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Intelligent Flight Control System Design for the Small UAV Based on the Adaptive Neuro-Fuzzy Inference System

Рассмотрена задача синтеза системы управления полетом малого беспилотного летательного аппарата с элементами искусственного интеллекта. Процедура синтеза показана на примере управления продольным движением беспилотного летательного аппарата с использованием адаптивной нейро-нечеткой модели.

Ключевые слова: система управления полетом, нечеткое управление, адаптивная нейро-нечеткая система логического вывода, метод градиентного спуска, процедура обратного распространения ошибки.

Розглянуто задачу синтезу системи керування польотом малого безпілотного літального апарату з елементами штучного інтелекту. Процедуру синтезу показано на прикладі керування повздовжнім рухом безпілотного літального апарату з використанням адаптивної нейро-нечіткої моделі.

Ключові слова: система управління польотом; нечітке управління; адаптивна нейро-нечітка система логічного виводу; метод градієнтного спуску; процедура зворотного розповсюдження помилки.

The paper considers a problem of flight control system design for small unmanned aerial vehicle with elements of intelligent control. The design procedure is illustrated by an example of unmanned aerial vehicle longitudinal control with application of adaptive neuro-fuzzy inference model.

Keywords: flight control system; successive loop control, fuzzy control, adaptive neuro-fuzzy inference system, gradient descent algorithm, back propagation technique.

Introduction. An intensive and wide application of small unmanned aerial vehicles (UAVs) in different areas of our life is explained by their ability to perform various tasks [1, 2]. Especially, small UAVs are successfully used in dangerous or inaccessible regions to avoid the physical injuries of the human pilot. The extensive application of UAVs leads to the problem of enhancing flight control laws. Moreover, the UAVs are subjected to various disturbances within the flight envelope. These perturbations could be internal and/or external as well as structured and/or unstructured [3]. Therefore, the problem of flight control system (FCS) design for small UAVs that possesses with desired level of performance and remains insensible to various perturbations remains a challenge for an engineer. A great number of works related to FCS design can be found in literature; some of them propose to use mixture of observer and linear quadratic regulator (LQR), where the desired level of performance and robustness of the developed FSC is achieved through the H_2/H_∞ – optimization technique [4–6]; Linear Matrix Inequalities approach also proposes alternative method of FCS design based on Lyapunov theory [7–15].

The most promising results of FCS design gives the combination of the traditional control and fuzzy control. The usage of fuzzy control gives an opportunity to supply the FCS with an artificial intelligence and in such a way to improve the UAV performance within the flight envelope under the influence of the internal and external disturbances [16–19].

The basic structure of FCS under consideration is developed based on successive loop closure method [2, 18]. This structure is typical for the majority of manned [3, 20] as well as unmanned aircraft [1, 2].

We develop the FCS for altitude hold mode (AHM), which is divided into two loops: an inner-loop and the outer one. The outer loop is designed based on fuzzy control theory, meanwhile the inner loop is designed based on classic control theory [2, 3, 20]. The application of fuzzy control theory to the design of FCS extends the flexibility and robust properties of the overall control system.

The outer loop controller is represented as Takagi–Sugeno fuzzy system. It is well known, that realization of fuzzy controller requires the choice of many parameters by the designer, such as the shape and number of membership functions, the choice of the rule base to represent the control strategy and the universe of discourse, where the input/output membership function are distributed [21, 22]. To facilitate the design procedure of the outer loop controller, an adaptive neuro-fuzzy inference system (ANFIS) is used.

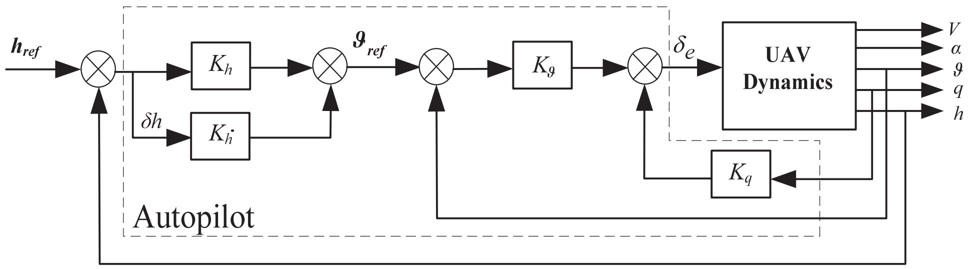


Fig. 1. Block diagram of the UAV longitudinal motion with successive loop control

To prove the efficiency of the proposed approach, the longitudinal motion of small UAV is considered as the case study.

Problem Statement

Let us consider the procedure of FCS design for small UAV, enhanced with elements of the intelligent control. The motion of the UAV can be described by the standard of equations:

$$\begin{cases} \dot{x} = Ax + Bu; \\ y = Cx, \quad x(0) = x_0, \end{cases} \qquad (1)$$

where $x \in R^n$ is the state space vector; $u \in R^m$ is the control vector; $u \in R^m$ $y \in R^p$ is the observation vector.

Taking into account the availability of the measured signals, the classic successive loop flight control structure for AHM is developed. The block diagram of the UAV longitudinal motion control system with the successive loop closure (SLC) and "crisp" control laws in each loop is shown in Fig. 1.

To improve the efficiency of the overall flight control system developed for AHM (see Fig.1), the system will be supplied with intelligent skills in the outer loop. Moreover, the developed FCS with intelligent skills should meet the flight requirements imposed on the UAV during flight mode.

Architecture of adaptive neuro-fuzzy inference system

The structure of ANFIS was proposed by Jang [23]. It was developed to overcome the disadvantage of the pure fuzzy control system, namely, the inability to learn. Thus, the ANFIS extends the ability of the fuzzy control systems to represent knowledge encoded in the rule-base which is derived from human experience and intuition, from practical and theoretical understanding of the dynamics of the controlled plant by involving the learning ability through the artificial neuron networks [21, 24, 25]. Usually, the neuro-fuzzy networks are trained by applying hybrid technique, where antecedent parts of the fuzzy rules are learned by using the back-propagation algorithm, meanwhile the consequent parts of the rules are adjusted through the gradient descent approach [22, 23, 26].

Let us consider the basic structure of ANFIS that has two inputs x and y and one output z. The fuzzy model is given as the first-order Takagi–Sugeno (T–S) form [21, 22], where the fuzzy rules are represented in the following way:

Rule 1: IF x is A_1 and y is B_1 then $z_1 = f_1(x, y)$.

Rule 2: IF x is A_2 and y is B_2 then $z_2 = f_2(x, y)$,

where $\{A_1, A_2, B_1, B_2\}$ are the fuzzy stets in the antecedent; $z_i = f_i(x, y), i = 1, 2$ is a crisp function in the consequent. The first-order T–S model approximates the consequent part of the fuzzy rules as a function of the input variables plus constant:

$$f_i = p_i x + q_i y + r_i, \qquad i = 1, 2.$$

Figure 2 shows the fuzzy reasoning procedure for the first-order T–S fuzzy model.

The architecture of ANFIS contains five layers (see Fig. 3), where the node functions in the same layer are of the same function family.

Layer 1: This layer is the input node in which fuzzification is performed. Thus, the outputs of the layer 1 are the fuzzy membership grade of the inputs. Every node i in this layer is an adjustable node with node function:

$$O_{1,i} = \mu_{A_i}(x), \qquad i = 1, 2,$$

$$O_{2,i} = \mu_{B_i}(x), \qquad i = 3, 4,$$

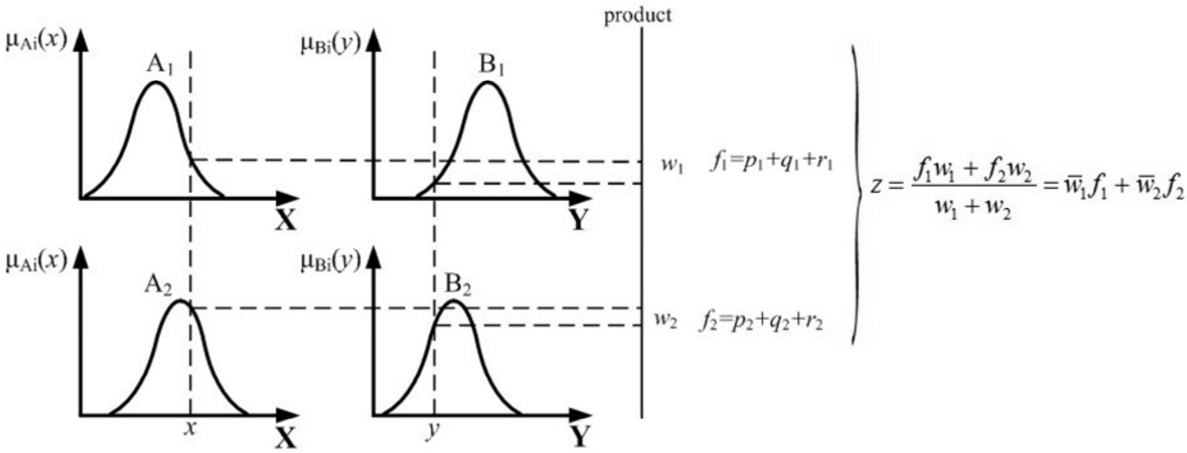


Fig. 2. First-order Takagi–Sugeno fuzzy model

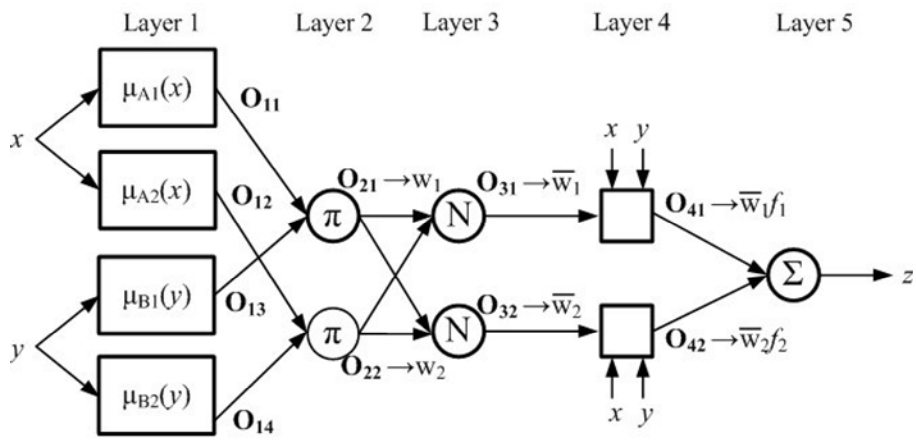


Fig. 3. ANFIS structure with 2 inputs and 1 output

where $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$ are membership functions of linguistic variables A_i and B_i, respectively. $O_{1,i}$ defines the membership grades of A_i and B_i. The membership functions can be any of type, but preferably the bell-shaped or Gaussian-shaped membership functions are used [21, 22]. In this study, the Gaussian membership function has been chosen as it is a continuous function and allows better differentiation during back propagation training. The Gaussian-shaped membership functions are given as:

$$\mu_{A_i}(x)=\exp\left\{-\frac{1}{2}\frac{(x-c_i)^2}{\sigma_i^2}\right\},$$

where $\{c_i, \sigma_i\}$ are centers and spreads of the Gaussian-shaped membership functions that which will be adjusted by the ANFIS. Parameters in this node are referred to as premise parameters.

Layer 2: Every node in this layer is a circle node labelled by π. This layer computes the firing strength of the rule by using t-norm operator (it performs generalized AND). In other words, every node in this layer multiplies the incoming signals and sends the product out as follows:

Layer node $O_{2,i}$

$$w_i=\mu_{A_i}(x)\times\mu_{B_i}(y), \qquad i=1,2.$$

Layer 3: Every node in this layer is a circle node labelled by N. In this layer the normalized ratio of the rule's firing strength to the total firing strengths is evaluated as:

$$\text{Layer node } O_{3,i}:\ \overline{w}_i=\frac{w_i}{w_1+w_2}, \qquad i=1,2.$$

Layer 4: Every node in this layer is an adaptive node. In this layer the consequence is produced. Square nodes (see Fig. 3) in this layer are the nodes function of the following form:

$$O_{4,i} = O_{3,i} f_i = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i \right), \; i = 1, 2.$$

where p_i, q_i, r_i are the consequent parameters to be adjusted by ANFIS.

Layer 5: In this layer the overall output is evaluated. The single circle node is label as Σ and sums all incoming signals coming to this layer:

$$O_{5,i} = \sum_i O_{4,i} f_i = \sum_i O_{3,i} f_i = \bar{w}_1 f_1 + \bar{w}_2 f_2 =$$

$$= \frac{w_1}{w_1 + w_2} \left(p_1 x + q_1 y + r_1 \right) + \frac{w_2}{w_1 + w_2} \left(p_2 x + q_2 y + r_2 \right),$$

$$i = 1, 2 .$$

The ANFIS model is tuned to produce the desired controller performance by adapting the membership functions and the ANFIS parameters [23].

As mentioned above, the neutral fuzzy systems have the properties of both neural networks and fuzzy systems. Therefore, such kind of systems is able for tuning both premise and consequent parameters. Thus, the ANFIS takes the initial fuzzy system and learns it with the help of hybrid technique. The hybrid learning combines the steepest descent method and least-square method. Basically, the hybrid learning involves two passes such as forward pass and backward pass. In the forward pass of the hybrid learning the consequent parameters are identified by applying least-square method. Meanwhile, in the backward pass the instantaneous error propagates backward and the premise parameters are updated by using the steepest descent method [22, 23, 26]. Still, it is necessary to remember that back-propagation learning algorithm is a local minimizer [22]. It can stick in a local minimum. Therefore, the initial parameters estimate is of crucial importance to this method [26].

Outer loop design with adaptive neuro-fuzzy inference controller

To improve the efficiency of the overall flight control system the fuzzy controller in the outer loop was developed. The supplementation with adaptive neuro-fuzzy controller in the control loop together with traditional controller allows increasing the robustness of the closed loop system and meeting the required flight performance [16–19].

To implement training procedure of fuzzy model data set should be available that establishes relationships between input/output of the training system. The available data set is used to evaluate the parameters of membership function that allow the associated fuzzy inference system to track the given input/output data in a desired and best manner [22–26]. Therefore, the training data is obtained from the training system. As the training system serves the classic successive loop control which is developed for altitude hold mode (see Fig. 1). Fig. 4 demonstrates the procedure of adjusting the membership parameters of T–S fuzzy controller during training.

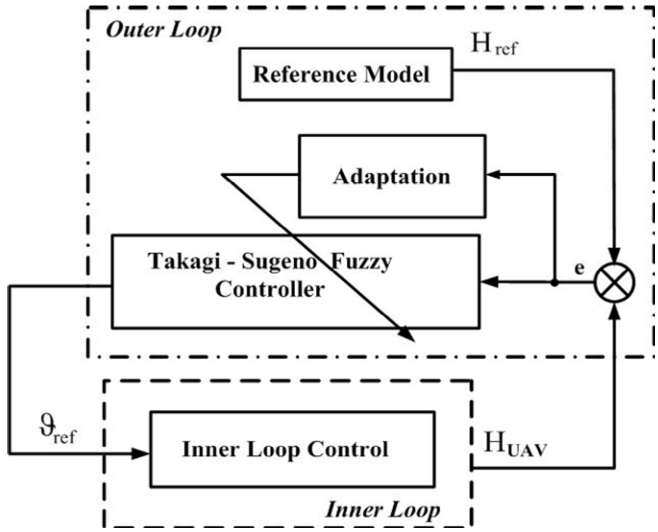


Fig. 4. Procedure for adjusting parameters of membership functions

It is necessary to point out that the reference model generates the desired performance of the overall system. In general, the reference model may be any type of dynamical system. The performance of the overall system is evaluated with respect to its output h_{ref} by generating an error signal between the reference signal and actual UAV output $e(t) = h_{ref}(t) - h(t)$.

An example

To demonstrate the efficiency of the proposed approach the longitudinal channel of small UAV is considered as a case study.

The main geometrical characteristics of the given aircraft are: wing area, $S = 0{,}896\ m^2$; wing span, $b = 2{,}34\ m$; mean aerodynamic chord, MAC = 0,3868; relative thickness of the airfoil $\bar{c} = 18{,}8\,\%$.

The state space vector of small UAV longitudinal channel comprises the following variables:

$x = [V_t, \alpha, q, \vartheta, h]^T$, where V_t is the true airspeed of aircraft, α is the angle of attack, ϑ is the pitch angle, q is the pitch rate and h is the altitude. The control input vector is represented by elevator deflection, $u = \delta_{elev}$.

It is considered operating mode with true airspeed at V_t = 14,0 m/s. The linear model in the state space is represented by the matrices:

$$A = \begin{bmatrix} -0,1816 & 43,9153 & -9,81 & 0 & 0 \\ -0,4292 & -12,7475 & -0,6711 & 0,6898 & 0 \\ 0 & 0 & 0 & 1.0 & 0 \\ 0,2988 & -130,2477 & 4,7433 & -21,9445 & 0 \\ 0 & -14,0 & 14,0 & 0 & 0 \end{bmatrix};$$

$$B = \begin{bmatrix} -0,0408 \\ -0,0553 \\ 0 \\ -14,8151 \\ 0 \end{bmatrix}.$$

The output vector of measured variables is given as follows $y_{est} = [q, \vartheta, h]^T$. Thus, the observation matrix has the following structure:

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

Disturbance, υ affecting the longitudinal motion of the aircraft involves the following components: the true airspeed, V_t, angle of attack, α and pitch rate, q, so that $\upsilon = \left[V_{t_g}, \alpha_g, q_g\right]^T$.

In order to simulate the atmospheric turbulence, the Dryden filter is used [3, 27]. It is considered that the aircraft flies at a light turbulence.

To generate a signal with the correct characteristics, a unit variance, band-limited white noise signal is passed through the appropriate forming filters.

The transfer the functions of forming filter according to the standard MIL-F-8785C [3, 20, 27] used in simulation to account external disturbances have the following structure:

$$H_u(s) = \sigma_u \sqrt{\frac{2L_u}{\pi V}} \frac{1}{1 + \frac{L_u}{V} s};$$

$$H_w(s) = \sigma_w \sqrt{\frac{L_w}{\pi V}} \frac{1 + \frac{\sqrt{3} L_w}{V} s}{\left(1 + \frac{L_w}{V} s\right)^2};$$

$$H_q(s) = \frac{\pm \frac{s}{V}}{\left[1 + \left(\frac{4b}{\pi V}\right) s\right]} H_w(s).$$

The parameters appearing in the transfer functions of the forming filters are given as follows [3, 20, 27]:

- dimensionless turbulence coefficients for the given model are $\sigma_u = 1,419$, $\sigma_w = 0,772$;
- turbulence scale lengths of respective gusts are $L_u = 310,787$ m and $L_w = h$, $h = 50$ m; b = = 2,34 m is the wingspan of the UAV.

The computation of these values depends on the altitude at which the aircraft is flying, the wing span and the type of turbulence according to the standard MIL-F-8785C [27].

The transfer function of forming filter along the variable w is possible to rewrite in terms of the variable the angle of attack, α according to the phase vector. Thus, for small angles

$$\alpha = \frac{w}{U_0}, \text{ where } U_0 = V_t.$$

The design procedure involves the several steps: (1) classic successive loop FCS design. This structure serves as a training system for the further training of fuzzy controller; (2) development of the combined flight control system structure, where the outer loop is accompanied with the intelligent control contour for altitude hold, meanwhile the inner loop is used for pitch angle control; (3) outer loop fuzzy controller design under ANFIS.

On the first design stage, the FCS for AHM is developed. The vector of adjustable autopilot unknown parameters, P is given as:

$$P = \left[K_h, \quad K_{\dot{h}}, \quad K_\vartheta, \quad K_q\right]^T,$$

We have applied PD-controller optimization technique. As a result, numerical values of autopilot parameters are obtained as follows:

$$P = \left[0,14, \quad 0,025, \quad 0,125, \quad 1,18\right]^T .$$

As stated before, the outer loop controller is designed using TSFC for altitude hold mode at the reference signal. The error between the reference signal and actual position of the UAV is removed through the fuzzy controller by adjusting the parameters using hybrid learning technique. The control signal from outer loop corresponds to the reference control signal, ϑ_{ref} for inner loop control. The set of training data $\left[e_h \ \dot{e}_h \ \vartheta_{ref}\right]$ are obtained from the classic loop control structure (see Fig. 1).

The task of the ANFIS based controller is to minimize the error between the reference and actual altitude signals by generating IF-THEN rules and tuning the parameters of the network [21–26].

As mention above, the developed TSFC comprises two inputs and one output. The five Gaussian-shaped membership functions (MF) are used to represent each input. Each of MFs represents one linguistic variable (from Negative Large to Positive Large), while each variable is determined on the some range of the universe of discourse. As there are two inputs with five membership functions the total amount of rules (or parameters to be tuned) is equal to 25. The standard rule base for fuzzy PD-controllers is represented in the Table 1.

T a b l e 1. Rule base of fuzzy controller

Output, u (ϑ_{ref})		Change-in-error, Δe				
		NB	**NS**	**ZE**	**PS**	**PB**
Error, e	**NB**	PB	PB	PB	PS	ZU
	NS	PB	PB	PS	ZU	NS
	ZE	PB	PS	ZU	NS	NB
	PS	PS	ZU	NS	NB	NB
	PB	ZU	NS	NB	NB	NB

We use the Gaussian membership functions that are specified with the centers, c^i and spreads σ^i for the premise part of control rules, the output is considered as singleton membership function. The Gaussian membership function is given by:

$$\mu_i\left(e(t),\, c^i, \sigma^i\right) = \exp\left(-\frac{1}{2}\left(\frac{e(t)-c^i}{\sigma^i}\right)^2\right). \quad (12)$$

Using the product for the premise of the implication, and weighted-average defuzzification, the overall output of the TSFC is computed as [21, 22]:

$$\vartheta_{ref}\left(e(t)\,\middle|\,\theta_k\right) = \frac{\sum_{i=1}^{R} f_i \mu_i}{\sum_{i=1}^{R} \mu_i} =$$

$$= \frac{\sum_{i=1}^{R} f_i \prod_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{e(t)-c^j}{\sigma^j}\right)^2\right)}{\sum_{i=1}^{R} \prod_{j=1}^{n} \exp\left(-\frac{1}{2}\left(\frac{e(t)-c^j}{\sigma^j}\right)^2\right)}, \quad (13)$$

$i = 1,\ldots,R$, $j = 1,\ldots,n$, where $k = n + R$, $f_i = b_i$.

Our goal is to optimize the shape of the input and the output membership functions in order to minimize the quadratic error function given by:

$$E = \frac{1}{2}\left(h_{ref}\left(e(t)\,\middle|\,\psi_k\right) - h(t)\right)^2, \quad (14)$$

where $h(t)$ denotes the target output of the system and ψ is a vector of parameters to be optimized, namely b_i, c^j, σ^j. The structure of ANFIS model is developed as shown in Fig. 5.

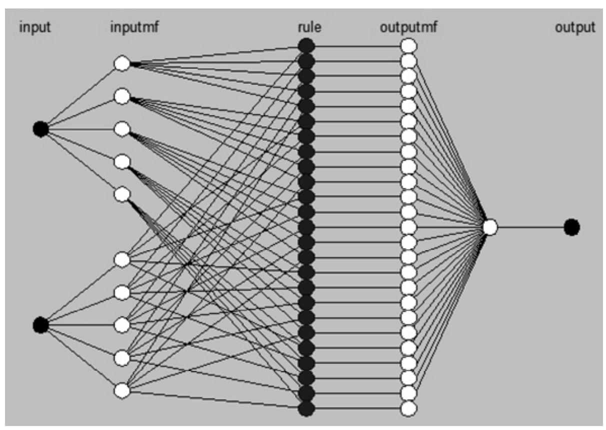
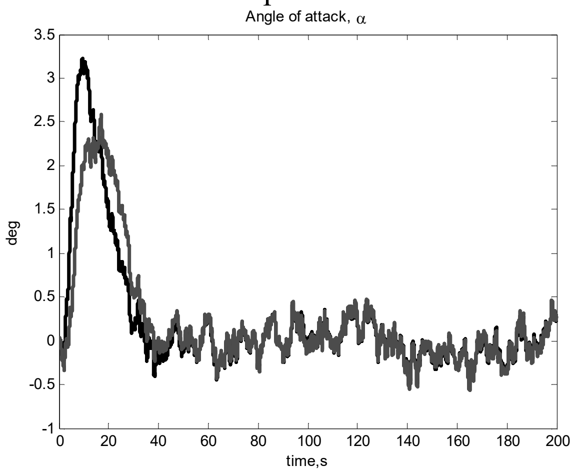


Fig. 5. ANFIS structure of fuzzy controller for AHM

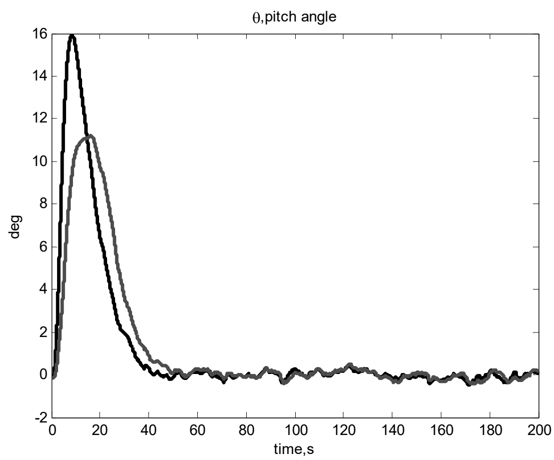
The simulation results of the closed loop system with the classic autopilot and intelligent autopilot are given in Fig. 6.

Figure 6 demonstrates the transient processes in the system with the classic autopilot structure by black line, meanwhile the transient processes in the system enhanced with the elements of intelligent control are represented by grey line.

Maximum deflections of the phase vector are within the acceptable intervals. Table 2 reflects the standard deviations of the aircraft outputs, where the structure of FCS is augmented with an adaptive neuro-fuzzy inference based controller. Table 3 represents the standard deviations of the aircraft outputs with the classic autopilot for altitude hold mode.



a



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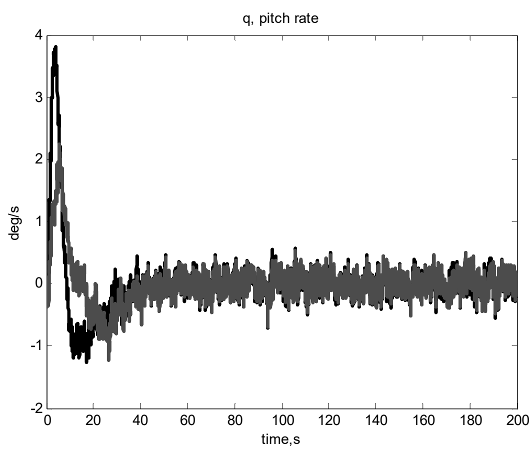

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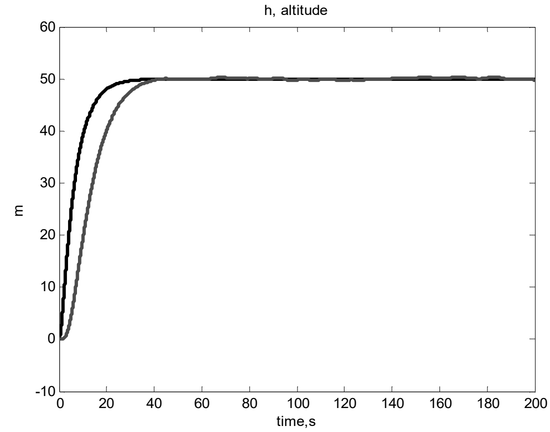

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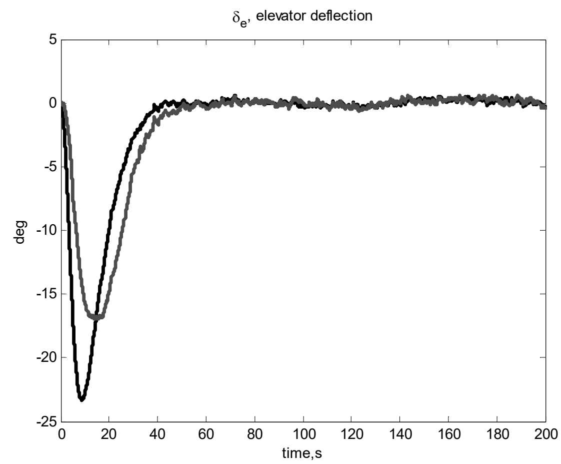

e

Fig. 6. Simulation results of longitudinal motion control in the presence of external disturbances: *a* – α is an angle of attack, deg; *b* – ϑ is a pitch angle, deg; *c* – q is a pitch rate, deg/s; *d* – is the altitude h, m; *e* – is an elevator deflection, deg

T a b l e 2. Standard deviations of small UAV outputs in a stochastic case (FCS with the adaptive neuro-fuzzy inference based controller)

Plant	Standard deviation					
	σ_u, m/s	σ_α, deg	σ_ϑ, deg	σ_q, deg/s	σ_h, m	σ_{elev}, deg
V = 14,0 m/s	0,0512	0,1840	0,1780	0,1635	0,1755	0,2070

T a b l e 3. Standard deviations of small UAV outputs in a stochastic case (the classic structure)

Plant	Standard deviation					
	σ_u, m/s	σ_α, deg	σ_ϑ, deg	σ_q, deg/s	σ_h, m	σ_{elev}, deg
V = 14,0 m/s	0,0488	0,1961	0,1795	0,1648	0,1975	0,2344

Conclusions. The simulation results demonstrate the efficiency of the flight control system enhanced with intelligent skills. The design of the intelligent flight control system for a small UAV is based on the adaptive neuro-fuzzy inference system. It can be seen from simulation results that ANFIS flight control system possesses with higher performance in comparison to its classic structure. The altitude is held at the reference value as well as angle deflections, the angular rates are within the respected intervals.

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