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PARAMETRIC SYNTHESIS OF FILTERING ALGORITHMS FOR INERTIAL NAVIGATION SYSTEMS OF UNMANNED AIRCRAFT

In inertial navigation systems of unmanned aerial vehicles, filtering algorithms, in particular the Kalman filter and its various modifications, are used to increase the accuracy of navigation measurements. The practical implementation of such filtering algorithms is complicated by their computational complexity and abstract form of representation, which does not reflect all the features of the implementation. That is why the task of synthesizing filtering algorithms that will meet the requirements of guaranteed convergence of the filtering process and minimal computational complexity of their implementation is relevant. The latter requirement is extremely important for navigation systems of small unmanned aerial vehicles, since their on-board equipment must be cheap and low-energy. In this regard, the article presents a parametric synthesis of an optimal algorithm for polynomial filtering of the measurement results of accelerometric orientation sensors in inertial navigation systems of unmanned aerial vehicles. Parametric synthesis refers to the determination of optimal internal parameters, which are the smoothing coefficients of the filter. The synthesis of parameters is performed under the condition of a given filter structure. The filter was synthesized using a method based on the invariance theory and described by the authors in previous works. The optimal smoothing coefficients were determined by conditional optimization of the objective function, which was chosen as the minimum of the mean square error of the estimation. The filter stability conditions, which are determined by an algebraic criterion, are chosen as constraints. Due to the scalar form of implementation, the synthesized optimal filtering algorithm has a low computational complexity. The effectiveness of the algorithm was confirmed by computer simulation based on the results of real measurements of the ADXL345 accelerometer, which is part of the Arduino UNO R3.

***Keywords**: smoothing filter; evaluation; measurement; unmanned aerial vehicle; accelerometer; navigation system; filtering algorithm.*

Problem statement in general. The expansion of the scope of application and widespread use of unmanned aerial vehicles (UAVs) necessitates their continuous technical improvement. One of the key requirements for UAVs is to ensure high-precision, reliable navigation and orientation [1].

The task of determining the angular orientation of the UAV and its coordinates is solved by a flight navigation system, which includes inertial and satellite navigation systems (INS and SNS) [2, 3]. INS is the basis of modern navigation systems. This is due to their complete autonomy and ability to provide complete information about navigation parameters: course, pitch, roll, acceleration, as well as speed and coordinates of the UAV. Thanks to their ability to determine the angular position of an object with high accuracy in any angle range and with a high frequency of information output, INS have no alternative, especially in the absence of their own satellite network [4].

In small-mass UAVs, platform-free INS (PfINS) based on accelerometers and gyroscopes manufactured using microelectromechanical systems (MEMS) technology have become widely used. Their main advantages are small size and weight, high noise immunity, reliability, and autonomy. The principle of operation of PfINS is based on calculating the linear and angular position of the UAV by integrating the linear and angular accelerations converted into the necessary coordinate system, which are measured by accelerometers and gyroscopes installed on board. The functions of the gyro-stabilized platform are performed by an onboard computer [5].

The set of measuring devices must be sufficient to obtain information about the vectors of apparent acceleration and absolute angular velocity. It may consist of the following: angular velocity measuring devices and accelerometers, only accelerometers, accelerometers and uncontrolled gyroscopes [5]. However, accelerometer measurements contain additive noise caused by design features and operating conditions, which are characterized by stochastic factors related to the operating environment: unwanted mechanical vibrations, electromagnetic interference from other electromechanical or mechanical elements, etc. Various filtering algorithms are used to combat noise, which are implemented in the form of computational procedures of the flight navigation complex. [5, 6].

Analysis of the latest research and publications. The classic method of eliminating noise and errors in accelerometer sensors is to use a Kalman filter [5, 7], which allows obtaining an estimate that is optimal in terms of the minimum mean square error of estimation, provided that there is prior information about the mathematical model of the measured data and the statistical characteristics of measurement errors [8, 9]. The possibility of using such algorithms in navigation systems is due to the fact that there are tasks that can be reduced to linear ones without noticeable losses in accuracy.

At the same time, for a number of tasks, the use of linear algorithms is unacceptable due to the nonlinear nature of the equations describing the dynamics of the state vector and measurements. That is why there are several modifications of the classical Kalman filter that allow it to be applied to nonlinear systems, namely: the Extended Kalman filter (EKF) [10, 11], the Unscented Kalman filter (UKF) [12, 13], and the Particle Kalman Filter (PKF) [14], the difference between which lies in the methods of linearization of nonlinear models.

The filtering algorithms considered belong to the Kalman type algorithms, they are quite universal in practical application, but are characterized by high complexity. Each subsequent modification of the filter requires significantly greater computing power. That is why their use in systems implemented on microcontrollers must be justified. In addition, engineers often face the problem of their practical implementation due to the abstract form of description, which does not reflect all the details of the process [15].

A relatively new approach to solving the problem of filtering orientation parameters in INS is the Majvik filter [16, 17], which calculates a single orientation estimate based on accelerometer and gyroscope measurements. Its accuracy is comparable to that of the Kalman filter, but unlike the latter, it requires fewer computational resources for its implementation, and the task of minimizing estimation errors in this filter is solved using a gradient descent algorithm, with the search for the minimum being implemented in only one iteration. To describe the orientation of an object in space, the Majvik filter uses quaternions, which are not intuitive for direct user understanding. In addition, the algorithm was designed for the conditions of a specific task, so it is not universal.

The simplest filter option capable of solving the problem of filtering measurements in INS is a complementary filter [17]. Its operation is based on mixing accelerometer and gyroscope measurements in a specific proportion. Despite the simplicity of this algorithm, the accuracy of the filter output values is lower than that of the algorithms discussed above. In addition, the smoothing coefficient of the complementary filter can only be adjusted experimentally.

When developing effective algorithms, it is necessary to take into account the specific conditions in which applied filtering problems are solved. In particular, polynomial filtering methods [18] are actively being developed, which take into account the fact that nonlinearities in dynamic and measurement equations are polynomial in nature, and that the measurement of navigation parameters is a one-dimensional data stream.

Quite often, evaluation tasks are simplified by limiting the class of algorithms, which involves selecting them, for example, in the class of linear algorithms [19]. For such assumptions, [15] presents a method that allows synthesizing effective smoothing filters in the case of scalar models of input actions and makes it possible to form algorithms of a given structure based on ensuring the required estimation accuracy in steady state. However, the method is presented only at the level of structural synthesis. The procedure for determining the optimal values of smoothing coefficients is not considered.

Despite the fact that a fairly large number of various filtering algorithms have been proposed at present, the task of their development remains relevant.

Formulation of the research task. The purpose of this article is to perform parametric synthesis of an optimal algorithm for polynomial filtering of measurement results from accelerometer orientation sensors in UAV INS. By parametric synthesis, we mean the determination of optimal internal parameters [20, 21], which are the filter smoothing coefficients. The filtering algorithm must meet the requirements of guaranteed convergence of the filtering process and minimal computational complexity in terms of its implementation. The latter requirement is extremely relevant in navigation systems for small UAVs, since their onboard equipment must be inexpensive, low-power, and have minimal weight and volume [3].

Core material

Given: equations of state and observations

$$x(n) = x(n-1) + \sum_{m=1}^{N} \frac{T^m}{m!} \Delta^m x(n-1),$$
$$g(n) = x(n) + f(n), \tag{1}$$

where x – true value of an information parameter;

$\Delta^m x$ – final difference of the *m*-th order;

N – model order;

T – speed of information processing;

$n = 0, 1, 2, \ldots$ – normalized with respect to the sampling interval discrete time;

f – measurement error.

Find: for a filtering algorithm with a known structure, it is necessary to synthesize an algorithm for calculating the optimal values of smoothing coefficients. Quality criterion:

$$P(n) = M\left[\varepsilon^2(n)\right] \to \min, \tag{2}$$

here

$$\varepsilon(n) = x(n) - \hat{x}(n) \tag{3}$$

– assessment error.

Limitations: measurement errors are uncorrelated white Gaussian noise:

$$M[x(n)f(n)] = 0, \quad M[f(n)f(n-i)] = 0, \quad i > 0,$$

$$R(n) = M\left[f^2(n)\right],$$

where M – symbol of mathematical expectation;

R – dispersion of measurement errors, the value of which is considered known.

Parametric synthesis of the filtering algorithm. For the conditions of the task set in [15], a method for synthesizing filtering algorithms is presented, the essence of which lies in the application of the following equations:

$$\begin{gathered} x_e(n) = \left[1 - A(z)\right]\hat{x}(n); \\ \tilde{u}(n) = g(n) - x_e(n); \\ \hat{x}(n) = \frac{B(z)}{A(z)}\tilde{u}(n), \end{gathered} \tag{4}$$

where $x_e(n)$ – extrapolated value of an information parameter;

$\tilde{u}(n)$ – inconsistency;

$A(z) = \left(1 - z^{-1}\right)^{\nu}\left[1 + \sum_{i=1}^{k} a_i z^{-i}\right]$ – the numerator of the filter transfer function by error, which determines the order of astaticity and is calculated based on the third form of invariance conditions

$$A(z)x(n) = 0; \tag{5}$$

$B(z) = \sum_{j=0}^{l} b_i z^{-j}$ – the numerator of the filter transfer function, which contains smoothing coefficients whose values characterize the quality of filtration.

For polinoms

$$A(z) = \left(1 - z^{-1}\right)^2 \left(1 + a_1 z^{-1}\right),$$
$$B\left(b_0\right) = b_0 \tag{6}$$

according to expressions (4), a smoothing filter [15] is synthesized, which is described by difference equations:

$$x_e(n) = (2 - a_1)\hat{x}(n-1) - (1 - 2a_1)\hat{x}(n-2) - a_1\hat{x}(n-3),$$
$$\tilde{u}(n) = g(n) - x_e(n), \tag{7}$$
$$\hat{x}(n) = b_0\tilde{u}(n) + \hat{x}_e(n),$$

where b_0 – aliasing coefficient;

a_1 – filter astigmatism order increasing coefficient.

Optimal values of coefficients b_0 and a_1 are determined by conditional optimization of the objective function using the following expressions:

$$\frac{\partial P}{\partial b_0} = 0, \quad \frac{\partial P}{\partial a_1} = 0, \tag{8}$$

in which $P(n)$ need to be determined.

The restrictions on the values are the stability conditions of the smoothing filter.:

$$0 < b_0 \leq 1, \quad -1 < a_1 < 0, \quad b_0 > -a_1 - 0{,}3.$$

To obtain the expression of the objective function $P(n)$ in equation (3) for evaluation errors, it is presented in the following form:

$$\varepsilon(n) = \varepsilon_e(n) - b_0\left[\varepsilon_e(n) + f(n)\right], \tag{9}$$

where

$$\varepsilon_e(n) = x(n) - x_e(n) \tag{10}$$

– extrapolation error.

Substituting equation (9) into (2) and taking into account conditions (1), we obtain

$$P(n) = P_e(n) - 2b_0\, P_e(n) + b_0^2\left[P_e(n) + R(n)\right], \tag{11}$$

where

$$P_e(n) = M\left[\varepsilon_e^2(n)\right] \tag{12}$$

– dispersion of extrapolation errors.

From the derivative calculation (8), we determine the expression for the optimal value of the smoothing coefficient:

$$b_0(n) = \frac{P_e(n)}{P_e(n) + R(n)}. \tag{13}$$

By substituting equation (13) into expression (11), we find the relationship between the variances of estimation and extrapolation errors:

$$P(n) = (1 - b_0) P_e(n). \tag{14}$$

To determine the dispersion of extrapolation errors included in equations (13) and (14), we obtain from (3) an expression for estimation in the following form:

$$\hat{x}(n) = x(n) - \varepsilon(n). \tag{15}$$

Substituting (15) into the equation for calculating the extrapolated value (4), taking into account condition (5), we derive (10) for the extrapolation error:

$$\varepsilon_e(n) = [1 - A(z)]\varepsilon(n). \tag{16}$$

Then expression (12) for the variance of extrapolation errors takes the following form:

$$P_e(n) = [1 - A(z)]^2 P(n). \tag{17}$$

To synchronize the filtration and extrapolation processes, the estimation error is presented as follows:

$$\varepsilon(n) = z\varepsilon(n-1),$$

where

$$P(n) = z^2 P(n-1), \tag{18}$$

where z – time advance operator.

Taking into account (18), the general expression (17) for calculating the variance of extrapolation errors takes the final form:

$$P_e(n) = [1 - A(z)]^2 z^2 P(n-1). \tag{19}$$

Substitution of a polynomial $A(n)$ to (19) obtain the equation for calculating the dispersion of extrapolation errors:

$$P_e(n)=(2+a_1)P(n-1)-2(2-3a_1-2a_1^2)P(n-2)+(1-8a_1+2a_1^2)P(n-3)+$$
$$+2a_1(1-2a_1)P(n-4)+a_1^2P(n-5). \quad (20)$$

Order of calculation of the coefficient value a_1 в is determined from expression (8) after substituting equation (20) into relation (14):

$$a_1(n)=-\frac{P(n-1)+6P(n-2)-8P(n-3)+2P(n-4)}{8P(n-2)+4P(n-3)-8P(n-4)+2P(n-5)}. \quad (21)$$

Therefore, combining equations (7), (13), (14), (20), and (21), the complete algorithm for filtering INS orientation sensor measurements using scalar input action models, in which quality criterion (2) is satisfied, will be as follows:

$$a_1(n)=-\frac{P(n-1)+6P(n-2)-8P(n-3)+2P(n-4)}{8P(n-2)+4P(n-3)-8P(n-4)+2P(n-5)},$$

$$x_e(n)=(2-a_1)\hat{x}(n-1)-(1-2a_1)\hat{x}(n-2)-a_1\hat{x}(n-3),$$

$$P_e(n)=(2+a_1)P(n-1)-2(2-3a_1-2a_1^2)P(n-2)+(1-8a_1+2a_1^2)P(n-3)+$$
$$+2a_1(1-2a_1)P(n-4)+a_1^2P(n-5),$$

$$b_0(n)=\frac{P_e(n)}{P_e(n)+R(n)}, \quad (22)$$

$$\tilde{u}(n)=g(n)-x_e(n),$$

$$\hat{x}(n)=b_0\tilde{u}(n)+\hat{x}_e(n),$$

$$P(n)=(1-b_0)P_e(n).$$

The synthesized algorithm consists of two stages: prediction (extrapolation) and correction.

Modeling results

The effectiveness of the synthesized algorithm was evaluated using computer modeling.

A simulation model was developed that allows the process of filtering input signals in real time to be simulated by performing a sequence of calculations followed by graphical display of the results. The input data used real measurements from a three-axis ADXL345 accelerometer, which was installed directly on board the UAV. The change in the UAV's roll angle was simulated (Fig. 1).

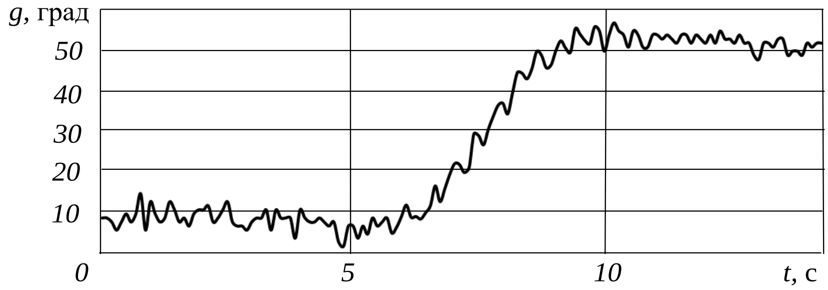

Fig. 1. Change in the UAV's roll angle, which is determined from the results of accelerometer measurements

The modeling was performed under the following conditions: T = 0,1 c, $P(0)$ = 5 deg^2. The result of filtering measurements using the synthesized algorithm is shown in Fig. 2.

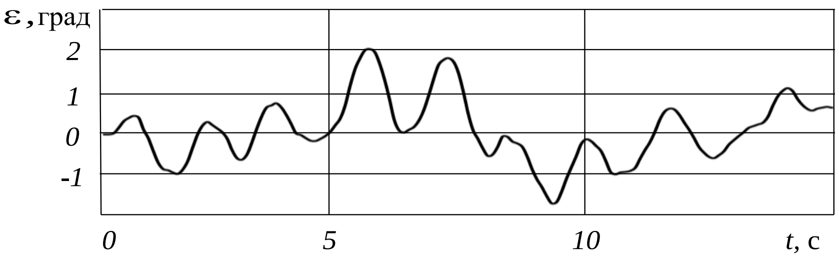

Fig. 2. Result of filtering the UAV roll angle when using the synthesized algorithm

The results obtained were compared with the results of the Kalman filter (Fig. 3), tuned to the model for $N = 1$.

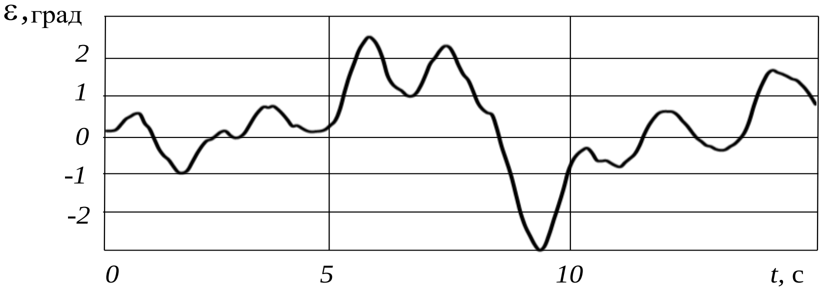

Fig. 3. Result of filtering the UAV roll angle when using the Kalman filter

Table 1 shows the average quality criterion value for the filters studied at observation intervals.

Table 1

The significance of the quality criterion at observation intervals

	Filter time interval, s		
	0–5	6–10	11–15
Synthesized filter	0,516 deg^2	0,875 deg^2	0,348 deg^2
Kalman filter	0,489 deg^2	1,419 deg^2	0,359 deg^2

The results show that at time intervals where the angular position of the UAV does not change, the synthesized algorithm provides filtration quality that corresponds to the Kalman filter. However, at time intervals when the angular position of the UAV body changes (t = 6–10 c), in the synthesized algorithm, the mean square error of estimation is 1.6 times smaller than in the Kalman filter.

Thus, under conditions of dynamic change in the angular position of the UAV, the use of the synthesized algorithm allowed for better filtration quality than the use of the Kalman filter.

Conclusions. The article presents a parametric synthesis of an optimal (according to the criterion of minimum mean square error of estimation) algorithm for filtering navigation measurements in the INS of UAVs. The algorithm is synthesized under the condition of a priori defined filter structure. Its performance and efficiency are confirmed by the results of computer modeling.

The main properties of the synthesized algorithm are:

low computational complexity due to the scalar form of the equations used to implement the filtering process;

non-stationarity, caused by the calculation of the optimal smoothing coefficient at each step of measurement processing;

recursive form: new estimates are obtained by adjusting old ones based on new observations.

The practical application of the synthesized algorithm allows:

quality control of filtering by the value of the selected performance indicator;

limit the value of the dynamic estimation error in case of a mismatch between the mathematical model of the input data and the filter.

To implement the synthesized algorithm, a priori information about the statistical characteristics of measurement errors is required.

Thus, the theoretical provisions set forth are a continuation of the research results described by the authors in [15]. The direction of further research should be considered to be the development of algorithms for identifying the statistical characteristics of measurement errors for conditions of their a priori uncertainty.

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