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DISCRETE FUZZY FILTER OF UAV'S FLIGHT PARAMETERS

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The robust discrete filter for flight information parameters estimation of Unman Arial Vehicle in conditions of nonstationary and not additive disturbance influence, with unknown parameters, is synthesized. The filter based on the theory of fuzzy measure and fuzzy-integral calculus. An estimation of the signal is determined by fuzzy images of the signal estimated value at the previous step of the measured signal and by selection of filtration function. The investigations of the efficiency of synthesized fuzzy filter are performed.

Синтезовано робастний дискретний фільтр для оцінки параметрів польотної інформації безпілотного літального апарата в умовах нестаціонарних, неадитивних збурень із невідомими параметрами. Фільтр реалізується на основі використання теорії нечіткої міри і нечітко-інтегрального числення. Для оцінки корисного сигналу фільтр використовує нечітке зображення оцінки сигналу на попередньому етапі сигналу, що вимірюється, та двовимірної фільтруючої функції. Проведено випробування працездатності та ефективності фільтра.

Синтезирован робастный дискретный фильтр для оценки параметров полетной информации беспилотных летательных аппаратов в условиях нестационарных, неаддитивных возмущений с неизвестными параметрами. Фильтр реализуется на основе использования теории нечеткой меры и нечетко-интегрального исчисления. Для оценки полезного сигнала фильтр использует нечеткие изображения оценки сигнала на предыдущем шаге измеряемого сигнала и двухмерной фильтрующей функции. Проведены исследования работоспособности и эффективности фильтра.

Statement of purpose

Nowadays, the use of unmanned aerial vehicles (UAV) provides an extensive range of tasks. The efficient solution to this problem is largely depends on appropriate control formation for autonomous control systems of UAV.

The control formation is largely depends on the flight accuracy of measurement. Therefore, to ensure the accuracy of flight parameters measurements a complex system of estimation and control optimization combined with filters is widely used. Particularly, the classical filters like Kalman-Bucy filters [1; 2] in a time domain, and Wiener based optimal filter construction [3] in a frequency domain are used while creating control systems.

The usage of these filters significantly increases the accuracy of signals with noises measurement. However, to date synthesis of the above optimal filter requires a clear knowledge of the model parameters of signal and noise, particularly the correlation characteristics of random signals. In addition, the model assumes stationarity and additiveness of the noises [1] that significantly complicates the application of these filters in practice. In actual flight conditions for the real measuring noises are non-stationary, not additive with unknown parameters, which requires the creation of robust filter in the cases of fuzzy information about the noise. Thus, the development of a fuzzy robust filter for determining the parameters of the UAV flight is an important scientific and practical challenge.

Problem Statement

In this paper the small UAV is considered as control plant. Generally, the control plant is represented with tuple set given below:

$$\langle \Omega, X, U, T, Y, \rho, \gamma, \xi \rangle, \qquad (1)$$

where Ω is the state space;

X are the set of characteristics, attributes, that describe the states from Ω control plant;

U is control space;

T is a time (discrete or continuous);

Y is a space of the output values;

ρ: (Ω × T) × U × T → Ω is a map that describes the changes in dynamics state of controlled plant;

γ: Ω × T→Y is output mapping that describes the parameters observation process of the control plant;

ξ is some uncontrollable external factors, conditions and disturbances.

This set of characteristics takes its values each in its own set of values $\{V_j\}$.

For the given control plant the estimation problem of the current state ω ∈ Ω (filtration problem) in general is possible to formulate as follows.

Let the plant is described by (1). It is necessary, basing on the observation state dynamics of the plant and its model under disturbance influence ξ to find such mapping γ: $\Omega \times T \to \Omega'$, $\Omega \equiv \Omega'$ under which the estimated plant state ω' ∈ Ω'brings maximum coincidence under the criteria {K} with the true state.

Let's consider the statement of the problem in detail. Accordingly to the stated above reasons we will consider the problem of filtering in terms of fuzzy noises. To describe the plant state we will use the fuzzy-integral model of signals and noises [3], which provide the possibility to represent data in the form of fuzzy measures distribution. It allows to represent the signal state by fuzzy mapping $s_u(\omega):\Omega\to[01]$, in the form of fuzzy measures distribution [4].

The efficiency of this approach to describe the fuzzy processes (FP) in real conditions with uncertainties is confirmed by a number of researches [4; 5].

In [3] it is shown that fuzzy integral equations could be used for the FP description. Let the true signal of UAV flight parameters is described by FP with a fuzzy-integral equation:

$$s_u(\omega) = \int_T h'(\omega,t) \circ \tilde{g}_{f_\Gamma(\omega)}(\cdot), \qquad (2)$$

where $h'(\omega t) : \Omega \times T \to [01]$ - fuzzy relation that shows the signal dynamics under the fixed initial condition $s_u^0(\omega):\Omega\to[01]$;

$g(\cdot):2^\Omega \to[01]$ is the fuzzy measure in the state space of signal Ω, $f_\Gamma(\omega)$ is the FP - similar to the Wiener process that defines uncertainties of FP in time domain.

It is considered that fuzzy relation is known.

Furthermore, the signal model is known and described with the fuzzy-integral equation:

$$s_u(\omega) = \int_T h(\omega,t) \circ \tilde{g}_{f_\Gamma(\omega)}(\cdot), \qquad (3)$$

where h(ω,t) is the fuzzy model relation (transient function of FP) that differs from real FP $h'(\omega,t)$. For the real FP equation (2) may be rewritten in the following form:

$$s_u(\omega) = \eta * \int_T h(\omega,t) \circ g_{f_\Gamma(\omega)}(\cdot),$$

where η is some non-additive component of FP, that describes its variation connected with observation plant errors (for example, wing gusts);

meanwhile (∗) is unknown operator that connects η and model equation.

Real state space Ω with defined fuzzy measure $g(\cdot)$ is connected with state space of observation $\Omega' \equiv \Omega$ via conditional fuzzy measure $Rs(\cdot|p)$. Mapping of space Ω to the observation space Ω′ is specified by measure $Rs(\cdot/p)$. It induces to the observation space Ω′ the fuzzy measure *P* that is connected with measure g by the following relation:

$$P(\cdot) = \int_\Omega R_P(\cdot|s) \circ g\,. \qquad (4)$$

Taking into account a fact that there is a relationship between spaces Ω and Ω′ then to the real state FP $s_u(\omega)$ in Ω′ corresponds an image given below:

$$p_u(\omega) = \int_\Omega s_u(\omega) \circ R_s(\cdot|p) = R_s(s_u(\omega)|p).$$

However, the FP observation is disturbed by some noises ξ thus, instead of $p_u(\omega)$ we obtain the following equation:

$$p_A(\omega) = p_u(\omega) * \xi = \xi * R_s(s_u(\omega)\,|\,p),$$

where (∗) is unknown operator that defines the character of measurements errors influence, ξ.

Thus, instead of real FP $s_u(\omega)$ we observe some process $p_A(\omega)$. Besides, it is possible to observe the state $s_M(\omega)$ of FP model, given in (3). Therefore, it is necessary to form a state estimation $\hat{s}(\omega)$ of FP as close as possible to the real state $s_u(\omega)$ of FP.

Synthesis of fuzzy discrete filter

Let's observe a continuous fuzzy filter. In order to synthesis the discrete fuzzy filter with some initial decisions of continuous fuzzy observer obtained in [2] would be given below. Block-scheme of the fuzzy observer can be depicted as shown in fig. 1.

On this scheme the operator $f(\cdot)$ provides such estimation of signal $\hat{p}(\cdot)$ in the space of observation Ω′ under the information about the model p_M and measurements p_A, that with known conditional fuzzy measure (7) $Rp(\cdot/s)$, conjugated to measure $Rs(\cdot/p)$, that satisfies criteria (5).

As [2] shows in order to satisfy the optimality criterion (5) the true state of FP fuzzy estimate should provide the following condition:

$$\int_\Omega \sigma(\omega) \circ \int_\Omega \hat{s}(\omega) \circ g \to \max_{\hat{s}(\omega)}, \tag{6}$$

where function σ(ω) is specified by a relation:

$$\sigma(\omega) = s_M(\omega) \wedge R_p(p_A(\omega)|s). \tag{7}$$

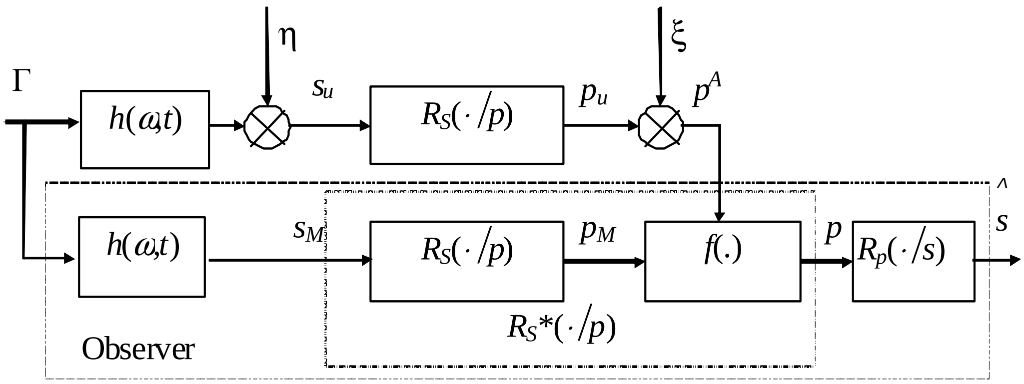

Fig. 1. Block-scheme of fuzzy observer

In this case, an optimization criterion of a fuzzy filter can be written as follows:

$$J = \int_\Omega \left[\hat{s}(\omega) \wedge s_u(\omega)\right] \circ g(\cdot) \to \max_{\hat{S}}. \tag{5}$$

In [3] a general form of the fuzzy observer for a continuous FP was proposed. It satisfies the criterion of optimization (5). However, its application is difficult in practice. In order to provide discrete control systems that are used in control loop of UAV it is necessary to synthesize a discrete fuzzy filter.

According to the equations (6) and (7) a structure of the fuzzy observer is determined via the following relation:

$$\hat{s}(\omega) = f(\hat{s}(\omega), \sigma(\omega) \wedge \varphi_R(\omega)), \tag{8}$$

where

$$\varphi_R(\omega) = \begin{cases} [R,1], \omega \in B_R(\omega), R \le J \in [01] \\ \varphi_R^{\min}, \omega \notin B(\omega), \varphi_R^{\min} \le R \end{cases}$$

is a filtering function on the state space for the current state of the FP (fig. 2).

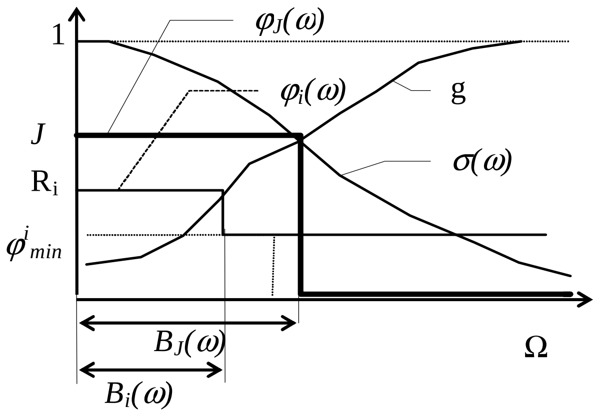

Fig. 2. The family of filter functions

The continuous fuzzy observer when a function $f(\cdot,\cdot)$ is used in the fuzzy integral expression (8) takes the following form :

$$\hat{s}_t(\omega) = \int_T \hat{s}(\omega, t') \circ \partial_\tau(\cdot \mid \omega, t), \qquad (9)$$

where

$\partial_\tau(\cdot \mid \omega, t) : 2^{(T\times\Omega)\times T} \to [01]$ - conditional fuzzy measure, that specifies a level of trust to the state of FP estimation on the previous time moment $t' \le t$, $t' \in \tau \subseteq T$ for fixed $\omega \in \Omega$.

In equation (9) the measurement at the time moment t ∈ T taking into account the state filtration function a value $\hat{s}(\omega, t)$ is specified and given below:

$$\hat{s}(\omega, t) = \sigma_t(\omega) \wedge \varphi_R^t(\omega),$$

where $\sigma_t(\omega)$ is determined by (7).

The time moment t can be uncertain. Thus, the expression (9) defines the fuzzy observer constructed basing on the fuzzy integral. At every time moment $t \in T$ two dimensional filtration function is realized. It is determined by Cartesian product

$$W_t(\omega, \tau) = \varphi_R^t(\omega) \times \partial_\tau(\cdot \mid \omega, t)\,. \qquad (10)$$

In particular time moment t∈T the filtration function $W_t(\omega, \tau)$ determines some subset in a space $\Omega \times T$ and specifies the filter characteristics.

To synthesis of discrete fuzzy filter let's assume that the sampling interval of FP is the fixed interval of time window τ.

Then for the discrete FP fuzzy observer (9) in general form it is possible to represent as a fuzzy-integral convolution of previous states estimation process:

$$\hat{s}_K(\omega) = \int_T \hat{s}(\omega, t') \circ \partial_\Gamma(\cdot \mid \omega, t'), \qquad (11)$$

where $\hat{s}(\omega, t')$ - defined as a cut of FP estimation in a discrete time moment t′=K–nΔ from the interval of time window τ;

supτ = K, and $\partial_\tau(\cdot \mid \omega, t)$ is a discrete fuzzy measure on the time interval τ.

For the discrete fuzzy filter synthesis only one previous evaluation of FP that differs from the current value at time interval τ ⊆ T is considered.

Then the fuzzy filter (11) would be:

$$\hat{s}_t(\omega) = \int_T \hat{s}(\omega, t') \circ \partial_\tau(\cdot \mid \omega, t) =$$

$$\left\{\hat{s}_{t-\tau}(\omega) \wedge \partial_\tau(t-\tau \mid \omega, t)\right\} \vee$$

$$\vee \left\{[\sigma_t(\omega) \wedge \varphi_R^t(\omega)] \wedge \partial_\tau(t \mid \omega, t)\right\} \vee$$

$$\vee \left\{\hat{s}_{t-\tau}(\omega) \wedge [\sigma_t(\omega) \wedge \varphi_R^t(\omega)]\right\}.$$

To obtain an estimation of fuzzy process it is necessary to know the parameters of filtration function (10), particularly function

$$\partial_\tau(\cdot \mid \omega, t), \varphi_R^t(\omega)\,.$$

To obtain the estimates of the unknown functions

$$\partial_\tau(\cdot \mid \omega, t), \varphi_R^t(\omega)$$

let's, firstly, consider the fuzzy integral on a two-point space (i.e., when CardΩ = 2).

According to definition in the case when CardΩ = 2 the value of fuzzy integral given below:

$$J = \int_\Omega \mu(\omega) \circ \partial_\Omega(\cdot)$$

is defined by a density value of fuzzy measure $\partial_\Omega(\cdot)$ in a point $\omega_i \in \Omega$, such that $\mu(\omega_i) \ge \mu(\omega_j)$, j≠i, $\omega_j \in \Omega$, namely:

$$J = \begin{cases} \min(\mu(\omega_i), \mu(\omega_j)), \ \partial(\omega_i) < \mu(\omega_j); \\ \partial(\omega_i), \ \mu(\omega_j) \le \partial(\omega_i) \le \mu(\omega_i); \\ \max(\mu(\omega_i), \ \mu(\omega_j)), \partial(\omega_i) > \mu(\omega_i). \end{cases} \quad (12)$$

The dependence of function J from $\partial(\omega_1)$ is shown on fig. 3.

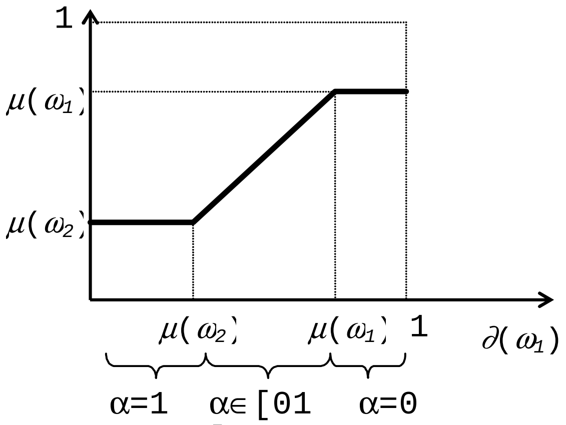

Fig. 3. Dependence between function J and $\partial(\omega_1)$

This dependence corresponds to relation (12). The value of integral J for CardΩ = 2 (fig. 3) is possible to approximate with the help of some defined parameter α:

$$J = (1-\alpha)\mu(\omega_1) + \alpha\mu(\omega_2), \alpha \in [01]. \quad (13)$$

Coefficient α defines the contribution of every component in the value of integral. By using function (13) let's show that the discrete fuzzy filter, which determines the estimated FP $\hat{s}_K(\omega)$ with Card $\tau = 2$ (only one previous value is considered) is described by fuzzy-integral equation:

$$\hat{s}_K(\omega') = (\hat{s}_{K-1}(\omega') \wedge \partial(\omega')) \vee$$
$$\vee \oint_{\hat{s}_{K-1}(\omega) \wedge a(\omega')} \{h_K(\omega,\omega') \wedge \bar{R}_p(p_K^A(\omega) \mid s,\omega')\} \circ g$$

where $\bar{R}_p(p_K^A(\omega) \mid s, \omega')$ is cylindrical extension of the function $R_p(p_K^A(\omega) \mid s)$,

$$a(\omega) = \{\varphi_R^K(\omega') \wedge \partial(\omega)\} \vee \{\hat{s}_{K-1}(\omega') \wedge \varphi_R^K(\omega')\},$$

$$\partial(\omega') = \partial_{K-1}(\omega) = \partial_K(\omega).$$

The following notations are used:

$$a_1(\omega) = \hat{s}_{K-1}(\omega) \wedge \partial_{K-1}(\omega);$$
$$a_2(\omega) = \varphi_R^K(\omega) \wedge \partial_K(\omega);$$
$$a_3(\omega) = \varphi_R^K(\omega) \wedge \hat{s}_{K-1}(\omega).$$

Basing on these notations the estimation process could be described by the following equation:

$$\hat{s}_K(\omega') = a_1(\omega') \vee \{\sigma_K(\omega') \wedge (a_2(\omega') \vee a_3(\omega'))\}.$$

For discrete FP $\sigma_K(\omega)$ is described by relation:

$$\sigma_K(\omega') = R_p(p_K^A(\omega)|s) \wedge \oint_{\hat{s}_{K-1}(\omega)} h(\omega,\omega') \circ g(\cdot) =$$
$$= \oint_{\hat{s}_{K-1}(\omega)} \left[\bar{R}_p(p_K^A(\omega)|s,\omega') \wedge h(\omega,\omega')\right] \circ g(\cdot).$$

Substituting this equation in to relation for $\hat{s}_K(\omega©)$ we obtain the following expression:

$$\hat{s}_K(\omega') = a_1(\omega') \vee \{\sigma_K(\omega') \wedge (a_2(\omega') \vee a_3(\omega'))\} =$$
$$= \{\hat{s}_{K-1}(\omega') \wedge \partial(\omega')\} \vee \{\sigma_K(\omega') \wedge a(\omega')\} =$$
$$= \{\hat{s}_{K-1}(\omega') \wedge \partial(\omega')\} \vee$$
$$\vee \left\{ \oint_{\hat{s}_{K-1}(\omega)} \left[\bar{R}_p(p_K^A(\omega) \mid s,\omega') \wedge h(\omega,\omega')\right] \circ g(\cdot) \wedge a(\omega')\right\}.$$

Taking into account a fact that $a(\omega')$ does not depend on $g(\cdot)$ according to the properties of integral we can derive the following expression:

$$\hat{s}_{K-1}(\omega') = \{\hat{s}_{K-1}(\omega') \wedge \partial(\omega')\} \vee$$
$$\vee \oint_{\hat{s}_{K-1}(\omega) \wedge a(\omega')} \left[\bar{R}_p(p_K^A(\omega')|s,\omega') \wedge h_K(\omega,\omega')\right] \circ g(\cdot).$$

Accordingly to (12) the
$\partial(\omega') = \partial_{K-1}(\omega) = \partial_K(\omega)$
and equation for the fuzzy discrete filter can be represented as follows:

$$\hat{s}_K(\omega) = (1-\alpha)\hat{s}_{K-1}(\omega) + \alpha\left[\sigma_K(\omega) \wedge \varphi_R^K(\omega)\right]. \quad (14)$$

In the case of restrictions absence in the state space of fuzzy dynamical system, ∀ωj∈Ω, $g(\{\omega j\}) = 1$ and with absence of process model the function $\sigma_K(\omega)$ is defined only by measurement.

The fuzzy discrete filter may be represented as follows:

$$\hat{s}_K(\omega)=(1-\alpha)\hat{s}_{K-1}(\omega)+\alpha\left[R_p(p_K^A(\omega)\,|\,s)\wedge\varphi_R^K(\omega)\right].$$

$\alpha\in[01]$ determines the convergence rate of the filter. Equation (14) can be transformed to a familiar with Kalman filter representation:

$$\hat{s}_K(\omega)=\hat{s}_{K-1}(\omega)+ +\alpha\left\{\left[R_p(p_K^A(\omega)\,|\,s)\wedge\varphi_R^K(\omega)\right]-\hat{s}_{K-1}(\omega)\right\}. \quad (15)$$

The block diagram of the discrete fuzzy observer that implements the relation (15) is shown on fig. 4.

The elements of this vector express fuzzy measure of input information correspondence u to a certain set of an a priori defined fuzzy measures

$$Q(\Omega)\subseteq F(\Omega),$$

where F(Ω) is set of all possible distributions of fuzziness on Ω.

Every measure $q:2^{\Omega}\rightarrow[01]$ defines the fuzzy variable [6].

Vector of the fuzzy image of input signal is given by:

$$u[\eta]=\int_{\Omega}\mu_u(\omega)\circ q_{\Omega}(\cdot|\eta). \quad (16)$$

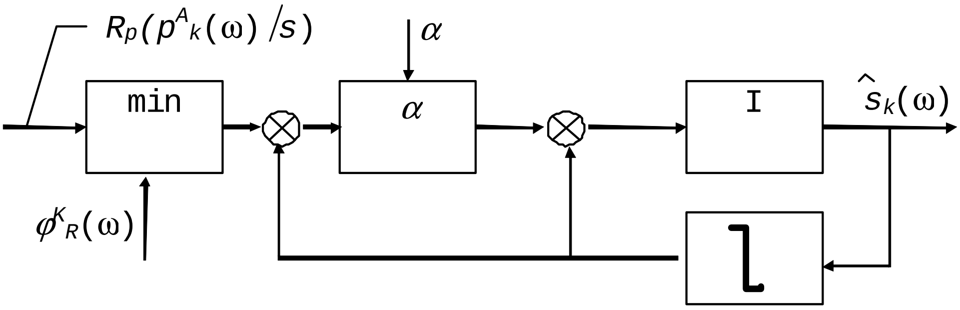

Fig. 4. Block diagram of discrete fuzzy observer

The fuzzy filtration algorithm of signal sensors flight information

Processing algorithm with fuzzy discrete filter (15) in a loop can be represented as shown on the block diagram (fig. 5).

To implement the fuzzy filter (fig. 4) input from the sensors must be converted into a fuzzy image [3] (input signal fuzzyfication). Vector $u[\eta]$, that is called the fuzzy map puts into the correspondence to the input information u (sensor measurement).

Basing on (15) we obtained fuzzy image of input sensor signal that in the discrete fuzzy filter, with accordance to notations in paragraph. 1, designated by function

$R_p(p^A{}_k(\omega)\,/s))$.

The current value of estimated $\hat{\omega}\in\Omega$ signal on the state space Ω is obtained basing on inverse transformation of the fuzzy image (defuzzyfucation procedure).

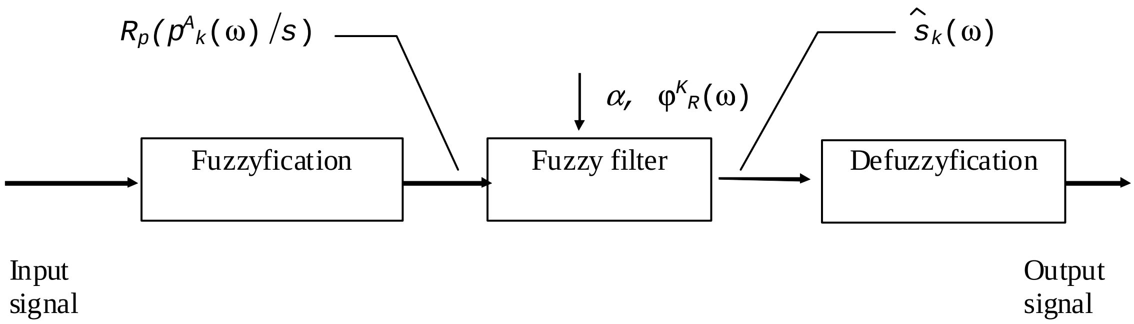

Fig. 5. Block diagram of the fuzzy filter

The inverse transformation of FP estimation is performed by applying the algorithm for calculating the center of mass of a fuzzy distribution [4] given below:

$$\hat{\omega}_K = \frac{\sum \hat{s}_K(\omega_i)\omega_i}{\sum \hat{s}_K(\omega_i)}. \quad (17)$$

Thus, relations in (15) and (17) allow us to obtain the sensor signals measurement estimations.

Note that given above fuzzy discrete filter does not need the requirements for the a priori knowledge of the noise parameters. This fact allows us to state about its robustness in a pretty wide range of input noise measurements.

Investigation of efficiency and convergence of fuzzy discrete filter estimation

Let's make some assumptions to investigate the discrete fuzzy filter. We assume that the state space and the space of measurements are identical Ω′ ≡ Ω. According to the given notations for discrete space Ω the conditional fuzzy measure which connects these spaces will be defined as identity matrix $R_p(\cdot/s)$=I. Thus, we obtain the following relation for input measurement:

$$R_p(p_K^A(\omega)\,|\,s) = p_K^A(\omega),$$

where $p_K^A(\omega)$ would be determined as fuzzy image of input disturbed signal of sensor according to dependence (16).

To represent performance of fuzzy discrete filter as fuzzy variables (q:2^Ω→[01] measures) we have used the simplest distributions of measures shown on fig. 6.

In order to investigate the efficiency and convergence of synthesized fuzzy discrete filter the input useful step signal is taken with the following constant values:

u_1=0, T_1=[20,21] s,

u_2=0.29, T_2=[21,22] s,

u_3=-0.29, T_3=[22,25] s

on the discrete time domain

T=[20,25], Δt=0.2 s.

Fuzzy image of the useful input signal is shown on fig. 7.

Disturbed signal is submitted on the input of the filter with constant but with unknown for filter parameters. The usage of filter (15) allows us to obtain the estimated signal. Filtration results are shown on fig. 8.

Filter convergence as a root-mean-square deviation of real and filtrated signal Δ on the first time interval T_1 is shown on fig. 9.

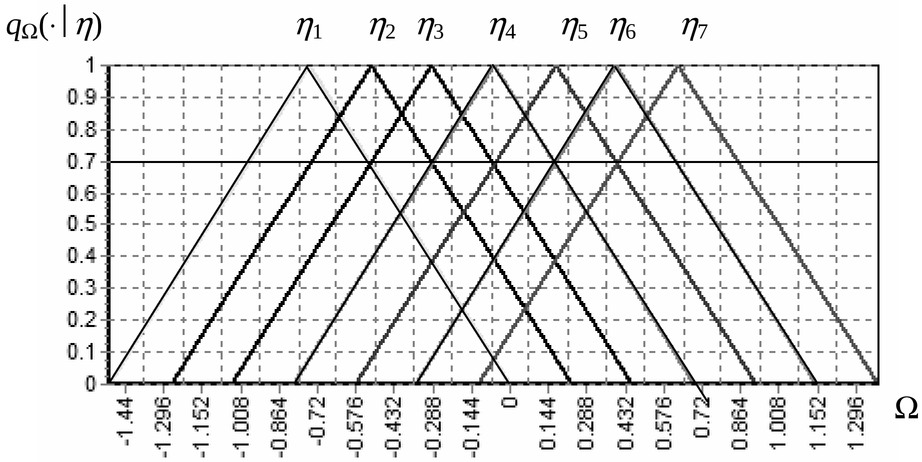

Fig. 6. Distribution of fuzzy variables measures for the fuzzyfication procedure

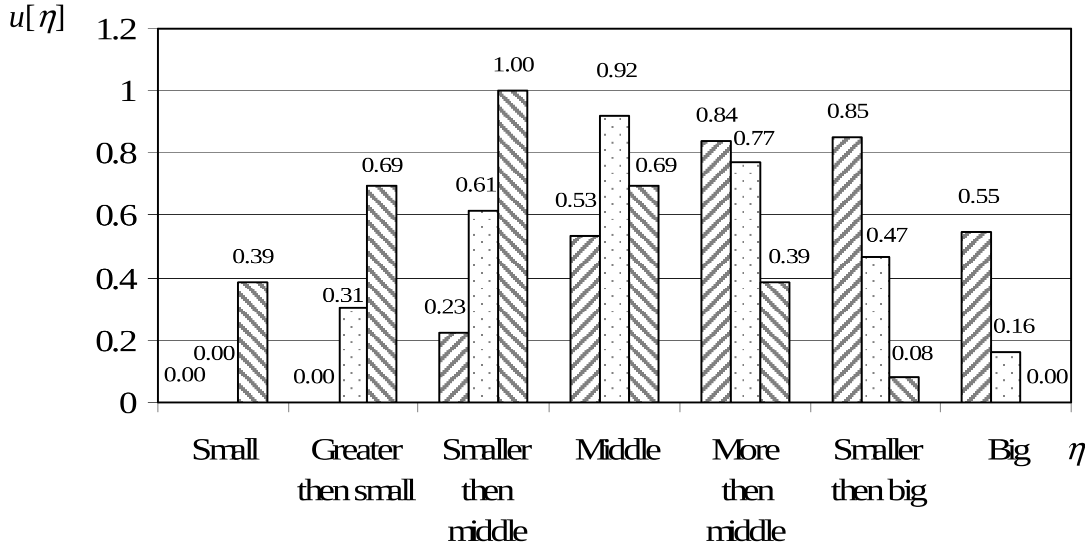

Fig. 7. Fuzzy image for a useful input signal

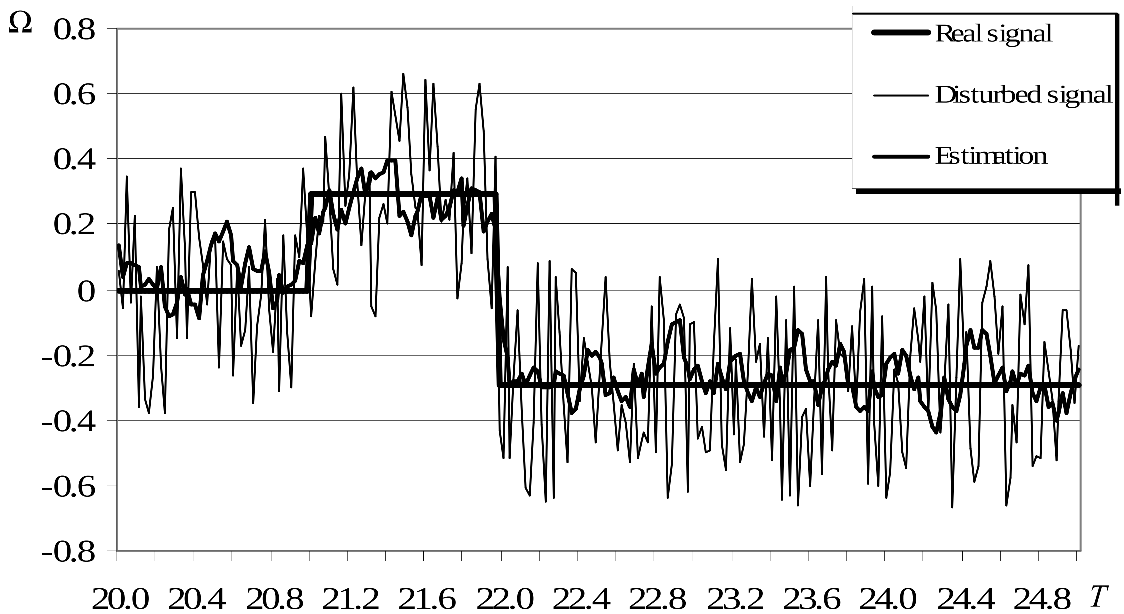

Fig. 8. Operation of fuzzy discrete filter with an unknown stationary noise

In the case of rapid change of measured signal noise parameters the filter continues to operate properly.

It can be observed on fig. 10, where the intensity of noise is increased in comparison to the previous noise to 86% (on the 23.1 s).

This investigation confirms the robust properties of the synthesized fuzzy discrete filter, its stability and efficiency in practice.

Investigation of discrete fuzzy filter operation with uav's flight parameters measurments

The model of longitudinal channel UAV motion is considered as a case study. The results of application and usage are given in [7; 8].

As the investigation element we will consider the UAV's sensor of pitch angle.

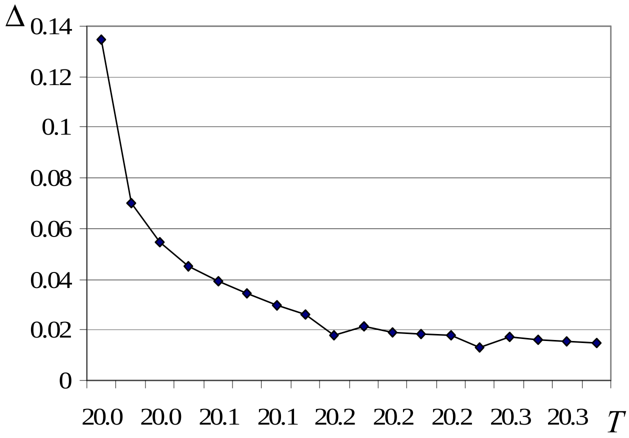

Fig. 9. Root-mean-square deviation of the true and the filtered signal

Conclusion

Thus, a robust fuzzy digital filter synthesized in this paper allows to obtain robust estimates of the UAV flight signals parameters and thereby improve the handling process of UAV in real flight conditions.

In further studies it is reasonable to define optimal parameters for two-dimensional filtering function, taking into account the possibility of considering the depth of the time window more then two. This possibility enables to enhance the estimation quality of the useful signal.

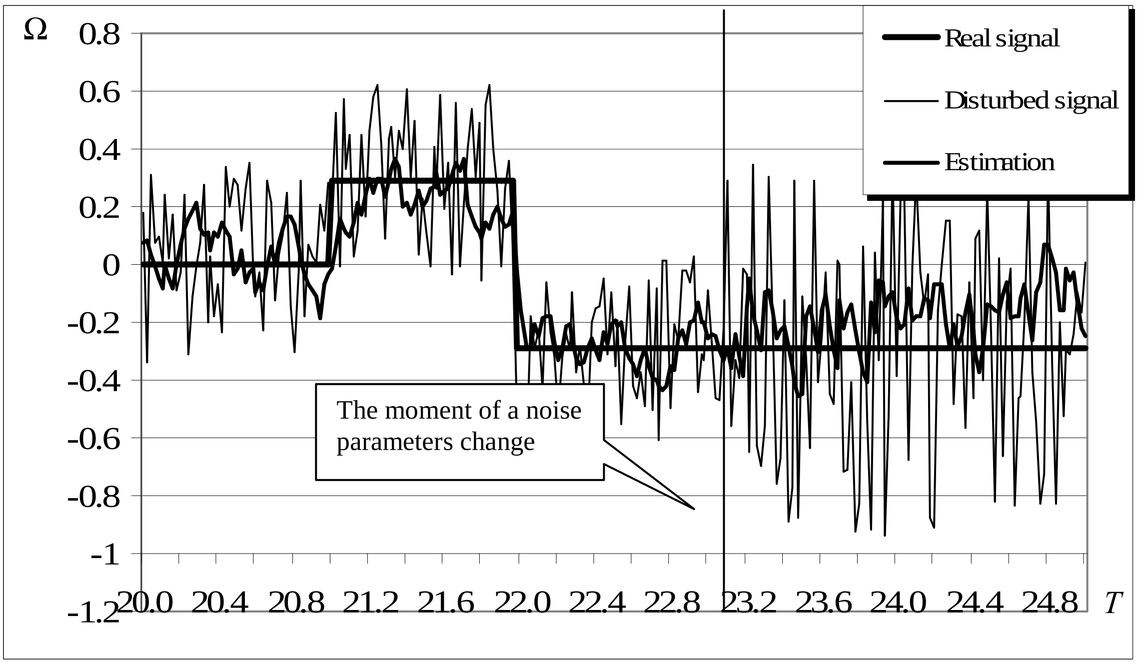

Fig. 10. Operation of fuzzy discrete filter with an unknown stationary noise

The true pitch angle signal, taking into account the noise of the object, caused by wind gusts and noisy signal from the sensor is shown in fig. 11.

The fuzzy filter use allows to get a robust estimation of the measured signal. The result of signal filtration is shown in fig. 12.

Root-mean-square deviation of filtrated and true signal of pitch angle is 0.65%, that confirms the fuzzy filter effectiveness and its robust properties in nonstationary noise with unknown characteristics.

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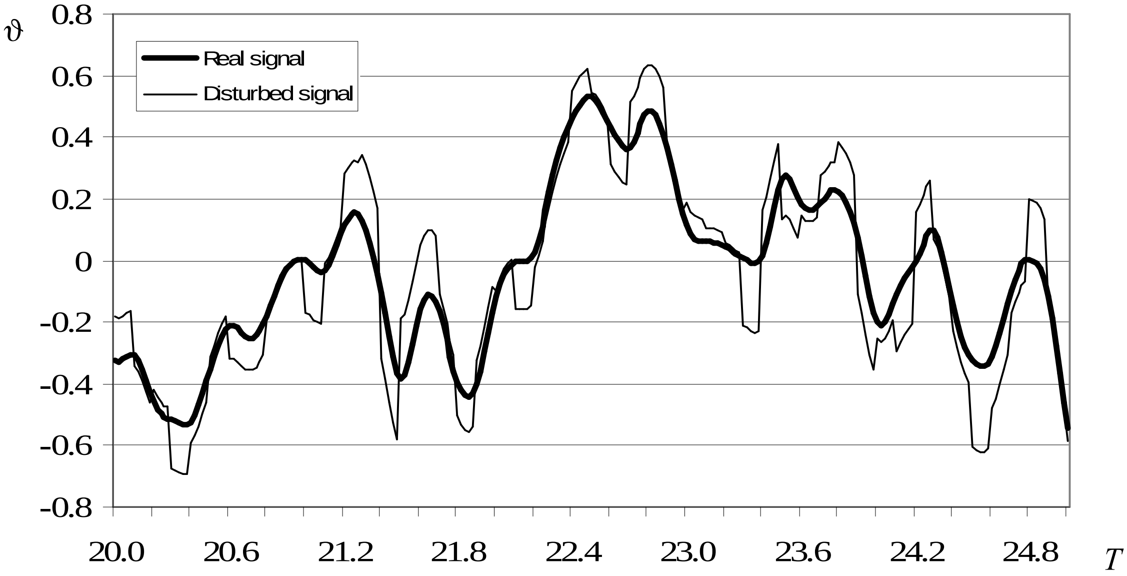

Fig. 11. The true signal of the pitch angle taking into account the object noise and the signal from the sensor

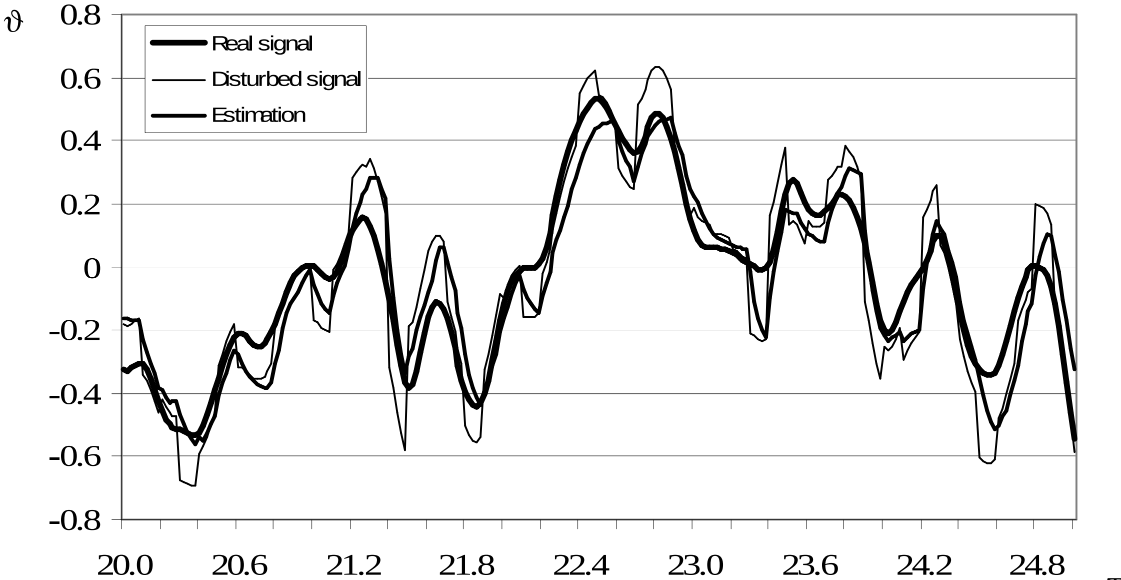

Fig. 12. Estimation of pitch angle after fuzzy filtration

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