The Technology for Integrating Observation Results with Sensors of Various Physical Fields with Automatic Guidance of Unmanned Aerial Vehicles at a Given Point

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***Abstract*— With the application of the theory of nonlinear filtering of conditioned Markov processes, a quasi-linear algorithm for automatically directing an unmanned aerial vehicle was synthesized. On the basis of the obtained algorithm, a method is defined for combining the results of observations in various physical fields and ranges of the wavelengths of the eigen and reflected radiation. On the basis of the algorithm, in the Gaussian approximation, the potential for accuracy of tracking of an automatic complex system of sensors is established.**

Keywords*— *integration of the results of observations; automatic tracking; tracking accuracy; the theory of nonlinear filtration; likelihood ratio; probability of detection

I. Introduction

The increasing use of unmanned aerial vehicles (UAVs) for the delivery of small cargoes to the population, in particular in hard-to-reach and sparsely populated areas [1, 2], automatically leads to the need to improve the accuracy and noise immunity of automatic systems for tracking the area of space , where the consignee of the goods or the object of interest is located. In connection with this, it is important to use information on the space-energy characteristics of objects and backgrounds, which are obtained both in various ways when observing own and / or reflected radiation of an object, and in various parts of the spectrum of electromagnetic radiation-ultraviolet, visible, infrared, radio-wave [3, 4]. At the same time, the image of the area of space that is viewed is not interpreted as a normal visual image perceived by a person, but is a three-, four- and more-dimensional image suitable for machine perception, which is a collection of information about the objects surrounding the observer. The desire to use the results of observations of the object in various parts of the spectrum of electromagnetic radiation leads to the need to develop systems with integrated tracking systems, which include television, thermal imaging, radar and other means of image formation [5, 6]. In addition, UAVs are equipped with an inertial navigation system [5], correlated by signals from the receiver of the global positioning system (GPS) [5, 6].

The aim of this article is to establish the principle of construction and determine the potential accuracy of tracking of automatic guidance systems of UAVs with the combination of tracking devices in different physical fields and ranges of the wavelengths of the own and reflected radiations.

II. The Formalization of the Problem and the Algorithm of the Solution

Automatic tracking consists in combining the optical axis of the complexed sensor system with the sighting line of the object. By the magnitude of the angles of the deflection of the optical axis of the sensors from the construction axis of the UAV in the vertical and horizontal planes, commands are developed to correct the movement of the UAV.

The method of solving similar problems is the application of the theory of nonlinear filtration of discrete and continuous Markov processes [7]. In this case, the nature of the changes in the type of the object in each of the observation channels, caused by rotations and deliberate modifications of the observed object, is described by the Markov chain, and the types of the object and their number are predetermined, and the character of the change in the continuous parameters for the images in all channels – angular deviations of the line sight from the optical axis in two mutually perpendicular planes – from the frame to the frame, due to the slowness of their variation, is described by a Gaussian Markov sequence .

We assume that the observation of an object is carried out in N channels, each of which corresponds to one of the physical fields, and the alignment of the line of sight and the optical axis must be performed in the same plane. Let the value of a discrete parameter be described by a sequence with independent states with equal one-step conditional transition probabilities $\pi_m\left(\mu_k^{(n)}\middle|\mu_{k-1}^{(n)}\right)=1/M_n$, where M_n is the number

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of discrete parameters being distinguished; $\mu^{(n)} = \overline{1, M_n}$ – values of discrete parameters that determine the type of the observed object in the n-th observation channel, $n = \overline{1, N}$. The a priori recurrent stochastic equation for variations of a continuous parameter in discrete time has the form

$$\lambda_k = R_\lambda \cdot \lambda_{k-1} + \sigma_\lambda \cdot \sqrt{1 - R_\lambda^2} \cdot \xi_k$$

where R_λ is the correlation coefficient of the parameter values at neighboring steps; σ_λ^2 – a priori dispersion of the parameter; ξ_k – sequence of standard normal numbers.

We will assume that in each channel, against the background of additive Gaussian noise, there are sequences of images of the object and the adjacent background on the flat-bone

$$\left\{ s_{ijk}^{(n)}\left(\lambda_k, \mu_k^{(n)}\right), i = \overline{1, I},\ j = \overline{1, J},\ n = \overline{1, N} \right\}$$

$$y_{ijk}^{(n)} = s_{ijk}^{(n)}\left(\lambda_k, \mu_k^{(n)}\right) + n_{ijk}^{(n)},$$

where $n_{ijk}^{(n)}$ – samples of white noise with dispersions σ_n^2; i, j – number of image elements; I_n, J_n – the size of the images in each of the n observation channels.

Since the noise is independent, the likelihood function of the parameters is written in the form [7, 8]

$$L\left(\lambda_k, \mu_k^{(n)}\right) = \prod_{m=1}^{M_n} \prod_{i=1}^{I_n} \prod_{j=1}^{J_n} w\left\{ y_{ijk}^{(n)} - s_{ijk}^{(m)}\left(\lambda_k, \mu_k^{(m)}\right)\right\}, \quad n = \overline{1, N},$$

where $w(\bullet)$- the density of the distribution of the probabilities of the values of the noise readings, μ_k, $n = \overline{1, N}$ - the values of the discrete parameters in the N observation channels at the k-th step. Then the logarithm of the one-step likelihood function (OSLF) is written as

$$\Pi_k\left(\lambda_k, \mu_k^{(n)}\right) = \sum_{m=1}^{M_n} \Pi_{km}\left(\lambda_k, \mu_k^{(m)}\right), \quad n = \overline{1, N}.$$

In the Gaussian character of the noise and in the case of non-energy parameters, the OSLF is written in the form [7, 8, 9]

$$\Pi_k\left(\lambda_k, \mu_k^{(n)}\right) = \sum_{m=1}^{M_n} \sigma_n^{-2} \sum_{i=1}^{I} \sum_{j=1}^{J} y_{ijk}^{(n)} \cdot s_{ijk}^{(m)}\left(\lambda_k, \mu_k^{(m)}\right), \quad n = \overline{1, N}$$

The final a posteriori joint probability distribution of the parameters $\lambda_k, \mu_k^{(n)}, n = \overline{1, N}$ is

$$w_{ps}\left(\lambda_k, \mu_k^{(n)}\right) = h_k \cdot \exp\left\{\Pi_k\left(\lambda_k, \mu_k^{(n)}\right)\right\} \cdot w^э\left(\lambda_k, \mu_k^{(n)}\right), n = \overline{1, N}, \quad (1)$$

where $h_k^{-1} = \sum_{n=1}^{N} \int_{\{\lambda_k\}} \exp\left\{\Pi_k\left(\lambda_k, \mu_k^{(n)}\right)\right\} \cdot w^э\left(\lambda_k, \mu_k^{(n)}\right) d\lambda_k$ is the constant normalization.

The extrapolated probability density of the continuous parameter included in this expression is

$$w^э\left(\lambda_k, \mu_k^{(n)}\right) = \int_{\{\lambda_{k-1}\}} \prod_{m=1}^{M_n} w\left(\lambda_k, \mu_k^{(m)} \middle| \lambda_{k-1}, \mu_{k-1}^{(m)}\right) w_{ps}\left(\lambda_{k-1}, \mu_{k-1}^{(m)}\right) d\lambda_{k-1}, \quad n = \overline{1, N} \quad (2)$$

where

$$w\left(\lambda_k, \mu_k^{(m)} \middle| \lambda_{k-1}, \mu_{k-1}^{(m)}\right) = w\left(\lambda_k \middle| \lambda_{k-1}\right) p\left(\mu_{k-1}^{(m)}\right) \pi\left(\mu_k^{(m)} \middle| \mu_{k-1}^{(m)}\right),$$

$p\left(\mu_{k-1}^{(m)}\right)$, $m = \overline{1, N}$ – a posteriori probabilities of discrete parameters in m channels at the $(k-1)$-th step.

The decision on the values of the parameters μ_k, $k = \overline{1, N}$, and λ_k is taken on the criterion of maximum a posteriori probabilities

$$P_{ps}\left(\mu_k^{(n)}\right) = \int_{-\infty}^{\infty} w_{ps}\left(\lambda_k, \mu_k^{(n)}\right) w(\lambda_k) d\lambda_k$$

$$\hat{\mu}_k = \arg\max_n P_{ps}\left(\mu_k^{(n)}\right).$$

With a small level of intrinsic noise in the case of moderate changes in the continuous parameter (constant in each frame), it is expedient to search for the unconditional final a posteriori probability distribution of the continuous parameter $w_{ps}(\lambda_k) = \sum_{n=1}^{N} w_{ps}\left(\lambda_k, \mu_k^{(n)}\right)$ in the form of a Gaussian law [7, 10], in which the posterior average m_k is an estimate of a continuous parameter $\hat{\lambda}_k = m_k$, and a posteriori variance d_k characterizes the accuracy of tracking.

Using the expansion of the OSLF in a Taylor series with respect to the continuous parameter in the neighborhood of the value $\lambda_k^э = R_\lambda \cdot \hat{\lambda}_{k-1}$ corresponding to the maximum of the extrapolated probability density of the continuous parameter, from expressions (1) and (2) we obtain the filtering algorithm in the form of three equations for the posterior probability of a discrete parameter, estimate and variance of the estimate of the continuous parameter

$$P_{ps}\left(\mu_k^{(n)}\right) = C_k \cdot \prod_{m=1}^{M_n} \left[\exp\left\{\Pi_k\left(\lambda_k^э, \mu_k^{(m)}\right)\right\} \cdot \sqrt{\chi_k\left(\mu_k^{(m)}\right) \cdot D^{-1}} \times \right.$$
$$\left. \times \exp\left\{ \frac{1}{2} \cdot \chi_k\left(\mu_k^{(m)}\right) \cdot \left[\Pi_\lambda'\left(\lambda_k^э, \mu_k^{(m)}\right)\right]^2 \right\} \right], n = \overline{1, N},$$

$$\hat{\lambda}_k = \lambda_k^э + \sum_{n=1}^{N} \pi_n\left(\mu_{kn} \middle| \mu_{k-1n}\right) \cdot \chi_k\left(\mu_k^{(n)}\right) \cdot \sum_{m=1}^{M_n} P_{ps}\left(\mu_k^{(m)}\right) \cdot \Pi_\lambda'\left(\lambda_k^э, \mu_k^{(n)}\right) \quad (3)$$

$$d_k = C_k \cdot \sum_{n=1}^{N} \sum_{m=1}^{M_n} \frac{\exp\left\{\Pi\left(\lambda_k^э, \mu_k^{(m)}\right)\right\}}{\sqrt{\chi_k\left(\mu_k^{(n)}\right) \cdot D^{-1}}} \cdot \exp\left\{ \frac{1}{2} \cdot \chi_k\left(\mu_k^{(n)}\right) \cdot \left[\Pi_\lambda'\left(\lambda_k^э, \mu_k^{(m)}\right)\right]^2 \right\} \times$$
$$\times \left[\left(\chi_k\left(\mu_k^{(n)}\right) \cdot \Pi_\lambda'\left(\lambda_k^э, \mu_k^{(m)}\right) + \lambda_k^э - \hat{\lambda}_k\right)^2 + \chi_k\left(\mu_k^{(n)}\right) \right]$$

where C_k – is the normalization constant; $d_0 = \left(1 - R_\lambda^2\right) \cdot \sigma_\lambda^2$ – variance of the transition probability density; $D = d_0 + R_\lambda^2 \cdot d_{k-1}$ – variance of the extrapolated estimate of a continuous parameter; $\Pi'_\lambda\left(\lambda_k^{э}, \mu_k^{(n)}\right)$ – derivative of OSLF; $\chi_k\left(\mu_k^{(n)}\right) = D / \left[1 - D \cdot \overline{\Pi}''_{\lambda\lambda}\left(\lambda_k^{э}, \mu_n\right)\right]$ – cumulant of the extrapolated probability distribution of a continuous parameter; $\overline{\Pi}''_{\lambda\lambda}\left(\lambda_k^{э}, \mu_k\right) = -q_{\mu k} \cdot R''_{\lambda\lambda}\left(0, \mu_k\right)$ – the signal part of the second derivative of OSLF [3]; $q_{\mu k}$ – signal to noise ratio; $R''_{\lambda\lambda}\left(0, \mu_k\right)$ – the second derivative of the correlation function of the observed image.

The minimum values of the values $\chi_k\left(\mu_k^{(n)}\right)$ are equal to D; therefore, to simplify the algorithms, the value $\chi_k\left(\mu_k^{(n)}\right)$ is assumed to be the same and equal to κ_n for all values of the discrete parameter of each channel and corresponding to the stationary monitoring regime that occurs after the preliminary indication of the location of the object and the inclusion of the tracking mode before launching the UAV. Then the algorithm for estimating the continuous parameter (3) takes the form

$$\hat{\lambda}_k = \lambda_k^{э} + \sum_{n=1}^{N} \kappa_n \cdot \sum_{m=1}^{M_n} P_{ps}\left(\mu_k^{(m)}\right) \cdot \Pi'_\lambda\left(\lambda_k^{э}, \mu_k^{(m)}\right). \quad (4)$$

The a posteriori probabilities of discrete parameters are equal [11] to

$$P_{ps}\left(\mu_k^{(n)}\right) \cong \exp\left\{\Pi_k\left(\lambda_k^{э}, \mu_k^{(n)}\right)\right\} \cdot \left[\sum_{m=1}^{M_n} \exp\left\{\Pi_k\left(\lambda_k^{э}, \mu_k^{(m)}\right)\right\}\right]^{-1}, \quad n = \overline{1, N}$$

The estimation of a continuous parameter is formed as the weight sum of the discrepancy signals with weights equal to the a posteriori probabilities of object detection in various physical fields [12].

III. Structure of the Tracking System

The structural scheme of the synthesized system is shown in Fig. 1.

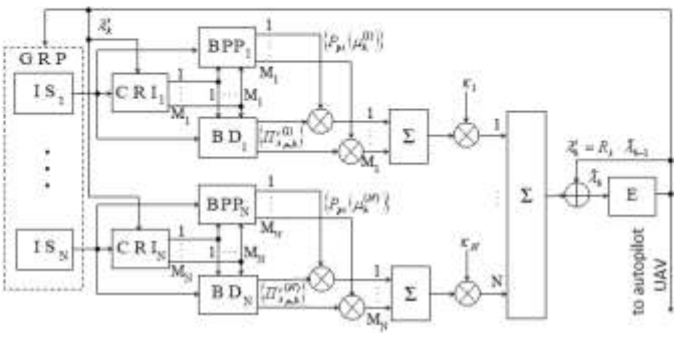

Fig. 1. Structural diagram of a complex automatic tracking system

Fig. 1 shows: *ISn*, $n = \overline{1, N}$ – image sensors; *GRP* – gyrostabilized rotary platform; *BDn* - blocks of discriminators; *CRIn* – cans of reference images; *BPPn* – blocks of a posteriori probabilities; Σ – totalizers; *E* – is an extrapolator. A distinctive feature of the synthesized structural scheme is its closure, as an automatic control system with feedback by decision. A similar result can not be obtained using the theory of continuous parameters estimation.

IV. Analysis of Accuracy of the Tracking System

The potential tracking accuracy is determined on the assumption that in each channel an object with constant contrast is observed on a uniform background and is detected with probability P_n [10]:

$$P_n = 0{,}5 - \Phi_0\left(\Phi_0^{-1}(F - 0{,}5) - q_n\right), \quad n = \overline{1, N}, \quad (5)$$

where

$\Phi_0(z) = \frac{1}{\sqrt{2\pi}} \int_0^z \exp\left\{-t^2/2\right\} dt$ is the normalized error function; q_n – object detection parameter; F – probability of false alarm.

The object detection parameter of a sensor-integrated sensor is equal to

$$q = \sum_{n=1}^{N} q_n \quad (6)$$

The probability of detection of an object by a system of image sensors integrated with the system is equal to [9]:

$$P = 0{,}5 - \Phi_0\left(\Phi_0^{-1}(F - 0{,}5) - q\right).$$

The tracking accuracy is determined from the recurrence equation for the a posteriori dispersion of the continuous parameter d_k estimation, which, with the introduction of the notion of relative a posteriori dispersion $\delta_k^2 = d_k / \sigma_\lambda^2$, where $\sigma_\lambda^2 = \left(\alpha_0 \cdot L\right)^2$ – the a priori dispersion of the continuous parameter with the α_0 value of the angular deviation of the unraveled UAV flight and the launching range L [11]:

$$\delta_k^2 = \frac{P}{\left[1 + R_\lambda^2 \cdot \left(\delta_{k-1}^2 - 1\right)\right]^{-1} + z} + \frac{1 - P}{\left[1 + R_\lambda^2 \cdot \left(\delta_{k-1}^2 - 1\right)\right]^{-1}} \quad (7)$$

where $z = \sigma_\lambda^2 q$ is the generalized object detection parameter of a complex system.

The probability of holding the optical axis of a complex tracking system within the visible projection of the object is [10]:

$$P_c = \left[0{,}5 - \Phi_0\left(\Delta\varphi_g / \left(\sigma_\lambda \cdot \delta\right)\right)\right] \cdot \left[0{,}5 - \Phi_0\left(\Delta\varphi_v / \left(\sigma_\lambda \cdot \delta\right)\right)\right], \quad (8)$$

where $\Delta\varphi_g, \Delta\varphi_v$ – angular dimensions of the visible projection of a given area of space; δ – is the stationary solution of the recurrence equation (7).

If one of the parameters q_N is not defined, but the probability of finding the object P_N is known, then from the expression (5) with the probability of false alarm F_N, the missing detection parameter is equal to

$$q_N = \Phi_0^{-1}(F_N - 0,5) - \Phi_0^{-1}(0,5 - P_N).$$

Since the main limiting factor in the use of the means of monitoring each channel is its range, the features of complex systems often consist in using each channel in turn.

Fig. 2a and 2b show the dependences of the errors of the tracking system Δ, m, on the parameter q and the probability P of detecting the object at different observation distances L by a complexed sensor system. When calculating tracking errors $\Delta = \delta \cdot \sigma_\lambda$ using the recurrence expression (7), it is assumed that α_0 = 10 mrad, R_λ = 0.99, F = 0.01.

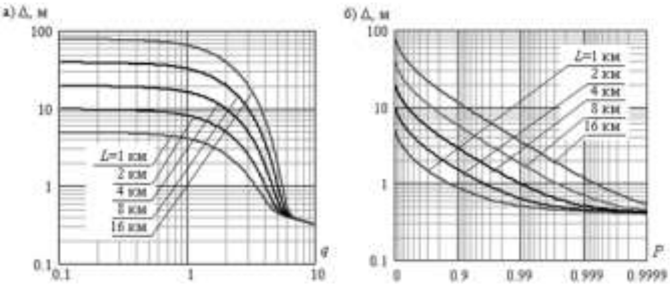

Fig. 2. Dependencies of tracking errors for different observation distances: (a) from the object detection parameter; b) the probability of finding an object.

Increasing the detection parameter of the object more than 7 does not lead to a decrease in tracking errors, therefore, deterioration of the conditions of object observation in each channel is parried by an increase in the number of observation channels. Therefore, in order to preserve the integrity of the complex sensor system, it is necessary to increase the parameter and the probability of detecting the object with each sensor in every possible way [6].

Conclusion

In complex automatic control systems, the optimal way of combining the results of observations with different systems is to form a single control signal for rotation of the combined optical axis, following the object as a result of the weight summation of the discrepancy signals produced by each of the observation systems. As weighting factors, the probability of detection of an object of each of the observation systems is used.

The analysis of the quality of the complex system showed that there is a value of the detection parameter, in which the tracking accuracy does not depend on the range of object observation. This can be done by exchanging the number of available observation channels for the quality of object detection in each of them. This is a manifestation of the synergistic effect: joint monitoring of several sensors with low quality indicators can be followed by a poorly visible or intentionally disguised object, which can not be achieved by using a single high-quality sensor.

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