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Analysis of the Efficiency of the Kalman-Type Correlation Algorithm for Tracking of a Small UAV in the Presence of Uncorrelated Interference

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The article shows the relevance of the problem of development and analysis of algorithms for tracking small-sized UAVs according to video surveillance. A Kalman-type correlation algorithm for tracking of a small-sized UAV in the presence of spatially uncorrelated interference, which is the most common in practice, is synthesized. In the obtained algorithm, the UAV motion parameters are estimated independently along the axes of a rectangular coordinate system. Positioning accuracy analysis using the correlation algorithm, as well as the correlation algorithm for tracking UAVs based on the Kalman filter, was carried out by statistical modeling in the Matlab programming environment.

Keywords: unmanned aerial vehicle; correlation algorithm; reference image; Kalman filter; positioning accuracy; probability of tracking failure

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Introduction

Despite the initial prerogative of using unmanned aerial vehicles (UAVs) mainly for military purposes, small (about 50 centimeters long) UAV technologies are now increasingly used in many sectors of the economy, as well as to meet the needs of commercial and private consumers [1, 2].

On the other hand, the development and spread of small UAVs have led to a new class of menace [3]: espionage, terrorism, transportation of prohibited goods, air traffic complications, property damage. Today in the leading countries of the world the solution of problems of neutralization of menace from the use of small UAVs and the creation of appropriate protection systems is brought to the level of national security [4, 5]. Therefore, important tasks are to track UAVs and control the activities allowed for them.

The low visibility of small UAVs necessitates the use of integrated surveillance systems [6, 7], an integral part of which is a video surveillance system. Therefore, the urgent task is to develop and analyze algorithms for tracking small UAVs according to video surveillance.

The correlation method [8–10] is used to detect objects in images, which is highly effective due to the indirect use not only of the brightness characteristics of objects, but also their shape and position. At the same time, the most common interference in practice, which distorts the image, is spatially uncorrelated additive noise [11]. According to the observation data of various electronic systems, the Kalman filter is widely used for tracking purposes [12, 13]. In [14, 15], a tracking system is presented that uses correlation filters and Kalman prediction to determine the position of an object in each frame of a video sequence. They consider the issues of improving the discrimination coefficient between objects and suppression of a complex background. Therefore, the relevant task is to analyze the influence of uncorrelated noise on the efficiency of tracking a small UAV by Kalman-type correlation algorithm.

1 Algorithm of correlation tracking of Kalman-type on small UAV

Consider the following model that allows you to monitor changes in the real target to be tracked. The target in the image (Fig. 1) is a set of connected points, the geometric center of which has coordinates x_e, y_e. Place the target in a rectangular area in which it fits with a margin. The amount of "margin" should be chosen from the maximum possible range of resizing the target on adjacent image processing cycles. Because the target configuration may change, the point taken as the center of the target and the size of the rectangular area may change during detection and tracking.

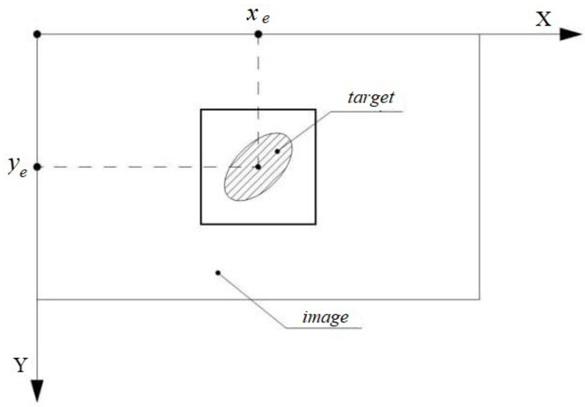


Fig. 1. Object model

The rectangular area is a model of the object of observation, so the tracking task is to track the center of the rectangular area of the current image, which is the real target, using a Kalman-type correlation algorithm for positioning images and tracking. An object model in the form of a rectangular area in correlation positioning algorithms is called a reference image. It is determined on the previous cycles of the Kalman filtering algorithm.

One of the main tasks of tracking is the formation of the gate – the search area of the set of measuring coordinates of the target, i.e. in this area the possible options for the position of the target are considered. The area of the gate has the form of a rectangle in Fig. 2, and its dimensions are determined depending on the size of the object of observation that get into this area. The center of the search gate is located at the point of the predicted position of the target in the current image (Fig. 2), so the coordinates of its center coincide with the coordinates of the center x_e, y_e of the reference image. Figure 2 also shows the dashed line of the boundaries of the object of observation in the current frame.

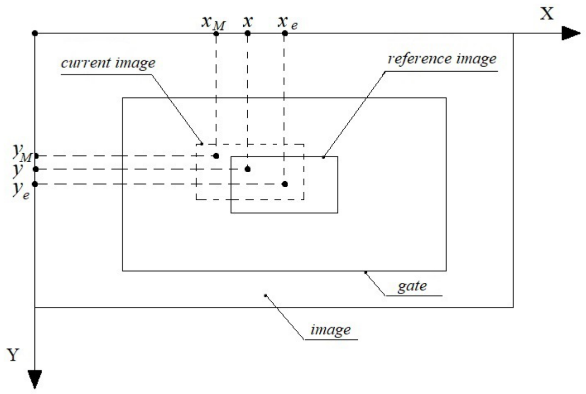


Fig. 2. Illustration of the gate, reference and current image

The correlation algorithm is used to determine the offset of the center of the object of observation relative to the center of the gate (reference image) [11, 16]. The correlation function is calculated when comparing a fragment of the current image in the gate and the reference image. In the absence of interfering factors, the correlation function assumes the maximum value if the image fragment in the gate contains the object to be tracked. This allows you to determine the offset Δx and Δy of the target relative to the reference image, because the gate fragment contains the image of the object and is most similar to the reference image. As a result of the influence of background, noise, interference, changes in geometric shape and size, the displacement of the target is determined with a certain error.

The calculated offsets of the center of the object of observation relative to the center of the gate are described by the following expressions:

$$\begin{aligned}\Delta x_M(k) &= \Delta x(k) + v_x(k);\\ \Delta y_M(k) &= \Delta y(k) + v_y(k),\end{aligned} \tag{1}$$

where $\Delta x_M(k)$, $\Delta y_M(k)$ – measured offsets of the center of the object of observation relative to the center of the reference image in the k-th step; $\Delta x(k)$, $\Delta y(k)$ – true offsets of the center of the object of observation relative to the reference image in the k-th step; $v_x(k)$, $v_y(k)$ – errors in measuring the displacement of the center of the object of observation relative to the reference image on the k-th step, which are Gaussian with zero mathematical expectation and correlation matrix $\mathbf{R}(k)$.

The next step in solving the problem of tracking the target is to determine the parameters of the movement of the object. When measuring the coordinates of the target, a rectangular coordinate system (CS) is used, so a rectangular CS is also used to describe the movement of a small UAV. The model of motion of the UAV image center in a rectangular CS in the form of a discrete dynamic system has the form:

$$\mathbf{u}(k) = \mathbf{F}\mathbf{u}(k-1) + \mathbf{G}\omega(k), \tag{2}$$

where $\mathbf{u}^T(k) = (x(k), \dot{x}(k), y(k), \dot{y}(k))$ – state vector including position coordinates $x(k), y(k)$ and the rate of change of position $\dot{x}(k), \dot{y}(k)$ on the corresponding axes of the rectangular CS; $\omega(k)$ – excitation noise with a correlation matrix

$$\mathbf{Q} = diag(\sigma_{ax}^2, \sigma_{ay}^2);$$

$$\mathbf{F} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix}; \quad \mathbf{G} = \begin{bmatrix} \sigma_{ax}\frac{T^2}{2} & 0 \\ \sigma_{ax}T & 0 \\ 0 & \sigma_{ay}\frac{T^2}{2} \\ 0 & \sigma_{ay}T \end{bmatrix}, \tag{3}$$

$\mathbf{F}$ – system transition matrix; $\mathbf{G}$ – known matrix in the current step; T – data rate; σ_{ax}^2, σ_{ay}^2 – dispersions accelerate the movement of the target on each axis, defined as follows:

$$\sigma_{ax}^2 = \frac{a_{mx}^2}{3}; \quad \sigma_{ay}^2 = \frac{a_{my}^2}{3}, \tag{4}$$

where a_{mx}, a_{my} – modules of the maximum value of acceleration of the target on each axis.

In the obtained model (2), the change of the target motion parameters along each axis of the rectangular CS is described by a second-order dynamic system [17], the state vector of which contains the coordinates of the position and the rate of change of position. The equations for observing a small UAV in the current frame are as follows:

$$\begin{aligned} x_M(k) &= x_e(k)+\Delta x_M(k)= \\ &= x_e(k)+\Delta x(k)+v_x(k)=x(k)+v_x(k); \\ y_M(k) &= y_e(k)+\Delta y_M(k)= \\ &= y_e(k)+\Delta y(k)+v_y(k)=y(k)+v_y(k). \end{aligned} \tag{5}$$

where $x_M(k)$, $y_M(k)$ measured coordinates of the target in a rectangular CS.

The equations of observation in vector-matrix form have the following form:

$$\mathbf{u_M}(k)=\mathbf{H}\mathbf{u}(k)+\upsilon(k), \tag{6}$$

where $\mathbf{u_M}(k) = (x_M(k), y_M(k))$ – the observation vector, including the measured coordinates of the target in the rectangular CS;

$\upsilon(k)=(v_x(k), v_y(k))$ – vector of measurement errors with a correlation matrix $\mathbf{R}(k)$ having the form:

$$\mathbf{R}(k) = \begin{bmatrix} \sigma_x^2(k) & \sigma_{xy}^2(k) \\ \sigma_{xy}^2(k) & \sigma_y^2(k) \end{bmatrix}; \tag{7}$$

$\mathbf{H}$ – observation matrix having the form:

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}.$$

Theoretically, the components of the correlation matrix of measurement errors $\mathbf{R}(k)$ are quite difficult to determine, because they depend on many factors: the size and statistical characteristics of the target image, the properties of the noise in the image, background, and so on. Components can be determined experimentally for different conditions and used depending on the case, based on the characteristics of the current image.

Expressions (2) and (6) specify the model of motion of the target and the equation of observation in the Cartesian coordinate system of the frame. The discrete Kalman filter synthesized by equations (2), (6) is described by the expressions [12,13]

$$\mathbf{u}^*(k)=\mathbf{F}\hat{\mathbf{u}}(k-1); \tag{8}$$

$$\hat{\mathbf{u}}(k)=\mathbf{u}^*(k)+\mathbf{K}(k)(\mathbf{u}_M(k)-\mathbf{H}\mathbf{u}^*(k)); \tag{9}$$

$$\mathbf{P}^*(k)=\mathbf{F}\hat{\mathbf{P}}(k-1)\mathbf{F}^T+\mathbf{G}\mathbf{Q}\mathbf{G}^T; \tag{10}$$

$$\mathbf{K}(k)=\mathbf{P}^*(k)\mathbf{H}^T\left(\mathbf{H}\mathbf{P}^*(k)\mathbf{H}^T+\mathbf{R}(k)\right)^{-1}; \tag{11}$$

$$\hat{\mathbf{P}}(k)=\mathbf{P}^*(k)-\mathbf{K}(k)\mathbf{H}\mathbf{P}^*(k), \tag{12}$$

where $\mathbf{u}^*(k)$, $\hat{\mathbf{u}}(k)$ – vectors of forecast and estimation of parameters of movement of the purpose at the moment of time; $\mathbf{P}^*(k)$, $\hat{\mathbf{P}}(k)$ – correlation matrices of forecast and estimation errors, respectively; $\mathbf{K}(k)$ – Kalman filter gain.

To run the Kalman discrete filter, you must specify the initial conditions. In the presence of two measurements at the same time $k=0$ and $k=1$ the vector of the initial estimate has the form

$$\hat{\mathbf{u}}^{\mathbf{T}}(1)=\left(x_M(1), \frac{x_M(1)-x_M(0)}{T}, y_M(1), \frac{y_M(1)-y_M(0)}{T}\right). \tag{13}$$

The correlation matrix of errors of the initial estimate is equal to

$$\hat{\mathbf{P}}(1) = \begin{bmatrix} \sigma_x^2(1) & \frac{\sigma_x^2(1)}{T} & \sigma_{xy}^2(1) & \frac{\sigma_{xy}^2(1)}{T} \\ \frac{\sigma_x^2(1)}{T} & \frac{\sigma_x^2(1)+\sigma_x^2(0)}{T^2}+\sigma_{ax}^2T^2 & \frac{\sigma_{xy}^2(1)}{T} & \frac{\sigma_{xy}^2(1)+\sigma_{xy}^2(0)}{T} \\ \sigma_{xy}^2(1) & \frac{\sigma_{xy}^2(1)}{T} & \sigma_y^2(1) & \frac{\sigma_y^2(1)}{T} \\ \frac{\sigma_{xy}^2(1)}{T} & \frac{\sigma_{xy}^2(1)+\sigma_{xy}^2(0)}{T} & \frac{\sigma_y^2(1)}{T} & \frac{\sigma_y^2(1)+\sigma_y^2(0)}{T^2}+\sigma_{ay}^2T^2 \end{bmatrix}. \tag{14}$$

In practice, to simplify the filtering algorithm, the cross-correlation between measurement errors in the rectangular CS $\sigma_{xy}^2(k)$ is neglected by setting to zero. As a result, the fourth-order Kalman filter is divided into two second-order filters and independent filtering is performed on the coordinates x and y.

The coordinates of the gate center are calculated at the forecast stage and are equal to

$$\begin{aligned} x_e(k) &= x^*(k); \\ y_e(k) &= y^*(k). \end{aligned} \tag{15}$$

2 Analysis of the accuracy of UAV positioning in the current frame

As noted above, theoretically standard deviation (SD) measurement errors $\sigma_x(k)$, $\sigma_y(k)$ are difficult to determine. Analysis of positioning accuracy using a correlation algorithm was performed by statistical modeling in the Matlab environment. Fig. 3 shows the original test images of UAVs of different sizes. They are obtained on the basis of images in JPEG format, which were normalized to the interval [0,1] and presented in floating-point format. These images are used to analyze the accuracy of positioning when moving the UAV in the cases when the reference image is ideal, as well as distorted by noise. As interference the discrete white Gaussian noise with dispersion σ_n^2 was used.

The gate with the reference image had the shape of a rectangle, in the center of which was the image of a UAV. Its sides were three times larger than the sides of the UAV test image. The observed image had the same dimensions as the strobe. But in each test, the test image of the UAV in it was located equally likely. The mutual correlation function was calculated using spectral transformations [3] based on the discrete Fourier transform.

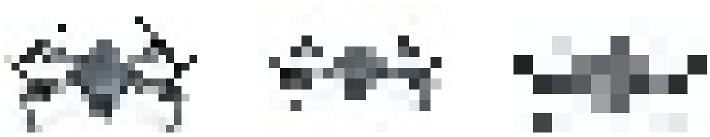
Fig. 4 presents the results of calculating the normalized mutual correlation function of the reference and current image of 10 by 6 pixels, distorted by noise with $\sigma_n = 0.1$.

The presence of noise leads to a decrease in the correlation coefficient of the images, as well as to the appearance of additional local extremes. The presence of local extrema leads to possible errors (erroneous decisions) in determining the offset of the current image relative to the reference image.

The Monte Carlo method was used to evaluate SD σ_X and σ_Y and UAV positioning errors along the X and Y axes in 1000 implementations. The study was performed at different SD of noise σ_n. In order to compare the positioning accuracy for different test images, the normalized SD $\bar{\sigma}_X$ and $\bar{\sigma}_Y$ and UAV positioning errors were calculated according to the formulas

$$\bar{\sigma}_X = 2\sigma_X / l_X, \quad \bar{\sigma}_Y = 2\sigma_Y / l_Y, \tag{16}$$

where l_X, l_Y – the sizes of the observed images on the corresponding axes.



(a) (b) (c)

Fig. 3. Reference image (a) 25 by 15 pixels, (b) 18 by 12 pixels, (c) 10 by 6 pixels

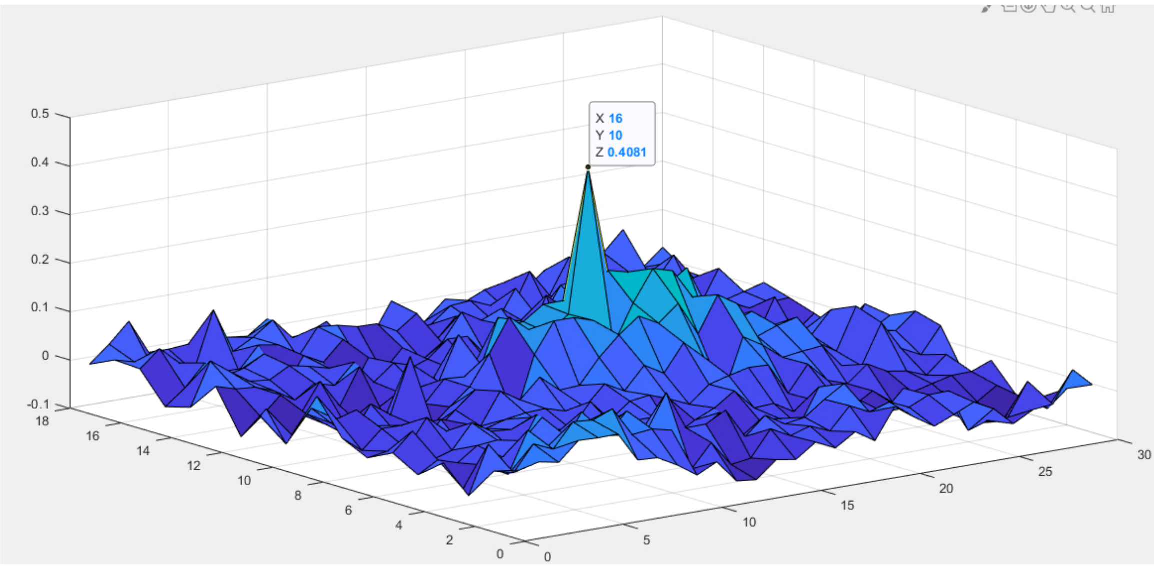
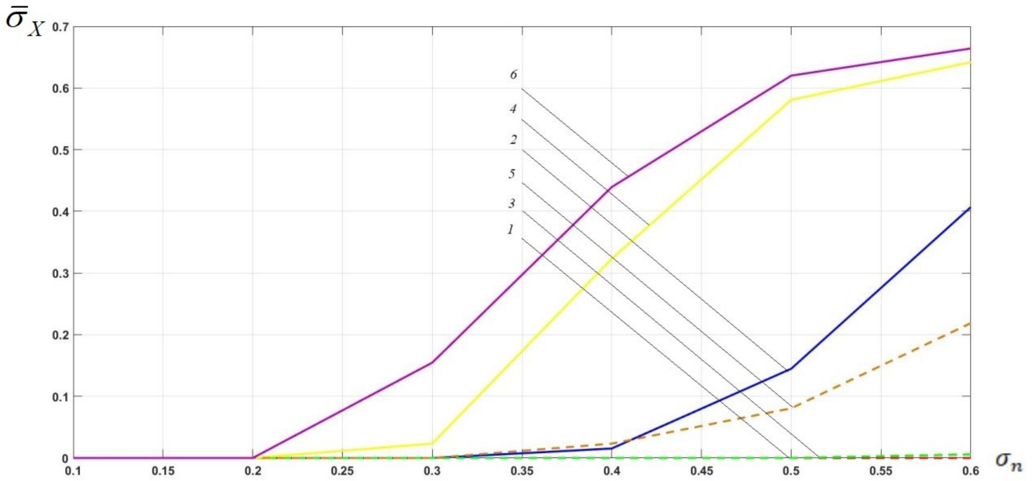


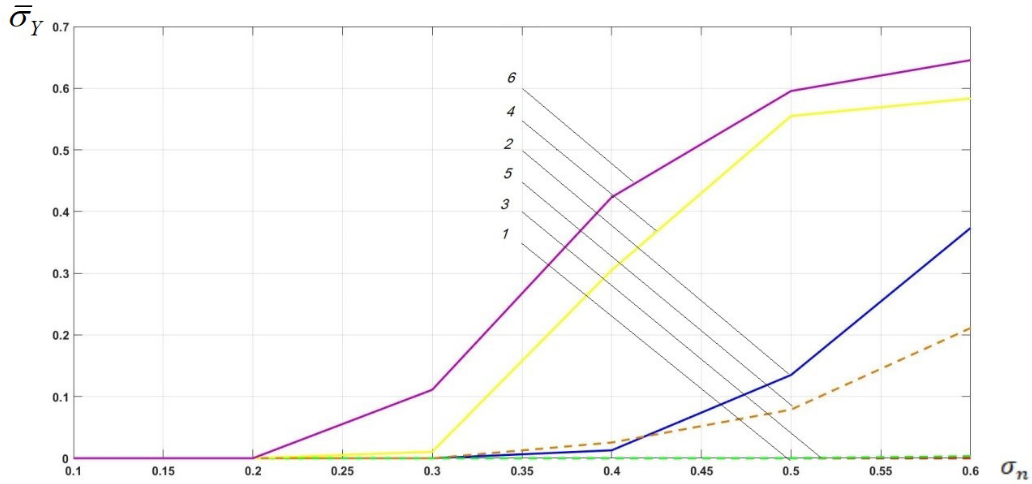
Fig. 4. Normalized mutual correlation function of noisy images

The simulation results are shown in Fig. 5. Curves 2, 4, 6 characterize situations when the reference image is ideal and curves 1, 3, 5 are provided for images distorted by noise. As follows from the curves, the correlation method provides subpixel positioning accuracy. The noise level of the reference image leads to the appearance of the noise component of the positioning error, which increases significantly with increasing

SD of noise σ_n and decreasing image size (energy of the signal component). The obtained results make it possible to determine the conditions for acceptable determination of UAV position and probable conditions when UAV support is disrupted, which in turn allows us to determine the conditions for effective use of correlation algorithms for unmanned aerial vehicle support in video surveillance systems.



(a)



(b)

Fig. 5. The results of experiments for images (a) SD on x, (b) SD on y
(1 - without the noise of the reference for 25 by 15 pixels, 2 - with the noise of the reference for 25 by 15 pixels, 3 - without the noise of the reference for 18 by 12 pixels, 4 - with the noise of the reference for 18 by 12 pixels, 5 - without the noise of the reference for 10 by 6 pixels, 6 - with the noise of the reference for 10 by 6 pixels)

3 Analysis of the efficiency of the Kalman-type correlation algorithm for UAVs tracking

The analysis of the correlation algorithm for UAV tracking based on the Kalman filter was also performed using the Monte Carlo method. The MATLAB program simulated the movement of the target in a rectangular coordinate system with the initial position $x_1 = 100$ pixels, $y_1 = 100$ pixels and speed $\dot{x} = 10$ pixels/tact, $\dot{y} = 10$ pixels/tact. The intensity of the maneuver is set to $\sigma_a = 1$ pixel/tact^2. The number of samples of trajectories N=20. The rate of information T=1 tact. Errors for measuring the rectangular coordinates of the target by the correlation method were set $\sigma_X = \sigma_Y = 1$ pixel. The number of implementations of the Monte Carlo method is equal to M=1000.

To analyze the features of the filtering algorithm, a test image of UAV with size 10 by 6 pixel was used, the accuracy of positioning of which by the correlation method significantly depends on the noise power in the image. In the experiment SD of noise in the image is $\sigma_n = 0.1$. Figure 6 a, c shows the mathematical expectations m_x^*, m_y^* (curves 1), SD target position prediction errors σ_x^*, σ_y^* (curves 2) obtained by the Monte Carlo method and SD target position prediction errors calculated by the filter $\sqrt{p_x^*}$, $\sqrt{p_y^*}$ (curves 3). Fig. 6, b , d shows the mathematical expectations $\hat{m}_x, \hat{m}_y$ (curves 1), SD errors in estimating the position of the target $\hat{\sigma}_x, \hat{\sigma}_y$ (curves 2), obtained by the Monte Carlo method and SD errors in forecasting the position of the target, calculated by the filter $\sqrt{\hat{p}_x}$, $\sqrt{\hat{p}_y}$ (curves 3). The actual SD of errors in estimating the coordinates of the target does not exceed the theoretical SD of estimation errors, which ensures the efficiency of the Kalman filtering algorithm.

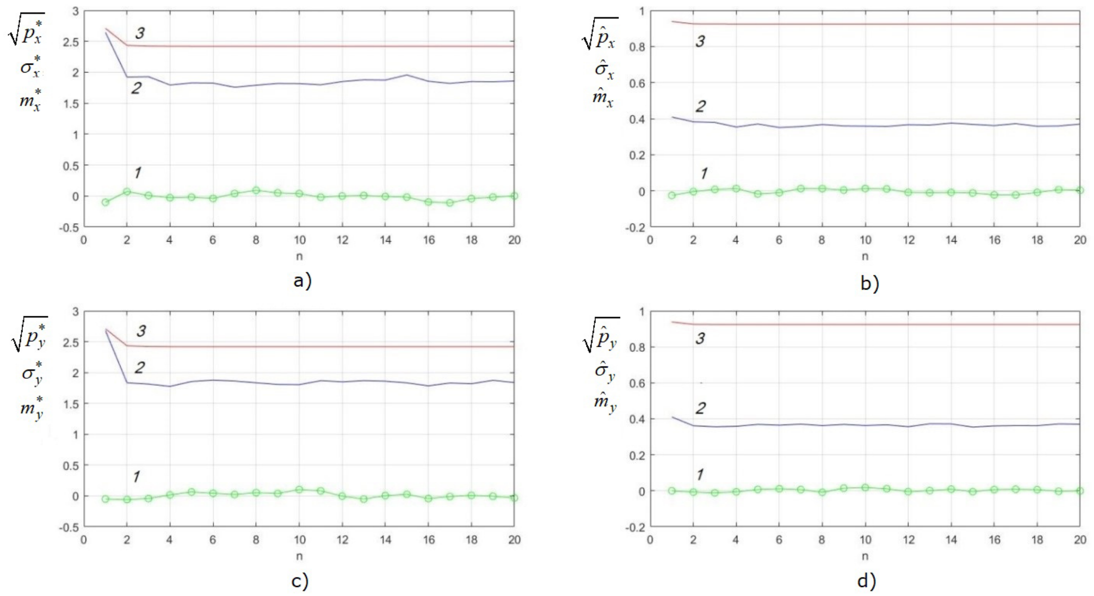


Fig. 6. Dependences of mathematical expectation and SD of forecast errors and estimates UAV coordinates on the X and Y axes

Using the Monte Carlo method, the probability of failure P_d of UAV tracking was calculated depending on the SD of noise in the image. The reference image was also distorted by noise. The decision to disrupt maintenance is made provided that the test image goes beyond the maintenance gate.

In Fig. 7 shows the probabilities of UAV tracking failure P_d obtained using the Monte Carlo method, and Fig. 8 shows the mathematical expectations m_t of the number of UAV tracking tact depending on the SD of noise σ_n for the three test images.

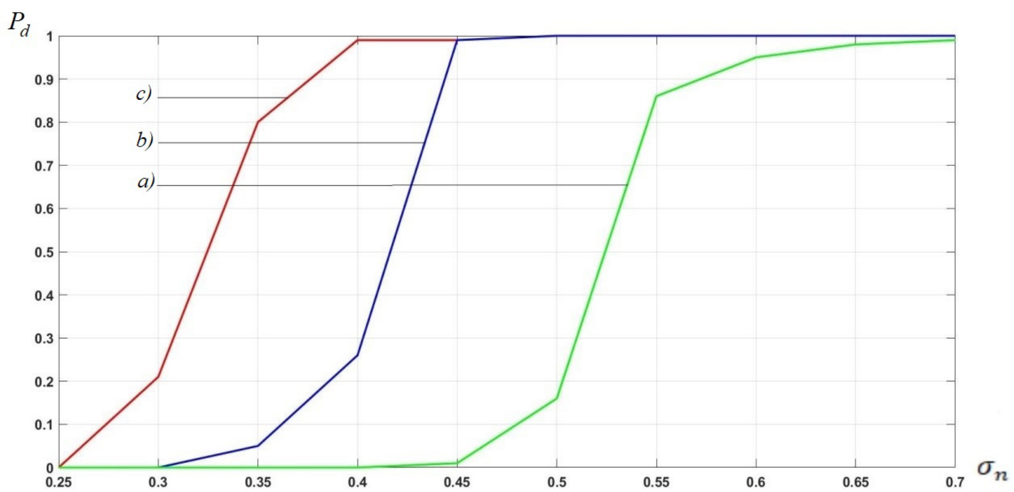


Fig. 7. Tracking failure probabilities for images a) 25 by 15, b) 18 by 12, c) 10 by 6 pixels

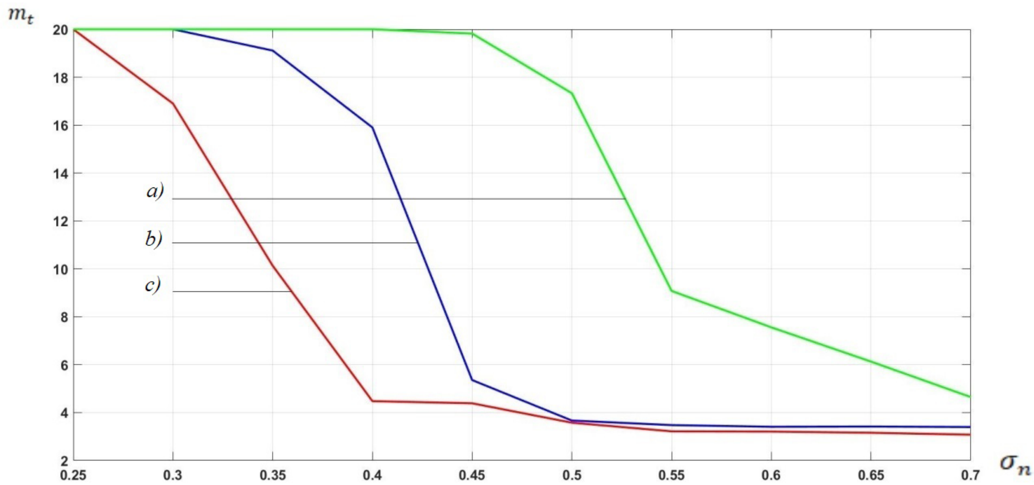


Fig. 8. Mathematical expectations of the number of tact for images a) 25 by 15, b) 18 by 12, c) 10 by 6 pixels

The considered algorithm provides high efficiency of UAV tracking in the presence of uncorrelated interference with SD $\sigma_n < 0.25\ldots0.45$ depending on the image size (energy of the signal component), which is due to the optimal properties of the correlation receiver, which maximizes the signal-to-noise ratio at its output. This is allows us to effectively use the Kalman-type correlation algorithm for tracking in practice.

Conclusions

The correlation method provides subpixel positioning accuracy $\sigma_X < 1$ pixel, $\sigma_Y < 1$ pixel. The noise of the reference image leads to a significant increase in the noise component of the positioning error compared to the noiseless standard, with a decrease in image size and an increase in SD of noise.

The cross-correlation of errors in measuring UAV coordinates by the correlation method is, as a rule, unknown in practice. Neglecting the cross-correlation between measurement errors makes it possible to simplify the tracking algorithm and to evaluate independently the parameters of UAV motion using the lowest order Kalman filters along the axes of a rectangular CS.

In the considered model the Kalman-type correlation algorithm of UAV tracking provides steady support of UAV in the presence of uncorrelated interference with SD $\sigma_n < 0.25\ldots0.45$ depending on the sizes of the image (energy of a signal component) that is caused by optimum properties of the correlation receiver which maximizes its output signal-to-noise ratio. This is allows us to effectively use the Kalman-type correlation algorithm for tracking in practice.

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Аналіз ефективності кореляційного алгоритму стеження калманівського типу за малорозмірним БПЛА при наявності некорельованих завад

Герасименко А .О., Жук С. Я.

У статті показано актуальність задачі розробки і аналізу алгоритмів стеження за малорозмірним безпілотним літальним апаратом (БПЛА) за даними відеоспостережень. Найбільш поширеною завадою на практиці, що спотворює зображення, є просторово некорельований адитивний шум. Для виявлення об'єктів на зображеннях застосовується кореляційний алгоритм, який має високу ефективність в силу непрямого використання не тільки характеристик яскравості об'єктів, але й їх форми та положення.

Моделлю об'єкту спостереження є прямокутна область, в якій знаходиться ціль. Задача стеження зводиться до позиціонування цілі в стробі супроводження на поточному зображенні з використанням кореляційного алгоритму і оцінювання параметрів її руху на основі алгоритму калманівської фільтрації. В синтезованому алгоритмі фільтрації оцінювання параметрів руху по осям прямокутної системи координат виконується незалежно фільтрами Калмана другого порядку.

Аналіз точності позиціонування з використанням кореляційного алгоритму, а також кореляційного алгоритму стеження за БПЛА на основі фільтру Калмана виконано шляхом статистичного моделювання у середовищі Matlab. Кореляційний метод забезпечує субпіксельну точність позиціонування. Зашумленість еталонного зображення призводить до появи шумової складової похибки позиціонування, яка значно зростає при зменшенні розмірів зображення і збільшенні середньоквадратичного відхилення (СКВ) шуму на зображенні. В розглянутих модельних прикладах кореляційний алгоритм стеження калманівського типу за БПЛА забезпечує стійке супроводження БПЛА при наявності некорельованої завади з СКВ $\sigma_n < 0.25 \ldots 45$ в залежності від розмірів зображення (енергії сигнальної складової), що обумовлено оптимальними властивостями кореляційного приймача, який максимізує відношення сигнал/шум на його виході. Це дозволяє ефективно використовувати кореляційний алгоритм стеження калманівського типу на практиці при наявності даних завад.

Ключові слова: безпілотний літальний апарат; кореляційний алгоритм; еталонне зображення; фільтр Калмана; точність позиціонування; ймовірність зриву супроводження

Анализ эффективности корреляционного алгоритма слежения калмановского типа за малоразмерным БПЛА при наличии некоррелированных помех

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Показана актуальность задачи разработки и анализа алгоритмов слежения за малоразмерным беспилотным летательным аппаратом (БПЛА) по данным видеонаблюдений. Синтезирован корреляционный алгоритм слежения калмановского типа за малоразмерным БПЛА при наличии пространственно некоррелированных помех, которые являются наиболее распространенными на практике. В полученном алгоритме оценивание параметров движения БПЛА выполняется независимо по осям прямоугольной системы координат. Анализ точности позиционирования с использованием корреляционного алгоритма, а также корреляционного алгоритма слежения за БПЛА на основе фильтра Калмана выполнен путем статистического моделирования в среде программирования Matlab.

Ключевые слова: беспилотный летательный аппарат; корреляционный алгоритм; эталонное изображение; фильтр Калмана; точность позиционирования; вероятность срыва сопровождения