Control System of the Aerial Vehicle with Kalman Filter using the Neural Network for Adjustment of its Parameters

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Abstract: Control system of the aerial vehicle with the Kalman filter using the neural network for adjustment of its parameters. The article considers a proposed control system with the Kalman filter that adapts itself to environmental noise conditions. The Kalman filter may be used in the control system under condition of remained control quality that is a problem to be solved. To solve this matter, it is required not only to adapt characteristics of the filter in compliance with actual environmental conditions, but make appropriate corrections within the law of control as well. The algorithm of adaptation is realized with use of the neural network, which instructs the control system by measured coordinates of the aerial vehicle. Under low level of noise as a component of an error of control the Kalman filter pass band is extended resulting in a more accurate processing of input effects. Under a high level of noise as a component of control error the Kalman filter pass band is narrowed to effectively suppress jamming and reduce errors in measurements. Simulation of operation of the control system with the Kalman filter considered in this article has demonstrated the effectiveness of the proposed technical concepts

Keywords: dynamic object, observer, Kalman filter, neural network

1. INTRODUCTION

In control systems of aircrafts raise of noise immunity to affecting noise of measurement is provided by means of Kalman filter (fig. 1).

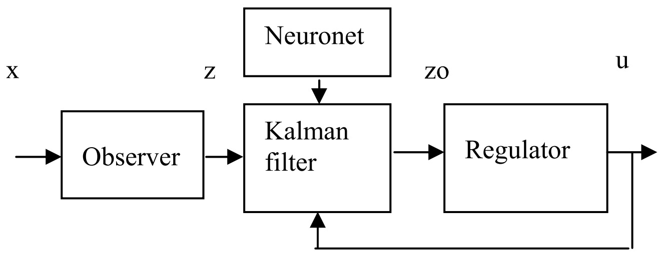

Fig. 1. The scheme of control system

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

$$\dot{x}(t) = F(t)x(t) + B(t)u(t) + G[t]w\,; \qquad (1)$$
$$z(t) = H(t)x(t) + v\,,$$

where $u(t)$ is a vector of control actions; $z(t)$ is a vector of observable signals; $x(t)$ is an extended state vector including parameters of dynamic objects; w is a vector of shaping noise of intensity $N_0(t)$; v is a vector of measurement noise of intensity $N(t)$; $F(t)$, $B(t)$ $G(x)$ is a matrixes of coefficients.

2. KALMAN FILTRATION

The continuous algorithm for a estimation of state of dynamic objects (1) has the following form (Sage and Melsa, 1976; Ponyatsky 2005):

$$\dot{x}_o(t) = F(t)x_o(t) + B(t)u(t) + S(t)P(t)H(t)N^{-1}(t)[z(t)\text{-}H(t)x_o(t)]; \quad (2)$$
$$\dot{P} = G(t)N_0(t)G^T(t) + PF^T(t) + PF^T(t) - PH^T(t)H(t)P,$$

where $x_o(t)$ is an estimation of the state vector ; $P(t)$ is a correlation matrix of the filtering errors; $S(t)$ - an attribute of type of the meter or absence of measurements $S(t) = 0$.

The discrete algorithm of Kalman filtering has the following form (Sage and Melsa, 1976; Ponyatsky 2005):

$$\begin{cases} X_o[n+1/n] = \Phi[n]X_o[n] + B[n]U[n]; \\ X_o[n] = X_o[n/n-1] + S[n]\,K[n]\,\{Z[n] - H[n]X_o[n/n-1]\}; \\ Z_o[n] = H[n]\,X_o[n/n-1]; \end{cases}$$

$$\begin{cases} P[n+1/n] = \Phi[n]P[n]\Phi^T[n] + N_o[n]; \\ K[n] = P[n/n-1]H^T\{H[n]P[n/n-1]H^T[n] + N[n]\}^{-1}; \\ P[n] = P[n/n-1] - K[n]H[n]P[n/n-1], \end{cases} \quad (3)$$

where $Z[n]$ – a vector of observations; $Z_o[n]$ – a vector of estimations of observations; $X_o[n]$ - an estimation of state vector of installation of control; $X_o[n+1/1]$ - an estimation of a vector of forecasting of a condition of installation of control; $\Phi[n]$ - a transition matrix; $H[n]$ - a matrix of observation; $K[n]$ - a matrix of coefficients; $P[n+1/1]$ – a dispersive matrix of state vector of installation; $P[n]$ - a dispersive matrix of an estimation of state vector of installation; $U[n]$ - a vector of control; $B[n]$ - a matrix of coefficients of control; $S[n]$ - an attribute of type of the meter or absence of measurements $S[n] = 0$.

For maintenance of stability of a control system with Kalman filter the return coupling on control instructions $U(t)$, proceeding from accomplishment of a condition is inducted:

$$W_g = W_f \ W_s \ ,$$

where W_g is a desirable transfer function of the closed system with Kalman filter; W_f is a transfer function of Kalman filter; and W_s is a transfer function of system without Kalman filter.

Formation of demanded dynamic characteristics of a control system (a pass band, stocks of stability, accuracy, etc.) can be lead by a method of frequency characteristics and is is possible at different relationships of a pass band of system without the filter f_s and a filter transmission band f_f. If demanded quality of control is provided with sampling of a pass band of system without the filter W_s smaller, than a filter transmission band W_f:

$$f_s < f_f \ ,$$

that dynamic properties of a control system are largely defined by algorithm of formation of control instructions, and the algorithm of a filtering provides necessary suppression in an error signal of control of handicapes of measurement.

Demanded properties of system at the task of a strip of system without the filter W_s of greater, than a filter transmission band W_f:

$$f_s > f_f$$

are provided due to raise of a transfer ratio of system (good quality) and decrease of a filter transmission band. In this case it is possible to provide a filter transmission band, commensurable with a working strip of system. If to provide substantial increase of good quality at reduction of frequency of a gating through of the filter the system will possess tall dynamic to properties, but thus шумовой a component the level increases in control instructions.

Designing Kalman filter (2) is traditional or (3) is carried out proceeding from the aprioristic information about intensity a legitimate signal and noise of measurement.

Real characteristics of a legitimate signal and handicapes of measurement can mismatch the aprioristic information in the filter. The opportunity of use of adaptive Kalman filter demands the solution of a problem of maintenance of conservation of accomplishment of demands to quality of control. For the solution of this problem it is necessary to change according to real circumstances not only characteristics of the filter, but also to make corresponding correction in the law of control.

3. NEURONET

A change to the neuronet technologies required to essentially revise traditional principles and approaches to formalization of problems concerning the study of dynamic properties of the control systems(Ponyatsky and Nadezhdin, 2007).

In works (Stepanov and Amosov, 2004a; Stepanov and Amosov, 2004b) calculation of a transfer ratio of Kalman filter with use of a neural network is considered:

$$K_N(y[n], \vartheta),$$

where the vector $y[n]$ includes a vector $x_o[n/n-1]$ and a vector of discrepancies $z[n]-H[n]x_o[n]$; ϑ - a matrix including a matrix of a displacement vector ϑ_o and a matrix of weight numbers ϑv: $x_o[y[n],\vartheta] = \vartheta_o + \vartheta y[n]$.

Thus it is offered to carry out all over again instruction of a neural network on test sample, i.e. to define a matrix ϑ from a condition of minimization of criterion of instruction:

$$J = (x[n]-x_o[y[n],\vartheta])^T (x[n]-x_o[y[n],\vartheta]) \ ,$$

and already then to use the received results for processing measured data. However such approach does not provide an opportunity of adaptation of factor of Kalman filter to real measurements. Therefore it is offered to carry out instruction of a neural network on leaking measurements.

4. RESULTS

Let's consider designing Kalman filter for a control system of the aircraft. The synthesis of algorithm of a filtering is lead proceeding from a hypothesis of the task of traffic of installation in the form of the equation

$$\dddot{y}(t) = a(t) \ ,$$

where $a(t)$ is a casual white noise by intensity $N_o(t)$. During traffic of installation mistakes of control in conditions of affecting of noise of measurement are defined by intensity $N(t)$.

The equations of the filter (2) in this case will enter the form (Ponyatsky 2005):

$$\begin{cases} \dot{x1}_o(t) = x2_o + s(t)k1(t)\{z(t) - x1_o(t)\}; \\ \dot{x2}_o(t) = x3_o + s^2(t)k2(t)\{z(t) - x1_o(t)\} - K_p(t)u(t); \\ \dot{x3}_o(t) = s^3(t)k3(t)\{z(t) - x1_o(t)\}, \end{cases}$$

where $z(t)$ is a mistake of control, $u(t)$ is control instructions from an exit of a regulator; $K_p(t)$ is a transfer ratio; $s(t)$ is an attribute of type of the meter, at absence of measurements: $s(t) = 0$; $k1(t)$ $k2(t)$, $k3(t)$ - factors of the filter.

From (2) follows, that for calculation of factors of the filter it is required to solve Rickati matrix equation for $P(t)$, i.e. system of the nonlinear differential equations. For simplification of scalings we shall count factors for the established case, at

$$\frac{dp_{11}}{dt} = \frac{dp_{12}}{dt} = \frac{dp_{13}}{dt} = \frac{dp_{22}}{dt} = \frac{dp_{23}}{dt} = \frac{dp_{33}}{dt} = 0 \ ,$$

whence $p_{11}=\sqrt[6]{N^5 N_0}$, $p_{12}=\sqrt[3]{N^2 N_0}$, $p_{13}=\sqrt{N\ N_0}$. Factors of the filter look like: $k_1=2\Omega$, $k_2=\frac{1}{2}k_1^2$, $k_3=0.125k_1^3$, $\Omega=\sqrt[6]{N_o/N}$.

Except for burnishing measured coordinates of installation of control the estimation of variables of a condition of traffic of installation of control is carried out also. Transfer functions of Kalman filter on variables of a condition look like:

$$W_{\Phi 1}=\frac{x_{1o}}{z}=\frac{s\ k_1p^2+s^2k_2p+s^3k_3}{p^3+s\,k_1p^2+s^2k_2p+s^3k_3};$$

$$W_{\Phi 2}=\frac{x_{2o}}{z}=\frac{p(s^2k_2p+s^3k_3)}{p^3+s\ k_1p^2+s^2k_2p+s^3k_3};$$

$$W_{\Phi 3}=\frac{x_{3o}}{z}=\frac{s^3k_3p^2}{p^3+s\ k_1p^2+s^2k_2p+s^3k_3}.$$

Product of factors $sk_1(t)$ defines Kalman filter transmission band and its equivalent time constant can be certain: $T_{\Phi K}(t)\approx 1/(sk_1(t))$. That is, the more the attitude of intensity No of a legitimate signal to intensity N of noise of measurement, the more widely Kalman filter transmission band. And on the contrary, the the attitude of intensity No of a legitimate signal to intensity N of noise of measurement, the already Kalman filter transmission band is less more effective suppression of handicapes of measurement also is provided. Change of a strip of the filter can be carried out by sampling of the attitude интенсивностей a legitimate signal to noise of measurement, and also the task of magnitude s. Factors $s^2k_2(t)$ and $s^2k_3(t)$ in Kalman filter define magnitude of phase delay in a pass band of a legitimate signal.

The discrete algorithm of a filtering (3) for digital implementation is presented as (Ponyatsky, 2005):

$$x_{10}1[n/n-1]=x_{10}[n\text{-}1]+x_{20}[n\text{-}1]T\ +x_{30}[n\text{-}1]T^2/2;$$
$$x_{20}[n/n-1]=x_{20}[n\text{-}1]+x_{30}[n\text{-}1]TK_p(n)u(n);$$
$$x_{30}[n/n-1]=x_{30}[n\text{-}1];$$
$$x_{10}n]=x_{10}[n/n-1]+s\,k_1[n](z[n]\text{-}x_{10}[n/n-1]);$$
$$x_{20}[n]=x_{20}[n/n-1]+\ s^2\ k_2[n](z[n]\text{-}x_{10}[n/n-1]);$$
$$x_{30}[n]=x_{30}[n/n-1]+\ s^3\ k_3[n](z[n]\text{-}x_{10}[n/n-1]),$$

where $z[n]$ – the measured coordinates of installation of control; $x_1[n]\ x_2[n]$, $x_3[n]$– estimations of variables of a condition of installation of control; $s[n]$ - an attribute of type of the meter, at absence of measurements: $s[n]=0$; T is the period of a digitization of a signal; $k_1[n]\ k_2[n]$, $k_3[n]$ - discrete factors of the filter. The estimation N_o also N is carried out with use of a neural network on leaking measurements $z[n]$ and the received estimations $x_o[n]$ and defined by the expressions:

$$N_o[n+1]=\ N_o[n]\tau[n]+$$
$$+\{(x_o[n]-\Phi[n]x_o[n-1])^T(x_o[n]-\Phi[n]x_o[n-1])\text{-}N_o[n]\tau[n]\}/(n+1);$$
$$N[n+1]=N[n]\tau[n]+$$
$$+\{(z[n]-H[n]x_o[n])^T(z[n]-H[n]x_o[n])\text{-}N[n]\tau[n]\}/(n+1).$$

The neural network provides at absence noise with a component in a mistake of control expansion of Kalman filter transmission band and accordingly more exact working off of operating signals. At presence noise the component in a mistake of control carries out decrease of a strip of the filter that provides effective suppression of handicapes of measurement.

Designing of a regulator is carried out by traditional methods of frequency characteristics.

The lead modeling work of the considered adaptive control system with Kalman filter has shown efficiency of the offered designs.

5. CONCLUSIONS

Thus, control system of the aerial vehicle with the Kalman filter using the neural network for adjustment of its parameters. The article considers a proposed control system with the Kalman filter that adapts itself to environmental noise conditions.

The Kalman filter may be used in the control system under condition of remained control quality that is a problem to be solved. To solve this matter, it is required not only to adapt characteristics of the filter in compliance with actual environmental conditions, but make appropriate corrections within the law of control as well.

The algorithm of adaptation is realized with use of the neural network, which instructs the control system by measured coordinates of the aerial vehicle. Under low level of noise as a component of an error of control the Kalman filter pass band is extended resulting in a more accurate processing of input effects. Under a high level of noise as a component of control error the Kalman filter pass band is narrowed to effectively suppress jamming and reduce errors in measurements. Simulation of operation of the control system with the Kalman filter considered in this article has demonstrated the effectiveness of the proposed technical concepts.

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