbf{U}[n]$ is an input signal (dimension $q \times 1$);

$\varphi[n] = |-\mathbf{Y}[n-1], \ldots, -\mathbf{Y}[n-n_a], \mathbf{U}[n], \ldots, \mathbf{U}[n-n_b], \mathbf{E}[n], \ldots, \mathbf{E}[n-n_c]|^T$

is a data vector of input and output signals (dimension $n_M \times p$); $\mathbf{F}[n+1/n]$ is a state transition matrix (dimension $n_M \times n_M$); $\upsilon[n]$ is a shaping noise of intensity $\mathbf{R}1[n] = E\upsilon[n]\upsilon^T[n]$ (dimension $n_M \times p$); $\mathbf{R}1[n]$ is a matrix (dimension $n_M \times n_M$); $\omega[n]$ are measurement noises of intensity $\mathbf{R}2[n] = E\omega[n]\omega^T[n]$ (dimension $p \times 1$); $\mathbf{R}2[n]$ is a matrix (dimension $p \times p$).

The Kalman filtration algorithm required for estimation of the dynamic process parameters has the following form (Ljung, 1991; Ponyatsky, 2004a; Fatuev *et al.*, 2004b):

$$\begin{cases} \mathbf{Q}_o[n+1/n] = \mathbf{F}[n+1/n]\mathbf{Q}_o[n]; \\ \mathbf{Q}_o[n] = \mathbf{Q}_o[n/n-1] + \mathbf{L}[n]\{\mathbf{Y}[n] - \mathbf{Y}_o[n]\}; \\ \mathbf{Y}_o[n] = \varphi_o^T[n]\mathbf{Q}_o[n/n-1], \end{cases} \quad (6)$$

where $\mathbf{Q}_o[n/n-1]$ is forecasting of the parameters matrix estimation;

$\mathbf{Q}_o[n] = |\mathbf{A}_{o1} \vdots \ldots \vdots \mathbf{A}_{on_a} \vdots \mathbf{B}_{o0} \vdots \ldots \vdots \mathbf{B}_{on_b} \vdots \mathbf{C}_{o0} \vdots \ldots \vdots \mathbf{C}_{on_c}|^T$ is a matrix of the parameters estimations; $\mathbf{Y}_o[n]$ is estimation of the signal of the dynamic object output;

$\varphi_o[n] = |-\mathbf{Y}_o[n-1], \ldots, -\mathbf{Y}_o[n-n_a], \mathbf{U}[n], \ldots, \mathbf{U}[n-n_b], \mathbf{E}[n], \ldots, \mathbf{E}[n-n_c]|^T$

is a vector of data with estimations of the output signal; $\mathbf{L}[n]$ is a matrix of the filter coefficients (dimension $n_M \times 1$):

$$\begin{cases} \mathbf{P}[n+1/n] = \mathbf{F}[n/n-1]\mathbf{PP}[n]\mathbf{F}^T[n/n-1] + \mathbf{R}1; \\ \mathbf{L}[n] = \mathbf{P}[n/n-1]\varphi_o[n]\{\varphi_o^T[n]\mathbf{P}[n/n-1]\varphi_o[n] + \mathbf{R}2\}^{-1}; \\ \mathbf{PP}[n] = \mathbf{P}[n/n-1] - \mathbf{L}[n]\varphi_o^T[n]\mathbf{P}[n/n-1], \end{cases} \quad (7)$$

where $\mathbf{P}[n+1/n]$ of errors of forecasting of the parameters matrix estimation (dimension $n_M \times n_M$); $\mathbf{PP}[n]$ is a variance matrix of errors of the parameters matrix estimation (dimension $n_M \times n_M$).

$\mathbf{R}1[n]$ is calculated using the following dependence:

$$\mathbf{R}1[n+1] = \mathbf{R}1[n] + (\upsilon[n]\upsilon^T[n]) - \mathbf{R}1[n])\,\tau[n],$$

where $\tau[n]$ is factor for forgetting the previous values.

Identification of time-dependent parameters of dynamic objects is realized within time intervals $T_I = s\,T_d$, where T_d – a step of time sampling, s = 1,2…N. In the beginning of each interval the calculation of initial values $\mathbf{Q}_{iv}[n] = |\mathbf{A}_{iv1} \vdots \ldots \vdots \mathbf{A}_{ivn_a} \vdots \mathbf{B}_{iv0} \vdots \ldots \vdots \mathbf{B}_{ivn_b}|^T$ and $\mathbf{R}1_{iv}[n]$ is carried out by using the method of least squares (Ponyatsky, 2003a):

$$\mathbf{R}1_{iv} = \sigma^2\,(\Phi^T\,\Phi)^{-1},$$

$$\mathbf{Q}_{iv} = \mathbf{R}1_{iv}\,\Phi^T\,\mathbf{Y}_m,$$

where $$\Phi^T = \begin{vmatrix} -\mathbf{Y}[n-1], & \ldots, & -\mathbf{Y}[n+m-1], \\ \ldots, & \ldots, & \ldots, \\ -\mathbf{Y}[n-n_a], & \ldots, & -\mathbf{Y}[n+m-n_a], \\ \mathbf{U}[n], & \ldots, & \mathbf{U}[n+m], \\ \ldots, & \ldots, & \ldots, \\ \mathbf{U}[n-n_b] & & \mathbf{U}[n+m-n_b] \end{vmatrix}$$

is a matrix of observations; $\mathbf{Y}_m = |\mathbf{Y}[n], \ldots, \mathbf{Y}[n+m]|^T$ is a vector of output signals.

Time window T_I shifts by magnitude ΔT_I, which does not exceed the size of this window. The current parameters estimations are obtained in the end of each time interval over the range $T_I - \Delta T_I \ldots T_I$ according to (6)-(7).

The algorithms of the Kalman filtration used for servo parameters identification have been developed on the basis of the object model presentation in the form of aperiodic link (Ponyatsky, 2003a; Ponyatsky, 2004a).

Let us assume that the dynamic object is described by the following linear difference equation (2):

$$y[n] + a1\,y[n-1] = b1\,u[n-1] + e[n], \quad (8)$$

where $a1 = -(1 - T_d/T[n])$, $b1 = K[n]T_d/T[n]$.

Then the algorithm of the dynamic object identification as aperiodic link has the following form (Figure 3):

$$\begin{cases} \mathbf{Q}_o[n+1/n] = \mathbf{Q}_o[n]; \\ \mathbf{Q}_o[n] = \mathbf{Q}_o[n/n-1] + \mathbf{L}[n]\{y[n] - y_o[n]\}; \\ y_o[n] = \varphi_o^T[n]\mathbf{Q}_o[n/n-1]; \end{cases}$$

$$\mathbf{L}[n] = \mathbf{P}[n-1]\varphi_o[n]\{\mathbf{R}2[n] + \varphi_o^T[n]\mathbf{P}[n-1]\varphi_o[n]\}^{-1};$$

$$\mathbf{P}[n] = \mathbf{P}[n-1] - \mathbf{P}[n-1]\,\varphi_o[n]\{\mathbf{R}2[n] + \varphi_o^T[n]\mathbf{P}[n-1]\,\varphi_o[n]\}^{-1}\varphi_o^T[n]\mathbf{P}[n-1] + \mathbf{R}1[n],$$

where $\mathbf{Q}_o[n] = |a1_o, b1_o|^T$,

$\varphi_o[n] = |-y_o[n-1],\ u[n-1]|^T$.

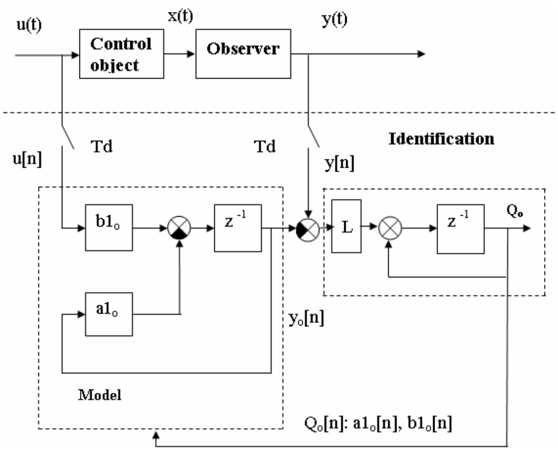


Fig.3. Kalman filtration for the control object identification as aperiodic link

The sought quantities for the aperiodic link $K_o[n]$ and $T_o[n]$ are defined according to the matrix of discrete parameters $Q_o[n]$ using dependencies:

$T_o[n] = T_d/(1 + a1_o[n])$,
$K_o[n] = b1_o[n]/(1 + a1_o[n])$.

2.3. Neuronet for parameter identification

A change to neuronet technologies required to essentially revise traditional principles and approaches to formalization of problems concerning the study of dynamic properties of the unmanned air vehicle servo control systems.
To design a neuronet identifier, which should recurrently estimate parameters of the control object it is possible to define the following system of required initial data: structure and order of the control object model; a range of input and output signal change; ranges of magnitudes and rates of change of the control object parameters.
In this case it is advisable to organize the procedure of the control object parameters identification using the neuronet with adjusted weighting factors, which (procedure) realizes its model. The process of the neuronet weighting factor adaptation or, this is identical, the identification of the control object parameters can be performed by means of a method of dynamic error back propagation.
For implementation of the neural identifier it is offered to use the multi-fiber neuronet of direct propagation in which the information follows directly from fiber to fiber and it can not be sent from the subsequent fibers on previous ones.
The general structure of neuronet, to within quantity of fibers, is defined as follows:
1. The quantity of the neuronet inputs is equal to quantity of used values of input and output signals plus an additional input with unit value, specifying the shift of functions of all neurons.
2. The first fiber realizes the function of the numerator and a denominator module and consists of neurons with the activation function of type semilinear with saturation.
3. The first fiber realizes the function of numerator and denominator ratio and the number of neurons in it depends on required accuracy of reproduction of threshold of activation function. The threshold of activation function is convenient for a hardware representation and also allows to analytically define weighting factors of a neuronet, based on required accuracy.
4. The third fiber consists of neurons, which are carrying out summation of neurons outputs of the second fiber.
5. Quantity of outputs – quantity of parameters to be identified.
Let's consider the principles of the neuron identifier design on an instance using a servodrive as an example in the form of aperiodic link (8). The presented equation allows to present the time constant and the transfer ratio in the form of the functions depending on input and output signals as follows:

$$T = \frac{T_d K u[n-1] - T_d y[n-1]}{y[n] - y[n-1]} \qquad (9)$$

$$K = \frac{T y[n] + (2T_d - T) y[n-2]}{2 T_d u[n-1]} \qquad (10)$$

Let's carry out the fiber organization of the neuronet identifier structure, which (identifier) is offered for identification of time constant and the motor transfer ratio, to within definition of the neurons quantity in each fiber and the values of weighting factors. The quantity of the neuronet inputs is equal five: ($x_1 = u[n-1]$, $x_2 = y[n]$, $x_3 = y[n-1]$, $x_4 = y[n-2]$, $x_5 = 1$).
The first fiber consists of eight neurons with the activation function of type semilinear with saturation. The first and third pairs of neurons realize a function of the module from numerator of equation (9) and (10) respectively, the next second and last pairs - from their denominators.
Values of weighting factors w_{lji} from inputs to the first fiber of neurons are defined according to expressions:

$$W_{111} = KT_d/M_1,\ W_{131} = -T_d/M_1,\ W_{151} = -1,$$
$$W_{112} = KT_d/M_1,\ W_{132} = -T_d/M_1,$$
$$W_{123} = 1/M_2,\ W_{133} = -1/M_2,\ W_{153} = -1,$$
$$W_{124} = 1/M_2,\ W_{134} = -1/M_2,\ W_{125} = T/M_3,$$
$$W_{145} = (2T_d - T)/M_3,\ W_{155} = -1,\ W_{126} = T/M_3,$$
$$W_{146} = (2T_d - T)/M_3,\ W_{117} = 2T_d/M_4,$$
$$W_{157} = -1,\ W_{118} = 2T_d/M_4,$$

where l - number of a fiber, j - number of input or neurons of the previous fiber, i - number of neurons of current fiber.

$M_1 \ldots M_4$ - are selected equal to the maximum possible values of numerators and denominators (9) and (10) respectively. Division of weighting factors by $M_1 \ldots M_4$ is required to transfer input values of neurons in a range from 0 to 1, corresponding to the neuron function

The number of neurons of the second fiber depends, as it was already marked, from required accuracy of reproduction of relationships (9) and (10). Under required accuracy of identification is meant in this work admissible error magnitude ΔT and ΔK, at which satisfactory quality of transients is kept. The performance criterion includes the following characteristics of transient: rise time, magnitude of overshoot, time of the transient termination etc. For definition of weighting factors from neurons of the first fiber to neurons of the second fiber and the values of thresholds for neurons of the third fiber, it is offered the following algorithm:

a) definition of a deviation ΔT and ΔK;

b) definition of quantity of neurons of the second fiber:

$$N1 = (T^{max} - T^{min})/\Delta T; \quad N2 = (K^{max} - K^{min})/\Delta K;$$

c) weighting factors:

$$w_{21i} = M_1/T,\ w_{22i} = -M_1/T,\ w_{23i} = -M_2,$$
$$w_{24i} = M_2,\ w_{29i} = M_2 - M_1/T, \quad i = 1,\ldots, N1$$

are calculated for all possible values T from minimum to maximum one with step ΔT;

$$w_{25i} = M_3/K,\ w_{26i} = -M_3/K,\ w_{27i} = -M_4,$$
$$w_{28i} = M_4,\ w_{210i} = M_4 - M_3/K,$$
$$i = N1+1,\ldots, N1+N2$$

are calculated for all possible values K from minimum to maximum one with step ΔK;

d) weighting numbers from neurons of the second fiber to neurons of the third fiber are set by following expressions:

$$w_{3j1} = -\Delta T,\ j = 1,\ldots, N1; \quad w_{3(N1+N2+1)1} = T^{max}$$
$$w_{3j2} = -\Delta K,\ j = N1+1,\ldots, N1+N2;$$
$$w_{3(N1+N2+2)2} = K^{max}.$$

Quantity of neurons of the third fiber is equal two; quantity of outputs - two (estimation T and K).

The estimation of time constant and transfer ratio can be carried out as follows. At output from the first neuron of the third fiber when changing K from minimum to maximum with step ΔK the function $T = f1(K_j), K_j = K^{min} + j\Delta K, j = 1,\ldots, N2$ is defined, and at output from the second neuron of the third fiber when changing T from minimum to maximum with step ΔT the function $K = f2(T_i), T_i = T^{min} + i\Delta T, i = 1,\ldots, N1$ is defined. The sought quantities T and K are obtained from joint solution of equations $T = f1(K_j), K_j = K^{min} + j\Delta K, j = 1,\ldots, N2$ and $K = f2(T_i), T_i = T^{min} + i\Delta T, i = 1,\ldots, N1$.

Enhancement of noise immunity of the neural networks can be provided owing to increase of outputs of the pertinent parameters.

The synthesis of a regulator can be based on the method of solution of inverse problem of dynamics. The aspect of the transfer function of the regulator providing the definition of regulating quality, is defined by desirable transfer function of the closed loop of the control system $W_d(p)$. The transfer function of the regulator when changing parameters of the control object is as follows:

$$W_r(p) = \frac{W_d(p)}{1 - W_d(p)} \frac{P(p) + \Delta P(p)}{Q(p) + \Delta Q(p)},$$

where $W_r(p)$ is the transfer function of regulator; $\frac{Q(p)}{P(p)}$ is the transfer function of the control object; $\Delta Q(p)$, $\Delta P(p)$ is increments of polynomials of numerator and denominator, caused by change of its parameters.

In case of the control object, described by two aperiodic links with electromechanical T_{em} and electric T_e time constants and the desirable transfer function of the closed system corresponding to the aperiodic link T_d, the given algorithm leads to the PID regulator in the form:

$$W_r(p) = \frac{k_1 + k_o p + k_2 p^2}{p},$$

where $k_o = \frac{T}{T_d K}$; $k_1 = \frac{1}{T_d K}$; $k_2 = \frac{T\,T_e}{T_d K}$; $T \approx T_{em}$.

The relation between estimations T and K and the regulator factors is linear. In presented case the implementation of obtained dependencies can be carried out directly on the neuronet used for identification T and K, adding in it additional neurons, according to quantity of defined parameters of the regulator and multiplying the weights by the constant factors considering linear relation of the regulator parameters and the control object.

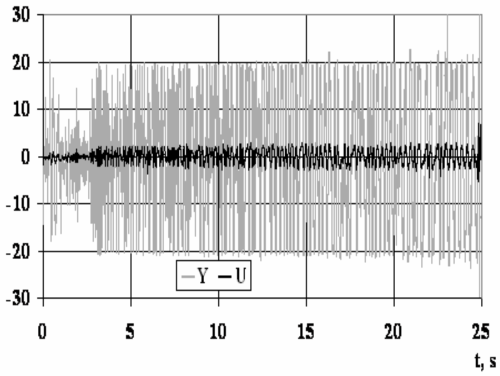
3. RESULTS

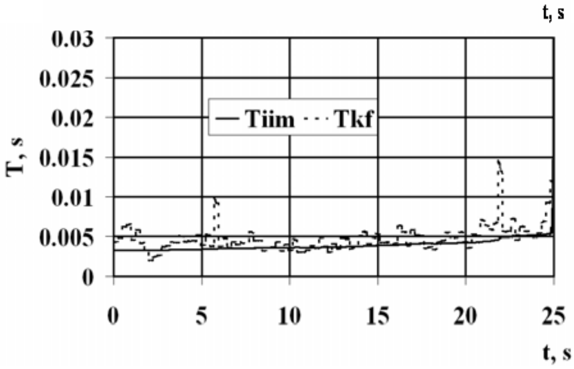
The considered methods can be also used at identification of models of dynamic objects using results of processing bench and full-scale experiment. For operative estimation of the characteristics of servo as a part of the aircraft control system the identification is performed in the form of linear time-dependent models of the low order. The procedure of determination of dynamic process output characteristics dependence on the effecting factors includes the following stages. (Fatuev *et al.*, 2004b). **Stage 1** – structural identification. The order of the model is determined by the loss function or moment matrix. **Stage 2** - parametric identification. The parametric identification is aimed to obtain the estimated unknown coefficients (parameters) of the model. The parametric identification uses the least-squares method and its modification, i.e. Kalman filtration method. At this stage Fourier transform method and correlation method can be used. **Stage 3** – estimation of the defined model. The adequacy and accuracy of the defined model is estimated by the residual value (discrepancy between actual and model output). The best model is to be selected. **Stage 4** – model transformation. It is possible to transform the model into the required type both by means of universal transformation and by direct transformation into typical transfer functions.

The identification of parameters of full nonlinear model is required to analyze the servo design operation. In this case the identification can be carried out stage by stage: first the processing of the bench test results with tentative assessment of the object parameters which don't depend on external effects is carried out. The final estimation of parameters of full model is performed after flight tests.

A program system has been worked out in the form of the program for OS Windows in medium of programming Visual C++, realizing the classical algorithm of the dynamic objects identification in the form of time-dependent linear models (Ponyatsky and Oberman, 2003b).

The results of estimation of time constant and the servo transfer ratio on a signal from the servo input and on a signal from the controls angular position sensor are given in Figure 4. As follows from given data, the estimation obtained by means of the invariant immersion method (T_{iim}, K_{iim}) gives a smoother law of the parameter change with lower fluctuations in comparison with the Kalman filtration (T_{kf}, K_{kf}).





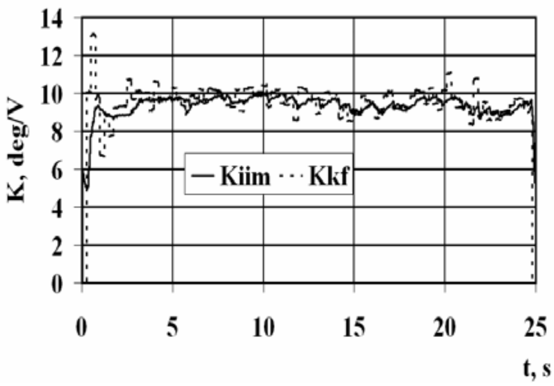


Fig.4. Results of estimation of time constant and servo transfer ratio by means of the invariant immersion method (T_{iim}, K_{iim}) and the Kalman filtration (T_{kf}, K_{kf})

Thus the servo regulator based on use of methods of the control object parameter identification on neronet systems expands opportunities, in particular the time-dependent object control.

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