Features of data processing in UAV control system with non-orthogonal measuring device and robust controller

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Abstract

This paper deals with data processing in the design of control systems for unmanned aerial vehicles, with the robust controller and the redundant non-orthogonal measuring system. The synthesis of the robust system intended for use on a UAV is considered. The peculiarity of the system is the use of non-orthogonal measuring devices. The controller was developed based on robust structural synthesis. Data processing features in a redundant non-orthogonal measuring device and control system are represented. An example of the matrix transformations between measuring and navigation reference frames is given. A model of the longitudinal motion of the aircraft was obtained. The state, control, and observation matrices were determined using Aerosim technology. The results of modeling the synthesized system are presented. The results can be useful for a wide range of mobile objects.

Keywords

data processing, control system, non-orthogonal measuring system, redundancy, robust controller

1. Introduction

Nowadays, using unmanned aerial vehicles (UAVs) is one of the important areas of aviation development. The most well-known UAV applications are aerial surveys, monitoring of environmental parameters in hard-to-reach areas, etc. UAVs operate in complex conditions accompanied by parametric and coordinate disturbances. The accuracy of the above-mentioned observation processes can be ensured using robust UAV motion control. Typically, navigation information on board UAVs is measured using inertial sensors such as accelerometers and gyroscopic devices built based on inertial (MEMS) technologies [1]. This approach ensures low cost, small size, and low power consumption of the inertial measurement system. At the same time, the problem of increasing the accuracy and reliability of measurements remains relevant, taking into account the accuracy indicators of existing inertial MEMS measuring devices. To improve the accuracy of the navigation information measurement system on board the UAV, it is possible to use the structural redundancy of the primary navigation meters based on the non-orthogonal orientation of their sensitivity axes [2 – 4]. There are several approaches to implementing the structural redundancy of inertial navigation sensors. The first approach is to use the actual redundant meters. However, in this case, the computing resources required to process the navigation information increase. In other words, it is necessary to use a high-power processor, which complicates the architecture and increases the cost of the navigation system as a whole. The second approach is to use the redundant individual components of the navigation meters. In this case, the requirements for the computing power and bandwidth of the information channels are significantly reduced. Thus, the advantages of the second approach to implementing structural redundancy are obvious [5, 6]. The generalized structure of the UAV navigation system using redundancy is shown in Figure 1. The use of non-orthogonal excessive combinations of meters of navigation information using devices grounded on

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MEMS technology are accompanied by definite benefits. Firstly, these combinations ensure decreasing the zero offset. It is worth noting that the availability of a zero offset belongs to the topical questions of functioning existing MEMS blocks. Thus, the application of non-orthogonal excessive combinations improves the precision measured navigation data. Secondly, the excessiveness of measured navigation data improves the dependability of UAV operation. Thirdly, such configurations provide the ability to arrange more navigation blocks within a structural unit with the same dimensions. Such a feature is actual yet with the small sizes of widespread navigation blocks. An additional excellence is the ability to increase the resistance to failures for navigation blocks [1].

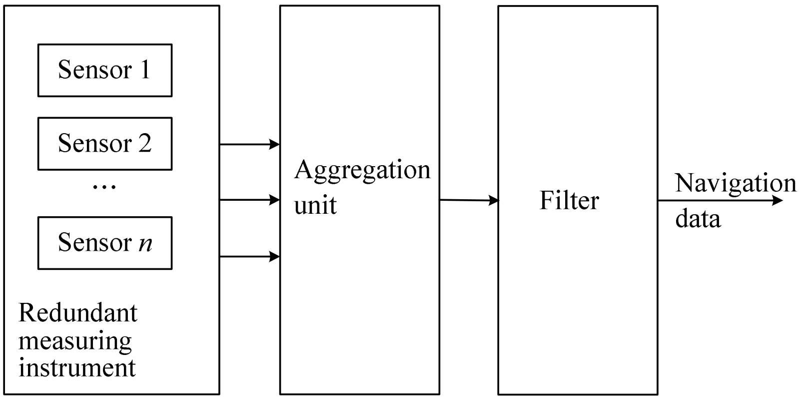

Figure 1: The skeleton diagram scheme of the redundant measuring system.

The organizational chart of the UAV motion control system is given in Figure 2.

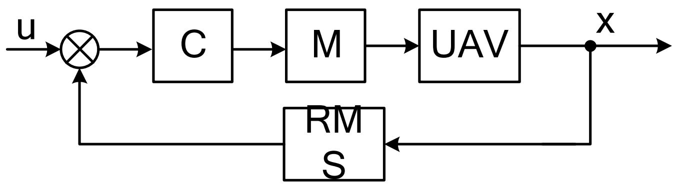

Figure 2: The organizational chart scheme of motion control measuring system: C is a controller; M is an electric motor; RMS is a redundant measuring system.

The stated task requires researching several interlinked challenges.

The first challenge is to select a non-orthogonal redundant configuration of inertial measuring units and develop an aggregation algorithm. The main goal of developing the aggregation algorithm is to transform the data coming from the redundant MEMS measuring units into projections of kinematic characteristics (accelerations, angle velocities) in the navigation reference frame. The second challenge is to create a robust controller. In this case, H_∞-synthesis can be used [7, 8].

The primary purpose of the paper is to consider features of data processing in designing of UAV motion control system with a non-orthogonal measuring device and robust controller. For this, it is necessary to process measuring information about the orientation parameters of a moving vehicle (UAV) into a navigation reference frame taking into consideration redundancy and non-orthogonality of the measuring device. The main feature in processing information in non-orthogonal measuring devices is the necessity to increase the precision of the navigation data and to ensure the possibility of identifying failures of separate inertial sensors. The main feature in processing information while designing a control system is the creation of robust control laws that require developing a mathematical model of the UAV control system and implementation of the procedure of the robust structural synthesis.

2. Data processing in non-orthogonal measuring devices

There are several approaches to handling the redundant information. The task of transforming redundant information of n sensors can be written as the determination of n components of the measured vector [9, 10]:

$$V_e = CV_m + \varepsilon, \tag{1}$$

where V_e is the vector of estimates with dimension n; C is the transformation matrix of dimension $n \times n$; V_m is the vector of measurement vectors; ε is the vector of measurement errors of dimension n.

The components of the vector (1), for example, projections of the angular velocity or acceleration, can be estimated based on the dependencies:

$$\begin{aligned} \hat{V}_x &= f(V_{1x}, V_{2x}, \dots, V_{nx}); \\ \hat{V}_y &= f(V_{1y}, V_{2y}, \dots, V_{ny}); \\ \hat{V}_z &= f(V_{1z}, V_{2z}, \dots, V_{nz}). \end{aligned} \tag{2}$$

Dependencies (2) can be determined using some approaches, for example, the determination of the average value, weighted average value, and median. In the case of an average value, the information processing algorithm has the form [11, 12]:

$$\hat{V}_{ij} = \frac{1}{n}\sum_{i=1}^{n} V_{ij},\ j = x, y, z. \tag{3}$$

You can increase the accuracy of the information processing algorithm (3) with the help of weighting factors:

$$\hat{V}_{ij} = \sum_{i=1}^{n} \lambda_i V_{ij}. \tag{4}$$

In expression (4), $\lambda_i = \frac{1/D_i}{\sum_{i=1}^{n} 1/D_i}$, where D_i is a variance of i-th sensor.

In some practical situations, it is convenient to use averaging by finding the median [13]:

$$V_1 < V_2 <\ldots< V_{(n+1)/2} <\ldots< V_{n-1} < V_n. \tag{5}$$

It can be said that the first approach to processing excessive information involves the selection of a separate non-excessive vector space according to the relations (3) – (5).

Secondly, you can use measurement information processing. In general, the amount of measured values exceeds the amount of estimated values. Therefore, the amount of equations exceeds the amount of unknown variables. Such a situation can be interpreted in the following way. The dimension of the vector of measurements exceeds the dimension of the vector of estimates. Therefore, in the generalized case, there is no single solution. Nevertheless, based on some selected criteria, a unique solution can be obtained, which ensures the achievement of the optimal solution for the above-mentioned criterion. One of the most common criteria used to handle information overload is the maximum likelihood criterion. It should be noted that using this approach requires knowledge of the posterior probability density. In a specific case, for a normal distribution law and known a priori information, the formula for estimating the vector components based on the likelihood function has the form [14, 15]:

$$\hat{V}_j = \frac{1}{n}\sum_{i=1}^{n} V_{ij}. \tag{6}$$

Another way is to use the method of least squares. The solution can be presented in the following way:

$$\hat{V} = H_{inv}V, \tag{7}$$

where H is the Moore-Penrose pseudo-inverse matrix.

It is remarkable that the method of least squares has some disadvantages. For example, it has limitations on attenuated noises such as zero mean, Gaussian noise, and uniform noise. This situation can be corrected using the method of weighted least squares:

$$\hat{V} = (H^{\mathrm{T}}R^{-1}H)^{-1}H^{\mathrm{T}}R^{-1}V. \tag{8}$$

Relationships (7), and (8) are algorithms for processing redundant information.

Fault finding can be implemented on the basis of neural networks. In this case, the three-layer perceptron can be used as a neutral network. Perceptron training can be implemented using measurement results.

To obtain navigational data based on non-orthogonal inertial blocks, it is essential to choose the navigational set of coordinates xyz and the appropriate measurement set of coordinates. Characteristics of the navigational set of coordinates for determination the angle rate projections relative to the longitudinal axis (x), normal axis (y), and lateral (z) axis of the UAV, respectively, are shown below. The direction of y coincides with orientation of the symmetry axis of the constructive unit and is above oriented. Directions of x, z in the navigation coordinate system coincide with the corresponding directions of the inertial measurement blocks arranged at the base of the constructive unit.

Some measuring axes are oriented in opposite direction that ensures the precision of the navigation data. These orientations are chosen in such a way that an angle between the different axes achieves a maximum possible value. Therefore, the zero offset is reduced while obtaining angle speed projections in the set of navigation coordinates. Using basic analytical laws of the theoretical mechanics [9], the formulas for direction cosines of a non-orthogonal configuration based on such a constructive unit as a triangle pyramid look like:

$$D_1 = A_x;\, D_2 = A_{y1}A_zA_y;\, D_3 = A_{y2}A_zA_y;\, D_4 = A_{y3}A_zA_y, \tag{9}$$

where D_1, D_2, D_3, D_4 are matrix representations of direction cosines, which define the mutual orientation between directions in the navigational set of coordinates and measurement set of coordinates.

The latter is connected with the blocks of inertial meters. The matrix A_x defines the orientation of the inertial measurement block using the triangle pyramid as a constructive unit. The matrix A_y defines the tilt of the sensitivity axes of the inertial measurement devices, located on the faces of the pyramid, concerning to the plane of the horizon. The matrices A_{y1}, A_{y2}, A_{y3} determine the location of the axes of the inertial measurement devices concerning to previously mentioned axes. The matrix A_z defines the orientation of the inertial measuring blocks arranged on the side edges along their medians at an angle of 120 degrees.

3. Data processing in fault resistance non-orthogonal measuring devices

The development of an algorithm for determining and locating a fault is a complex process, which is accompanied by many transformations and calculations. An excessive non-orthogonal meter can be considered as a set of individual devices. A neural network of this type consists of two layers. The neurons of the first layer are connected to the measurement of all the sensors included in the excessive non-orthogonal meter. Suppose that there are n measurement results. The deviation of the *j*th measurement from the average value can be determined using the expression. The development of an algorithm for determining and locating a fault is a complex process, which is accompanied by many transformations and calculations [16 – 19]:

$$\Delta_j = x_j - \frac{1}{n-1}\sum_{\substack{i=1 \\ i\neq j}}^{n} x_i. \tag{10}$$

To estimate the deviation (10) from the average measurement result, some threshold value ε is used. The condition of sensor performance can be presented in the form:

$$\Delta_j^2 \leq \varepsilon^2, \tag{11}$$

Expression (11) for estimating the measurement error was chosen taking into account the quadratic approach [10]. The neural network activation functions can be described by the following formulas:

$$f_1 = x_j^2; \tag{12}$$

$$f_2 = \sigma(x) = \frac{1}{1+e^{-kx}}, \tag{13}$$

where k is the gain coefficient.

Expressions (12), and (13) describe the quadratic and sigma functions, respectively [20, 21]. The weight of the inputs and outputs of the first neural network layer is equal to 1. The weight of the outputs of the second layer is determined in the following way:

$$w_{ij} = \begin{cases} 1,\ i = j; \\ \dfrac{-1}{n-1},\ i \neq j, \end{cases} \tag{14}$$

where $y = \Delta_j^2$.

Consider a neural network using expressions (12) – (14) and taking into account the fact that a set of n inertial sensors is combined into an excessive non-orthogonal configuration. For certainty, let us stop at the inertial device designed to measure the angular velocity of a moving object.

The structural diagram of such a neural network is presented in Figure 3.

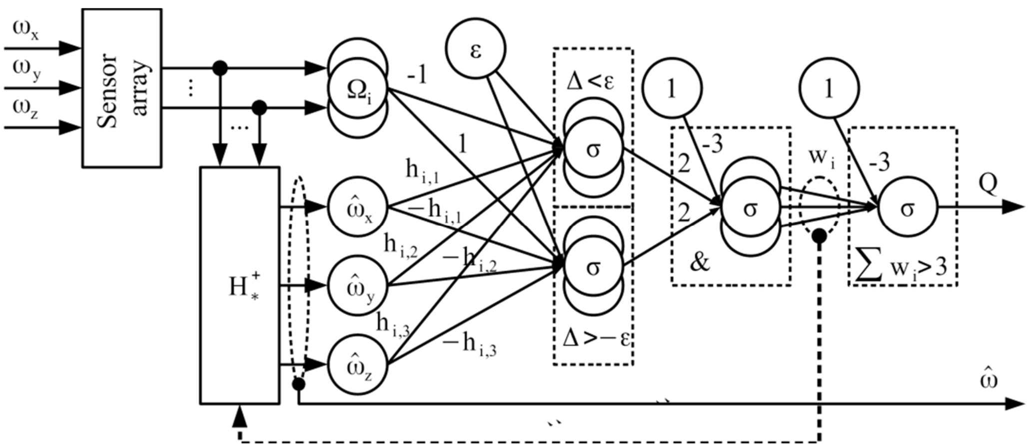

Figure 3: The implementation of the neural network.

Using the matrix of guiding cosines, it is possible to determine real projections of the angular velocity on the measuring axes of the non-collinear configuration of inertial sensors [16, 22]:

$$\Omega = \mathrm{H}\omega. \tag{15}$$

where Ω has the dimension n×1; H is a matrix of dimension n×3; ω has – matrix of dimension 3×1.

In general, the matrix H is not square. Therefore, it is possible to restore the value of the vector ω at a given angular velocity using the Moore-Penrose theorem [9]:

$$\widehat{\omega} = H_{ps}\Omega_m, \tag{16}$$

where $\widehat{\omega}$ is the vector of estimates of the measured angular velocities; H_{ps} is the pseudo-inverse matrix; $H_{ps} = (H^{\mathrm{T}}H)^{-1}H$; Ω_m is the vector of measured angular velocities.

The measurement error for each measurement channel can be defined as

$$\Delta = \Omega_i - \Omega. \tag{17}$$

The condition for deciding the ability to operate the measuring channel looks like:

$$|\Delta| < \varepsilon. \tag{18}$$

The matrix of direction cosines H is used to determine the estimates of the projections of the angular velocity of the moving object on the measuring axes of the excessive non-orthogonal meter. Expression (19) can be described as follows:

$$\Delta_i = \Omega_i - h(i,1)\omega_x - h(i,2)\omega_y - h(i,3)\omega_z. \tag{19}$$

To simplify the calculation procedure (15) – (19), condition (18) can be divided into two linear functions:

$$\Delta_i < \varepsilon \ \text{ and } \Delta_i > -\varepsilon \quad \text{or} \quad \varepsilon - \Delta_i > 0 \ \text{ and } \ \varepsilon + \Delta_i > 0.$$

The function of the first layer of the neural network is to estimate the deviation of the measurement results from the probably measured values.

At the same time, this layer of the neural network performs normalization of measurement estimates using the sigma function (13).

The second level of the neural network implements the logical AND function. In this way, it is possible to determine the error of the measuring channel, which does not exceed the permissible limits. At the same time, it allows you to define a weighting function for a given measuring axis. The second level of the neural network implements the logical AND function. In this way, it is possible to determine the error of the measuring channel, which does not exceed the permissible limits. At the same time, it allows you to define a weighting function for a given measuring axis

The effectiveness of the proposed approach to fault finding is proven by the simulation results presented in Figure 4.

The input signals entering the three-axis inertial measuring sensors are normalized sinusoids. Additive random noise with an amplitude of 0.075 (normalized value) is added to the sensor outputs. In the scenario, the third sensor of the excessive meter fails for a short time. In the first layer of the neural network, the deviation of the sensor readings from the weighted average value was determined (Figure 4d, 4e). With the help of the second layer of the neural network, the logical signal of the sensor's weight coefficient was formed. (Figure 4f). The matrix H+ is formed by the matrix of weighting coefficients of three sensors. In the future, this matrix will be used to form the output signal. In the absence of correction of the weighting coefficients, the output signal of the meter, formed based on averaging the output signals of individual sensors, will be distorted, as shown in

Figure 4h. Such a measuring system with a neural network implements the functions of a quorum element.

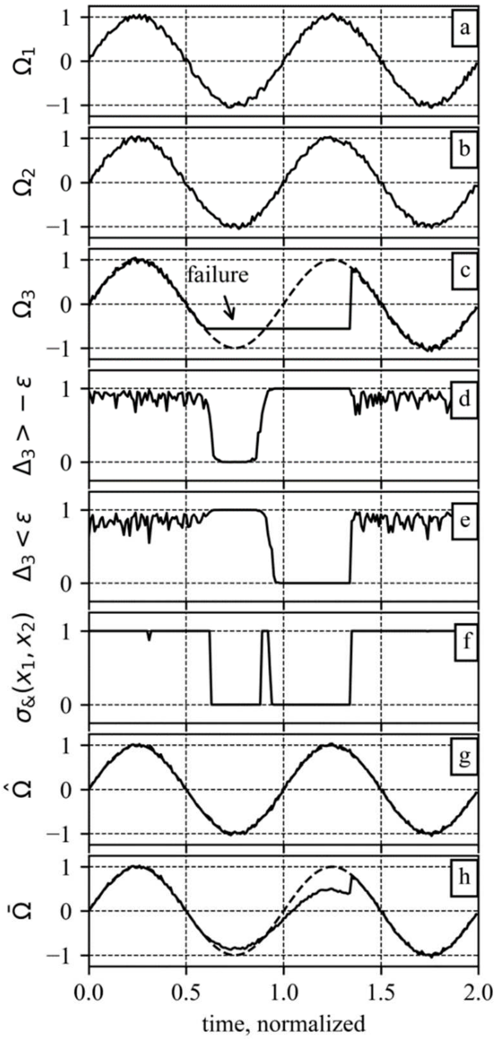

Figure 4: The simulation results.

4. Mathematical description of UAV

The problem posed can be solved using the example of the Aerosonde UAV, which is a small UAV designed to monitor weather conditions, including temperature, atmospheric pressure, humidity, and wind effects over the ocean and remote areas [23, 24]. The linearized model of the Aerosonde as a control object can be obtained in the space of states:

$$\begin{cases} \dot{x} = Ax + Bu; \\ y = Cx + Du. \end{cases} \tag{20}$$

To describe the longitudinal dynamic movement of the Aerosonde it is essential to use a state vector [23, 24]:

$$x = [v,\ w,\ q,\ \theta,\ h,\ \Omega]^{\mathrm{T}}, \tag{21}$$

where v, and w are the horizontal and vertical airspeed constituents; q is the angle velocity of the pitch; θ is the pitch angle; h is the flight height; Ω is the engine speed.

Longitudinal motion is controlled using elevators and engine thrust control. The control vector has the form:

$$u = [\delta_e, \delta_{th}]^{\mathrm{T}}, \tag{22}$$

where δ_e, δ_{th} are the deflections of the elevator and engine thrust control rudder.

The vector of output signals can be represented as

$$y = [V_a, \alpha, q, \theta, h], \tag{23}$$

where V_a is the true airspeed, α is the angle of attack.

The linearized equations of longitudinal motion have the form:

$$\begin{cases} \dot{v} = Y_v v + Y_w w + Y_q q + Y_\theta \theta + Y_h h + Y_\Omega \Omega + Y_{\delta_e}\delta_e + Y_{\delta_{th}}\delta_{th}; \\ \dot{w} = Z_v v + Z_w w + Z_q q + Z_\theta \theta + Z_h h + Z_\Omega \Omega + Z_{\delta_e}\delta_e + Z_{\delta_{th}}\delta_{th}; \\ \dot{q} = M_v^y v + M_w^y w + M_q^y q + M_\theta^y \theta + M_h^y h + M_\Omega^y \Omega + M_{\delta_e}^y \delta_e + M_{\delta_{th}}^y \delta_{th}; \\ \dot{\theta} = H_{\omega_y}^{-1} q; \\ \dot{h} = \theta + H_v v + H_w w; \\ \dot{\Omega} = h + T_v v + T_w w + T_{\delta_{th}}\delta_{th}. \end{cases} \tag{24}$$

The non-orthogonality of the redundant measuring system in the set of equations (21) is taken into account by the matrix of transformations of navigation information. Considering expression (24), matrices and models in the state space (20) can be represented in this form:

$$A = \begin{bmatrix} Y_v & Y_w & Y_q & Y_\theta & Y_h & Y_\Omega \\ Z_v & Z_w & Z_q & Z_\theta & Z_h & Z_\Omega \\ M_v & M_w & M_q & M_\theta & M_h & M_\Omega \\ 0 & 0 & H_{\omega_y}^{-1} & 0 & 0 & 0 \\ H_v & H_w & 0 & 1 & 0 & 0 \\ T_v & T_w & 0 & 0 & 1 & 0 \end{bmatrix}, B = \begin{bmatrix} Y_{\delta_e} & Y_{\delta_{th}} \\ Z_{\delta_e} & Z_{\delta_{th}} \\ M_y & M_y \\ 0 & 0 \\ 0 & 0 \\ 0 & T_{\delta_{th}} \end{bmatrix}. \tag{25}$$

The elements of the matrix A (25) are determined by the UAV aerodynamics and engine design. In expressions (22), the matrix B is presented for the general case when there are two control signals [24, 25].

Robust control synthesis requires the use of a state-space model (20) – (25). For the UAV mentioned above, the state-space model matrices can be obtained using the AeroSim package of the MatLab computing system [25].

Robust structural synthesis is a powerful tool for designing feedback control systems based on determining frequency characteristics as a function of singular values. A well-known approach to designing robust systems is when the robust stability condition is formulated in terms of norms limited by weight transfer functions [26 – 28]. This approach is implemented in such automated optimal design tools as Robust Control Toolbox. The modeling results are shown in Figure 5.

The synthesized system is believed to be a control object and a regulator, described by matrix transfer functions.

The generalized control object is characterized by two input and output signals. Vector w is an external input, which generally consists of disturbances, measurement noise, and command signals. Input u represents control signals. Output z allows us to estimate control characteristics. For example, it can be characterized by the error in tracking the command signal, equal to zero in the ideal case. Vector of output y includes observed signals. It can be used for feedback implementation [29, 30].

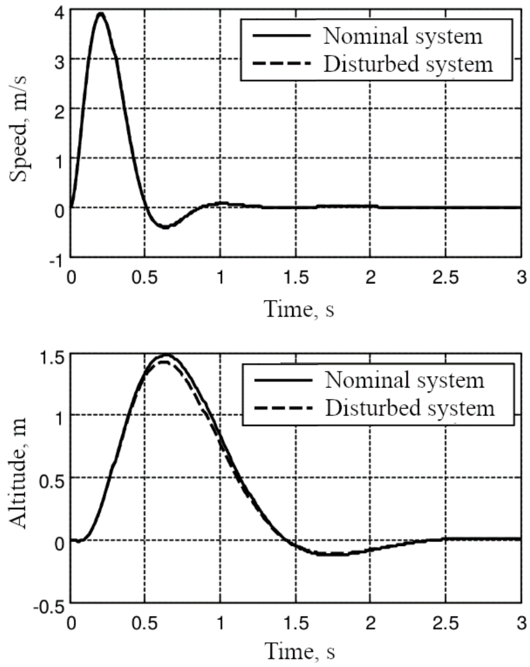

Figure 5: Simulation results of the synthesized robust system for the input impulse signal.

The simulation results confirm the robust stability of the system.

The main task of H_∞ synthesis is to select a controller that minimizes H_∞ norms. Implementation of H_∞ synthesis is based on solving the Riccati equations, taking into account the fulfilment of certain restrictions. One of the methods used in H_∞ synthesis is the mixed sensitivity method with the optimization criterion [12, 31]:

$$J(G,K) = \left\| \begin{bmatrix} W_1(I+\mathrm{GK})^{-1} \\ W_2K(I+\mathrm{GK})^{-1} \\ W_3\mathrm{GK}(I+\mathrm{GK})^{-1} \end{bmatrix} \right\|_\infty \tag{26}$$

where are the weight transfer functions of the system sensitivity, the control sensitivity functions, and the complementary function of the system sensitivity [23]. The formulation of the optimization problem taking into account expression (4) takes the form:

$$K_{opt} = \arg \inf_{K_{opt} \in K_{per}} J(G,K). \tag{27}$$

5. Conclusions

The UAV control system with a non-orthogonal measuring device and robust controller is considered. Features of data processing in non-orthogonal measuring devices is considered including processing redundant information and transformation of redundant measuring information in navigation parameters is supposed.

The algorithm of data processing in searching failures of separate sensors is developed. A mathematical model of the UAV longitudinal motion channel was obtained taking into account the redundancy of the measuring system based on single-axis inertial sensors.

A robust control system was designed based on H_∞ synthesis. The combination of redundancy of navigation information and a robust controller improves the quality of UAV operation in difficult real-life operating conditions.

The proposed approaches for data processing ensure the quality of designing a UAV control system. Simulation results prove the efficiency of the proposed approaches.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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