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Indirect Adaptive Fuzzy Control of Unmanned Aerial Vehicle

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Abstract: The design and application of indirect adaptive fuzzy controller is developed and applied to Unmanned Aerial Vehicles (UAVs). The parameters of identified model are adapted on-line based on the error between the identified model and the actual output. The model process sensitivity factor $\frac{\partial y_m}{\partial u}$ and the error between the reference input and process output are used to adapt the controller parameters. The model process sensitivity is seen to improve the convergence in addition to improving the response of the UAV, when applied to the attitude control of a typical UAV. Simulation results show the superiority of the proposed controller in the attitude control of the UAV.

1. INTRODUCTION

The dynamics of the Unmanned Aerial Vehicle (UAV) are not well documented, unlike the conventional aircraft. They fly at very low speeds and Reynolds numbers, have nonlinear coupling, and tend to exhibit time varying characteristics with uncertainty. In addition, the success of the UAVs is completely dependent on the accuracy of the control provided by the flight controllers. Thus there is a necessity for accurate, robust and adaptive flight controllers.

The control challenge for UAV arises from the nonlinear equations governing the dynamics that do not lend themselves to the standard methods for controlling linear systems such as PID (Proportional + Integral + Derivative) or state feedback (Jang and Liccardo, 2006 and Beard et al., 2005). Although the simplicity in structure and ease of design of these linear controllers is attractive, their performance is highly affected by the presence of nonlinearity, disturbances, and time varying parameters (Chao et al., 2007).

Intelligent and adaptive control systems such as fuzzy and neural networks provide the appropriate solutions for such systems. In Johnson and Kannan (2002) a Neural Network adaptive control has been developed and applied for rotary wing UAV. Fuzzy logic control is proposed for small UAV and unmanned helicopter in Kumonet et al. (2006) and Sugeno el al. (1995) respectively. The major challenge with these adaptive techniques is the tuning of the controller parameters in real time (Kumonet al. 2006). Due to their simplicity in design and implementation, fuzzy controllers provide an advantage over the neural nets.

This paper presents an application of an adaptive fuzzy control in the attitude control of UAV. There are two approaches of adaptive fuzzy control, the direct and the indirect. In direct adaptive fuzzy control (Phan and Gale 2006; Wu-xi 2006; Spooner et al. 1997a; Zhang and Ge 2006), the controller parameters are directly adapted to reduce the error between the reference input and the process output. On the other hand, in indirect adaptive fuzzy control (Park 2004; Ruiyun and Brdys 2006; Spooner et al. 1997a ; Wang 2004), the parameters of the process are identified and then the controller is designed based on the identified model of the process. Process sensitivity (Ku and Lee 1995; Chen and Teng 1995) is an important parameter in adaptive controller design. In general, most of the indirect adaptive fuzzy controllers do not give consideration to this process sensitivity. A recurrent neural network based control architecture using process sensitivity is presented in Ku and Lee 1995. Chen and Teng 1995 proposed a model reference control structure that uses a fuzzy neural network.

In the present work, an indirect adaptive fuzzy controller is designed for the UAV using the process sensitivity to adapt the controller for varying flight conditions as shown in Fig.1. The identification of the UAV model is carried out by fuzzy system identification (Salman et al. 2006). The feedback of process sensitivity in adapting the controller for varying models is shown to improve the performance of the controller significantly, both in terms of convergence as well as performance. Simulation results for a representative UAV in tracking the pitch and roll angles are provided.

Section 2 explains the design of indirect adaptive fuzzy controller, its stability and convergence analysis whereas Section 3 gives a brief description of the UAV attitude dynamics. Simulation results and concluding remarks are given in section 4 and 5 respectively.

2. INDIRECT ADAPTIVE FUZZY CONTROL

2.1 Fuzzy Model

Consider a general nonlinear discrete-time system described by a state–space model of the form

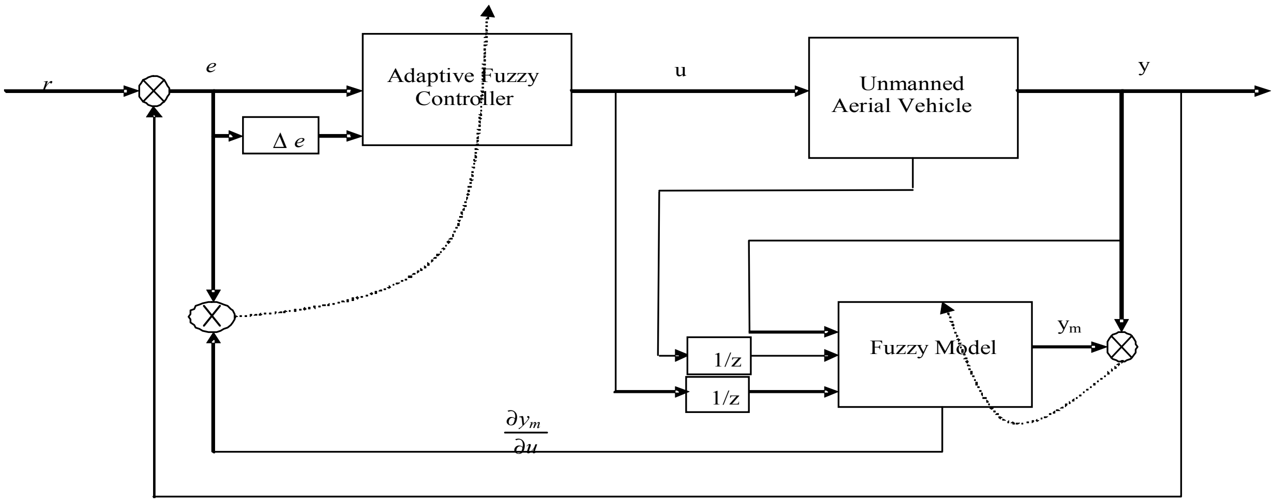


Fig. 1. Indirect Adaptive fuzzy control

$$y(k+1) = f(x(k), u(k)) \tag{1}$$

where $x(k)$ is the state vector of the process at instant k, f is the nonlinear function, $u(k)$ is a control signal and $y(k+1)$ is the process output. The corresponding fuzzy model can be represented as,

$$\begin{aligned} R_j^{FM} :\ &\text{IF } x(k) \text{ is } A_j^x \text{ and } u(k) \text{ is } A_j^u \\ &\qquad \text{THEN } \mathrm{y}_m(k+1) \text{ is } B_j^{y_m} \end{aligned} \tag{2}$$

where A_j^x and A_j^u are the fuzzy sets for state and control inputs respectively, $B_j^{y_m}$ is the rule consequent parameter for fuzzy singletons and y_m is the fuzzy identified model output.

Using the fuzzy inference based upon product sum gravity at given input $(x(k), u(k))$ and the Gaussian membership function (Fig. 2, c and σ are the membership parameters) for all the fuzzy sets, the final output of the fuzzy model is given by (3), with $cx_{i,j}$ and $\sigma_{i,j}$ representing the centre and width of Gaussian memberships for state variable x_i for the rule j, and cu_j and σu_j representing the centre and width of Gaussian membership functions for input u for the rule j along with l and n being the number of rules of fuzzy model and number of states respectively.

The gradient method is used to adapt $cx_{i,j}$, cu_j and $B_j^{y_m}$ based on the following objective function,

$$E_{FM}(k) = \frac{1}{2}\sum_{i=1}^{p}(y_i(k) - y_{m_i}(k))^2 \tag{4}$$

where $E_{FM}(k)$ is the summation of the outputs errors between the system and the fuzzy model and p is the number of outputs.

If $z_{FM}(k)$ represents the parameter to be adapted at iteration k in the Fuzzy Model, the back propagation algorithm seeks to decrease the value of the objective function by,

$$\begin{aligned} z_{FM}(k+1) &= z_{FM}(k) + \eta_{FM}\frac{\partial E_{FM}(k)}{\partial z_{FM}(k)} \\ &= z_{FM}(k) - \eta_{FM} E_{FM}(k)\frac{\partial y_{m_i}(k)}{\partial z_{FM}(k)} \end{aligned} \tag{5}$$

where η_{FM} represents the learning rate of the fuzzy model.

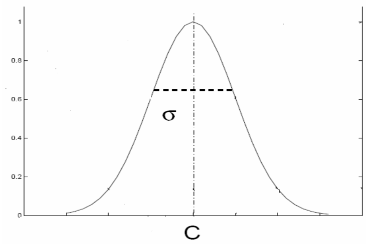


Fig. 2. Gaussian membership

$$y_m(k+1) = \frac{\sum_{j=1}^{l} B_j \left[\prod_{i=1}^{n} \exp\left(-0.5\left(\frac{x_i(k) - cx_{i,j}}{\sigma x_{i,j}}\right)^2\right)\right]\left[\exp\left(-0.5\left(\frac{u(k) - cu_j}{\sigma u_j}\right)^2\right)\right]}{\sum_{j=1}^{l}\left[\prod_{i=1}^{n} \exp\left(-0.5\left(\frac{x_i(k) - cx_{i,j}}{\sigma x_{i,j}}\right)^2\right)\right]\left[\exp\left(-0.5\left(\frac{u(k) - cu_j}{\sigma u_j}\right)^2\right)\right]} \tag{3}$$

2.2 Adaptive Fuzzy Controller

The adaptive fuzzy controller is shown in Fig. 1, where the inputs to the fuzzy controller are the error and error difference. The adaptive fuzzy controller can be represented as $u(k) = f(e(k), \Delta e(k))$ (6)

where $u(k)$ is control signal, $e(k)$ is the error between the reference and the process output and $\Delta e(k)$ is the error difference. The fuzzy controller rule base is represented by,

$$R_j^{FC} : \textit{If } \mathrm{e}(k) \text{ is } A_j^e \text{ and } \Delta\mathrm{e}(k) \text{ is } A_j^{\Delta e} \text{ THEN } u(k) \text{ is } B_j^u \tag{7}$$

where A_j^e and $A_j^{\Delta e}$ are the fuzzy sets for error and change of error respectively and B_j^u is the rule consequent parameter for fuzzy singletons.

Using the fuzzy inference based upon product sum gravity at given input $(e(k), \Delta e(k))$ and the Gaussian membership functions for all fuzzy sets, the final output of the fuzzy controller is shown in (8). ce_j, σe_j and $c\Delta e_j$ and $\sigma\Delta e_j$ represent the centre and width of Gaussian memberships for the error $e(k)$ and error difference $\Delta e(k)$ respectively for the rule j and h are the number of rules of fuzzy controller.

The gradient method is used to adapt ce_j , $c\Delta e_j$, σe_j, $\sigma\Delta e_j$ and B_j based on the following objective function.

$$E_{FC}(k) = \frac{1}{2}(r(k) - y(k))^2 \tag{9}$$

The back propagation algorithm seeks to decrease the value of the objective function by,

$$\begin{aligned} z_{FC}(k+1) &= z_{FC}(k) + \eta_{FC}\frac{\partial E_{FC}(k)}{\partial z_{FC}(k)} \\ &= z_{FC}(k) - \eta_{FC}E_{FC}(k)\frac{\partial y(k)}{\partial u(k)}\frac{\partial u(k)}{\partial z_{FC}(k)} \end{aligned} \tag{10}$$

When the identified model matches the actual process output very well, the process sensitivity can be approximated as

$$\frac{\partial y(k)}{\partial u(k)} \simeq \frac{\partial y_m(k)}{\partial u(k)},$$

hence (10) becomes

$$z_{FC}(k+1) \simeq z(k) - \eta_{FC}E_{FC}(k)\frac{\partial y_m(k)}{\partial u(k)}\frac{\partial u(k)}{\partial z_{FC}(k)} \tag{11}$$

Thus, the process sensitivity function plays an important role in adapting the parameters of the Fuzzy Controller. In addition, the use of the process sensitivity function ensures an indirect adaptive control as against direct adaptive control in its absence. This is seen to improve the performance of the controller in the present paper.

The learning rates η_{FM} and η_{FC} in (5) and (11) respectively (Ku and Lee 1995; Chen and Teng 1995) have a significant effect on the stability and convergence of the system. A higher learning rate may enhance the convergence rate but can reduce the stability of the system. A smaller value of learning rate guarantees the stability of the system but slows the convergence. The proper choice of the learning rate is thus very important. The following theorems provide the bounds on the learning rate.

2.3 Convergence of Fuzzy Identifier

Theorem 1 (Ku and Lee 1995; Chen and Teng 1995): Let η_{FM} be the learning rate for the parameters of fuzzy model and $g_{FM,\max}$ be defined as $g_{FM,\max} := \max_k \|g_{FM}(k)\|$ where $g_{FM}(k) = \frac{\partial ym_i(k)}{\partial z_{FM}(k)}$ and $\|.\|$ is the usual Euclidean norm in $\Re^n$. Then the convergence is guaranteed if η_{FM} is chosen as

$$0 \prec \eta_{FM} \prec \frac{2}{g^2{}_{FM,\max}} \tag{12}$$

2.4 Convergence of Fuzzy Controller

*Theorem 2(*Ku and Lee 1995; Chen and Teng 1995): Let η_{FC} be the learning rate for the parameters of fuzzy controller and $g_{FC,\max}$ be defined as $g_{FC,\max} := \max_k \|g_{FC}(k)\|$ where $g_{FC}(k) = \frac{\partial u(k)}{\partial z_{FC}(k)}$ and $\|.\|$ is the usual Euclidean norm in $\Re^n$ and let $S = \frac{\partial y_m(k-1)}{\partial u(k-1)}$ Then the convergence is guaranteed if η_{FC} is chosen as

$$u(k) = \frac{\sum_{j=1}^{h} B_j \left[\exp\left(-0.5\left(\frac{e(k)-ce_j}{\sigma e_j}\right)^2\right)\right]\left[\exp\left(-0.5\left(\frac{\Delta e(k)-c\Delta e_j}{\sigma\Delta e_j}\right)^2\right)\right]}{\sum_{j=1}^{h}\left[\exp\left(-0.5\left(\frac{e(k)-ce_j}{\sigma e_j}\right)^2\right)\right]\left[\exp\left(-0.5\left(\frac{\Delta e(k)-c\Delta e_j}{\sigma\Delta e_j}\right)^2\right)\right]} \tag{8}$$

$$0 \prec \eta_{FC} \prec \frac{2}{S^2 g^2{}_{FC,\max}} \tag{13}$$

3. UAV ATTITUDE DYNAMICS

The attitude dynamics of UAVs considered in this paper are mapped by a set of six highly coupled, nonlinear differential equations: (Salman et al. 2006a,b)

$$\left.\begin{aligned}
\dot{p} &= \frac{1}{I_x I_z - I_{xz}^2}\begin{Bmatrix} I_z[L+(I_y-I_z)qr]+ \\ I_{xz}[N+(I_x-I_y+I_z)pq- \\ I_{xz}qr] \end{Bmatrix} \\
\dot{q} &= \frac{1}{I_y}[M+pr(I_z-I_x)+(r^2-p^2)I_{xz}] \\
\dot{r} &= \frac{1}{I_x I_z - I_{xz}^2}\begin{Bmatrix} I_x[N+(I_x-I_y)pq]+ \\ I_{xz}[L+(I_y-I_x-I_z)qr+ \\ I_{xz}pq] \end{Bmatrix} \\
\dot{\phi} &= q\tan\theta\sin\phi + p + r\tan\theta\cos\phi \\
\dot{\theta} &= q\cos\phi - r\sin\phi \\
\dot{\varphi} &= q\cos^{-1}\theta\sin\phi + r\cos^{-1}\theta\cos\phi
\end{aligned}\right] \tag{14}$$

where p, q, r are the angular rates of roll, pitch and yaw respectively. L, M, N represent aerodynamic moments about roll, pitch and yaw respectively. I_x, I_y, I_z, I_{xz} are the moments of inertia and $\delta_e, \delta_r, \delta_a$, and δ_{th} are the elevator, rudder, aileron and throttle servo deflections respectively. ϕ, θ and ψ are the roll, pitch and yaw angles respectively.

When the yaw angle is held constant, i.e. straight flight, the equations in the discrete format can be represented by (1) where

$x(k) = (p(k), q(k), r(k), \phi(k), \theta(k))$,

$u(k) = (\delta_e(k), \delta_a(k))$, and $y(k) = (\phi(k), \theta(k))$

Fuzzy identification and controller design presented in section 2 are applied for a representative UAV. The simulation results presented in the next section indicates the benefits of the chosen control scheme.

4. SIMULATIONS RESULT

The Aerosonde simulation model has been chosen to apply the indirect adaptive fuzzy controller developed here. The aerosonde model is introduced in AeroSim Blockset (http://www.u-dynamics.com/aerosim/default.htm).

The fuzzy model is a two input (elevator and aileron deflections) two output (roll and pitch angles) system. Roll and pitch angles are manipulated using the elevator and aileron deflections. It is represented as

$$\phi_m(k+1) = f(p(k), q(k), r(k), \phi(k), \theta(k), \delta_e(k), \delta_a(k))$$
$$\theta_m(k+1) = f(p(k), q(k), r(k), \phi(k), \theta(k), \delta_e(k), \delta_a(k))$$

where $x(k) = (p(k), q(k), r(k), \phi(k), \theta(k))$,

$u(k) = (\delta_e(k), \delta_a(k))$, and $y_m(k+1) = (\phi_m(k+1), \theta_m(k+1))$

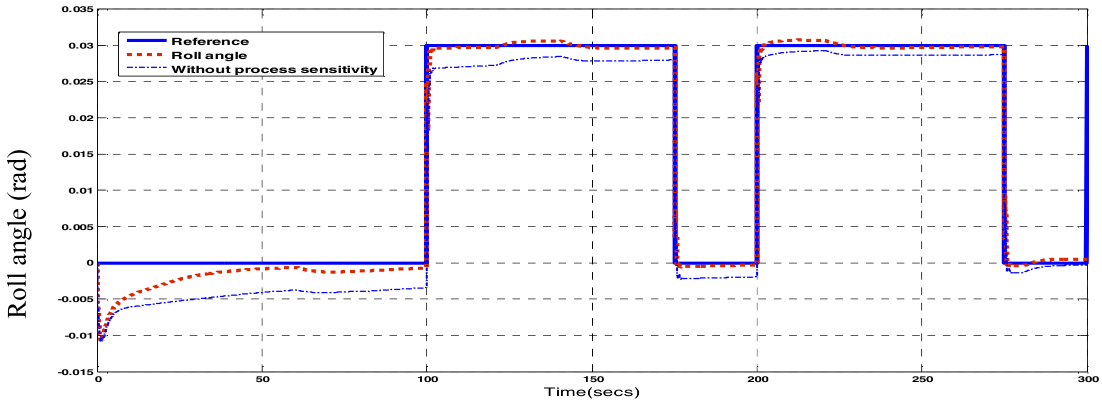
The Gaussian membership functions A_j^x and A_j^u are adapted on line using the back propagation algorithm according to $E_{FM}(k)$. The initial parameters of the fuzzy model, $cx_{i,j}$ and cu_j and the singleton values $B_j^{y_m}$ for the output are determined by normal equal partitioning. The total number of rules used for the fuzzy model is 101. The learning rate η_{FM} based on the convergence limit for fuzzy identifier was set to 0.05 for both the centres and the singleton output parameters. The values of $\sigma x_{i,j}$ and σu_j are taken to be fixed in the present work.

The inputs to fuzzy controller are the roll and pitch angle errors and their error differences. The outputs of the fuzzy controller are the elevator and aileron deflections. The Gaussian membership functions A_j^e and $A_j^{\Delta e}$ are adapted on line using the back propagation algorithm according to $E_{FC}(k)$ and $\frac{\partial y_m(k)}{\partial u(k)}$ where the signal $\frac{\partial y_m(k)}{\partial u(k)}$ is obtained from the fuzzy model. The initial values for membership centres ce_j and $c\Delta e_j$ and the singletons values B_j^u for the output, are determined by normal equal partitioning. The total number of rules used for fuzzy controller is 25. The learning rate η_{FC} based on the convergence limit for fuzzy controller was set to 0.05 for both centres and singleton output parameters.

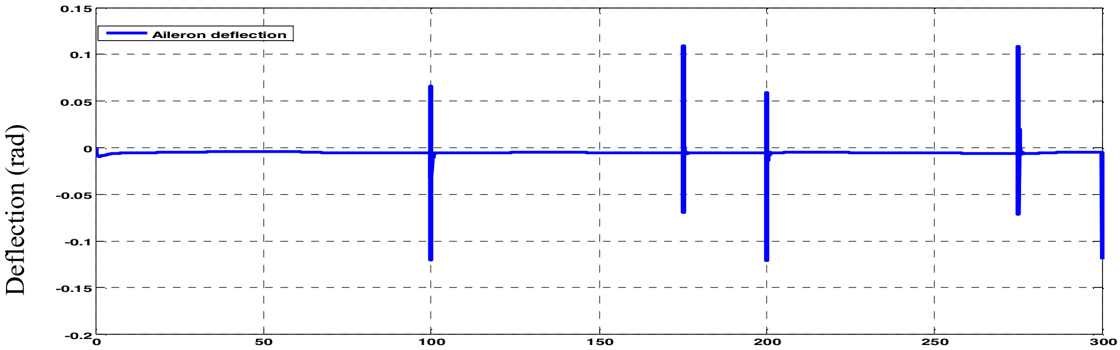
Figure 3 shows the simulation results of the proposed indirect adaptive controller when applied to the aerosonde model. Both the roll angle and the pitch angles are tracked by the adaptive controller with negligible overshoot and steady state errors. As can be seen from the figures, initially (first 60 samples) the response is not very good since the model as well as the controller are trying to adapt. The simulation results are also presented without the feedback of process sensitivity (direct adaptive controller). The indirect adaptive controller seems to be doing a better job both in the transient as well as steady state components. This can be attributed to the correction to the membership parameters provided by the sensitivity function. A sample set of the variation of the centre of membership functions for two membership sets are provided in Fig. 4. It can be seen that the sensitivity function is enhancing the speed of convergence which is reflected in the transient responses as well.

5. CONCULUDING REMARKS

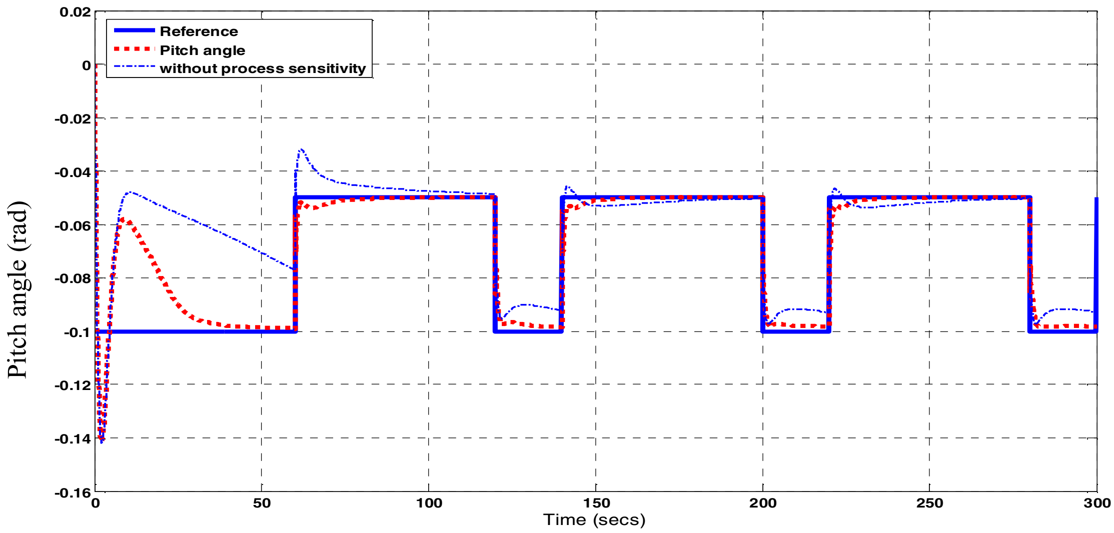
The paper provides the design of an indirect adaptive controller using the model sensitivity function. The feedback of the model sensitivity function to adapt the parameters of the controller is shown to have beneficial effects. Numerical simulations applied to the control of roll and pitch angle of a UAV demonstrate the improvement compared to the direct adaptive controller.



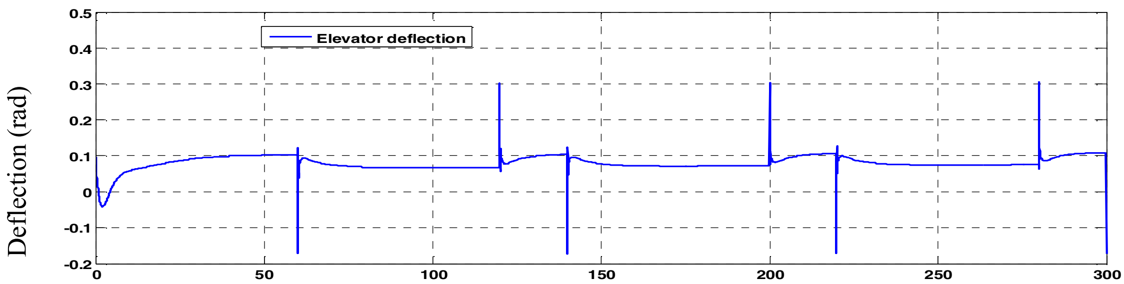
(a) Roll angle response



(b) Aileron deflection



(c) Pitch angle response



(d) Elevator deflection

Fig. 3. Process outputs and control signals responses for direct and indirect controller.

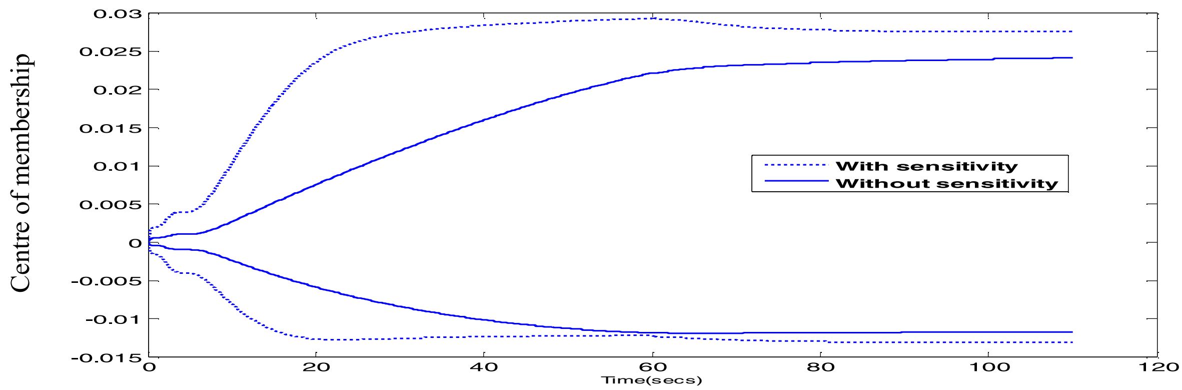


Fig. 4 Variation of the center of membership function

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