Inverse Dynamics Approach to Adaptive Damage-Tolerant Control for Unmanned Aerial Vehicles

Alexey Kondratiev and Yury Tiumentsev[1]
Moscow Aviation Institute (MAI),
Flight Dynamics and Control Department,
Volokolamskoye Shosse 4, 125993, GSP-3, Moscow, Russia

Abstract

A control problem is discussed for unmanned aerial vehicle (UAV) as applies to its short-period longitudinal motion. The problem is formulated taking into account various uncertainty factors such as imperfect knowledge about UAV parameters and characteristics as well as environment exposure. One more class of the uncertainty factors includes failures of UAV systems and its structural damages. A preliminary step is needed to synthesize adaptive damage-tolerant control systems. This step consists in plant identification using artificial neural network (ANN) techniques. Next step is a synthesis of appropriate neural controller. An adaptive control scheme based on inverse dynamics problem (IDP) approach is used to achieve control goals for the conditions mentioned above. The scheme is implemented basing on ANN tools. Simulation is carried out to confirm efficiency of the adaptive damage-tolerant neural control. Appropriate computer experiment results are presented and discussed to demonstrate features of the proposed approach.

1 Introduction

We need to provide a motion control for modern and advanced UAVs under such conditions as considerable various uncertainties in values of their parameters and characteristics, flight regimes and environment exposure. Besides numerous failure conditions can emerge during UAV flight including equipment failures and structure damages. These conditions should be counteracted by means of reconfiguration for control system and control surfaces of the UAV.

Therefore the UAV faces each time circumstances that can vary considerably and unpredictably. The UAV control system must be able to conform efficiently to these variations by means of on-line changes in parameters and/or structure of control laws used to manage UAV behavior. A way based on theory of adaptive control allows us to satisfy these requirements [1]–[9].

An approach basing on neural network simulation and control is one of the most effective tools to implement adaptive systems [7], [8]. An important part of the implementation process for the proposed approach is generation of artificial neural network based model (ANN-model) for the UAV which is interpreted as a plant. An example of ANN-model generation is presented in subsequent sections as applies to simulation of longitudinal short-period motion for a mini-UAV.

2 General adaptive control scheme based on inverse dynamics approach

There are problems which consist in generation of control laws providing realization some prescribed motion for a plant [10], [11]. We designate these problems as inverse dynamics problems (IDP). As applies to the IDP problem we need to implement a motion of the dynamic system which fits to some desired or reference motion

(1) $x_m(t), \dot{x}_m(t), t \geq 0$

with prescribed accuracy. The desired motion in this case can be defined by means of a reference model (RM). In other words we need to satisfy relationship

$$e = \left\| x(t) - x_m(t) \right\| + \lambda \left\| \dot{x}(t) - \dot{x}_m(t) \right\| \leq \varepsilon,$$

where ε is the prescribed accuracy for tracking of the reference model output. In the perfect case we have $e = 0$ therefore

(2) $\dot{x}(t) = \dot{x}_m(t).$

This relationship is satisfied only if following conditions are fulfilled:

- mathematical model of the plant fits precisely to the plant itself;
- initial conditions for the plant model and reference model coincide precisely;
- no disturbances affect on the plant.

However these conditions are not satisfied usually for real world application problems because of uncertainties in the DS behavior caused by external factors as well as approximate nature of the plant model.

To prevent a rise of the tracking error in time we need to add in Eq. (1) an auxiliary member providing elimination of the tracking error:

(3) $\dot{x} = \dot{x}_m + K(x_m - x).$

We have in such case, that

(4) $\dot{e} = -Ke.$

If source equations of motion for the plant had the form

(5) $\dot{x} = f(x, u)$

then we can rewrite Equation 2 in the form

(6) $\dot{x} = \dot{x}_m + K(x_m - x) = f(x, u(x, x_m, \dot{x}_m)).$

We cannot derive analytically the required control function (control law) $u(x, x_m, \dot{x}_m)$ from Equation 6. Therefore we

[1] E-mail: tium@mai.ru

have to build an approximate solution which we can obtain using a feedforward multilayer neural network named here as neurocontroller (NC) and learned with the error backpropagation algorithm as a standard tool for such kind of the networks.

3 SYNTHESIS OF A NEURAL NETWORK BASED MOTION MODEL FOR UAV

A plant model is needed in many of adaptive control schemes. Deriving of the plant model basing on some experimental data corresponds to the classical identification problem for dynamic systems [12]. We know from experience that using of ANN-based techniques and tools is very efficient way to solve this identification problem with regard to nonlinear systems [13]–[15]. Neural network simulation allows us to build rather accurate and computationally effective models of dynamic systems.

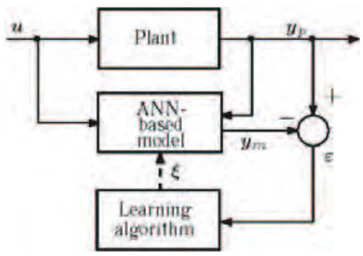

Figure 1: Neural network based scheme for plant identification. Here u is control, y_p is plant output, y_m is reference model output; ε is divergence between outputs of plant and ANN based model; ξ is corrective action.

Computational efficiency roots of ANN-based models is based on the following fact: an artificial neural network is algorithmically universal mathematical model [16], [17] which allows us to represent with arbitrary accuracy any nonlinear mapping $\varphi : R^n \to R^m$. In other words we can represent with arbitrary accuracy any nonlinear relationship between n-dimensional input vector and m-dimensional output vector.

A synthesis of ANN-based model for controlled nonlinear plant motion is interpreted below as generation of a neural network approximation for some source mathematical model of UAV motion. This source model is formulated frequently as a system of ordinary differential equations.

General scheme of neural network plant identification is presented on Figure 1.

Squared difference between plant output y_p and ANN-based model output y_m both under control signal u is used as an error signal ε guiding a learning process for the ANN-based model. A trained ANN-based model realizes recurrent-type computational scheme using output signal $\hat{y}$ and control signal u values for instant time t_i to compute output signal $\hat{y}$ value for instant time t_{i+1}.

The NARX (Nonlinear AutoRegressive network with eXogeneous inputs) model was chosen to represent the dynamic plant because it corresponds well with UAV control problem. This model is a recurrent dynamic layered neural network with feedbacks between layers and with TDL (Time Delay Line) units before its inputs.

Validation of the ANN-based model is carried out with regard to angular longitudinal motion of UAV described with a mathematical model which is rather common for aircraft flight dynamics [18]:

$$\dot{\alpha} = q - \frac{\bar{q}S}{mV} C_L(\alpha, \varphi) + \frac{g}{V},$$

$$\dot{q} = \frac{\bar{q}Sc}{I_{yy}} C_m(\alpha, \varphi, q),$$

$$T^2\ddot{\varphi} = -2T\zeta\dot{\varphi} - \varphi + \varphi_{act},$$

where α is angle of attack, deg; q is pitch angular velocity, deg/sec; φ is deflection angle of elevator or elevons, deg; C_L is lift coefficient; C_m is pitching moment coefficient; m is mass of UAV, kg; V is airspeed, m/sec; $\bar{q} = \rho V^2/2$ is airplane dynamic pressure; ρ is mass air density, kg/m^3; g is acceleration of gravity, m/sec^2; S is wing area of UAV, m^2; c is mean aerodynamic chord, m; I_{yy} is pitching-moment inertia, kg·m^2; dimensionless coefficients C_L and C_m are nonlinear functions with respect to their arguments; T, ζ are time constant and relative damping factor for actuator, φ_{act} is command signal value for elevator actuator limited in the $\pm 20^0$ range. Variables α, q, φ and $\dot{\varphi}$ in the model are plant states and variable φ_{act} is plant control.

This ANN-based model were built and described in [18] as applies to the considered UAV control problem. Validation of the model is carried out for X-04 mini-UAV [18] with airborne weight 4.2 kg.

It was suggested some special way to generate training samplings intended to learn considered ANN-based UAV model. This way relates to using of very aggressive actions (often and strong random variations) which are carried out with elevator as longitudinal motion control surface to obtain command signal φ_{act} for the relevant actuator. The purpose of such approach to command signal generation is to ensure diversity of simulated system states as large as possible and to cover the system state space as uniformly and tightly as possible. Besides it is necessary to provide variety of differences between states in adjacent instant times as large as possible to represent dynamics of the simulated system in the ANN-based model with maximum adequacy.

The similar approach under similar reasons is used below to generate training samplings for neurocontroller in the IDP-based scheme. It also was used for two another adaptive control schemes (MRAC and MPC) considered in [18].

Validation results presented on Figure 2 were obtained for closed-loop ANN-based UAV model using simulation. These data demonstrate the model efficiency as applies to the UAV angle of attack tracking problem for dynamically specified reference values of this angle. The results show us rather high simulation accuracy of the suggested approach. Simulation error which equals a difference between UAV state and ANN-model output does not exceed 0.3 deg for all experimentally studied conditions.

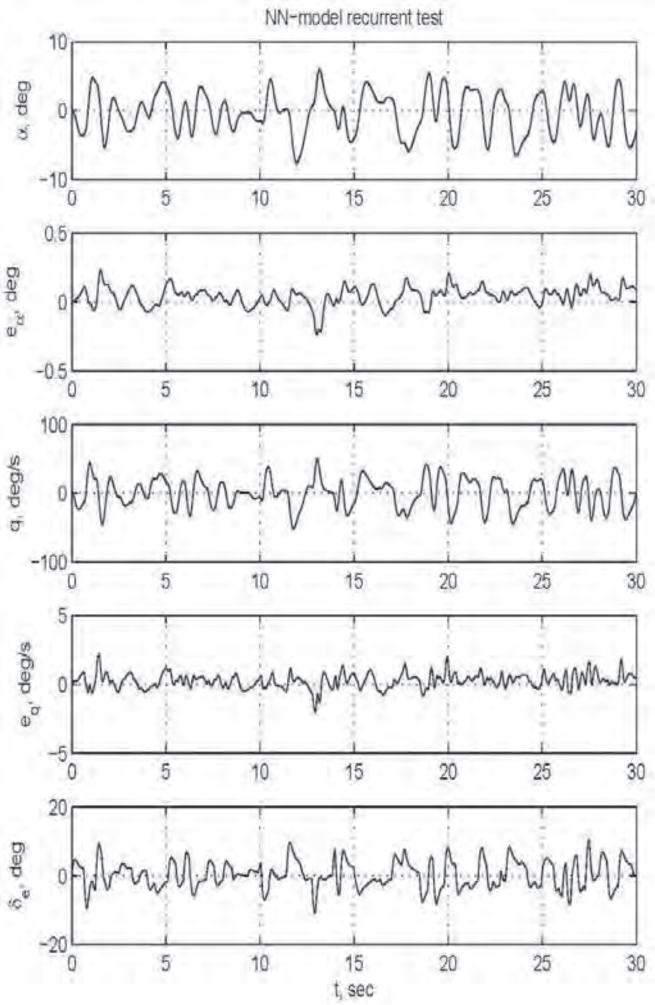

Figure 2: Synthesis of ANN-based plant model for X-04 UAV in respect to flight regime with indicated airspeed $V_i = 70$ km/h and altitude $H = 10$ m. Here α is angle of attack, deg; e_α is difference between angle of attack values for the plant and ANN-based model, deg; q is pitch angular velocity, deg;/sec; δ_e is angle of elevator deflection, deg; e_q is difference between pitch angular velocities for the plant and ANN-based model, deg/sec; t is time, sec.

4 SYNTHESIS OF INVERSE DYNAMICS BASED DAMAGE TOLERANT ADAPTIVE CONTROL FOR UAV

An application of traditional control theory requires us to know plant mathematical model as well as values of plant and environment parameters and characteristics. These requirements can be satisfied not always in practice. Besides values of plant parameters and characteristics can change in the course of its operation. Traditional control theory methods lead often to unacceptable results in that case.

Because of such situation a demand arises to build control systems which do not require full a priori knowledge about the plant and its environment. These systems must afford to adjust themselves to changing conditions including plant and environment properties. Adaptive systems satisfy such demand. They use current available information not only to generate control actions just as it occurs in traditional control systems but to correct a control law.

A general structure of adaptive system can be represented as it is shows on Figure 3. As we can see from Fig. 6, corrective action $\xi(t)$ for the controller is generated by means of some adaptation mechanism which uses control signal $u(t)$, plant output signal $y(t)$ and some additional "external" information $\psi(\lambda),\ \lambda \in \Lambda$ to provide the corrective action. The additional information can be necessary to take into account some data enter into the UAV motion model as parameters, e.g. airspeed and altitude in model of UAV angular motion.

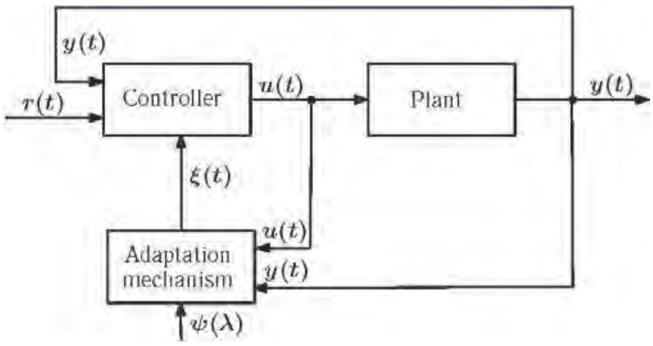

Figure 3: A controlled system scheme with adjustable control law: Here $r(t)$ is reference signal; $u(t)$ is control; $y(t)$ is plant output; $\xi(t)$ is corrective action for controller; $\psi(\lambda),\quad \lambda \in \Lambda$ is some additional information we need to take into account while generating control signal value, for example, velocity and altitude values for UAV as applies to angular motion control problem.

There are numerous adaptive control schemes including ANN-based ones [1]–[8]. The MRAC (Model Reference Adaptive Control) and MPC (Model Predictive Control) schemes belong to the most frequently used ones (see Figures 4 and 5 respectively).

A controller in the MRAC scheme can be implemented basing on an artificial neural network. A learning process for the ANN-based controller named below as neurocontroller is accomplished to satisfy proximity condition for motions realized with the reference model and the plant under synthesized control law. The reference model shows an idea of control system designer about "good" or appropriate behavior of the plant which need to be tracked with the neurocontroller.

The MPC scheme exploits a plant model used to predict future behavior of the plant together with some optimization algorithm to choose appropriate control actions providing best values of predicted characteristics for the considered system.

We have considered MRAC and MPC schemes as applies to control UAV longitudinal short-period motion in our previous paper [18]. One more scheme is discussed in this article. This scheme is based on the inverse dynamics problem (IDP) approach. It is used to stabilize a prescribed value for UAV angle of attack which transmits from the pitch control channel.

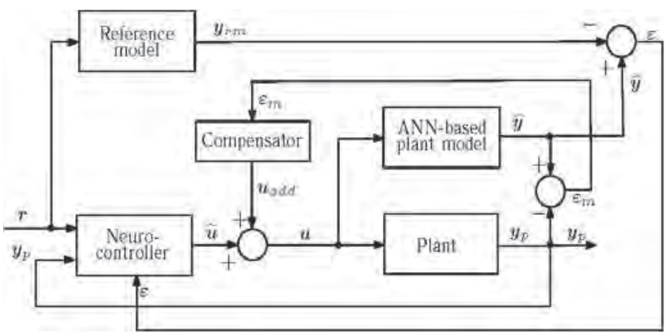

Figure 4. General scheme for a model reference adaptive control. Here $r(t)$ is a reference signal; $y_p(t)$ is a plant output; $\hat{y}(t)$ is an output of the ANN-model; $y_{rm}(t)$ is a reference model output; $u^*(t)$ control signal generating with neurocontroller; $u_{add}(t)$ is additional control signal generated with a compensator; $u(t)$ is combined control input acting on the plant; $\varepsilon(t) = y_p(t) - y_m(t)$ is a difference between outputs of plant and reference model.

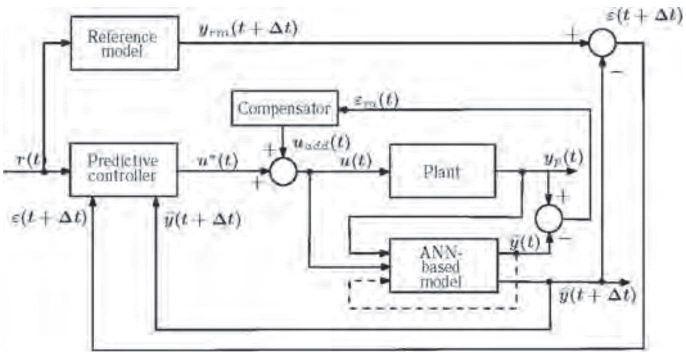

Figure 5. General scheme for a model predictive control. Here $r(t)$ is a reference signal; $y_p(t)$ is a plant output; $\hat{y}(t)$ is an output of the ANN-model; $y_{rm}(t)$ is a reference model output; $u^*(t)$ control signal generating with predictive controller based on optimization algorithm; $u_{add}(t)$ is additional control signal generated with a compensator; $u(t)$ is combined control input acting on the plant; $\varepsilon(t) = y_p(t) - y_m(t)$ is a difference between outputs of plant and reference model.

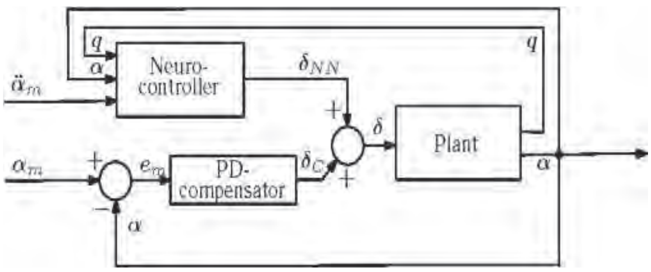

Figure 6: Structure of the IDP-controlled system. Here α and α_m is angle of attack from UAV and reference model, q is pitch angular velocity, e_m is divergence between outputs of plant and reference model; δ, δ_e and δ_{NN} are control signals.

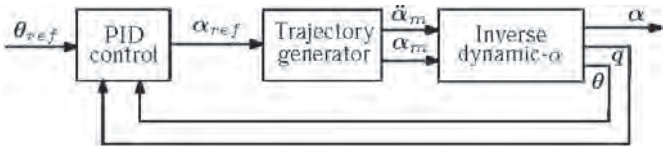

Figure 7: Neural network based scheme for plant identification. Here θ_{ref} and α_{ref} are required values for pitch angle and angle of attack; α_m is angle of attack from reference model; q is pitch angular velocity. ‘Trajectory generator’ here is the reference model and ‘Inverse dynamic-α’ is the IDP-based neurocontroller.

A flowchart for the IDP-controlled system is shown on Figure 6. The neurocontroller generates here a control signal to track precisely the reference trajectory generated by the reference model and the dynamic PD-compensator $K(x_m - x)$ adjust the control signal to decrease a value of difference between actual trajectory $x, \dot{x}$ and reference one $x_m, \dot{x}_m$, i.e. a value of the tracking error.

The neurocontroller shown on Figure 6 is a part of the UAV pitch control channel presented on Figure 7. Input of the pitch channel is prescribed value for UAV pitch angle transmitted from the trajectory control channel.

The controller in the IDP scheme is implemented basing on an artificial neural network. A learning process for the controller named here as neurocontroller is accomplished to satisfy proximity condition for motions realized with the reference model and the plant under synthesized control law. The reference model shows an idea of control system designer about “good” or appropriate behavior of the plant which need to be tracked with the neurocontroller.

The reference model can be defined in a variety of ways. Within this article the reference model is built basing on an oscillatory link with rather high damping ratio in aggregate with an aperiodic link interpreted as a prefilter. It is accepted that the reference model defined as

$$(7)\quad W_\alpha = \frac{\omega_{RM}^2}{((1/\omega_{PF})p + 1)(p^2 + 2\omega_{RM}\varsigma_{RM}p + \omega_{RM}^2)}$$

if the UAV motion is described by means of equations mentioned above. In model (7) parameter values are specified as $\omega_{RM} = 5\,1/\sec$, $\omega_{PF} = 80$, $\zeta_{RM} = 0.8$ for mini-UAV X-04. Here ω_{RM} and ω_{PF} are natural frequencies of the oscillatory and aperiodic links; ζ_{RM} is damping ratio for the oscillatory link.

The ANN-based plant model obtained above is used to implement learning process for the neurocontroller. The adjustment purpose specified for the neurocontroller consists in minimization of the error $y_{rm} - \hat{y}$. In other words it is needed to bring the plant under neurocontroller behavior nearer as possible to the reference model behavior. If the ANN-based model has appropriate accuracy then the neurocontroller will minimize “genuine” error $y_{rm} - y$ too, i.e. it will try to reduce a difference between behavior of the ANN-based plant model and the real plant under the same neurocontroller actions.

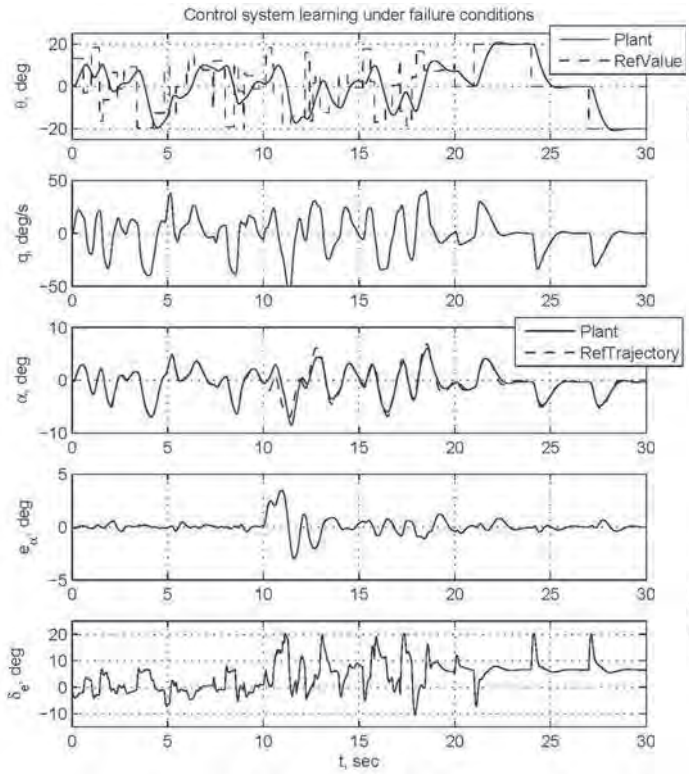

Figure 8: Simulation results for the IDP-based system with adaptation in the angle of attack stabilization loop.

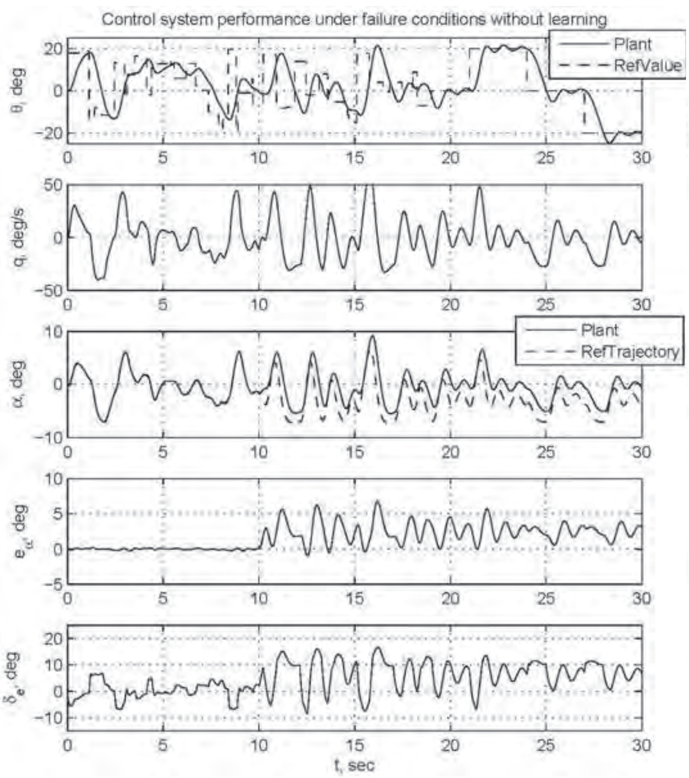

Figure 9: Simulation results for the IDP-based system without adaptation in the angle of attack stabilization loop.

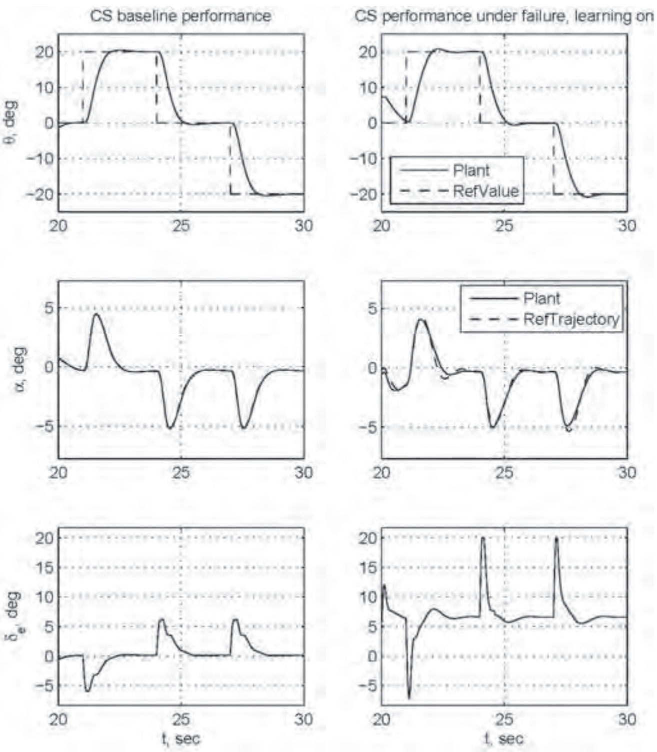

Figure 10: Comparison of control quality for pitch angle before and after damage with adaptation in the angle of attack stabilization loop.

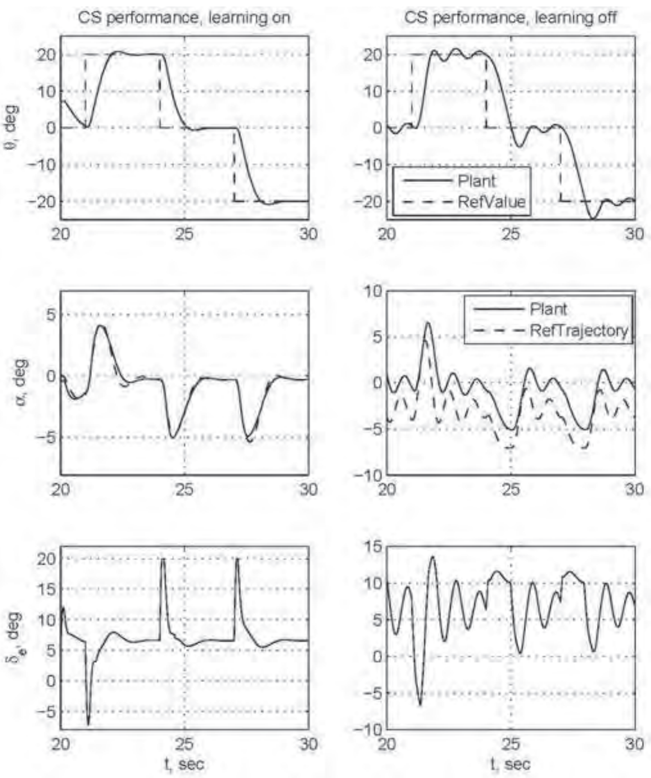

Figure 11: Comparison of control quality for pitch angle before and after damage without adaptation in the angle of attack stabilization loop.

Simulation results for the IDP-based adaptive control scheme are presented on Figures 8 and 9. All of computational experiments were carried out for X-04 mini-UAV [18]. An indicated airspeed V_i is used here as an external parameter to specify aircraft flight regime. All data presented on Figures 8 and 9 were obtained for $V_i = 70$ km/h. Here θ is pitch angle, deg; α is angle of attack, deg; e_α is tracking error for angle of attack, deg; q is pitch angular velocity, deg/sec; δ_e is elevator deflection angle, deg; t is time, sec; *RefTrajectory* is output of the reference model.

Capabilities are demonstrated here for adaptation to abrupt changes of plant dynamics: 1) center of gravity aft shift on 15% in instant time $t = 10$ sec; 2) decreasing of elevator efficiency on 50% at the same instant time.

Figures 10 and 11 shows us comparison results for control quality as applies to pitch angle channel with and without adaptation in the angle of attack stabilization loop (Figures 8 and 9 respectively). Besides we can see an influence of damage on control quality for conventional controller to compare it with IDP-based one.

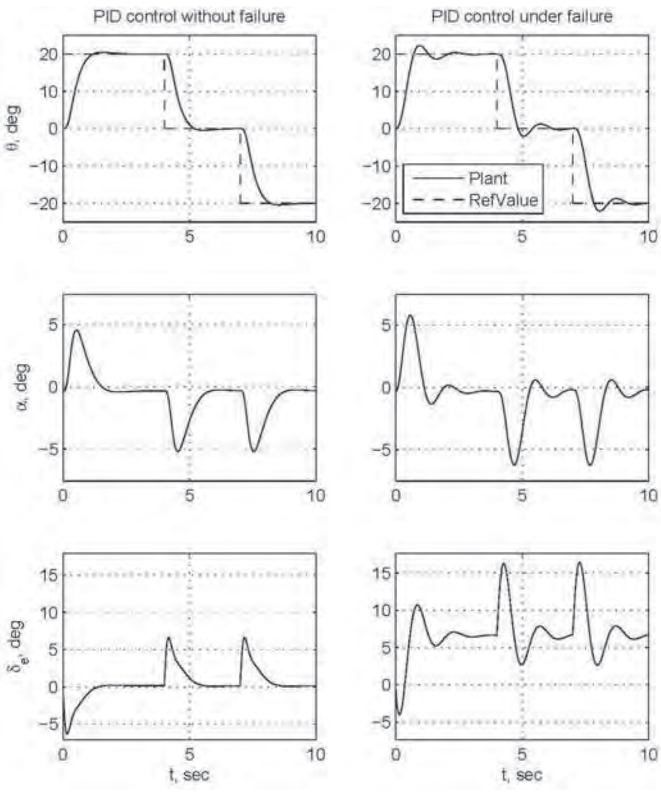

Figure 12: Influence of damage on control quality for conventional controller.

Simulation results (see Figures from 8 through 12) demonstrate how the IDP-based system equipped with the PD-compensator manage effects of two simultaneous damages influencing significantly on the plant dynamics. First of the damages leads to UAV center of gravity aft shift on 15%. It occurs in instant time $t = 10$ sec. The second damage causes decreasing of longitudinal control efficiency on 50% at the same instant time. We can see that the IDP-based scheme provides operation with a slight error (as a rule $e_\alpha \approx \pm 0,05$ deg) until the first failure occurs. Adaptation to the plant dynamic change in this case executes quite rapidly taking 1.2–1.5 sec approximately. The tracking error is now larger than before the failure but its value still lies in the range $e_\alpha \approx \pm 0.2$ deg and the system stability is unbroken. After the second failure the system stability is still unbroken although the tracking error values become rather large, their values belong mostly to the range $e_\alpha \approx \pm 0.5$.

Thus the suggested reconfiguration scheme for the UAV motion control law proves its efficiency as a tool which allows us to suppress on-the-fly effects of equipment failures and structural damages. Therefore we can ensure some specified level of fault tolerance and damage tolerance for the UAV control system.

We can compare these results with simulation results obtained in [18] for the MRAC and MPC control systems equipped with the PD-compensator as applies to the same X-04 UAV under the same failure cases. Both MRAC and MPC schemes provide operation with the same error value ($e_\alpha \approx \pm 0.05$ deg) until the first failure as it occurs for the IDP scheme. Adaptation to the plant dynamic change for MRAC and MPC schemes executes taking 1.2–1.6 sec approximately. The tracking error values are $e_\alpha \approx \pm(0.18 - 0.22)$ deg after the first failure and the system stability is unbroken. After the second failure the system stability is still unbroken for both MRAC and MPC cases [17]. The relevant tracking error values are $e_\alpha \approx \pm(0.48 - 0.52)$ deg after the second failure. Thus the MRAC-based and MPC-based reconfiguration schemes for the UAV motion control law have in whole very similar properties in comparison with IDP-based scheme.

The most important conclusion following from the simulation results for the IDP-based system as well as for MRAC-based and MPC-based systems (see [18]) consists in the fact that all of these systems can operate successfully including cases with UAV equipment faults and structural damages.

5 CONCLUSION

Investigations considered above show us that the ANN-based approach to build models of complex nonlinear dynamic systems is very effective from the standpoint of simulation accuracy as well as processing speed while using these models. Such ANN-based model features are especially important for on-board implementation of UAV control laws.

The obtained results demonstrate clearly that the ANN-based approach to control complex nonlinear dynamic systems under uncertainty conditions using adaptation mechanisms allows us to adjust control systems effectively in respect to a current situation including emergence of various failures and damages in UAV equipment and structure. Neural network based techniques and tools show us very high efficiency concerning adaptive fault-tolerant and damage-tolerant control for nonlinear systems under various kinds of uncertainty.

Comparison of the MRAC, MPC, and IDP systems do not allow us to prefer explicitly one of these adaptive control schemes. Each of these systems has both positive and negative properties. Some final choice between MRAC, MPC, and IDP control systems can be carried out only with regard to specific application problem performing sufficiently large sequence of computational experiments.

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Design Approach for Selection of Wing Airfoil with Regard to Micro-UAVs

Vladimir Brusov [1] and Vladimir Petruchik
Moscow Aviation Institute (MAI),
Flight Dynamics and Control Department,
Volokolamskoye Shosse 4, 125993,GSP-3, Moscow, Russia

ABSTRACT

A reasonable selection of wing airfoil is very important part of aerodynamic design process for micro-UAVs. The selected airfoil predetermines substantially performances of the designed UAV. This reason causes us to pay attention to the problem of UAV wing airfoil selection taking into account properties specific for micro-UAVs. A concept of multitask design is suggested to solve this kind of problems. This concept is explained in regard to selection process for micro-UAV airfoil. Presented simulation results demonstrate that using of multitask approach to aerodynamic design of micro-UAV enables us to enhance UAV efficiency due to improvement of its aerodynamic perfection.

1 INTRODUCTION

A class of very-small unmanned aerial vehicles (micro-UAVs) includes UAVs with a mass in the range from several dozen grams up to 1 kg or up to 5 kg according to other appraisals. Micro-UAVs are equipped mostly with electric propulsion system consists of rechargeable battery and electric engine to drive propeller. There are many papers related to reasonable selection of design parameters for a micro-UAV including selection of its airfoil [1]–[8], [10], and [14]. A reasonable selection of wing airfoil is very important part of aerodynamic design process for any micro-UAV. The selected airfoil predetermines substantially lift to drag ratio, altitude-airspeed performance, stalling performance as well as takeoff and landing performance for the designed UAV. These reasons stimulate us to investigate the problem of UAV wing airfoil selection taking into account properties specific for micro-UAVs.

2 AN INFLUENCE OF FLIGHT REGIMES ON SELECTION OF WING AIRFOIL FOR MICRO-UAVS

The wing airfoil selection problem for micro-UAVs has some peculiarities caused by reasons discussed below.

1. *Low airspeeds and low Reylolds number values.* Airspeed values for typical micro-UAVs are usually in the range from 8–10 m/sec to 25–30 m/sec. This range is specified by requirements which are formulated usually to the UAV. According to these requirements the UAV should have capability to carry out flight tasks both during calm and at strong enough wind. In combination with small UAV dimensions it leads to a situation when UAV flies in about critical Reynolds number values if it is near to the bottom of the UAV airspeed range. It is important because of almost all aerodynamic characteristics change considerably for critical Reynolds number values [1], [2], and [14].

Critical Reynolds number values are from 80000 to 140000 for various wing airfoils. A transition from subcritical Reynolds number values to supercritical ones causes essential enhancement of UAV aerodynamic characteristics. For example UAV lift to drag ratio rises approximately on 50% in this case.

For subcritical Reynolds number values, i.e. for low airspeed, airfoils with small relative thickness (5–7%) and with large relative concavity (even downstream airfoil face is concave in this case) are preferable if we need to maximize airfoil lift to drag ratio. These airfoils become inefficient if airspeed increases because of enhancement for airfoil profile drag.

For middle airspeed values (U=15–20 m/sec) airfoils with relative thickness approximately 14–16% and with almost flat or even convex downstream face are most preferable.

Finally, for large airspeeds (for micro-UAV airspeed about U=25–30 м/с is large enough) sufficiently thin airfoils (8–12%) become preferable again but this time they need to be close to symmetrical one with small relative concavity. The fact is that we do not need high values of UAV lift coefficient for these relatively large airspeeds but it is very desirable to decrease airfoil profile drag.

Thus, the requirements claimed to airfoils in regard to various flight regimes are obviously contradictory.

2. *Nonstationarity of aerodynamic characteristics for micro-UAV with respect to Reynolds number and angle of attack values.* If micro-UAVs flied all the time on small Reynolds numbers including subcritical ones then it would leads only to some decreasing of their lift to drag ratio in comparison with the flight within supercritical Reynolds number region. However, micro-UAVs have very small flight weight and small wing load values. Then micro-UAV under a gust influence can transits very quickly (for few seconds) from subcritical Reynolds numbers to supercritical ones and back to subcritical Reynolds numbers. These transitions cause significant changes in UAV aerodynamic characteristics.

Micro-UAVs have small values for moments of inertia about X, Y, and Z body axes. For this reason micro-UAVs have large angular accelerations and large angular velocities p, q, and r. Moreover, instantaneous center of rotation for micro-UAV do not coincide as a rule with center of gravity for the UAV. Quick changes in angle of attack and sideslip values caused by the rotation lead to emergence of additional aerodynamic moments which depend not only from these angles but also from their rate of change as well as from roll angular velocity. We can see in this case that

[1] E-mail: vsb@mai.ru