Metrol. Meas. Syst., Vol. 26 (2019) No. 3, pp. 541–550
DOI: 10.24425/mms.2019.129580

METROLOGY AND MEASUREMENT SYSTEMS

Index 330930, ISSN 0860-8229
www.metrology.pg.gda.pl

NAVIGATION COMPLEX WITH ADAPTIVE NON-LINEAR KALMAN FILTER FOR UNMANNED FLIGHT VEHICLE

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Abstract

A navigation complex of an unmanned flight vehicle of small class is considered. Increasing the accuracy of navigation definitions is done with the help of a nonlinear Kalman filter in the implementation of the algorithm on board an aircraft in the face of severe limitations on the performance of the special calculator. The accuracy of the assessment depends on the available reliable information on the model of the process under study, which has a high degree of uncertainty. To carry out high-precision correction of the navigation complex, an adaptive non-linear Kalman filter with parametric identification was developed. The model of errors of the inertial navigation system is considered in the navigation complex, which is used in the algorithmic support. The procedure for identifying the parameters of a non-linear model represented by the SDC method in a scalar form is used. The developed adaptive non-linear Kalman filter is compact and easy to implement on board an aircraft.

Keywords: unmanned aerial vehicle, non-linear Kalman filter, parametric identification, SDC representation, implementation in the special calculator.

1. Introduction

A *navigation complex* (NC) of a small class *unmanned aerial vehicle* (UAV), which is used to monitor the underlying surface of the Earth, in urban conditions in the interest of the Ministry of Emergency Situations and the Fire Department is examined. The UAVs of Russian company ZALA, Chinese company DJI, and others belong to the small class. An NC of UAV must have a high accuracy of determining the navigation parameters for the effective functioning of specialized measurement equipment.

Modern UAV's NCs of the studied class consist of an *inertial navigation system* (INS), a GPS signal receiver and a special calculator, which implements the information processing algorithms of the INS and GPS, as well as the UAV control [1, 2]. On small UAVs, special calculators (microcontrollers) of the STM32 version (ARM Cortex-M) are installed. UAV is equipped with NC of INS/GPS. NC has errors associated with the insecurity of the radio channel and the use of low-accuracy INS. During the operation of UAV in the city, NC errors appear due to reflecting GPS signals from the buildings and passive interference of operating equipment, as well as INS errors caused by instability of MEMS elements.

Improving accuracy of the existing NC should be carried out by an algorithmic method. Usually, the algorithmic support for NC includes a linear Kalman filter [3, 4] or its adaptive modifications [5], which perform the evaluation of INS errors and subsequent compensation in the system output signal. The model used in the Kalman filter determines the INS error relationships.

Strap-down INSs (SINSs) made on the basis of MEMS elements are economically efficient, but their errors are clearly non-linear in nature [6]. Gimbaled INS are well established in practice, but more costly. When an aircraft is making manoeuvers, the deviation angles of the *gyro-stabilized platform* (GSP) of the INS relative to the accompanying trihedron of the selected coordinate system increase and the linear model of its errors obtained with the assumption of horizontal movement of the aircraft and small stabilization angles becomes inadequate to the real process [7]. In this connection, it is not possible to carry out high-precision correction of NC using linear Kalman filtering [8, 9].

High-precision correction of NC is carried out using a *non-linear Kalman filter* (NKF) [3, 10]. In flight vehicle manoeuvring conditions, a priori nonlinear models for changing INS errors become inadequate to the actual process, so NKF modifications are used [9, 11], which are carried out using self-organizing algorithms, *neural networks* (NN), genetic algorithms (GA) and self-organizing algorithms, for example, *Group Method of Data Handling* (GMDH) [12, 13]. But such modifications of NKF require increased performance of a special calculator aboard a UAV.

Simplification of the on-board implementation of estimation algorithms is achieved by identifying the models of the process being evaluated, for example, using the least squares method (OLS) [10], but the estimation accuracy is reduced compared with the mentioned NKF modifications.

Thus, when an aircraft is making manoeuvers, in order to maintain the adequacy of the INS error model, it is necessary to perform a parametric identification or model construction (determination of the structure and its parameters). But the implementation of the algorithms for building models requires increased performance of the special calculator and it is not possible to use them to improve the accuracy of NC of the examined class of UAVs. Simplification of implementing identification algorithms using the scalar approach is applied only to linear models; for parametric identification of nonlinear models it is proposed to use the *State Dependent Coefficient* (SDC) representation [14], which enables to represent the nonlinear model as a linear one.

In this paper, an NC with adaptive NKF is developed. The NKF is equipped with a scalar parametric identification procedure for a class of nonlinear INS error models, which is compact and easily implemented in a UAV special calculator [15, 16].

2. Navigation complex with non-linear Kalman filter

Let the equation of the state vector be:

$$\mathbf{x}_k = \mathbf{f}_{k,k-1}(\mathbf{x}_{k-1}) + \mathbf{w}_k, \tag{1}$$

where $\mathbf{x}_k$ – state vector; $\mathbf{f}_{k,k-1}(\mathbf{x}_{k-1})$ – vector of nonlinear system model.

Part of the state vector is measured by:

$$\mathbf{z}_k = \mathbf{H}_k(\mathbf{x}_k) + \mathbf{v}_k, \tag{2}$$

where $\mathbf{z}_k$ – measurement vector; $\mathbf{H}_k$ – measurement matrix; $\mathbf{w}_k$ and $\mathbf{v}_k$ – discrete analogues of Gaussian white noise with zero mathematical expectations and covariance matrices $\mathbf{Q}_k$ and $\mathbf{R}_k$ respectively, both of which are mutually uncorrelated.

NFC equations are as follows [10]:

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_{k,k-1} + \mathbf{k}_k\left(\hat{\mathbf{x}}_{k-1}\right)\left[\mathbf{z}_k - \mathbf{H}_k\hat{\mathbf{x}}_{k,k-1}\right], \tag{3}$$

$$\hat{\mathbf{x}}_{k,k-1} = \mathbf{f}_{k,k-1}(\hat{\mathbf{x}}_{k-1}), \tag{4}$$

$$\mathbf{k}_k\left(\hat{\mathbf{x}}_{k-1}\right) = \mathbf{P}_{k,k-1}\mathbf{H}_k^T\left[\mathbf{H}_k\mathbf{P}_{k,k-1}\mathbf{H}_k^T + \mathbf{R}_k\right]^{-1}, \tag{5}$$

$$\mathbf{P}_{k,k-1} = \frac{\partial\mathbf{f}_{k,k-1}\left(\hat{\mathbf{x}}_{k-1}\right)}{\partial\mathbf{x}_{k-1}^T}\mathbf{P}_{k-1}\left[\frac{\partial\mathbf{f}_{k,k-1}\left(\hat{\mathbf{x}}_{k-1}\right)}{\partial\mathbf{x}_{k-1}^T}\right]^T + \mathbf{Q}_k, \tag{6}$$

$$\mathbf{P}_k = \left[\mathbf{I} - \mathbf{k}_k\left(\hat{\mathbf{x}}_{k-1}\right)\mathbf{H}_k\right]\mathbf{P}_{k,k-1}. \tag{7}$$

Here $\mathbf{k}_k\left(\hat{\mathbf{x}}_{k-1}\right)$ – gain vector of the Kalman filter; $\mathbf{P}_{k,k-1}$ – a priori covariance matrix of estimation errors; $\mathbf{P}_k$ – a posteriori covariance matrix of estimation errors; $\mathbf{I}$ – identity matrix.

Based on the state vector and the object matrix estimation, a forecast is made for the next step of calculating the estimate, using (4). At the same time, this forecast is corrected by using an updated sequence. The updated sequence is the sum of the prediction error and the measurement noise.

The filter gain matrix (6) determines the weight with which the updated sequence is included in the state vector estimate. In the case of ideal measurements, *i.e.* when measurement noise is absent, the gain matrix is chosen as the maximum. The larger the measurement noise, the lower the weight of the updated sequence is taken into account when forming the assessment of the state vector by (3).

With the help of the Kalman filter, not only the reconstruction of the entire system state vector is carried out, but also the influence of the measurement noise is suppressed.

- On the basis of values $\hat{\mathbf{x}}_k$ and $\mathbf{P}_k$ their forecast $x_{k+1,k}$ and $P_{k+1,k}$ is made for the next interval according to (4) and (5), respectively.
- The calculation of the optimal vector of gain coefficients $\mathbf{k}_{k+1}$ (6).
- According to new observation results, a priori value $\mathbf{x}_{k+1,k}$ is improved and becomes the a posteriori estimation value $\hat{\mathbf{x}}_{k+1}$ (3).
- The definition of the a posteriori correlation matrix $\mathbf{P}_{k+1}$ by (7) is carried out for the next step of calculation.

There are various ways of implementing NKF [10, 11]. NKF implementations suggest the linearization of the INS error model using the Taylor series, representing the a posteriori density as a set of delta functions, or replacing the a posteriori density with a system of private Gaussian densities taken with different weights. As a result, only linear models of INS errors are used.

The use of nonlinear Kalman filter models is generally difficult due to the fact that the a posteriori density of the state vector is not Gaussian; therefore, it is not possible to obtain algorithms of recurrent relations for calculating estimates of the state vector. The solution of a stochastic partial differential equation in the form of Ito or Stratonovich involves the integration of equations using special rules, what leads to a significant increase in the volume of required computational resources.

Most fully taking into account all the features of the nature of INS error changes and, most importantly, a specific INS in the conditions of each specific flight, can be achieved by constructing a nonlinear model using algorithms of GMDH, a neural network or a genetic algorithm. The nonlinear model is used as a reference model to ensure the adequacy of the NKF model and the real process of INS error changes.

Figure 1 shows a scheme of the NC, including INS, GPS and NKF when using GMDH.

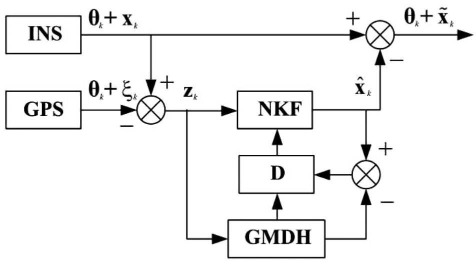

Fig. 1. A block diagram of NC with NFK when using GMDH.

Here θ_k – true navigation information; ξ_k – error vector of GPS; $\mathbf{x}_k$ – error vector of INS; $\mathbf{z}_k$ – measurement vector; $\hat{\mathbf{x}}_k$ – error vector estimate of INS; $\widetilde{\mathbf{x}}_k$ – errors of the INS error estimation; D – indicator of the divergence of the estimation process.

The presented NC is designed for a highly manoeuvrable aircraft and is implemented in the on-board computer. To use NKF on a small UAV, it is necessary to develop a simpler and more compact procedure for identifying the parameters of nonlinear matrix of the INS error model, which provides for implementation in a special calculator.

3. SDC representation of non-linear model of navigation system errors

We represent the system (1), (2) in an equivalent form: the model has the structure of linear differential equations with parameters that depend on the state. Such a representation is called *extended linearization* or *parameterization using system state* (SDC representation).

Consider the SDC representation of a nonlinear model of INS errors, which has the form [14]:

$$\mathbf{x}_k = \mathbf{\Phi}(t_{k-1}, \mathbf{x}_{k-1})\mathbf{x}_{k-1} + \mathbf{w}_{k-1}\,, \tag{8}$$

where:

$$\mathbf{\Phi}(t_{k-1}, \mathbf{x}_{k-1})\mathbf{x}_{k-1} = \begin{bmatrix} 1 & 0 & 0 & -gT & -gx_{3,k-1}T & 0 & 0 & 0 \\ 0 & 1 & gT & 0 & gx_{4,k-1}T & 0 & 0 & 0 \\ 0 & -\dfrac{T}{R} & 1 & 0 & 0 & T & 0 & 0 \\ \dfrac{T}{R} & 0 & 0 & 1 & 0 & 0 & T & 0 \\ \dfrac{T}{R}\tan\varphi & 0 & 0 & 0 & 1 & 0 & 0 & T \\ 0 & 0 & 0 & 0 & 0 & 1-\mu T & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1-\mu T & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1-\mu T \end{bmatrix} \begin{bmatrix} x_{1,k-1} \\ x_{2,k-1} \\ x_{3,k-1} \\ x_{4,k-1} \\ x_{5,k-1} \\ x_{6,k-1} \\ x_{7,k-1} \\ x_{8,k-1} \end{bmatrix},$$

DOI: 10.24425/mms.2019.129580

$$\mathbf{x}_k = \begin{bmatrix} \delta V_{E,k} \\ \delta V_{N,k} \\ \varPhi_{E,k} \\ \varPhi_{N,k} \\ \varPhi_{H,k} \\ \varepsilon_{E,k} \\ \varepsilon_{N,k} \\ \varepsilon_{H,k} \end{bmatrix} = \begin{bmatrix} x_{1,k} \\ x_{2,k} \\ x_{3,k} \\ x_{4,k} \\ x_{5,k} \\ x_{6,k} \\ x_{7,k} \\ x_{8,k} \end{bmatrix}, \qquad \mathbf{w}_{k-1} = \begin{bmatrix} B_{E,k-1} \\ B_{N,k-1} \\ 0 \\ 0 \\ 0 \\ w_{E,k-1} \\ w_{N,k-1} \\ w_{H,k-1} \end{bmatrix}.$$

δV_E, δV_N – errors in determining the speed of the UAV; $\varPhi_E$, $\varPhi_N$, $\varPhi_H$ – deviation angles of the GSP relative to the reference coordinate system; ε_E, ε_N, ε_H – GSP drift velocity; φ – latitude location; w_E, w_N, w_H – external disturbing influences; B_E, B_N – accelerometer zero offset; μ – mean frequency of random change in gyro drift; R – Earth radius; g – gravity acceleration; T – sampling period.

A nonlinear system is fully observable, if the observability condition is satisfied. Gramian observability should exist and be a solution of the Lyapunov equation [16].

Using the SDc representation, it becomes possible to use not only (2) as the measurement equation, but also the equation without limitation – with the nonlinear dependence of the measurement matrix on the state $\mathbf{x}_k$.

$$z_k = h_k(\mathbf{x}_k) + \mathbf{v}_k, \tag{9}$$

where $h_k(\mathbf{x}_k)$ is a function.

The measurement (9) after conversion with the SDC method is:

$$\mathbf{y}_k = \mathbf{H}(t_k, \mathbf{x}_k)\mathbf{x}_{k-1} + \mathbf{v}_k\,. \tag{10}$$

It is assumed that $\mathbf{w}_k$ and $\mathbf{v}_k$ are Gaussian “white” uncorrelated noises, and for any j and k, v_j and w_k are mutually uncorrelated (*i.e.* $M[\mathbf{v}_j\,\mathbf{w}_k^T] = 0$).

The measurement expression $\mathbf{y}_{k+1}$ for the state vector, using n measurements taken is:

$$\begin{aligned}
\mathbf{y}_k &= \mathbf{H}(t_k, \mathbf{x}_k)\,\mathbf{x}_k + \mathbf{v}_k\,,\\
\mathbf{y}_{k+1} &= \mathbf{H}(t_{k+1}, \mathbf{x}_{k+1})\,\mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{x}_k + \mathbf{H}(t_{k+1}, \mathbf{x}_{k+1})\,\mathbf{w}_k + \mathbf{v}_{k+1}\,,\\
&\dots \qquad \dots \qquad \dots\\
\mathbf{y}_{k+n-1} &= \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\,\mathbf{\Phi}(t_{k+n-2}, \mathbf{x}_{k+n-2})\cdots\mathbf{\Phi}(t_k, \mathbf{x}_k)\,\mathbf{x}_k +\\
&\quad + \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\,\mathbf{\Phi}(t_{k+n-2}, \mathbf{x}_{k+n-2})\cdots\mathbf{\Phi}(t_{k+1}, \mathbf{x}_{k+1})\,\mathbf{w}_k +\\
&\quad + \cdots + \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\,\mathbf{w}_{k+n-2} + \mathbf{v}_{k+n-1}\,.
\end{aligned} \tag{11}$$

In the matrix form:

$$\mathbf{y}_k^* = \mathbf{O}_k^*\mathbf{x}_k + \mathbf{v}_k^*, \tag{12}$$

where:

$$\mathbf{y}_k^* = \begin{bmatrix} \mathbf{y}_k \\ \mathbf{y}_{k+1} \\ \vdots \\ \mathbf{y}_{k+n-1} \end{bmatrix}, \qquad \mathbf{O}_k^* = \begin{bmatrix} \mathbf{H}(t_k, \mathbf{x}_k) \\ \mathbf{H}(t_{k+1}, \mathbf{x}_{k+1})\,\mathbf{\Phi}(t_k, \mathbf{x}_k) \\ \dots \quad \dots \quad \dots \\ \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\,\mathbf{\Phi}(t_{k+n-2}, \mathbf{x}_{k+n-2})\cdots\mathbf{\Phi}(t_k, \mathbf{x}_k) \end{bmatrix},$$

$$\mathbf{v}_k^* = \begin{bmatrix} \mathbf{v}_k \\ \mathbf{H}(t_{k+1}, \mathbf{x}_{k+1})\mathbf{w}_k + \mathbf{v}_{k+1} \\ \cdots \quad \cdots \quad \cdots \\ \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\mathbf{\Phi}(t_{k+n-2}, \mathbf{x}_{k+n-2}) \cdots \mathbf{\Phi}(t_{k+1}, \mathbf{x}_{k+1})\mathbf{w}_k + \\ + \cdots + \mathbf{H}(t_{k+n-1}, \mathbf{x}_{k+n-1})\mathbf{w}_{k+n-2} + \mathbf{v}_{k+n-1} \end{bmatrix},$$

the vectors $\mathbf{y}_k^*$, $\mathbf{v}_k^*$ and the matrix $\mathbf{O}_k^*$ include parameters that depend on the state.

When NC is functioning, some parameters of the matrix of the model of (8) change and compensation of INS errors with the help of NKF becomes ineffective. Therefore, in order to preserve the adequacy of the model to the process of the INS error changes, these parameters should be identified during the flight of UAV. For this it is necessary to develop a procedure for parametric identification.

4. Parametric identification procedure

Consider the SDC representation of the model (8) and the measurement (11). In this case, the state vector $\mathbf{x}_{k+n}$ can be expressed by its value at the initial moment $\mathbf{x}_k$ of time in the form:

$$\begin{aligned} \mathbf{x}_{k+n} = {} & \mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{x}_k \\ & + \mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_{k+1}, \mathbf{x}_{k+1})\mathbf{w}_k \\ & + \cdots + \mathbf{w}_{k+n-1} \,. \end{aligned} \tag{13}$$

Substituting the expression for $\mathbf{x}_{k+n}$ into the measurement equation $\mathbf{y}_{k+n}$, we obtain:

$$\begin{aligned} \mathbf{y}_{k+n} = {} & \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{x}_k \\ & + \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_{k+1}, \mathbf{x}_{k+1})\mathbf{w}_k \\ & + \cdots + \mathbf{H}_{k+n}\mathbf{w}_{k+n-1} + \mathbf{v}_{k+n} \,. \end{aligned} \tag{14}$$

Substituting the expression $\mathbf{x}_k$ in (13), we obtain:

$$\begin{aligned} \mathbf{y}_{k+n} = {} & \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{O}_k^+\mathbf{y}_k^* \\ & - \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{O}_k^+\mathbf{v}_k^* \\ & + \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_{k+1}, \mathbf{x}_{k+1})\mathbf{w}_k \\ & + \cdots + \mathbf{H}_{k+n}\mathbf{w}_{k+n-1} + \mathbf{v}_{k+n} \,, \end{aligned} \tag{15}$$

where $\mathbf{O}_k^+ = \left[\mathbf{O}_k^{*T}\mathbf{O}_k^*\right]^{-1}\mathbf{O}_k^{*T}$ – pseudo-inverse matrix $\mathbf{O}_k^*$.

We introduce the notation:

$$\begin{bmatrix} \lambda_{1,k} & \lambda_{2,k} & \cdots & \lambda_{n,k} \end{bmatrix} = \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{O}_k^+ \,, \tag{16}$$

$$\begin{aligned} \mathbf{v}_k^0 = {} & \mathbf{H}_{k+n}\mathbf{\Phi}(t_{k+n-1}, \mathbf{x}_{k+n-1}) \cdots \mathbf{\Phi}(t_k, \mathbf{x}_k)\mathbf{O}_k^+\mathbf{v}_k^* \\ & + \cdots + \mathbf{H}_{k+n}\mathbf{w}_{k+n-1} + \mathbf{v}_{k+n} \,. \end{aligned} \tag{17}$$

Metrol. Meas. Syst., Vol. 26 (2019), No. 3, pp. 541–550
DOI: 10.24425/mms.2019.129580

Then, the setting of the identification problem is reduced to the determination of unknown elements of the column vector $[\lambda_{1,k}\ \lambda_{2,k}\ \ldots\ \lambda_{n,k}]$ from the newly formed measurements, *i.e.*:

$$\begin{aligned} \lambda_{1,k} &= f_{1,k}\left(y_k, \cdots, y_{k+2n-1}\right) + v_k^{00}, \\ \lambda_{2,k} &= f_{2,k}\left(y_k, \cdots, y_{k+2n-1}\right) + v_{k+1}^{00}, \\ &\ldots \qquad \ldots \qquad \ldots \\ \lambda_{n,k} &= f_{n,k}\left(y_k, \cdots, y_{k+2n-1}\right) + v_{k+n-1}^{00}, \end{aligned} \tag{18}$$

where:

$$\begin{bmatrix} f_{1,k}\left(y_k, \cdots, y_{k+2n-1}\right) \\ f_{2,k}\left(y_k, \cdots, y_{k+2n-1}\right) \\ \cdots \\ f_{n,k}\left(y_k, \cdots, y_{k+2n-1}\right) \end{bmatrix} = \begin{bmatrix} y_k & y_{k+1} & \cdots & y_{k+n-1} \\ y_{k+1} & y_{k+2} & \cdots & y_{k+n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{k+n-1} & y_{k+n} & \cdots & y_{k+2n-2} \end{bmatrix}^{-1} \begin{bmatrix} y_{k+n} \\ y_{k+n+1} \\ \cdots \\ y_{k+2n-1} \end{bmatrix},$$

$$\begin{bmatrix} v_k^{00} \\ v_{k+1}^{00} \\ \cdots \\ v_{k+n-1}^{00} \end{bmatrix} = \begin{bmatrix} y_k & y_{k+1} & \cdots & y_{k+n-1} \\ y_{k+1} & y_{k+2} & \cdots & y_{k+n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{k+n-1} & y_{k+n} & \cdots & y_{k+2n-2} \end{bmatrix}^{-1} \begin{bmatrix} v_k^{0} \\ v_{k+1}^{0} \\ \cdots \\ v_{k+n-1}^{0} \end{bmatrix}.$$

Thus, the formal dependence (18) is used to identify the parameters of the matrix $\mathbf{\Phi}(t_k, \mathbf{x}_k)$.

The dispersion of the original measurement noise is either determined from practical considerations in accordance with the mode of operation of the measurement system or is taken from the passport of the measurement device.

Figure 2 shows a scheme of NC with NKF and identification procedure.

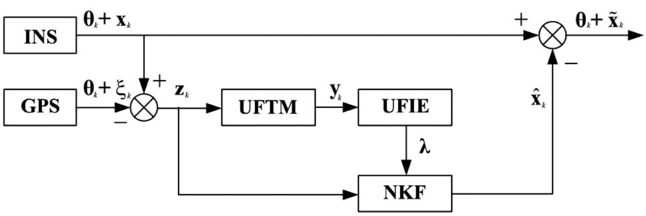

Fig. 2. A block diagram of NC with NKF and identification procedure.

Here UFTM – unit for forming the taken measurements; UFIE – unit for forming the identifiable elements.

An adaptive modification of the NKF was developed, which enables to identify unknown coefficients of the estimated model during the flight of a small UAV.

5. Experiment results

In order to test the performance of the proposed algorithm, full-scale tests of the UAV with NC equipped with various algorithms were carried out. A UAV of vertical take-off and landing was used, *i.e.* an aircraft which can take off and land at zero horizontal speed. 180 experiment flights of UAVs (20 flights for each configuration of the algorithmic support of the UAV UC) were carried out in similar weather conditions and time of day.

The flight was carried out along a distance of 500 m. In the course of the experiment, the UAV automatically carried out a vertical flight, moving at a constant height with a constant speed to a landing point, and a vertical landing. The coordinates of landing point are known. The real deviation of the UAV from the landing point is recorded. The obtained values of the deviations of the UAV from a given landing point depend on the accuracy of the NC. The errors of the INS over time accumulate; therefore, complex processing of the GPS and INS signals is performed in the NC. In the course of the experiment, the accuracy of NC with linear *Kalman filter* (KF), *adaptive linear KF* (AKF), NKF, NKF with OLS, NKF with GMDH, NKF with GA, NKF with NC and NKF with the developed parametric identification procedure (NKF + PI) is estimated.

In the estimation algorithms, when assigning the input and measurement noise covariance matrices, the following values are taken: w_E, w_N, w_H – disturbing effects caused by the drift of gyroscopes, the corresponding values of the covariance matrix of the input noise in the estimation algorithms are taken as $1.7 \cdot 10^{-10}$ rad/s; the errors caused by zero offset in accelerometer readings: B_E, $B_N = 10^{-3}$ m/s^2. These values are used to form the covariance matrix of the input noise in the estimation algorithms.

For the Ublox-M8N GPS receiver, the following values are commonly used in the covariance matrix of the KF measurement noise: $r = 3 \cdot 10^{-3}$ m^2/s^2. They are constant values of the covariance matrix adopted in Kalman filter, due to GPS errors in determining the speed.

In the conditions of the experiment, the accuracy of estimation is reduced due to interference (signals reflected from buildings, *etc*.). Therefore, in the estimation algorithms, overestimated values are used in the covariance matrices of measurement noise: r = 0.06 m^2/s^2.

The accuracy of NC equipped with various algorithms for complex information processing was compared with the accuracy of an autonomous INS. Autonomous INS errors without algorithmic correction are taken as 100%. With the help of KF in NC 72% of the autonomous INS error is compensated. The residual error of NC with KF is 28% of the nominal value (autonomous INS error).

Characteristics of the algorithms: the accuracy of the NC correction with the help of the mentioned algorithms and the required amount of memory when they are implemented in the special calculator are given in Table 1.

Table 1. Characteristics of the algorithms.

Algorithms	**Correction accuracy**	**Required memory**	**Required amount of calculation**
KF	72%	4 k	80 k
AKF	78%	5 k	100 k
NKF	81%	8 k	150 k
NKF + OLS	84%	16 k	180 k
NKF + GMDH	89%	20 k	1,000 k
NKF + PI	89%	10 k	200 k
NKF + NN	90%	30 k	3,000 k
NKF + GA	91%	50 k	7,000 k

The memory capacity of the special calculator of a small UAV is 256 kB. Under severe constraints on computing resources, a developed adaptive NKF with a parametric identification procedure has maximum accuracy.

DOI: 10.24425/mms.2019.129580

The accuracy characteristics of UAV's NC equipped with various algorithmic software are presented in Table 2.

Table 2. Accuracy characteristics of UAV's NC.

NC algorithms	**Correction accuracy required memory**	
	Location error	**Speed error**
Autonomous INS	45−55	0.4−0.5 m/s
KF	12−15 m	0.12 m/s
AKF	11−12 m	0.10 m/s
NKF	10 m	0.08 m/s
NKF + OLS	8 m	0.07 m/s
NKF + GMDH	5 m	0.04 m/s
NKF + PI	4−5 m	0.04 m/s
NKF + NN	3−5 m	0.03 m/s
NKF + GA	1−2 m	0.02 m/s

Table 2 shows the average values obtained from a series of experiments.

Thus, NC with the developed correction algorithm enables to obtain navigation information with greater accuracy, which increases the efficiency of a small UAV.

6. Conclusions

An adaptive NKF with a parametric identification procedure for nonlinear INS error models has been developed. The nonlinear models are represented in the form of models with a linear structure with the use of the SDC method. Such a representation of the models enabled to use the scalar form of the model of measurements to simplify the implementation of the algorithm in the special calculator of a small UAV. Thus, for the correction of NC, an adaptive NKF was obtained with a procedure for identifying the parameters of a nonlinear model of a single class of nonlinear systems, which can be easily implemented in the special calculator of a small class UAV.

Acknowledgements

The work was performed in the framework of the State Mission of the Ministry of Education and Science of the Russian Federation (Project No. 2.7486.2017/BC) .

References

[1] Moir, I., Seabridge, A.G. (2008). *Aircraft Systems: Mechanical, electrical and avionics subsystems integration*. 3rd edition, Chichester: John Willey and Sons Ltd.

[2] Selezneva, M.S., Neusypin, K.A. (2016). Development of a measurement complex with intelligent component. *Measurement Techniques*, 59(9), 916–922.

[3] Julier, S.J., Uhlmann, J.K. (1997). A New Extension of the Kalman Filter to Nonlinear Systems. *Defense Sensing, Simulation and Controls*, 3068, 182–193.

[4] Kalman, R.E. (1960). A new approach to linear filtering and prediction problems. *Trans. ASME. Ser.D, Journal of Basic Engeneering*, 82, 35–45.

[5] Mirosław, Ś., Magdalena, D. (2015). Application of Kalman filter in navigation process of automated guided vehicles. *Metrol. Meas. Syst.*, 22(2), 443–454.

[6] Salychev, O.S. (2012). MEMS-based inertial navigation: Expectations and reality. *Moscow: Bauman MSTU Press*.

[7] Groves, P.D., Handley, R.J., Runnalls, A.R. (2006). Optimising the integration of terrain-referenced navigation with INS and GPS. *Journal of Navigation*, 59(1), 71–89.

[8] Carlson, N.A. (1990). Federated square root filter for decentralized parallel processors. *IEEE Transactions on Aerospace and Electronic Systems*, 26(2), 517–525.

[9] Xing, Z.R., Xia, Y.Q. (2016). Distributed federated Kalman filter fusion over multi-sensor unreliable networked systems. *IEEE Transactions on Circuits and Systems*, 63(8), 1714–1725.

[10] Verhaegen, M., Verdult, V. (2007). Filtering and system identification: a least squares approach. *Cambridge University Press*.

[11] Shen K., *et al.* (2018). Quantifying observability and analysis in integrated navigation. *Navigation, Journal of the Institute of Navigation*, 65(1), 169–181.

[12] Shen, K., Selezneva, M.S., Neusypin, K.A., Proletarsky, A.V. (2017). Novel variable structure measurement system with intelligent components for flight vehicles. *Metrol. Meas. Syst.*, 24(1), 347–356.

[13] Shen, K., Proletarsky, A.V., Neusypin, K.A. (2016). Algorithms of constructing models for compensating navigation systems of unmanned aerial vehicles. *2016 International Conference on Robotics and Automation Engineering*, Aug. 27–29, Jeju-Do, South Korea, 104?108.

[14] Tayfun, Ç. (2008). State-Dependent Riccati Equation (SDRE) Control: A Survey Tayfun Cimen Proceedings of the 17th World Congress. *The International Federation of Automatic Control*. Seoul, Korea, Jul. 6–11, 3761–3775.

[15] Prošek, J., Šímová, P. (2019). UAV for mapping shrubland vegetation: Does fusion of spectral and vertical information derived from a single sensor increase the classification accuracy? *International Journal of Applied Earth Observation ad Geoinformation 75*, 151–162.

[16] Qiao, Y., Zhang, Y., Du, X. (2018). A Vision-Based GPS-Spoofing Detection Method for Small UAVs. *Proc. – 13th International Conference on Computational Intelligence and Security, CIS 2017*, 312–316.

[17] Afanas'ev, V.N., Kaperko, A.F., Kulagin, V.P., Kolyubin, V.A. (2017). Method of adaptive filtering in the problem of restoring parameters of cosmic radiation. *Automation and Remote Control*, 78(3), 397–411.