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ADAPTIVE FILTRATION OF PARAMETERS OF THE UAV MOVEMENT BASED ON THE TDOA-MEASUREMENT SENSOR NETWORKS

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Abstract - On the basis of a mathematical apparatus of the mixed Markov processes in discrete time optimum and quasioptimum adaptive algorithms for filtration of parameters of the UAV movement based on the TDOA-measurement sensor networks are synthesized. Devices that they are realized, are multichannel and belongs to the class of devices with feedback between channels. The analysis of a quasioptimum adaptive algorithm is made by means of statistical modeling.

Keywords - UAV, wireless sensor networks, optimum and quasioptimum adaptive algorithms, parameters of the movement, TDoA.

Introduction

At the present time the development of technologies for construction of unmanned aerial vehicles (UAVs) are used for the solution of a wide range of tasks, such as: emergency rescue operations, autonomous observation and monitoring of industrial processes and environment (fauna monitoring), etc. On the other hand, their availability and massive use for a wide range of problems has led to the emergence of a new class of threats [1-3]: application in terrorist purposes, photographing of secret objects, receiving unauthorized access to information in WLAN networks, invasion on the forbidden territory, etc. This leads to the need to develop security systems that solve the problem of detection, positioning and movement parameters of the UAV.

When an UAVs emits, its location can be determined by wireless sensor networks (WSN) [4,5] with use of methods of a passive location. Wide circulation in this case finds the time difference of arrival method (TDOA), in which the differences of times of reception of signals received by various sensors and the reference sensor WSN are used. This method has an essential advantage in simplicity of implementation and finds broad practical application [6,7].

A feature of modern UAVs is the ability to perform sudden maneuvers, and keep the same position in the point in space. Changing of the type of UAV movement occurs in a random, unknown to the observer moments of time, and this allows to represent a trajectory in the form of stochastic process with random change of structure. At intervals of unresponsiveness and the movements UAVs without maneuver it is possible to increase the accuracy of estimation of it's coordinates considerably. Thus, in practice, also often the interest is to determine the types of UAV movement.

Therefore, the importance have the synthesis of adaptive algorithms of parameters filtration of parameters of the UAV movement according to sensor network data, in which recognition of different types of it's movement is also carried out.

Problem definition

The movement UAV with different types of maneuver in rectangular system of coordinates can be described by a stochastic dynamic system with random structure in the form [8]:

$$u(k) = F_j u(k-1) + G_j \omega(k), \quad j = \overline{1,M};. \qquad (1)$$

where $u(k)$ - the state vector including parameters of the UAV movement for axes of rectangular system of coordinates; F_j, G_j - the matrixes describing different types of movement; $\omega(k)$ - the uncorrelated sequence of Gaussian vectors with a single correlation matrix.

For a description of the type of model structure of UAV movements (1), corresponding to a certain type of maneuver there is applied switching variable $a_j(k)$, $j = \overline{1,M}$. It belongs to the class of Markov chains that allows to consider transitions between different types of the UAV movement at random times.

For definition of UAV location the wireless sensor network has to consist not less than of four sensors. When using TDOA, differences of signals reception times between sensors $s = \overline{1,S}$ and the basic sensor with coordinates of $x^0 = 0$, $y^0 = 0$ are measured.

During propagation of a signal from the UAV to sensors of network, it's coordinate don't change. Therefore, it is assumed that the measurements of the differences of distances between the sensors and the reference sensor are received in the *k*-th moment of time, as which the moment of receipt of a signal to the basic sensor with coordinates of x^0, y^0 is used. In this case observation equation that describes the process of measuring the coordinates of UAV by sensor network has the form

$$\Delta^s(k) = h^s(u(k)) + \upsilon^s(k), \; s = \overline{1,S}, \tag{2}$$

where $\Delta^s(k)$ – the measured difference of distances between the *s*–th sensor and the reference sensor in the *k*–th moment of time, $s = \overline{1,S}$; $\upsilon^s(k)$ – the measurement error of *s*–th sensor with dispersion d^s; $h^s(u)$ – the nonlinear function, which is described by the expression

$$\begin{aligned} h^s(u(k)) &= \sqrt{(x(k) - x_s)^2 + (y(k) - y_s)^2} - \\ &- \sqrt{x^2(k) + y^2(k)} - \upsilon^0(k); \end{aligned} \tag{3}$$

$x(k), y(k)$ – coordinates of the UAV position; x^s, y^s – coordinates of the *s*-th sensor position; $\upsilon^0(k)$ – the distances measurement error for the reference sensor with dispersion d^0. Measurements obtained from all sensors is denoted as a vector $u_\Delta(k) = (\Delta^1(k), ..., \Delta^S(k))^T$.

On the basis of the model of the UAV movement (1) and the observation equation for sensor network (2) it is necessary to synthesize optimum and quasioptimum adaptive algorithms the filtration of parameters of the UAV movement according to sensor network, in which the detection of different types of motion is carried out.

Development

The equation (1) describes the process to be estimated, and (2) - the process of formation of data accessible to observation. For a description of the type of maneuver there is used the random variable $a_j(k)$, $j = \overline{1,M}$, which belongs to the class of chains of Markov, accepting the M values with a matrix of probabilities of transitions $\Pi_{i,j}(k, k-1), i, j = \overline{1,M}$ and initial probabilities $p_i(0)$, $i = \overline{1,M}$. Measurement errors $\upsilon^s(k)$, $s = \overline{1,S}$ are independent.

Applying the technique of expansion of a condition vector of the filtered process considered in the monograph [8] it is possible to show that the expanded process, which includes a continuous component $u(k)$, belongs to the class of the mixed Markov processes (MMP) in discrete time.

The problem of synthesis of an optimum algorithm comes down to calculation of aposteriori probability density (PD) of expanded process $W(u(k), a_j(k)) = P(u(k), a_j(k) / U_\Delta(k))$, where $U_\Delta(k) = u_\Delta(1), ..., u_\Delta(k)$ - the sequences of measurements received to *k*-th moment, inclusive. Introducing also designation of the extrapolated PD $W^*(x(k), a_j(k)) = P(u(k), a_j(k) / U_\Delta(k-1))$ for expanded process and following the technique of synthesis, considered in the monograph [8], it is possible to show that the optimum algorithm of a filtration can be presented in the form of two recurrent equations

$$\begin{aligned} W^*(u(k), a_j(k)) &= \sum_{i=1}^{M} \Pi_{ij}(k, k-1) \times \\ &\times \int_{-\infty}^{\infty} \Pi(u(k) / u(k-1), a_j(k)) \times \\ &\times W(u(k-1), a_i(k-1)) du(k-1); \end{aligned} \tag{4}$$

$$\begin{aligned} W(u(k), a_j(k)) &= \prod_{s=1}^{S} P(\Delta^s(k) / u(k)) \times \\ &\times W^*(u(k), a_j(k)) / P(u_\Delta(k) / U_\Delta(k-1)), \end{aligned} \tag{5}$$

where $P(u_p(k) / u(k))$ - one-step-likelihood function, defined on the basis of equation (4); $\Pi(u(k) / u(k-1))$ - the conditional PD defined by the equation (1); $W(u(k), a_j(k))$ - the joint posterior PD $u(k), a_j(k)$; $U_\Delta(k) = u_\Delta(1), ..., u_\Delta(k)$ - the sequences of measurements received.

The equation (4) describes evolution of the extrapolated PD $W^*(u(k), a_j(k))$ and is also an optimum algorithm of extrapolation of MMP $\xi(k)$ for one step. With the help of the relation (5) adjustment of extrapolated PD based on the obtained measurement $u_\Delta(k)$ is made and aposteriori PD $W(u(k), a_j(k))$ is defined.

Further transformation of expressions (4), (5) can be executed by means of the theorem of multiplication of probabilities. In this case the optimal filtering algorithm can be represented as the following system of recurrent equations

$$W_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1)\ ; \qquad (6)$$

$$W_j^*(u(k)) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) \times$$
$$\times \int_{-\infty}^{\infty} \Pi(u(k)/u(k-1), a_j(k)) \times \qquad (7)$$
$$\times W_i\ (u(k-1)) du(k-1) / W_j^*(k);$$

$$W_j\ (u(k)) = P(u_\Delta(k)/u(k)) \times$$
$$\times W_j^*(u(k)) / P(u_\Delta(k)/a_j(k), U_\Delta(k-1)); \qquad (8)$$

$$W_j\ (k) = \prod_{s=1}^{S} P(\Delta^s(k)/a_j(k), U_\Delta(k-1)) \times$$
$$\times W_j^*(k) / P(u_\Delta(k)/U_\Delta(k-1)), \qquad (9)$$

where $W_j^*(u(k))$, $W_j\ (u(k))$ - the conditional extrapolated and aposteriori PD of the vector $u(k)$ on condition $a_j(k)$; $W_j^*(k)$, $W_j\ (k)$ - extrapolated and a posterior probabilities $a_j(k)$; $P(u_\Delta(k)/a_j(k), U_\Delta(k-1))$ - the conditional PD determined by the formula

$$P(u_\Delta(k)/a_j(k), U_\Delta(k-1)) =$$
$$= \int_{-\infty}^{\infty} P(u_\Delta(k)/u(k), a_j(k)) W_j\ (u(k)) du(k),$$

$P(u_\Delta(k)/U_\Delta(k-1))$ - determined by the formula

$$P(u_\Delta(k)/U_\Delta(k-1)) =$$
$$= \sum_{j=1}^{M} P(u_\Delta(k)/a_j(k), U_\Delta(k-1)) W_j^*(k).$$

The initial conditions for the algorithm (6)...(9) have the form

$$W_i\ (0) = p_i\ (0), W_i(u(0)) = P(u(0))\ ,\ i = \overline{1,M}\ .$$

By means of the equations (6), (9) the filtration of discrete components is carried out and filtration of a continuous component by means of the equations (7), (8). The feature of the algorithm is the indissoluble connection of the filtration equations for discrete and continuous components.

The optimum device, that implements the algorithm (6)... (8), is multichannel with number of channels M. It belongs to the class of devices with feedback between channels. Existence of feedback between channels is caused by Markov property of a discrete component $a_j(k)$.

The disadvantage of the optimum algorithm is the large computational cost associated with the need for integration of the multidimensional PD. When synthesizing a quasioptimum algorithm, we will use a sequential method of processing incoming data. We will enter the index l, which characterizes the sequence of receipts of measurements from the corresponding sensors of network. The quasioptimum algorithm of an adaptive filtration can be received by decomposition of vector-valued function (2), in a Taylor series in the vicinity of the points $u(k)$ and restriction by linear members of decomposition, and also application on each step of Gaussian approximation of the conditional extrapolated PD $W_j^*(u(k))$. In this case the equation of calculation of the conditional extrapolated PD $W_j^*(u(k))$ (7) comes down to calculation of it's first $u_j^*(k)$ and second $P_j^*(k)$ $P_j^*(k)$ moments by the formulas [8]

$$u_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) F \hat{u}_i\ (k-1) / W_j^*(k)\ ;(10)$$

$$P_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) \times$$
$$\times \left\{ F_j\ \hat{P}_i\ (k-1) F_j^{\ T} + G_j G_j^{\ T} \right\} / W_j^*(k). \qquad (11)$$

Equation of calculation of conditional aposteriori PD $W_j\ (u(k))$ (8) at seqentially processing of the arriving measurements $\Delta^l(k), l = \overline{1,S}$ comes down to calculation of it's first $\hat{u}_j(k)$ and second $\hat{P}_j\ (k)$ moments using the recurrent procedure [9]

$$K_j^l(k) = \hat{P}_j^{l-1}(k) \frac{\partial h^{lT}(\hat{u}_j^{l-1}(k))}{\partial u(k)} \left(D_j^l(k) \right)^{-1}; \qquad (12)$$

$$\hat{u}_j^l(k) = \hat{u}_j^{l-1}(k) + K_j^l(k)(\Delta^l(k) - h^l(\hat{u}_j^{l-1}(k)))\ ; \qquad (13)$$

$$\hat{P}_j^l(k) = \hat{P}_j^{l-1}(k) - K_j^l(k) \frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)} \hat{P}_j^{l-1}(k)\ , \qquad (14)$$

where $\hat{u}_j^l(k)$, $\hat{P}_j^l(k)$ - expected value and correlation matrix of conditional aposteriori PD $W_j(u(k))$, refined by measurements $\Delta^s(k), s=\overline{1,l}$. In this case the initial conditions for the procedure (12)…(14) at l=0 has the form $\hat{u}_j^0(k)=u_j^*(k), \hat{P}_j^0(k)=P_j^*(k), j=\overline{1,M}$, and $\hat{u}_j(k)=\hat{u}_j^L(k), \hat{P}_j(k)=\hat{P}_j^L(k), \quad j=\overline{1,M}$. The advantage of this method is an opportunity to organize processing with limited computing resources.

The algorithm of the filtration of discrete components doesn't change and is described by the equations (6), (9).

In this case conditional PD $P(u_\Delta(k)/a_j(k),U_\Delta(k-1))=N(H(u_j^*(k)),D_j(k))$ is Gaussian, and correlation matrix $D_j(k)$ is determined by the expression

$$D_j^l(k)=\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)}\hat{P}_j^{l-1}(k)\frac{\partial h^{lT}(\hat{u}_j^{l-1}(k))}{\partial u(k)}+d^l(k). \quad (15)$$

The quasioptimum device, that implements the algorithm (6),(9) … (14), also is multichannel with number of channels M and generally keeps the structure and all feedback inherent for the optimum device. Their difference is that in quasioptimum device only the first and second moments of conditional PD $W_j^*(u(k))$ and $W_j(u(k))$ is calculates. In this case the quasioptimum algorithm allows to keep representation of aposteriori PD $W(u(k))$ in the form of the sum of the M Gaussian densities.

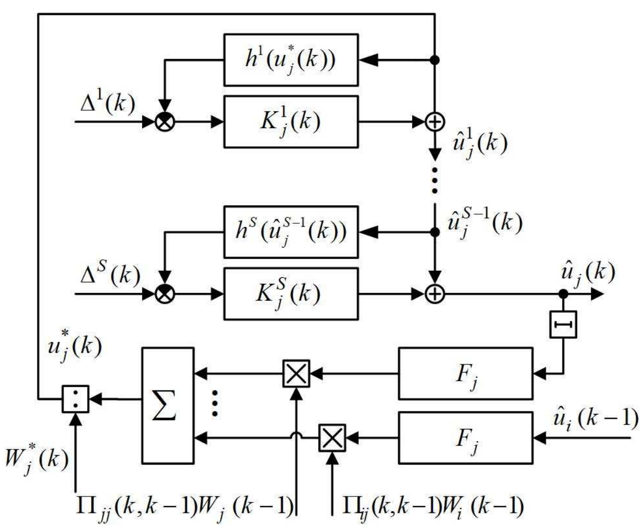

Fig. 1. Block diagram of one channel quasioptimum filter at consecutive realization of calculations

The block diagram of the j-th channel of such quasioptimum filter is shown in Fig. 1. In this case, the processing of observations $\Delta^l(k), l=\overline{1,L}$, in j - th channel is carried out parallel to the L channels that allows to increase information processing speed.

The effectiveness of the algorithm analysis

Efficiency analysis of a developed quasioptimum adaptive filtering algorithm of parameters of the target movement (6),(9)…(14) is carried out by means of statistical modeling.

Modeling of algorithms is carried out for a configuration of sensor network (fig. 2) which consists of nine sensors for definition of UAV location with coordinates: $S_0(0;0;0)$, $S_1(0;100;44)$, $S_2(70.71;70.71;6)$, $S_3(100;0;48)$, $S_4(70.71;-70.71;10)$, $S_5(0;-100;52)$, $S_6(-70.71;-70.71;14)$, $S_7(-100;0;56)$, $S_8(-70.71;70.71;18)$.

For formation of the target movement, model (1), (2) was used. For descriptive reasons of the algorithm works the test trajectory of the UAV movement (fig. 1) has been created. The trajectory consists of five sections: first 1<k<19 – uniform motion, second 20<k<27 – maneuver, height reduction, third 28<k<42– uniform motion, fourth 43<k<45 – maneuver, fifth 46<k<59 – uniform motion, sixth 60<k<67 – maneuver, rise to height, seventh 68<k<85 – uniform motion, eighth 85<k<114 – hanging, ninth 115<k<130 – uniform motion. Error RMS of measurement $\sigma_v=2.4$ m, rate of receipt of information T=1s. Tests were carried out for hundred realizations.

For the description of the UAV movement the model with random structure (1) which considers three main types of the movement $M=3$ was used: hanging $j=1$, almost uniform motion $j=2$, movement with maneuver $j=3$.

The state vector $u^T(k)=(x(k),\dot{x}(k),\ddot{x}(k),y(k),\dot{y}(k),\ddot{y}(k),z(k),\dot{z}(k),\ddot{z}(k))$ includes position coordinates, velocity and acceleration along the axes X, Y, Z. The matrixes included in the motion model (1) have the form

$$F_j(k,k-1)=\begin{bmatrix} F_j^b & 0 & 0 \\ 0 & F_j^b & 0 \\ 0 & 0 & F_j^b \end{bmatrix}, \quad G_j(k)=\begin{bmatrix} G_j^b & 0 & 0 \\ 0 & G_j^b & 0 \\ 0 & 0 & G_j^b \end{bmatrix},$$

where F_j^b, G_j^b, $j=\overline{1,3}$ have the form

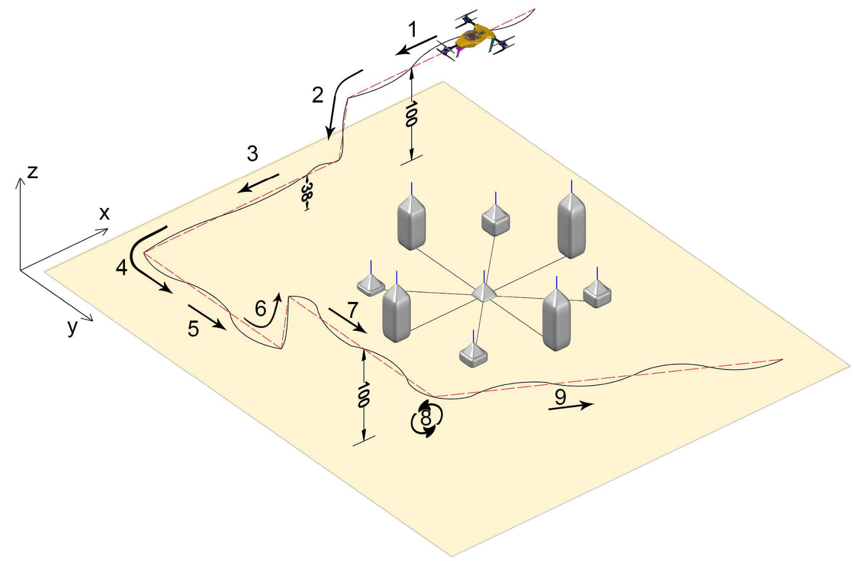

Fig. 2. The configuration of the sensor network with 9 sensors and the trajectory of UAV movement.

$$F_1^b = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}; \; F_2^b = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}; \; F_3^b = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix};$$

$$G_1^b = \begin{bmatrix} a_1 \cdot T \\ 0 \\ 0 \end{bmatrix}; \; G_2^b = \begin{bmatrix} \frac{a_2 \cdot T^2}{2} \\ a_2 \cdot T \\ 0 \end{bmatrix}; \; G_3^b = \begin{bmatrix} \frac{a_3 \cdot T^3}{6} \\ \frac{a_3 \cdot T^2}{2} \\ a_3 \cdot T \end{bmatrix};$$

a_1, a_2, a_3 — RMS of random fluctuations of speed, acceleration and speed of change of acceleration of the UAV respectively. When modeling relied: $a_1 = 0.05\,\text{m/s}$; $a_2 = 0.1\,\text{m/s}^2$; $a_3 = 6\,\text{m/s}^3$.

The partial derivatives $\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)}$ included in equation (12)...(15), have the form

$$\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)} = \left[\frac{\hat{x}^{l-1}(k) - x_s}{\hat{R}^l} - \frac{\hat{x}^{l-1}(k)}{\hat{R}^0}; 0; 0; \right.$$

$$\left. \frac{\hat{y}^{l-1}(k) - y_s}{\hat{R}^l} - \frac{\hat{y}^{l-2}(k)}{\hat{R}^0}; 0; 0; \frac{\hat{z}^{l-1}(k) - z_s}{\hat{R}^l} - \frac{\hat{z}^{l-2}(k)}{\hat{R}^0}; 0; 0; -1 \right].$$

where $\hat{R}^l = \sqrt{(\hat{x}^{l-1}(k) - x_s)^2 + (\hat{y}^{l-1}(k) - y_s)^2 + (\hat{z}^{l-1}(k) - z_s)^2}$ – estimate the distance between l – th sensor and UAV, $l = \overline{1, S}$; $\hat{R}^0 = \sqrt{\hat{x}^{l-1}(k)^2 + \hat{y}^{l-1}(k)^2 + \hat{z}^{l-1}(k)^2}$ – estimate the distance between the reference sensor and the UAV.

The initial conditions $\hat{u}_j(0), \hat{P}_j(0), j = \overline{1,3}$ for the first hypothesis $j = 1$ were created on the current measurements, and for $j = \overline{2,3}$ – according to the observations at the two neighboring steps.

Fig. 3 shows the dependence of the probability of recognition of movement of the first (curve 1, continuous line), second (curve 2, the dashed line) and third (curve 3, the dash-dotted line) types, obtained by Monte Carlo method. This filter allows to recognize hanging and almost uniform motion of the UAV with probability close to unit. The probability of recognition of maneuver is lower that is caused by its short duration.

Fig. 4 shows dependences of expected value (curve 1) and RMS (curve 2) errors of the position estimation of the UAV along coordinates of *X, Y, Z* and also RMS (curve 3) errors of assessment calculated by the adaptive filter obtained by Monte Carlo method. Also fig. 4 shows dependences of RMS error of measurement of position of the UAV which corresponds to the lower bound of Rao-Cramer (curve 4) which characterizes the potential possible accuracy of determination of coordinates of the UAV. Application of a trajectory filtration allows to reduce RMS error of definition of location of the UAV in comparison with RMS error of definition of location by TDOA method [10] by 2 – 4 times.

For the purpose of comparative evaluation algorithms for trajectory filtering of a UAV using Kalman

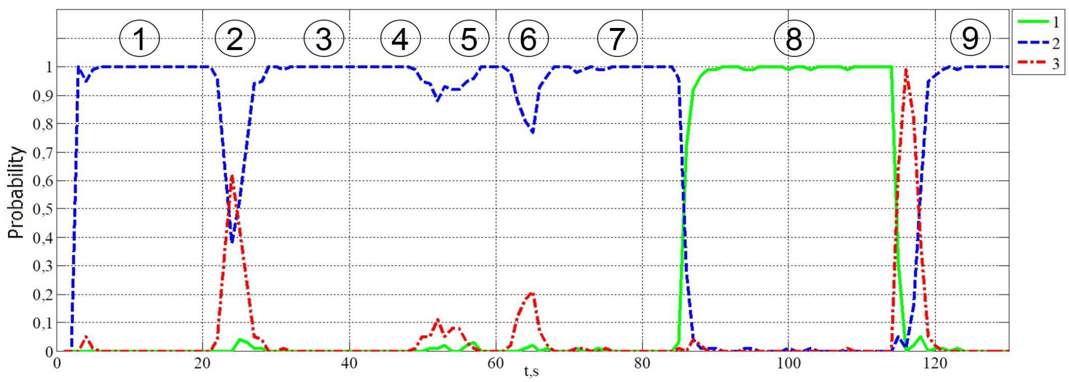

Fig.3. The probability of determining maneuvers

filtering, derived from models of almost uniform motion and motion maneuver $j=3$ was also investigated. When using the Kalman filter based on the model of $j=2$, estimation errors of the UAV position contain systematic components. This components exceeded RMS error of the position estimation more than for an order, that is caused by existence of maneuvers. In comparison with Kalman filter on the basis of the $j=3$ model, the developed adaptive algorithm allows to increase the accuracy of estimation of parameters of the UAV movement in the areas of hanging and movement without maneuver more than by 2-3 times and to avoid emergence of systematic errors of estimates.

Conclusions

The optimum algorithm of the adaptive filtering (6)…(9) is recurrent and describes evolution of aposteriori PD of the expanded mixed Markov process

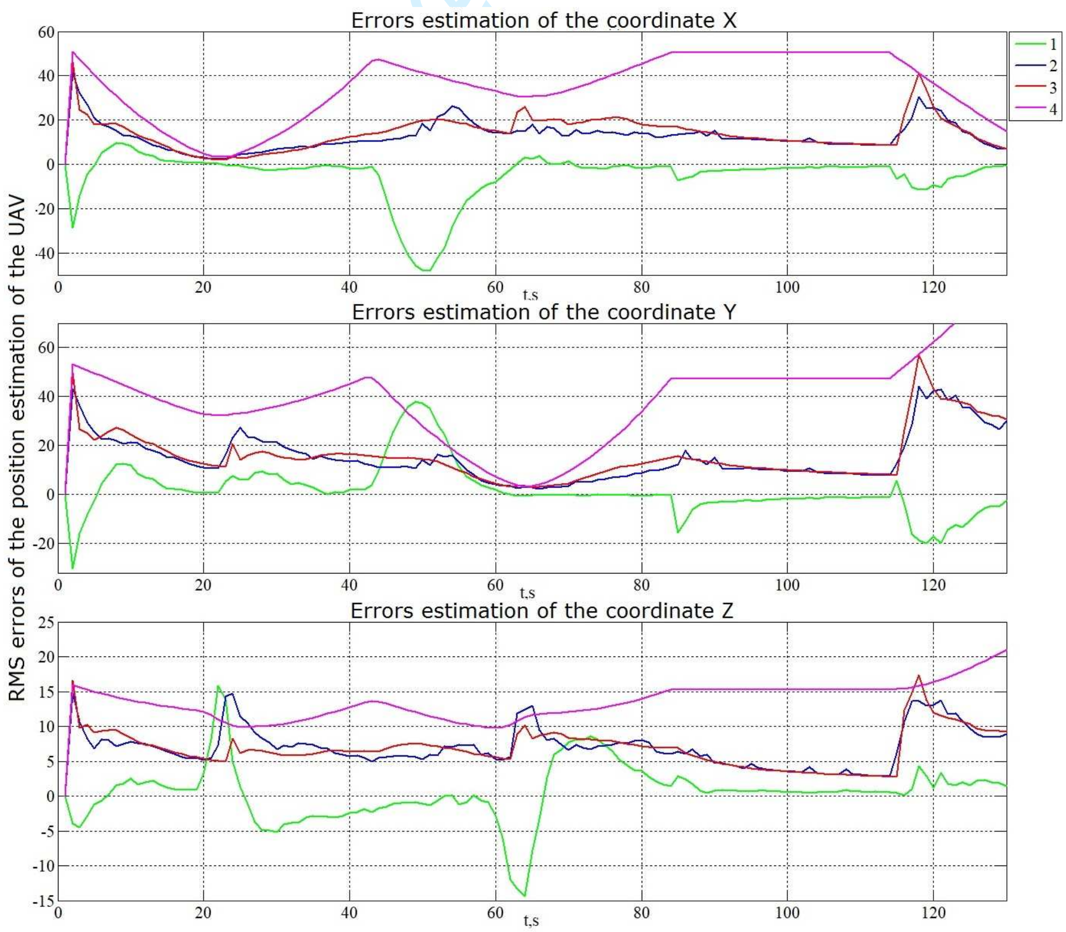

Fig. 4. RMS errors of the position estimation of the UAV when using adaptive filter

including continuously valued vector of parameters of movement of the UAV and discretely valued variable of switching describing type of its movement. The optimum device that implements the algorithm (6)…(9) is multichannel with number of channels M and belongs to the class of devices with feedback between channels. Existence of feedback between channels results from Markov property of a discrete component.

In obtained by linearization of the measurement equation (2) quasioptimum algorithm of adaptive filtering (6),(9)...(14) first and second moments of the conditional aposteriori distributions of the vector of motion parameters of the UAV are calculated and it allows to keep the representation of the aposterior PD for continuous component as a sum of M Gaussian PD. In this case the sequential procedure of performance of calculations at receipt of measurements from sensors of sensor network is realized in it. The quasioptimum device, that implements the algorithm (6),(9) … (14) also is multichannel with number of channels M and generally keeps the structure and all feedback inherent in the optimum device.

As appears from results of modeling, application of a trajectory filtration allows to reduce RMS of errors of definition of the UAV location in comparison with RMS of errors of location definition by TDOA method by 2 – 4 times. In comparison with Kalman filter on the basis of the model of the UAV movements with maneuver, the developed adaptive algorithm allows to increase the accuracy of estimation of parameters of the UAV movement in the areas of hanging and movement without maneuver more than by 2-3 times and to avoid the emergence of systematic errors of estimates. At the same time the adaptive filter allows to distinguish hanging and almost uniform motion of the UAV with probability close to unit.

References

1. Kenzo Nonami, Farid Kendoul, Satoshi Suzuki, Wei Wang, Daisuke Nakazawa «Autonomous Flying Robots Unmanned Aerial Vehicles and Micro Aerial Vehicles» Springer 2010.

2. Wallace, R. J., & Loffi, J. M. (2015). Examining Unmanned Aerial System Thr eats & Defenses: A Conceptual Analysis. International Journal of Aviation, Aeronautics, and Aerospace, 2(4). http://dx.doi.org/10.15394/ijaaa.2015.1084

3. Zashchita ot dronov – nebesnyy rubezh vashey bezopasnosti [Electron resource] – Access mode to the resource: http://dronebouncer.com/.

4. Noha El Gemayel, Holger Jakel, Friedrich K. Jondral (2014). Error analysis of a low cost TDoA sensor network, Position, Location and Navigation Symposium - PLANS 2014, 2014 IEEE/ION, pp.1140-1145.

5. Pengwu Wan, Zan Li, Benjian Hao (2016). Time Delay Estimation of Co-Frequency Signals in TDOA Localization Based on WSN, Computer, Information and Telecommunication Systems (CITS), 2016 International Conference on.

6. Jose L. Rullan-Lara, Guillaume Sanahuja, Rogelio Lozano, Sergio Salaza, Ramon Garcia-Hernandez, Jose A. Ruz-Hernandez . “Indoor Localization of a Quadrotor Based on WSN: A Real-Time Application”, International Journal of Advanced Robotic Systems, 2013, Vol. 10, 48:2013.

7. Ahmed Makki, Abubakr Siddig, Mohamed Saad, Joseph R. Cavallaro, and Chris J. Bleakley (2015). Indoor Localization Using 802.11 Time Differences of Arrival, IEEE Transactions on Instrumentation and Measurement, Vol. 65, № 3, pp. 614 - 623, March 2016.

8. Zhuk S.Ya. (1989) Synthesis of digital detector-meters for mixed Markovian processes, Izvestiya VUZ. Radioelektronika, Vol. 32, No. 11, pp. 31-37.

9. Yevlanov P.A., Zhuk S.YA. Kompleksirovaniye izmeriteley s otkazami // Izvestiya vuzov USSR. Radioelektronika. -1990.-t.33.-№7. -pp.49-53.

10.I.O. Tovkach, S.Ya. Zhuk (2017). Recurrent Algorithm for TDOA Localization in Sensor Networks, J. Aerosp. Technol. Manag., São José dos Campos, Vol.9, №4, pp.489-494, Oct.-Dec., 2017. http://dx.doi.org/10.5028/jatm.v9i4.727

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Introduction

At the present time the development of technologies for construction of unmanned aerial vehicles (UAVs) are used for the solution of a wide range of tasks, such as: emergency rescue operations, autonomous observation and monitoring of industrial processes and environment (fauna monitoring), etc. On the other hand, their availability and massive use for a wide range of problems has led to the emergence of a new class of threats [Nonami *et al* 2010; Wallace and Loffi 2015; Electron resource]: application in terrorist purposes, photographing of secret objects, receiving unauthorized access to information in WLAN networks, invasion on the forbidden territory, etc. This leads to the need to develop security systems that solve the problem of detection, positioning and movement parameters of the UAV.

When an UAVs emits, its location can be determined by wireless sensor networks (WSN) [Gemayel *et al* 2014; Wan *et al* 2016] with use of methods of a passive location. Wide circulation in this case finds the time difference of arrival method (TDOA), in which the differences of times of reception of signals received by various sensors and the reference sensor WSN are used. This method has an essential advantage in simplicity of implementation and finds broad practical application [Rullan-Lara *et al* 2013; Makki *et al* 2016].

A feature of modern UAVs is the ability to perform sudden maneuvers, and keep the same position in the point in space. Changing of the type of UAV movement occurs in a random, unknown to the observer moments of time, and this allows to represent a trajectory in the form of stochastic process with random change of structure. At intervals of unresponsiveness and the movements UAVs without maneuver it is possible to increase the accuracy of estimation of it's coordinates considerably. Thus, in practice, also often the interest is to determine the types of UAV movement.

Therefore, the importance have the synthesis of adaptive algorithms of parameters filtration of parameters of the UAV movement according to sensor network data, in which recognition of different types of it's movement is also carried out.

Problem definition

The movement UAV with different types of maneuver in rectangular system of coordinates can be described by a stochastic dynamic system with random structure in the form [Zhuk 1989]:

$$u(k) = F_j u(k-1) + G_j \omega(k), \quad j = \overline{1, M}; . \qquad (1)$$

where $u(k)$ - the state vector including parameters of the UAV movement for axes of rectangular system of coordinates; F_j, G_j - the matrixes describing different types of movement; $\omega(k)$ - the uncorrelated sequence of Gaussian vectors with a single correlation matrix.

For a description of the type of model structure of UAV movements (1), corresponding to a certain type of maneuver there is applied switching variable $a_j(k)$, $j = \overline{1, M}$. It belongs to the class of Markov chains that allows to consider transitions between different types of the UAV movement at random times.

For definition of UAV location the wireless sensor network has to consist not less than of four sensors. When using TDOA, differences of signals reception times between sensors $s = \overline{1, S}$ and the basic sensor with coordinates of $x^0 = 0,\ y^0 = 0$ are measured.

During propagation of a signal from the UAV to sensors of network, it's coordinate don't change. Therefore, it is assumed that the measurements of the differences of distances between the sensors and the reference sensor are received in the *k*-th moment of time, as which the moment of receipt of a signal to the basic sensor with coordinates of x^0, y^0 is used. In this case observation equation that describes the process of measuring the coordinates of UAV by sensor network has the form

$$\Delta^s(k) = h^s(u(k)) + \upsilon^s(k),\ s = \overline{1,S}, \tag{2}$$

where $\Delta^s(k)$ – the measured difference of distances between the *s*–th sensor and the reference sensor in the *k*–th moment of time, $s = \overline{1,S}$; $\upsilon^s(k)$ – the measurement error of *s*–th sensor with dispersion d^s; $h^s(u)$ – the nonlinear function, which is described by the expression

$$h^s(u(k)) = \sqrt{(x(k) - x_s)^2 + (y(k) - y_s)^2} - \\ -\sqrt{x^2(k) + y^2(k)} - \upsilon^0(k); \tag{3}$$

$x(k), y(k)$ – coordinates of the UAV position; x^s, y^s – coordinates of the *s*-th sensor position; $\upsilon^0(k)$ – the distances measurement error for the reference sensor with dispersion d^0. Measurements obtained from all sensors is denoted as a vector $u_\Delta(k) = (\Delta^1(k),...,\Delta^S(k))^T$.

On the basis of the model of the UAV movement (1) and the observation equation for sensor network (2) it is necessary to synthesize optimum and quasioptimum adaptive algorithms the filtration of parameters of the UAV movement according to sensor network, in which the detection of different types of motion is carried out.

Development

The equation (1) describes the process to be estimated, and (2) - the process of formation of data accessible to observation. For a description of the type of maneuver there is used the random variable $a_j(k),\ j = \overline{1,M}$, which belongs to the class of chains of Markov, accepting the M values with a matrix of probabilities of transitions $\Pi_{i,j}(k,k-1), i, j = \overline{1,M}$ and initial probabilities $p_i(0),\ i = \overline{1,M}$. Measurement errors $\upsilon^s(k),\ s = \overline{1,S}$ are independent.

Applying the technique of expansion of a condition vector of the filtered process considered in the monograph [Zhuk 1989] it is possible to show that the expanded process, which includes a continuous component $u(k)$, belongs to the class of the mixed Markov processes (MMP) in discrete time.

The problem of synthesis of an optimum algorithm comes down to calculation of aposteriori probability density (PD) of expanded process $W(u(k), a_j(k)) = P(u(k), a_j(k) / U_\Delta(k))$, where $U_\Delta(k) = u_\Delta(1),\ ..., u_\Delta(k)$ - the sequences of measurements received to *k*-th moment, inclusive. Introducing also designation of the extrapolated PD $W^*(x(k), a_j(k)) = P(u(k), a_j(k) / U_\Delta(k-1))$ for expanded process and following the technique of synthesis, considered in the monograph [Zhuk 1989], it is possible to show that the optimum algorithm of a filtration can be presented in the form of two recurrent equations

$$W^*(u(k), a_j(k)) = \sum_{i=1}^{M} \Pi_{ij}(k, k-1) \times \\ \times \int_{-\infty}^{\infty} \Pi(u(k) / u(k-1), a_j(k)) \times \\ \times W(u(k-1), a_i(k-1)) du(k-1); \tag{4}$$

$$W(u(k), a_j(k)) = \prod_{s=1}^{S} P(\Delta^s(k) / u(k)) \times \\ \times W^*(u(k), a_j(k)) / P(u_\Delta(k) / U_\Delta(k-1)), \tag{5}$$

where $P(u_p(k) / u(k))$ - one-step-likelihood function, defined on the basis of equation (4); $\Pi(u(k) / u(k-1))$ - the conditional PD defined by the equation (1); $W(u(k), a_j(k))$ - the joint posterior PD $u(k), a_j(k)$; $U_\Delta(k) = u_\Delta(1),\ ..., u_\Delta(k)$ - the sequences of measurements received.

The equation (4) describes evolution of the extrapolated PD $W^*(u(k), a_j(k))$ and is also an optimum algorithm of extrapolation of MMP $\xi(k)$ for one step. With the help of the relation (5) adjustment of extrapolated PD based on the obtained measurement $u_\Delta(k)$ is made and aposteriori PD $W(u(k), a_j(k))$ is defined.

Further transformation of expressions (4), (5) can be executed by means of the theorem of multiplication of probabilities. In this case the optimal filtering algorithm can be represented as the following system of recurrent equations

$$W_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1)\,; \qquad (6)$$

$$W_j^*(u(k)) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) \times$$
$$\times \int_{-\infty}^{\infty} \Pi(u(k)/u(k-1), a_j(k)) \times \qquad (7)$$
$$\times W_i\ (u(k-1)) du(k-1) / W_j^*(k);$$

$$W_j\ (u(k)) = P(u_\Delta(k)/u(k)) \times$$
$$\times W_j^*(u(k)) / P(u_\Delta(k)/a_j(k), U_\Delta(k-1)); \qquad (8)$$

$$W_j\ (k) = \prod_{s=1}^{S} P(\Delta^s(k)/a_j(k), U_\Delta(k-1)) \times$$
$$\times W_j^*(k) / P(u_\Delta(k)/U_\Delta(k-1)), \qquad (9)$$

where $W_j^*(u(k))$, $W_j\,(u(k))$ - the conditional extrapolated and aposteriori PD of the vector $u(k)$ on condition $a_j(k)$; $W_j^*(k)$, $W_j\ (k)$ - extrapolated and a posterior probabilities $a_j(k)$; $P(u_\Delta(k)/a_j(k), U_\Delta(k-1))$ - the conditional PD determined by the formula

$$P(u_\Delta(k)/a_j(k), U_\Delta(k-1)) =$$
$$= \int_{-\infty}^{\infty} P(u_\Delta(k)/u(k), a_j(k)) W_j\ (u(k)) du(k),$$

$P(u_\Delta(k)/U_\Delta(k-1))$ - determined by the formula

$$P(u_\Delta(k)/U_\Delta(k-1)) =$$
$$= \sum_{j=1}^{M} P(u_\Delta(k)/a_j(k), U_\Delta(k-1)) W_j^*(k).$$

The initial conditions for the algorithm (6)...(9) have the form

$$W_i\ (0) = p_i\ (0), W_i(u(0)) = P(u(0))\,,\ i = \overline{1,M}\,.$$

By means of the equations (6), (9) the filtration of discrete components is carried out and filtration of a continuous component by means of the equations (7), (8). The feature of the algorithm is the indissoluble connection of the filtration equations for discrete and continuous components.

The optimum device, that implements the algorithm (6)... (8), is multichannel with number of channels M. It belongs to the class of devices with feedback between channels. Existence of feedback between channels is caused by Markov property of a discrete component $a_j(k)$.

The disadvantage of the optimum algorithm is the large computational cost associated with the need for integration of the multidimensional PD. When synthesizing a quasioptimum algorithm, we will use a sequential method of processing incoming data. We will enter the index l, which characterizes the sequence of receipts of measurements from the corresponding sensors of network. The quasioptimum algorithm of an adaptive filtration can be received by decomposition of vector-valued function (2), in a Taylor series in the vicinity of the points $u(k)$ and restriction by linear members of decomposition, and also application on each step of Gaussian approximation of the conditional extrapolated PD $W_j^*(u(k))$. In this case the equation of calculation of the conditional extrapolated PD $W_j^*(u(k))$ (7) comes down to calculation of it's first $u_j^*(k)$ and second $P_j^*(k)$ $P_j^*(k)$ moments by the formulas [Zhuk 1989]

$$u_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) F \hat{u}_i\ (k-1) / W_j^*(k)\,; \qquad (10)$$

$$P_j^*(k) = \sum_{i=1}^{M} \Pi_{ij}(k,k-1) W_i\ (k-1) \times$$
$$\times \left\{ F_j\ \hat{P}_i\ (k-1) F_j^{\ T} + G_j G_j^{\ T} \right\} / W_j^*(k). \qquad (11)$$

Equation of calculation of conditional aposteriori PD $W_j\,(u(k))$ (8) at seqentially processing of the arriving measurements $\Delta^l(k), l = \overline{1,S}$ comes down to calculation of it's first $\hat{u}_j(k)$ and second $\hat{P}_j(k)$ moments using the recurrent procedure [Yevlanov and Zhuk 1990]

$$K_j^l(k) = \hat{P}_j^{l-1}(k) \frac{\partial h^{lT}(\hat{u}_j^{l-1}(k))}{\partial u(k)} \left(D_j^l(k) \right)^{-1}; \qquad (12)$$

$$\hat{u}_j^l(k) = \hat{u}_j^{l-1}(k) + K_j^l(k)(\Delta^l(k) - h^l(\hat{u}_j^{l-1}(k)))\,; \qquad (13)$$

$$\hat{P}_j^l(k) = \hat{P}_j^{l-1}(k) - K_j^l(k) \frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)} \hat{P}_j^{l-1}(k)\,, \qquad (14)$$

where $\hat{u}_j^l(k)$, $\hat{P}_j^l(k)$ - expected value and correlation matrix of conditional aposteriori PD $W_j(u(k))$, refined by measurements $\Delta^s(k), s=\overline{1,l}$. In this case the initial conditions for the procedure (12)…(14) at l=0 has the form $\hat{u}_j^0(k)=u_j^*(k), \hat{P}_j^0(k)=P_j^*(k), \ j=\overline{1,M}$, and $\hat{u}_j(k)=\hat{u}_j^L(k), \hat{P}_j(k)=\hat{P}_j^L(k), \quad j=\overline{1,M}$. The advantage of this method is an opportunity to organize processing with limited computing resources.

The algorithm of the filtration of discrete components doesn't change and is described by the equations (6), (9).

In this case conditional PD $P(u_\Delta(k)/a_j(k),U_\Delta(k-1))=N(H(u_j^*(k)),D_j(k))$ is Gaussian, and correlation matrix $D_j(k)$ is determined by the expression

$$D_j^l(k)=\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)}\hat{P}_j^{l-1}(k)\frac{\partial h^{lT}(\hat{u}_j^{l-1}(k))}{\partial u(k)}+d^l(k). \quad (15)$$

The quasioptimum device, that implements the algorithm (6),(9) … (14), also is multichannel with number of channels M and generally keeps the structure and all feedback inherent for the optimum device. Their difference is that in quasioptimum device only the first and second moments of conditional PD $W_j^*(u(k))$ and $W_j(u(k))$ is calculates. In this case the quasioptimum algorithm allows to keep representation of aposteriori PD $W(u(k))$ in the form of the sum of the M Gaussian densities.

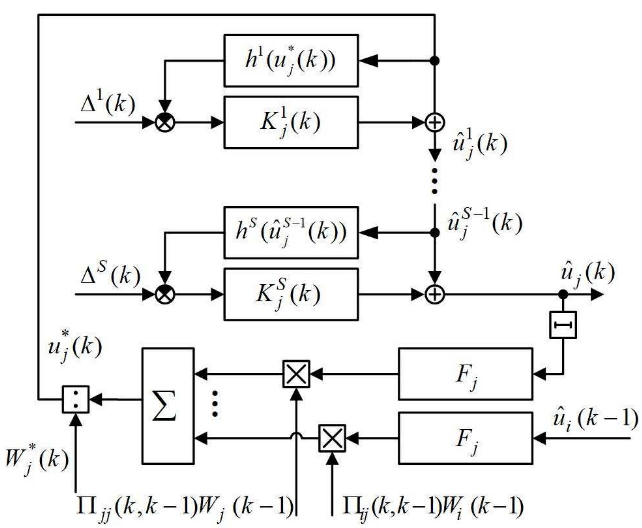

Fig. 1. Block diagram of one channel quasioptimum filter at consecutive realization of calculations

The block diagram of the j-th channel of such quasioptimum filter is shown in Fig. 1. In this case, the processing of observations $\Delta^l(k), l=\overline{1,L}$, in j - th channel is carried out parallel to the L channels that allows to increase information processing speed.

The effectiveness of the algorithm analysis

Efficiency analysis of a developed quasioptimum adaptive filtering algorithm of parameters of the target movement (6),(9)…(14) is carried out by means of statistical modeling.

Modeling of algorithms is carried out for a configuration of sensor network (fig. 2) which consists of nine sensors for definition of UAV location with coordinates: $S_0(0;0;0)$, $S_1(0;100;44)$, $S_2(70.71;70.71;6)$, $S_3(100;0;48)$, $S_4(70.71;-70.71;10)$, $S_5(0;-100;52)$, $S_6(-70.71;-70.71;14)$, $S_7(-100;0;56)$, $S_8(-70.71;70.71;18)$.

For formation of the target movement, model (1), (2) was used. For descriptive reasons of the algorithm works the test trajectory of the UAV movement (fig. 1) has been created. The trajectory consists of five sections: first 1<k<19 – uniform motion, second 20<k<27 – maneuver, height reduction, third 28<k<42– uniform motion, fourth 43<k<45 – maneuver, fifth 46<k<59 – uniform motion, sixth 60<k<67 – maneuver, rise to height, seventh 68<k<85 – uniform motion, eighth 85<k<114 – hanging, ninth 115<k<130 – uniform motion. Error RMS of measurement $\sigma_v=2.4$ m, rate of receipt of information T=1s. Tests were carried out for hundred realizations.

For the description of the UAV movement the model with random structure (1) which considers three main types of the movement $M=3$ was used: hanging $j=1$, almost uniform motion $j=2$, movement with maneuver $j=3$.

The state vector $u^T(k)=(x(k),\dot{x}(k),\ddot{x}(k),y(k),\dot{y}(k),\ddot{y}(k),z(k),\dot{z}(k),\ddot{z}(k))$ includes position coordinates, velocity and acceleration along the axes *X, Y, Z.* The matrixes included in the motion model (1) have the form

$$F_j(k,k-1)=\begin{bmatrix} F_j^b & 0 & 0 \\ 0 & F_j^b & 0 \\ 0 & 0 & F_j^b \end{bmatrix}, \ G_j(k)=\begin{bmatrix} G_j^b & 0 & 0 \\ 0 & G_j^b & 0 \\ 0 & 0 & G_j^b \end{bmatrix},$$

where F_j^b, G_j^b, $j=\overline{1,3}$ have the form

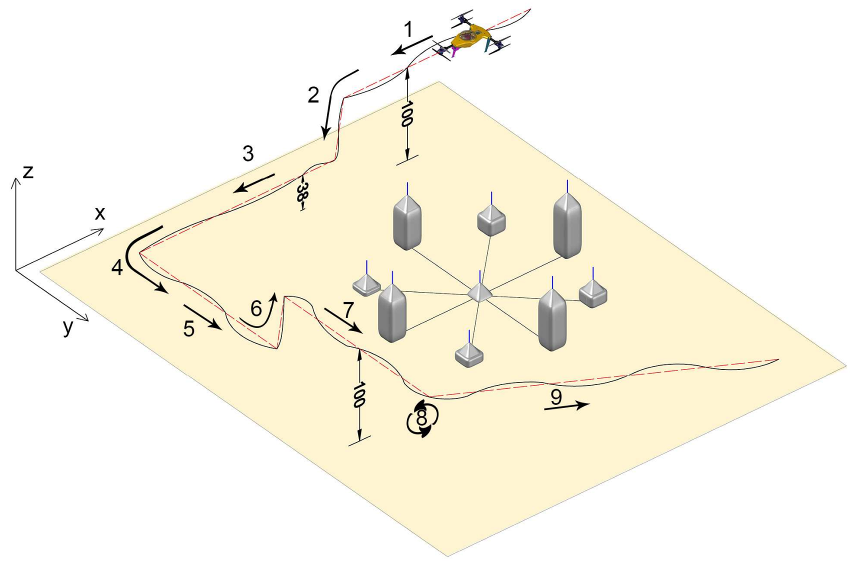

Fig. 2. The configuration of the sensor network with 9 sensors and the trajectory of UAV movement.

$$F_1^b = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix};\ F_2^b = \begin{bmatrix} 1 & T & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix};\ F_3^b = \begin{bmatrix} 1 & T & \frac{T^2}{2} \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix};$$

$$G_1^b = \begin{bmatrix} a_1 \cdot T \\ 0 \\ 0 \end{bmatrix};\ G_2^b = \begin{bmatrix} \frac{a_2 \cdot T^2}{2} \\ a_2 \cdot T \\ 0 \end{bmatrix};\ G_3^b = \begin{bmatrix} \frac{a_3 \cdot T^3}{6} \\ \frac{a_3 \cdot T^2}{2} \\ a_3 \cdot T \end{bmatrix};$$

a_1, a_2, a_3 — RMS of random fluctuations of speed, acceleration and speed of change of acceleration of the UAV respectively. When modeling relied: $a_1 = 0.05\,\text{m/s}$; $a_2 = 0.1\,\text{m/s}^2$; $a_3 = 6\,\text{m/s}^3$.

The partial derivatives $\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)}$ included in equation (12)...(15), have the form

$$\frac{\partial h^l(\hat{u}_j^{l-1}(k))}{\partial u(k)} = \left[\frac{\hat{x}^{l-1}(k) - x_s}{\hat{R}^l} - \frac{\hat{x}^{l-1}(k)}{\hat{R}^0}; 0; 0; \frac{\hat{y}^{l-1}(k) - y_s}{\hat{R}^l} - \frac{\hat{y}^{l-2}(k)}{\hat{R}^0}; 0; 0; \frac{\hat{z}^{l-1}(k) - z_s}{\hat{R}^l} - \frac{\hat{z}^{l-2}(k)}{\hat{R}^0}; 0; 0; -1 \right].$$

where $\hat{R}^l = \sqrt{(\hat{x}^{l-1}(k) - x_s)^2 + (\hat{y}^{l-1}(k) - y_s)^2 + (\hat{z}^{l-1}(k) - z_s)^2}$ – estimate the distance between l – th sensor and UAV, $l = \overline{1, S}$; $\hat{R}^0 = \sqrt{\hat{x}^{l-1}(k)^2 + \hat{y}^{l-1}(k)^2 + \hat{z}^{l-1}(k)^2}$ – estimate the distance between the reference sensor and the UAV.

The initial conditions $\hat{u}_j(0), \hat{P}_j(0), j = \overline{1,3}$ for the first hypothesis $j = 1$ were created on the current measurements, and for $j = \overline{2,3}$ – according to the observations at the two neighboring steps.

Fig. 3 shows the dependence of the probability of recognition of movement of the first (curve 1, continuous line), second (curve 2, the dashed line) and third (curve 3, the dash-dotted line) types, obtained by Monte Carlo method. This filter allows to recognize hanging and almost uniform motion of the UAV with probability close to unit. The probability of recognition of maneuver is lower that is caused by its short duration.

Fig. 4 shows dependences of expected value (curve 1) and RMS (curve 2) errors of the position estimation of the UAV along coordinates of *X, Y, Z* and also RMS (curve 3) errors of assessment calculated by the adaptive filter obtained by Monte Carlo method. Also fig. 4 shows dependences of RMS error of measurement of position of the UAV which corresponds to the lower bound of Rao-Cramer (curve 4) which characterizes the potential possible accuracy of determination of coordinates of the UAV. Application of a trajectory filtration allows to reduce RMS error of definition of location of the UAV in comparison with RMS error of definition of location by TDOA method [Tovkach and Zhuk 2017] by 2 – 4 times.

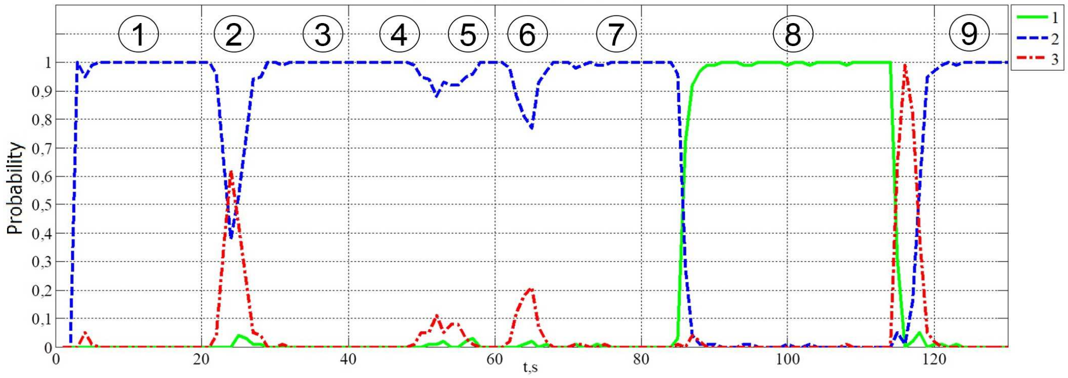

Fig.3. The probability of determining maneuvers

For the purpose of comparative evaluation algorithms for trajectory filtering of a UAV using Kalman filtering, derived from models of almost uniform motion and motion maneuver $j=3$ was also investigated. When using the Kalman filter based on the model of $j=2$, estimation errors of the UAV position contain systematic components. This components exceeded RMS error of the position estimation more than for an order, that is caused by existence of maneuvers. In comparison with Kalman filter on the basis of the $j=3$ model, the developed adaptive algorithm allows to increase the accuracy of estimation of parameters of the UAV movement in the areas of hanging and movement without maneuver more than by 2-3 times and to avoid emergence of systematic errors of estimates.

Conclusions

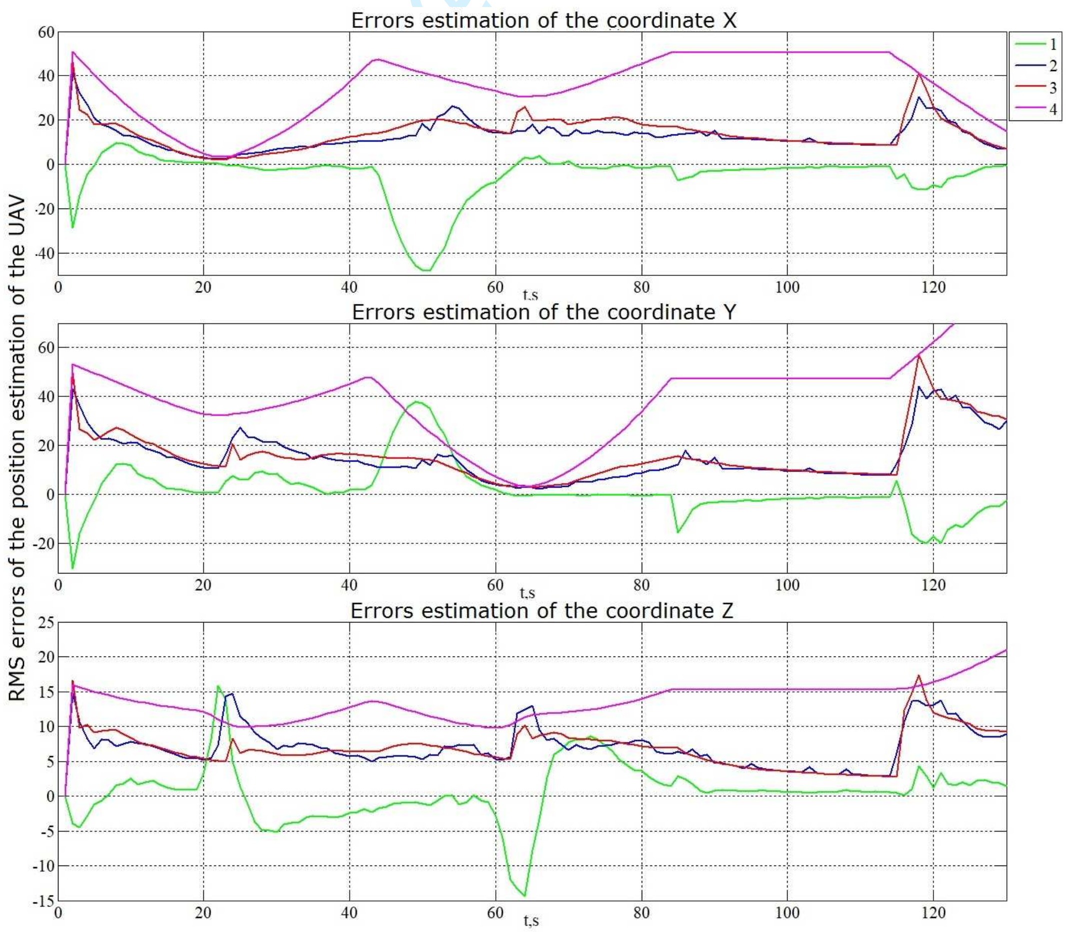

Fig. 4. RMS errors of the position estimation of the UAV when using adaptive filter

The optimum algorithm of the adaptive filtering (6)…(9) is recurrent and describes evolution of aposteriori PD of the expanded mixed Markov process including continuously valued vector of parameters of movement of the UAV and discretely valued variable of switching describing type of its movement. The optimum device that implements the algorithm (6)…(9) is multichannel with number of channels M and belongs to the class of devices with feedback between channels. Existence of feedback between channels results from Markov property of a discrete component.

In obtained by linearization of the measurement equation (2) quasioptimum algorithm of adaptive filtering (6),(9)...(14) first and second moments of the conditional aposteriori distributions of the vector of motion parameters of the UAV are calculated and it allows to keep the representation of the aposterior PD for continuous component as a sum of M Gaussian PD. In this case the sequential procedure of performance of calculations at receipt of measurements from sensors of sensor network is realized in it. The quasioptimum device, that implements the algorithm (6),(9) … (14) also is multichannel with number of channels M and generally keeps the structure and all feedback inherent in the optimum device.

As appears from results of modeling, application of a trajectory filtration allows to reduce RMS of errors of definition of the UAV location in comparison with RMS of errors of location definition by TDOA method by 2 – 4 times. In comparison with Kalman filter on the basis of the model of the UAV movements with maneuver, the developed adaptive algorithm allows to increase the accuracy of estimation of parameters of the UAV movement in the areas of hanging and movement without maneuver more than by 2-3 times and to avoid the emergence of systematic errors of estimates. At the same time the adaptive filter allows to distinguish hanging and almost uniform motion of the UAV with probability close to unit.

References

1. Kenzo Nonami, Farid Kendoul, Satoshi Suzuki, Wei Wang, Daisuke Nakazawa «Autonomous Flying Robots Unmanned Aerial Vehicles and Micro Aerial Vehicles» Springer 2010.
2. Wallace, R. J., & Loffi, J. M. (2015). Examining Unmanned Aerial System Thr eats & Defenses: A Conceptual Analysis. International Journal of Aviation, Aeronautics, and Aerospace, 2(4). http://dx.doi.org/10.15394/ijaaa.2015.1084
3. Zashchita ot dronov – nebesnyy rubezh vashey bezopasnosti [Electron resource] – Access mode to the resource: http://dronebouncer.com/.
4. Noha El Gemayel, Holger Jakel, Friedrich K. Jondral (2014). Error analysis of a low cost TDoA sensor network, Position, Location and Navigation Symposium - PLANS 2014, 2014 IEEE/ION, pp.1140-1145.
5. Pengwu Wan, Zan Li, Benjian Hao (2016). Time Delay Estimation of Co-Frequency Signals in TDOA Localization Based on WSN, Computer, Information and Telecommunication Systems (CITS), 2016 International Conference on.
6. Jose L. Rullan-Lara, Guillaume Sanahuja, Rogelio Lozano, Sergio Salaza, Ramon Garcia-Hernandez, Jose A. Ruz-Hernandez . “Indoor Localization of a Quadrotor Based on WSN: A Real-Time Application”, International Journal of Advanced Robotic Systems, 2013, Vol. 10, 48:2013.
7. Ahmed Makki, Abubakr Siddig, Mohamed Saad, Joseph R. Cavallaro, and Chris J. Bleakley (2015). Indoor Localization Using 802.11 Time Differences of Arrival, IEEE Transactions on Instrumentation and Measurement, Vol. 65, № 3, pp. 614 - 623, March 2016.
8. Zhuk S.Ya. (1989) Synthesis of digital detector-meters for mixed Markovian processes, Izvestiya VUZ. Radioelektronika, Vol. 32, No. 11, pp. 31-37.
9. Yevlanov P.A., Zhuk S.YA. Kompleksirovaniye izmeriteley s otkazami // Izvestiya vuzov USSR. Radioelektronika. -1990.-t.33.-№7. -pp.49-53.
10. I.O. Tovkach, S.Ya. Zhuk (2017). Recurrent Algorithm for TDOA Localization in Sensor Networks, J. Aerosp. Technol. Manag., São José dos Campos, Vol.9, №4, pp.489-494, Oct.-Dec., 2017. http://dx.doi.org/10.5028/jatm.v9i4.727