INTEGRATED PROCESSING OF NAVIGATION INFORMATION IN A UAV GROUP USING A SIGMA-POINT KALMAN FILTER

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This article examines the problem of improving the accuracy and reliability of navigation support for unmanned aerial vehicles (UAVs) operating in a organized group. The solution is based on integrating information from various navigation systems. A method is proposed for integrating navigation information from an onboard GNSS receiver, an onboard local navigation system that measures the range and direction between UAVs, and navigation data received from other UAVs in the swarm using a data transmission system. When navigating a UAV in a group, several coordinate systems are used: local coordinate systems associated with individual UAVs and the group (leader UAV), as well as a global inertial coordinate system. Therefore, transitions between these coordinate systems require the use of rotation matrices containing nonlinear sine and cosine functions. Because of this, the UAV is considered a nonlinear system, and the resulting error distribution for position measurements will deviate from a Gaussian distribution. To solve this problem, nonlinear filtering methods are proposed. The use of a sigma-point Kalman filter as the primary processing algorithm is justified. This filter provides higher parameter estimation accuracy compared to the extended Kalman filter by approximating the distribution with a deterministic set of sigma points. A procedure for rejecting anomalous measurements (majority voting) and weighted averaging of normalized navigation parameters is proposed. It is shown that the use of a sigma-point Kalman filter allows efficient solution of the problem of integrated processing of navigation information at the level of secondary parameters from heterogeneous sources while maintaining acceptable computational complexity. A functional diagram of the onboard integrated navigation system is described.

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Introduction

Unmanned aerial vehicles (UAVs) are increasingly used not only in the military but also in civilian applications, including agricultural and forestry monitoring, construction, remote sensing, logistics, reconnaissance, and more. The use of UAVs opens up enormous prospects for the implementation of precision farming technologies, crop monitoring, pest detection and crop condition assessment, especially under conditions of limited human and material resources [1, 2]. In the construction industry, the use of UAVs makes it possible to monitor the progress of construction work, inspect dangerous or hard-to-reach objects, identify defects using high-definition photography and video, and promptly identify dangerous situations [3]. UAVs also provide clear advantages for goods delivery in remote areas and during emergencies such as fires, earthquakes, or floods, as well as for transporting small mail items and urgent cargo [4].

In recent years, there has been a trend toward using UAVs in organized groups. This significantly increases their effectiveness, enabling simultaneous monitoring and mapping of large areas, distributing targets and missions among group members, reducing mission execution time by evenly distributing tasks within the group, and so on. It is possible to use a organized group of small UAVs instead of medium and heavy UAVs. The wide range of missions performed by small UAVs operating in a swarm, their relatively low cost, their low visibility compared to medium and heavy UAVs, and the high interchangeability of individual UAVs during missions make research in this area very promising.

One of the main problems hindering the widespread use of UAVs in organized groups is the inadequate quality of their navigation support. Given the stringent limitations on the weight and power consumption of the UAV platform and payload, the use of GNSS receivers is the only alternative for UAV positioning. However, GNSS receivers are characterized by poor resistance to interference and accuracy in environments with discontinuous radio navigation fields – in urban areas, mountainous terrain, when exposed to radio electronic interference, etc. Differential operation modes of GNSS receivers or the use of RTK and PPP technologies can achieve coordinate measurement accuracy in the centimeter range. However, these technologies require the creation of a complex ground-based differential network infrastructure and the organization of communication channels for transmitting corrections, which is difficult to implement in Russia [5]. A significant improvement in the accuracy of navigation measurements can be achieved by incorporating additional onboard navigation systems that enable autonomous and group navigation even in the absence of GNSS signals, such as inertial systems, radio rangefinders (Wi-Fi, UWB), and optoelectronic systems [6, 7].

One of the most promising areas in navigation support for group use of UAVs is the use of local onboard navigation systems that provide highly accurate measurements of distances and directions between individual UAVs – members of the group [8]. Range measurement in such systems is based on measuring the propagation time of navigation radio signals between the transceivers installed on UAVs. The directions between UAVs (azimuths and elevations) are measured using direction finding and super-resolution algorithms in antenna arrays. These methods typically offer high accuracy for range and angular measurements and do not require synchronization of the UAVs' reference oscillators.

Further improvements in navigation accuracy can be achieved by integrating information from the various navigation systems available onboard UAVs. Moreover, for group operations, it is essential to integrate navigation data received from multiple UAVs in the group and to process it onboard the leader UAV together with its own navigation information. This paper considers such integration for the case of combined processing of navigation data from two onboard systems – a GNSS receiver and an inertial navigation system – as well as information on relative distances and angular positions between UAVs obtained via the data link [8].

1 Features of navigation support for UAVs and their group operations

To create modern navigation systems that are resistant to radio frequency interference and have acceptable accuracy in the intermittent GNSS radio navigation field, various methods for integrating navigation systems are used. The most effective methods are closely coupled ones implemented at the level of primary processing of navigation information [9]. However, despite their effectiveness, they have not found widespread use in onboard UAV navigation systems. This is due to the need for significant hardware modifications to the integrated navigation systems and complex joint processing of the estimated navigation parameters. Loosely coupled integration methods offer undeniable advantages due to their minimal hardware and software requirements and can be easily implemented in existing navigation systems. However, these methods do not allow for the full realization of all the benefits of integration. Integration at the level of secondary information processing (loosely coupled method) is somewhat more complex, but requires only software modification. of the UAV's onboard navigation system. At the same time, this integration method enables correction of inertial sensors (gyroscopes and accelerometers) based on GNSS receiver data, including in flight. The inertial navigation system allows for improved reliability of UAV coordinate measurements when GNSS signals are lost and for the implementation of algorithms for quickly capturing GNSS signals in the GNSS receiver when they are re-captured.

Often, the accuracy of autonomous navigation provided by onboard navigation systems may not be sufficient to support coordinated movement of UAVs in a group. This is due to several factors, including:

– variable positioning accuracy of UAVs in a group due to varying levels of navigation equipment sophistication or different conditions during navigation when using GNSS signals;

– ow resistance to radio interference;

– discontinuity of the radio navigation field due to GNSS signal obscuring conditions, malfunctions of onboard GNSS receivers, etc.

Typically, the design of integrated onboard navigation systems is based on the joint processing of information from several devices or systems that measure the same or functionally related navigation and other parameters. The result of integrating several navigation systems is an improvement in the accuracy, interference immunity and reliability of navigation measurements compared to measurements by individual systems.

One of the promising areas of development for UAV navigation systems today is the integrated use of GNSS receivers, inertial navigation systems and onboard local navigation systems, and a data transmission system operating in time-division multiple access (TDMA) mode within the UAV's onboard navigation and communication system.

In the proposed complex, the onboard GNSS receiver ensures ensures high accuracy in measuring the coordinates and components of the UAV velocity vector in autonomous mode, as well as global positioning and timing capabilities. The onboard local navigation system provides measurement of range and angles (azimuth and elevation) between adjacent UAVs operating as part of an organized group [8]. An inertial navigation system using accelerometers and angular velocity sensors provides measurement of the spatial orientation and angular velocity of the UAV.

Distances between UAVs in the onboard local navigation system are measured using a symmetrical two-way measurement method. This method is highly accurate and does not require synchronization of the reference oscillators of individual UAVs in the group. It is based on measuring the propagation time of a radio signal between the transceivers mounted on the UAV during symmetrical two-way signal transmission. The azimuth β and elevation angle ε of the signal source emitted by the leader UAV are measured using an antenna array mounted on the UAV. The required accuracy and resolution for angular measurements are achieved using an antenna array and MUSIC super-resolution algorithms.

The UAV's state is estimated based on information from navigation sensors and the state evolution determined by a dynamic model of UAV motion. Several coordinate systems are used to describe UAV movement within a group. The first is the local coordinate system, attached to the UAV's center of mass. The inertial and onboard local navigation systems provide information in this coordinate system. The second is the global inertial coordinate system, in which the GNSS receiver operates. The third is the local group coordinate system, whose origin is located at the center of mass of the leader UAV.

The exchange of coordinate information enables relative navigation problems to be solved in both local and global coordinate systems. However, the need to transmit large amounts of information increases the bandwidth requirements of the data transmission system. These requirements can be reduced by setting a minimum data exchange rate that will ensure the specified accuracy. Since navigation information accuracy requirements vary at different stages of flight, the required navigation information exchange rate will also vary. A compromise must be reached between the desired accuracy and minimizing the exchange rate. The solution to the problem of controlling the rate of data exchange for different flight modes is considered in [10, 11].

2 Application of Kalman filter for joint processing of navigation information

Methods for integrating various navigation systems are based on the theory of optimal filtering of Markov processes. In the classical formulation of the optimal filtering problem, a large amount of a priori information is known about the system. This data includes information on useful signals and interference, their functional interactions, and the relationship between the observed and estimated parameters. The results of the performance evaluation of navigation systems obtained as a result of such a formulation of the problem should be considered the theoretical maximum [12]. Using a priori information about the system's operation, a recursive algorithm can be developed for calculating the posterior probability density of the state vector. The posterior probability density is a sufficient statistic and allows one to obtain an estimate of the state vector by any criterion, as well as the accuracy of such an estimate (the posterior variance) [12, 13].

Filtering equations are often nonlinear, lack a rigorous analytical solution, and require the use of approximate numerical methods. One of the most widely used methods is the extended Kalman filter. In such a filter, the current linearization of the observation equations is carried out in the vicinity of the optimal estimate of the trajectory parameters, and the nonlinear filtering problem is reduced to a linear one, for which an analytical solution is known [12].

The accuracy of the estimation of the navigation parameters when using filtering algorithms is determined by the correlation matrix of the filtering errors of the state vector $\mathbf{R}(t)$, the equation for which has the form:

$$\frac{d\mathbf{R}}{dt} = \mathbf{N}_{\lambda}(t) + \mathbf{F}(t) + \mathbf{R}\mathbf{F}^{T}(t) - \mathbf{R}\mathbf{H}^{T}(t)\mathbf{N}_{0}^{-1}\mathbf{H}(t)\mathbf{R}, \quad (1)$$

where:

$\mathbf{N}_{\lambda}(t)$ is the covariance matrix of the noise forming the parameters of the state vector with dimensions $n \times n$, n is the dimension of the state vector to be estimated;

$\mathbf{F}(t)$ is the matrix of the system dynamics with dimensions $n \times n$, included in the equation of state of the object;

$\mathbf{H}(t)$ is the observation matrix with dimensions $m \times n$, m is the dimension of the observation vector;

$\mathbf{N}_0$ is the matrix of variances of the observation noise with dimensions $m \times n$.

The last term in (1) characterizes the observation process and depends on the composition of the observed parameters (matrix $\mathbf{H}(t)$) and their accuracy (matrix $\mathbf{N}_0$). If the observer can vary the choice of observed parameters or the accuracy of their measurements, then the product $\mathbf{H}^{T}(t)\mathbf{N}_{0}^{-1}\mathbf{H}(t)$ can be considered a control function. In this case, equation (1) will describe the dynamics of change in the magnitude of the error (equivalent to accuracy) depending on the control function. Algorithms for finding the optimal control function that ensures the extreme value of a given criterion can be obtained based on the use of optimal control theory.

The Kalman filter algorithm operates in two stages. In the prediction stage, the current state variables and their uncertainties are estimated. In the update stage, the new measurement is incorporated using a weighted average, where the weights depend on the uncertainties of the prediction and the measurement.

Because of its recursive nature, the algorithm can operate in real time using only current measurements and the previously estimated state. The underlying filter model is Bayesian and resembles a hidden Markov model; it is discrete in time, and both hidden and observed variables follow Gaussian distributions [12, 13]. Figure 1 illustrates the general operating principle of the Kalman filter.

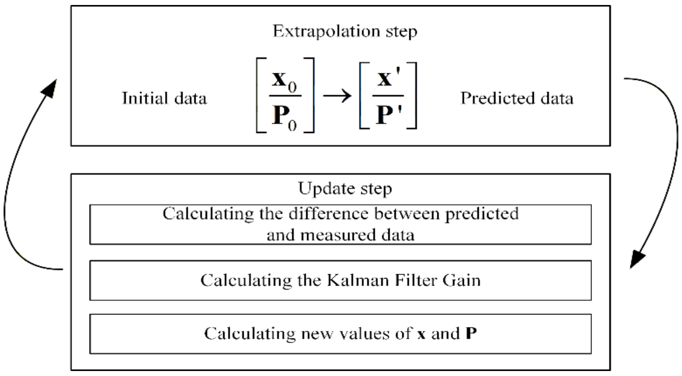

Fig. 1. General diagram of Kalman filter operation. In the diagram, $\mathbf{x}_0$ is the state vector estimate, $\mathbf{P}_0$ is the error covariance matrix

In general, the equation for the extrapolation step is given by [15]:

$$\mathbf{x}=\begin{bmatrix} p \\ s \\ a \end{bmatrix}, \quad \mathbf{x}'=\mathbf{F}\mathbf{x}_{k-1}+\mathbf{B}\boldsymbol{\mu}_{k-1}+\nu, \tag{2}$$

where:

$\mathbf{x}'$ is the predicted state of the system vector;

p is the object's coordinates;

s is the object's velocity;

a is the object's acceleration;

$\mathbf{F}$ is the system dynamics matrix;

$\mathbf{B}$ is the control matrix;

$\boldsymbol{\mu}_{k-1}$ is the control vector at the previous time step;

ν is the process noise.

The system dynamics matrix $\mathbf{F}$ represents the UAV motion model and has the following form:

$$\mathbf{F}=\begin{pmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{pmatrix}. \tag{3}$$

The control matrix $\mathbf{B}$ accounts for changes in the state caused by external or internal forces, such as gravity or aerodynamic drag.

The extrapolation equation for the error covariance matrix is:

$$\mathbf{P}'=\mathbf{F}\mathbf{P}_{k-1}\mathbf{F}^T+\mathbf{Q}, \tag{4}$$

where:

$\mathbf{F}$ is the system dynamics matrix;

$\mathbf{P}_{k-1}$ is the error covariance matrix at the previous time step;

$\mathbf{F}^T$ is the transposed transition matrix;

$\mathbf{Q}$ is the process noise matrix.

The process noise $\mathbf{Q}$ accounts for uncertainties due to changes in direction or speed, so the covariance increases by $\mathbf{Q}$ over time Δt. To calculate the update step, it is necessary to determine the difference between the measured value and the predicted value of the object parameter [15]:

$$\mathbf{y}=\mathrm{z}-\mathbf{H}\mathbf{x}', \tag{5}$$

where:

z is the measurement vector;

$\mathbf{H}$ is the transition matrix.

Using the transition matrix $\mathbf{H}$, unnecessary information can be eliminated from the predicted state value. Technically, the matrix $\mathbf{H}$ performs the same function as the matrix $\mathbf{F}$ did in the extrapolation step. The following formula is used to calculate the innovation covariance in determining the system state [16]:

$$\begin{aligned} \mathbf{S}&=\mathbf{H}\mathbf{P}'\mathbf{H}^{\mathrm{T}}+\mathbf{R}, \\ \mathbf{K}&=\mathbf{P}'\mathbf{H}^{\mathrm{T}}\mathbf{S}^{-1}, \end{aligned} \tag{6}$$

where:

$\mathbf{R}$ is the measurement noise matrix;

$\mathbf{K}$ is the Kalman filter gain.

The Kalman filter gain is a parameter that determines the weight of the predicted value and the current measurement. The gain ranges from 0 to 1. If a large measurement error is obtained, the gain value will be close to 0. This means that the extrapolated value is closer to the actual value than the measured one. If a smaller error is obtained during extrapolation, the gain value will tend to 1. This means that the measured value is closer to the actual value than to the extrapolated one. The a posteriori estimates of the state vector and the error covariance matrix are determined by the following equations [16]:

$$\begin{aligned} \mathbf{x}&=\mathbf{x}'+\mathbf{K}\mathbf{y} \\ \mathbf{P}&=(1-\mathbf{K}\mathbf{H})\mathbf{P}'. \end{aligned} \tag{7}$$

The dynamics matrix of the system for the three-dimensional case with acceleration will have the form:

$$\mathbf{F}=\begin{pmatrix} 1 & \Delta t & \frac{\Delta t^2}{2} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & \Delta t & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & \Delta t & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & \Delta t & \frac{\Delta t^2}{2} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \Delta t & \frac{\Delta t^2}{2} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \end{pmatrix} \times \begin{pmatrix} x_k \\ p_{x,k} \\ a_{x,k} \\ y_k \\ p_{y,k} \\ a_{y,k} \\ z_k \\ p_{z,k} \\ a_{z,k} \end{pmatrix}. \tag{8}$$

The algorithm discussed here allows for estimating the UAV's state vector by combining measured and extrapolated coordinates, velocity vectors, accelerations, etc. However, this algorithm will be quasi-optimal only if the distributions of measurement or extrapolation errors correspond to a Gaussian distribution. This is only possible if the system being evaluated is linear.

This condition is not met for UAV group deployments. The steps for measuring the relative position of UAVs in a group, described previously, involve transitioning from one coordinate system to another. This procedure is performed using rotation matrices containing nonlinear sine and cosine functions. For this reason, UAVs should be considered as a nonlinear system, and the resulting distribution of the error in measuring the position of UAVs in a group will differ from the Gaussian distribution.

3 Using the sigma-point Kalman filter

An exact solution to the optimal filtering problem can be obtained using the particle filter framework (the Monte Carlo method). However, this method requires significant computational effort. Given the limited computational and energy resources of the onboard computer system, this method cannot currently be implemented on small and medium-sized UAVs. An alternative approach to solving this problem may be to use one of the varieties of nonlinear filters – the Kalman sigma-point filter (Fig. 2) [16].

The basic idea of this algorithm is to use sigma points to approximate the actual values of the covariance matrix of measurement errors. To do this, a small number of deterministic sigma points are selected around the original distribution. They are chosen such that their sample mean (mathematical expectation) and covariance exactly match the original distribution. Next, nonlinear transformations are performed on each sigma point in accordance with a given function, that captures the nonlinearity of the nonlinearity of the measurement process.

Figure 2 illustrates the bias in the mean and the distortion of the variance that occur when an analytical method (e.g., linear approximation as in the extended Kalman filter) is used. By applying the nonlinear transformation to each sigma point and then computing the weighted mean and covariance of the transformed points, the resulting distribution is significantly more accurate. In this example, the estimated mean closely matches the true mean of the transformed points, and the covariance accurately reflects the effect of the nonlinearity. Thus, the sigma-point method first deforms the original distribution through the nonlinear transformation and then fits a Gaussian distribution to the result, achieving much higher accuracy with the same computational cost.

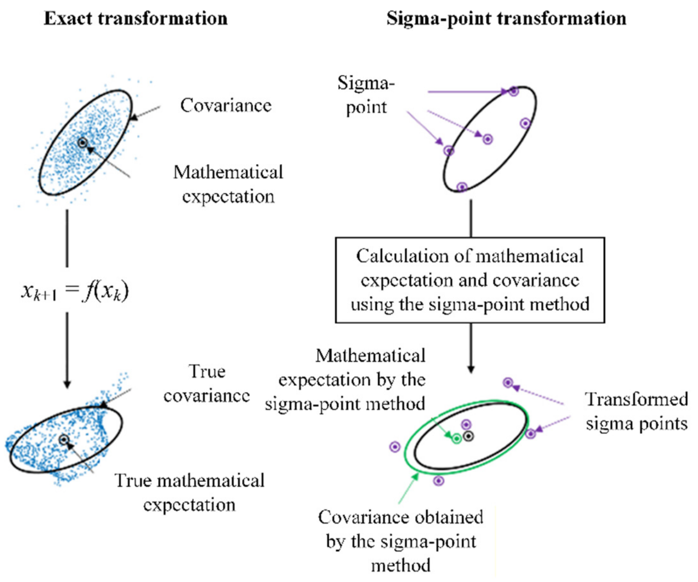

Fig. 2. Differences between exact transformation and approximate transformation using the sigma-points method

In practice, it is impossible to apply the nonlinear transformation to every point of a continuous distribution. Therefore, it is necessary to select a set of points that most accurately reflect the original distribution. To implement the above method, it is necessary to define an algorithm for selecting sigma points. According to [17], sigma points are determined according to the following equation:

$$\begin{aligned}
&\chi^{[0]} = \mu, \\
&\chi^{[i]} = \mu + \left(\sqrt{(n+\lambda)\mathbf{P}}\right)_i \quad for\ i = 1,\dots,n, \\
&\chi^{[i]} = \mu - \left(\sqrt{(n+\lambda)\mathbf{P}}\right)_{i-n} \quad for\ i = 1,\dots,2n, \\
&n = 2N+1,
\end{aligned} \tag{9}$$

where:

χ is the sigma points matrix;

μ is the mathematical expectation of the original distribution;

λ is the scaling factor;

$\mathbf{P}$ is the covariance matrix;

N is the system dimension.

Each column of the sigma-point matrix χ describes a set of sigma-points for one dimension. Thus, for the three-dimensional case, the matrix dimension is 3×5. The scaling factor λ determines how far from the mathematical expectation the sigma points should be selected. The next step involves calculating the weighting coefficients w for the sigma points:

$$\begin{aligned}
&w^{[0]} = \frac{\lambda}{n+\lambda}, \\
&w^{[i]} = \frac{1}{2(n+\lambda)}, \\
&i = 1,\dots,2n.
\end{aligned} \tag{10}$$

It is important to note that the sum of the values of the weight coefficients of all sigma points must be equal to 1. Next, the updated values of the mathematical expectation and the covariance matrix are calculated [17]:

$$\begin{aligned}
&\mu' = \sum_{i=0}^{2n} w^{[i]} g\left(\chi^{[i]}\right), \\
&\mathbf{P}' = \sum_{i=0}^{2n} w^{[i]} \left(g\left(\chi^{[i]}\right) - \mu'\right)\left(g\left(\chi^{[i]}\right) - \mu'\right)^T,
\end{aligned} \tag{11}$$

where:

μ' is the updated mathematical expectation of the original distribution;

w is the weights of the sigma points;

$\mathbf{P}'$ is the updated covariance matrix;

$g(\ )$ is the nonlinear function;

n is the system dimension.

4 Integrated processing of navigation information in a UAV group using a sigma-point Kalman filter

The application of the sigma-point Kalman filter for integrated processing of navigation information in a UAV group at a given time instant can be summarized by the following algorithm:

1) Extrapolation:

– Calculate sigma points using (9).

– Ca culate weighting coefficients using (10).

2) Transformation of sigma points and calculation of new values of the mathematical expectation and covariance matrix in accordance with (11).

3) Update: transformation from state space to measurement space:

$$Z = h(\chi),$$
$$\hat{z} = \sum_{i=0}^{2n} w^{[i]} Z^{[i]}, \tag{12}$$
$$\mathbf{S} = \sum_{i=0}^{2n} w^{[i]} \left(Z^{[i]} - \hat{z}\right)\left(Z^{[i]} - \hat{z}\right)^T + \mathbf{Q},$$

where:

Z is the transformed sigma points in the dimension space;

$\hat{z}$ is the mathematical expectation in the dimension space;

S is the covariance matrix in the dimension space;

$h(\chi)$ is the function representing the sigma points in the dimension space.

4) Kalman gain calculation. This is done by calculating the cross-correlation function between the sigma points in the state space and the sigma points in the Z-dimensional space. The $h(\chi)$ function maps the system's state space to its measurement space. This is necessary to enable comparison of measurement values and extrapolation. To calculate the prediction error, the cross-correlation between the sigma points in the state space and the sigma points in the measurement space must be calculated:

$$\mathbf{T} = \sum_{i=0}^{2n} w^{[i]} \left(\chi^{[i]} - \mu'\right)\left(Z^{[i]} - \hat{z}\right)^T, \tag{13}$$
$$K = \mathbf{T}\mathbf{S}^{-1},$$

where

T is the correlation matrix between the state space and the predicted space.

5) Optimal filtering of the UAV state vector at a fixed point in time for the values of coordinates x^g, y^g, z^g, determined by the navigation systems of the UAV autonomously, the UAV group and received through the data transmission system.

$$\mathbf{p}_i^g = \mathbf{M}_i^u \left(x^g, y^g, z^g\right)\mathbf{p}_i, \tag{14}$$

where $\mathbf{M}_i^u$ – $\begin{pmatrix} 1 & 0 & 0 & x^g \\ 0 & 1 & 0 & y^g \\ 0 & 0 & 1 & z^g \\ 0 & 0 & & 1 \end{pmatrix}$.

The elements of the matrix $\mathbf{M}_i^u$ will have the following values:

$$\begin{pmatrix} x^g \\ y^g \\ z^g \end{pmatrix} = \begin{pmatrix} d \cdot \sin\beta\cos\varepsilon \\ d \cdot \sin\beta\sin\varepsilon \\ d \cdot \sin\beta \end{pmatrix}. \tag{15}$$

The values of d, β, ε were obtained using the methods of UAV navigation in a group described in [8] and providing measurements of the range and directions between individual UAVs. To reduce the complexity of the algorithm, it can be assumed that the measurements of the coordinates of each UAV in the group are equally accurate, and the obtained values of the measured coordinates of each UAV will be centered relative to the leader UAV. In this case, averaging the obtained coordinate values would be optimal in terms of minimizing the root-mean-square measurement error. However, it should be noted that, although the measurements are equally accurate, a failure in one or more UAVs is possible, causing the coordinate measurement error at a given moment to exceed the permissible limit. In this case, before the averaging stage, it is necessary to perform a threshold screening step – a majority vote. This procedure involves excluding from the calculation process the measured UAV coordinate values that exceed a threshold. The threshold is determined by the difference in the measured coordinate values between two UAVs after transferring them to the group coordinate system.

$$\mathbf{\Lambda} = \begin{pmatrix} 0 & \left|\mathbf{p}_1^g - \mathbf{p}_2^g\right| < \mathbf{\Lambda}_{\lim} & \ldots & \left|\mathbf{p}_1^g - \mathbf{p}_n^g\right| < \mathbf{\Lambda}_{\lim} \\ 0 & 0 & \ldots & \left|\mathbf{p}_2^g - \mathbf{p}_n^g\right| < \mathbf{\Lambda}_{\lim} \\ \ldots & \ldots & \ldots & \left|\mathbf{p}_{n-1}^g - \mathbf{p}_n^g\right| < \mathbf{\Lambda}_{\lim} \\ 0 & 0 & \ldots & 0 \end{pmatrix}, \tag{16}$$

where:

$\mathbf{\Lambda}_{\lim}$ is the specified maximum value of the difference in coordinate measurements by two UAVs.

After this, the remaining values of the measured coordinates undergo an averaging stage:

$$\mathbf{p}^{mid} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{p}_i^g. \tag{17}$$

The resulting value will represent an estimate of the UAV's position in the group. If the coordinate measurements for each UAV are not equally accurate and are characterized by standard measurement errors σ_i, then averaging is performed taking these errors into account:

$$\mathbf{p}^{mid} = \frac{1}{n}\sum_{i=1}^{n} \mathbf{p}_i^g. \tag{18}$$

To improve the accuracy of coordinate measurements and enhance the reliability of navigation support for UAVs operating in an organized group, it is necessary to integrate coordinate information from all onboard navigation systems. The functional diagram of the UAV's integrated onboard navigation system is shown in Fig. 3. It is proposed to carry out the integration at the level of processing secondary information, which is characterized by redundancy of information about the measured navigation parameters.

The processing of navigation parameters is based on an algorithm for compensating for errors in integrated measuring instruments [17]. The integration of navigation information from the GNSS receiver, the onboard local navigation system, the inertial navigation system and navigation information from the UAVs of the group members, received through the data transmission system, is carried out.

The implementation of the UAV navigation method as part of an organized group based on the integration of navigation information from all sources consists of the following stages:

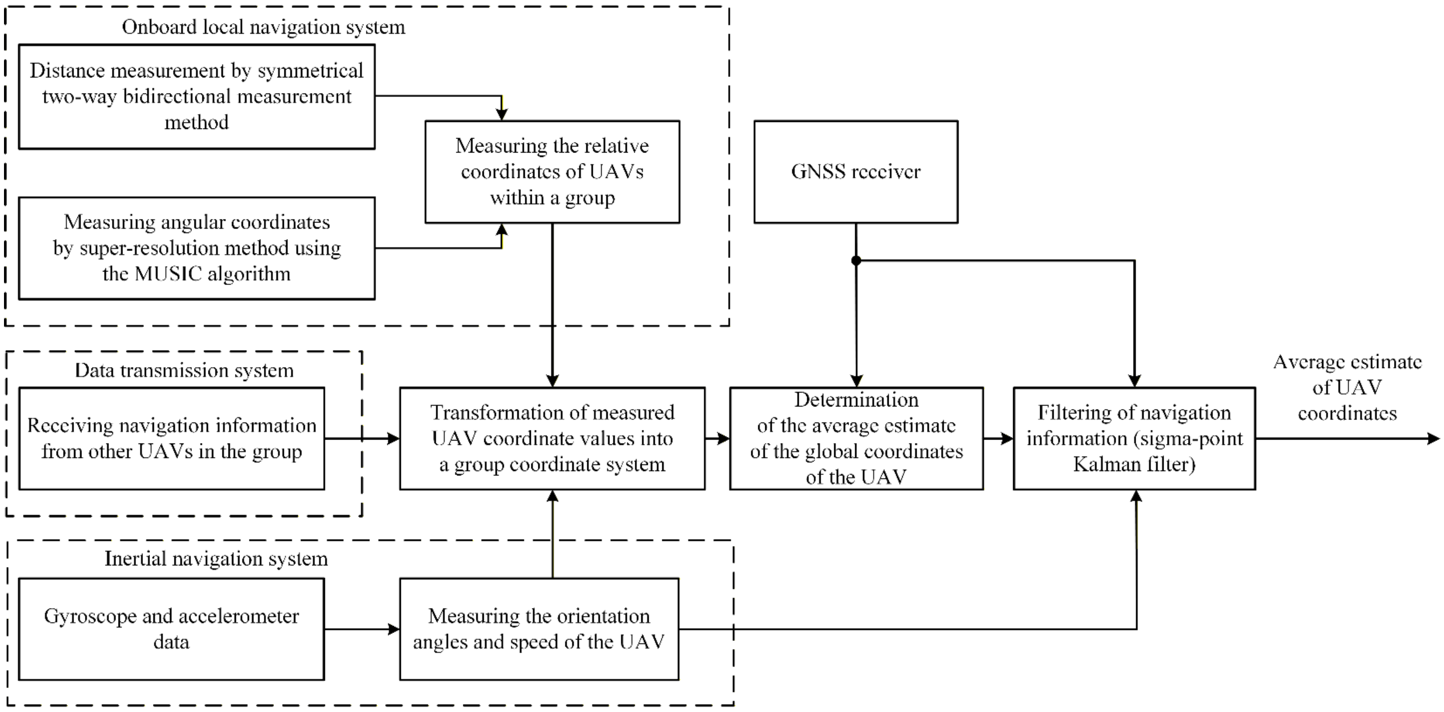

Fig. 3. Integrated onboard navigation system of the UAV

1. Obtaining, via the data transmission system, estimates of the navigation parameters of all group members at the current time in the group coordinate system. The state vectors for the *i*-th UAV are represented by the following equation:

$$\mathbf{p}_i^g\left(x^g, y^g, z^g\right) = \begin{pmatrix} x^g \\ y^g \\ z^g \end{pmatrix}, \qquad (19)$$

where:

x^g, y^g, z^g is the coordinates of the *i*-th UAV in the group coordinate system.

2. The root-mean-square errors of UAV relative coordinate measurements using the onboard local navigation system are significantly smaller than those of the GNSS receiver. Therefore, it is advisable to estimate the relative positions of UAVs participating in the group using data from the onboard local navigation system:

- range between the *i*-th and *j*-th UAVs $D_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$;
- relative azimuth on the UAV $\gamma_{ij} = \mathrm{arctg}\dfrac{x_i - x_j}{y_i - y_j}$;
- relative orientation of the axes of the local coordinate system $\alpha_{ij} = \mathrm{arctg}\dfrac{V_{x_i}}{V_{y_i}} - \mathrm{arctg}\dfrac{V_{x_j}}{V_{y_j}}$, where *x*, *y*, *z* are the coordinates of the UAV in the local coordinate system; V_x, V_y are the components of the velocity along the axes in the horizontal plane.

3. Transformation of the values of the estimated navigation parameters of all UAVs of the group members into the group coordinate system in accordance with to equation (14).

4. Filtering the obtained values to determine whether they contain values that exceed the cut-off threshold in accordance with equation (16).

5. Weighted averaging of centered navigation parameters according to equation (18).

6. Generating a UAV state matrix, which will include additional information about the averaged position estimate of the leader UAV, and transmitting it to the input of the sigma-point Kalman filter. After completing this step, the resulting filtered averaged estimate of the leader UAV's true position in the global coordinate system is transmitted to the other UAVs in the group to refine their own coordinates.

Conclusion

Thus, the required reliability and accuracy of UAV navigation support are ensured through the integrated processing of information from multiple navigation systems within the onboard navigation system. These systems are proposed to be implemented using a GNSS receiver, an inertial navigation system, and an onboard local rangefinder and angle measuring system. The highest accuracy characteristics of such navigation systems can be achieved by integrating and jointly processing navigation information generated by individual navigation systems. In this case, the output data is the navigation information averaged across all sources.

Given the technical complexity of implementing closely coupled integration methods, filtering methods based on extended Kalman filters have found widespread use for joint processing of navigation measurements based on output parameters. These filters perform ongoing linearization of observation equations in the vicinity of the optimal trajectory parameter estimate. Thus, the nonlinear filtering problem is reduced to a linear one, for which an exact analytical solution is known. This algorithm allows for estimating the UAV's state vector by combining current measurement data and extrapolation. However, this algorithm will be quasi-optimal only if the distribution of measurement or extrapolation errors are normal. At the same time, measuring the relative position of UAVs within a group requires a transition from local autonomous coordinate systems to local group and global inertial coordinate systems. This operation is performed using rotation matrices containing nonlinear sine and cosine functions. For this reason, UAVs must be treated as nonlinear systems, resulting in a non-Gaussian distribution of the error in measuring UAV positions within a group. This leads to biased estimates of the mathematical expectation and covariance.

Using a sigma-point Kalman filter to solve a nonlinear filtering problem yields a significantly more accurate distribution. As a result, the mathematical expectation practically coincides with the mean value of the actual dispersion of the sigma points, and the covariance accurately reflects the effect of the nonlinear transformation on the original distribution. In relation to the problem of determining the navigation parameters of a UAV as part of an organized group, the algorithm for implementing the sigma-point Kalman filter will consist of the following stages:

– extrapolation – calculation of sigma points and their weights;

– transformation of sigma points and calculation of new values of the mathematical expectation and covariance matrix;

– update – transformation of the state from the state space to the measurement space;

– calculation of the gain of the sigma-point Kalman filter based on the values of the cross-correlation function between the sigma-points in the state space and the sigma-points in the measurement space;

– optimal filtering of the UAV state vector at a fixed point in time for the values of coordinates, determined by the navigation systems of the UAV autonomously, the UAV group and received through the data transmission system.

Thus, the use of a sigma-point Kalman filter allows for a highly effective solution to the problem of complex processing of navigation information at the secondary parameter level. Navigation information sources can include a GNSS receiver, an inertial navigation system, an onboard local navigation system, and information from the UAVs of the group members, received via the data transmission system. Moreover, such a system allows for the use of data from other navigation systems and sensors – optical-electronic systems, barometric altimeters, radar and lidar systems, etc. – in complex processing without significantly complicating the algorithm.

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КОМПЛЕКСНАЯ ОБРАБОТКА НАВИГАЦИОННОЙ ИНФОРМАЦИИ В ГРУППЕ БПЛА С ИСПОЛЬЗОВАНИЕМ СИГМА-ТОЧЕЧНОГО ФИЛЬТРА КАЛМАНА

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Аннотация
В статье рассматривается задача улучшения точности и надежности навигационного обеспечения беспилотных летательных аппаратов (БПЛА), действующих в составе организованной группы, за счет комплексирования информации от различных навигационных систем. Предложен метод комплексирования навигационной информации от бортового ГНСС-приемника, инерциальной навигационной системы, бортовой локальной навигационной системы, измеряющей дальность и направления между БПЛА группы, а также навигационных данных, полученных от других БПЛА – членов группы с использованием системы передачи данных. В связи с использованием нескольких систем координат – глобальной инерциальной и локальных, связанных с отдельным БПЛА и с БПЛА-лидером, требуется использование матриц поворота при переходе между этими системами координат, которые содержат нелинейные функции синуса и косинуса, из-за чего БПЛА рассматривается как нелинейная система и результирующий закон распределения погрешности измерения положения БПЛА в группе будет отличаться от нормального. Для решения этой проблемы предложено применение нелинейных методов фильтрации. В качестве основного алгоритма обработки обосновано применение сигма-точечного фильтра Калмана, который обеспечивает более высокую точность оценки параметров по сравнению с расширенным фильтром Калмана за счет аппроксимации распределения детерминированным набором сигма-точек. Предложена процедура отбраковки аномальных измерений (мажоритарное голосование) и взвешенного усреднения центрированных навигационных параметров. Показано, что применение сигма-точечного фильтра Калмана позволяет эффективно решать задачу комплексной обработки навигационной информации на уровне вторичных параметров от разнородных источников при сохранении приемлемой вычислительной сложности. Описана функциональная схема бортового интегрированного навигационного комплекса.

Ключевые слова: *БПЛА, групповая навигация, комплексирование навигационных систем, сигма-точечный фильтр Калмана, ГНСС, дальномерно-угломерная навигационная система, нелинейная фильтрация.*

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