GENETIC FUZZY CONTROL FOR AUTONOMOUS DUCTED-FAN VTOL UAV

Zamri Omar[†], Cees Bil[*]
[†]UTHM University, Pt.Raja 86400, Johor, Malaysia
[*]RMIT University, Melbourne VIC 3000, Australia

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Abstract

An optimized fuzzy logic has been considered to control a VTOL ducted fan UAV during the vertical flight. The control design goal is to have stable vertical flight in the presence of wind disturbance. Genetic Algorithm has been used as the tool for optimization. The controller inputs are body components velocity and roll rate error, whereas the output are the commanded signal to the vehicle's control surfaces. The results of this work are illustrated by simulation, showing that the UAV is able to operate autonomously in vertical flight and maintain it stable orientation.

1 Introduction

Using unmanned aerial vehicles (UAVs) for monitoring purposes is beneficial in both military and civil applications. The UAVs that are small, easy to manoeuver and able to operate autonomously are usually needed to perform these duties. It necessity becomes manifest for the operations in restricted environment, where ducted fan configuration offers some distinct advantages [7] over conventional UAV designs since it has vertical take-off and landing (VTOL) capabilities, in addition to ascribing the typical aircraft characteristics.

One of the greatest challenges in the design on this class of UAV is to automate the entire operations of the ducted fan UAV which involve; VTOL, hovers, manoeuvres, and transitions between vertical and horizontal flights. By considering the design uniqueness, the existence of some uncertainties in the vehicle characteristics and in predicting the stability, and the requirements to perform all necessary flight regimes in the presence of wind disturbance, the use of an intelligence control system for this type of UAV has becomes apparent [3]. In this paper, we develop an autonomous vertical flight using an optimized fuzzy logic control system.

2 Vehicle Configuration

The configuration of the ducted-fan VTOL UAV has the novelty in a way that it blends the design features of the following; existing UAVs, rotary-wing airplanes and fixed-wing airplanes. This ducted-fan UAV has approximately 3 kg in maximum take-off weight and its propeller is enclosed in an annular wing for extra thrust and lifting force. This vehicle with the acronym of RUAV is shown in multiple views in Figure 1. The RUAV take off and lands vertically and will be able to hover. Once the RUAV is in vertical flight, it can transit 90^o into the horizontal flight, making its fuselage parallel to the horizon.

The top diagram in Figure 2 shows this transition flight. The low speed forward flight is performed by tilting the vehicle towards the direction of flight, so that the inclined thrust vector is resolved as the lift and forward thrust. The motion of low speed forward flight is shown in the middle diagram in Figure 2. The reverse transition flight is showing in the bottom diagram in Figure 2. In this manoeuvre, the RUAV is bring to hover, before it can ascend vertically to the landing platform.

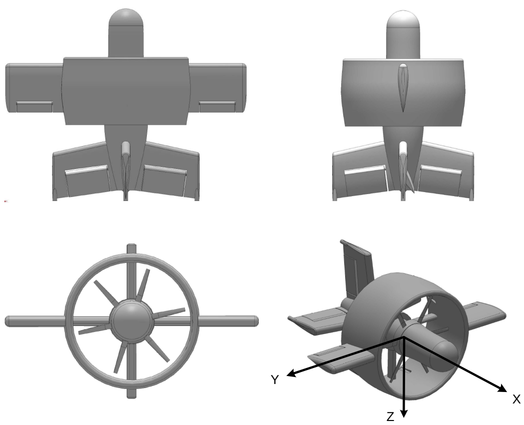

Fig. 1 RUAV hover diagram

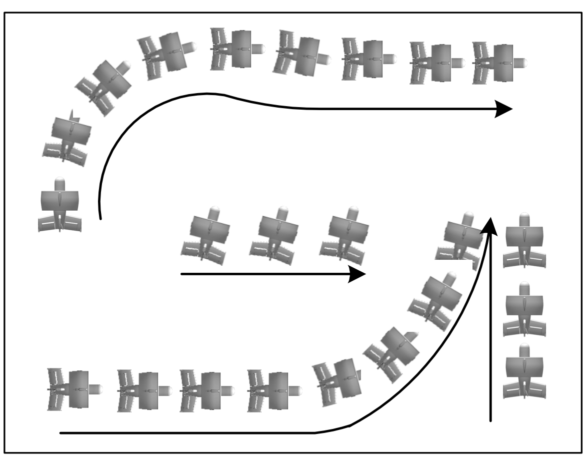

Fig. 2 The motions of RUAV

3 The FLC Design for Vertical Flight

In the search for an easy, efficient, cost-effective control, fuzzy logic seems to provide a method of reducing system complexity while increasing control performance. Fuzzy logic seems to provide a method for reducing system complexity while providing enough control performance. It also provides an easy, efficient, and cost-effective control system technique [5]. Fuzzy theory was originally investigated by Lukasiewicz and Knuth. But it was finally formalized by Zadeh in the 60's. Since then, many researchers have introduced fuzzy logic techniques to solve different types of problems.

Theoretically, fuzzy logic is a set of mathematical principles for knowledge representation based on the degree of membership rather than on crisp membership of classical binary logic [6]. This section describing the development of fuzzy logic controller (FLC) to automate the RUAV in vertical flight. In vertical flight, the desired flying characteristic and stability can be achieved by assigning the controller to control the velocity components of w, v, $\dot{h}$, and also roll rate p. The corresponding control surfaces for these velocities and angular rate are elevators, rudders, engine throttle, and ailerons.

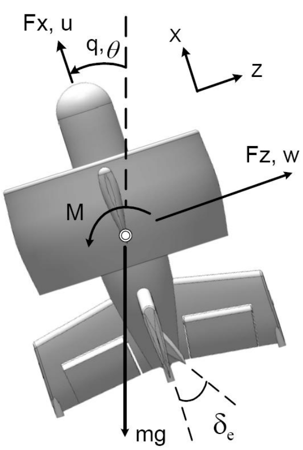

Fig. 3 RUAV vertical flight diagram.

Figure 3 shows the RUAV in symmetric xz plane. In the figure, u and w represent velocity components along x and z axes respectively, pitch rate q, vehicle weight mg, and F and M which are the force and moments with respect to the subscripted axes. All the quantities shown in the figure are in their positive sense. The governing equations for the FLC are derived from the six degree of freedom equation of motions for aircraft. Representing the equations in the matrix forms, we have:

$$\begin{bmatrix} \dot{w} \\ \dot{q} \\ \dot{\theta}_v \end{bmatrix} = \begin{bmatrix} \bar{Z}_w & \bar{Z}_q & -g \\ \bar{M}_w & \bar{M}_q & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} w \\ q \\ \theta_v \end{bmatrix} + \begin{bmatrix} \bar{Z}_{\delta e} \\ \bar{M}_{\delta e} \\ 1 \end{bmatrix} \delta_e \tag{1}$$

$$\begin{bmatrix} \dot{u} \\ \dot{p} \\ \dot{\phi}_v \end{bmatrix} = \begin{bmatrix} \bar{X}_u & 0 & 0 \\ 0 & \bar{L}_p & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} u \\ p \\ \phi_v \end{bmatrix} + \begin{bmatrix} 0 & \bar{X}_{\delta_{th}} \\ \bar{L}_{\delta_a} & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_{th} \end{bmatrix} \tag{2}$$

$$\begin{bmatrix} \dot{v} \\ \dot{r} \\ \dot{\psi}_v \end{bmatrix} = \begin{bmatrix} \bar{Y}_v & \bar{Y}_r & -g \\ \bar{N}_v & \bar{N}_r & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} v \\ r \\ \psi_v \end{bmatrix} + \begin{bmatrix} \bar{Y}_{\delta_r} \\ \bar{N}_{\delta_r} \\ 1 \end{bmatrix} \delta_r \tag{3}$$

The overscore force and moment terms in Equation 1 to 3 indicate the terms have been divided by the vehicle mass and inertia respectively, and these terms are stated in a standard mechanic of flights notation for stability and control derivatives. As mentioned previously, these force and moment derivatives are estimated from the theoretical methods. Vertical flight control is analogous to the control problem of the inverted pendulum, except in vertical flight, it has the upward or downward motions. Thus, the control effort is to maintain the RUAV in a straight vertical motion. Furthermore, the presence of wind makes the control system more challenging.

Figure 4 shows a typical vertical flight of RUAV. The v and w velocity components will cause the RUAV to sway on the horizontal plane, thus the FLC need to control its desired magnitude. For example, if the RUAV is slanted towards the starboard that possibly due to the wind gust, the control action is to bring the RUAV back to vertical motion by controlling the v velocity. Physically, this could be done by deflecting the ailerons. The controller also need to correct vehicle orientation and heading angle that may deviate due to external disturbances. Based on this principle, the FLC is designed to control the deflection of control surfaces so that the generated forces and moments can finally can maintain the RUAV in a stable vertical motion.

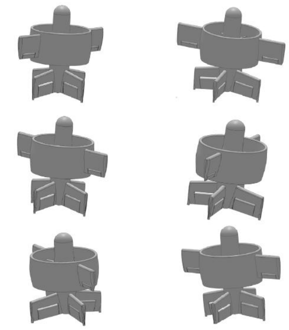

Fig. 4 RUAV in vertical flight.

3.1 Fuzzy Rules, Input, and Output Variables

The error in three velocities components and roll rate that need to be controlled become FLC input variables for vertical flight FLC. The different between the actual and commanded signals in these variables are the error. Thus, we have four input variables in this vertical flight FLC; w error (Δw), v error (Δv), p error (Δ_p), and $\dot{h}$ $(\Delta \dot{h})$ error. The FLC is to drive the system to minimize these error. Five linguistic terms represent the inputs variables which are $NegativeBig(NB)$, $NegativeMedium(NM)$, $Rathersmall(NS)$, $PositiveMedium(PM)$, and $PositiveBig(PB)$. The method for giving precise meaning to these linguistic terms is described in the membership function that uses the triangular type as shown in Figure 5. The vehicle control surfaces are the FLC output variables. In the case of vertical flight, the useful control surfaces of the RUAV are

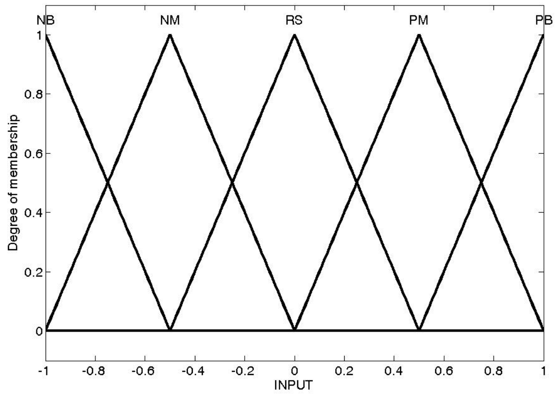

Fig. 5 Membership function of input variables.

elevator (δ_e), rudder (δ_r), aileron (δ_a), throttle (δ_{th}). From the dynamical relationship in equation 1 to 3, it can be observed that these control surfaces are controlling the vehicle's velocity components v, w, $\dot{h}$, and roll rate p. A simple first order lag was used to model the control surfaces actuator dynamic response.

The motion of vertical flight is initiated by the throttle and the corresponding velocity component is $\dot{h}$. An offset of the throttle setting at 40% is maintain throughout the vertical flight and this setting required for ascending at 0.5 m/sec. For each deflection angle of the control surface, the respective forces and moments are obtained from the equations of motion developed earlier. These forces and moments drive the vehicle to perform the vertical flight in a ascending or descending manners.

The linguistic terms that represent the control surfaces deflection are similar to those applied on the input variables that are ; $NegativeBig(NB)$, $NegativeMedium(NM)$, $Rathersmall(NS)$, $PositiveMedium(PM)$, and $PositiveBig(PB)$. The chosen linguistic terms of the input and output variables has result in a 20 fuzzy rules. The development of these rules is based on consecutive tests on the system, and example of the rules are demonstrated as:

If Δw *is PB Then* δ_e *is NB*
If Δp *is PB Then* δ_a *is NB*

4 Optimization of Fuzzy Logic Controllers

Although the use of fuzzy logic for control purposes has proved great advantages, the designer should be made aware of several important factors that evidently effect the performance of the FLC. Careful attention must specifically be given in choosing these parameters ; the number of linguistic terms and rules that should be used and how they are being connected, the defuzzification method, and the best membership functions of the conditions and actions variables the FLC.

The fuzzy logic control has many parameters, and its control depends on the tuning of its parameters. Therefore, a FLC contains several parameters that can be altered to modify the controller performance. They are ;the scaling factors for each variable, the fuzzy set representing the meaning of linguistic values,and the selection of the rules. Post-analysis from previous work [8] deduced that by tuning the membership functions of the input variables, a better controller performance is achieved in term of reducing the overshoot.

However, the tuning process which is the adjustment of all membership functions shape was done off-line and by trial and error approach. Rather than carrying the task manually, this paper presents the tuning of the membership functions online and automatically, by using a genetic algorithm. According to Chin et al [4], genetic algorithms(GAs) are stochastic search algorithms based on natural selection, genetics, and evolution, through which the survival of the fittest principle is firmly applied.

A GA links with the problem it is solving by two mechanisms or processes, namely encoding and evaluation. Possible solutions are encode into artificial chromosomes or strings, then it will go through the natural processes; mating, crossover and mutation, and generates new offspring (chromosome). Then the fitness or the performance of the newly generated chromosome is evaluates by using a pre-defined fitness function. These processes will be repeated for a number of generations until the termination criteria is met, that is to say the optimal solution has been obtained.

GAs techniques have been acknowledged to be efficient tools for dealing with global optimization problems and have been used in wide ranges of applications [1]. Because GAs are based on the natural evolution process, it exchanges information between the peaks, thus ending at global minimum, rather than at local minimum in which the conventional optimization methods such as hill climbing and random walk search cannot comprehend.

4.1 Constraints and Encoding Scheme

In previous section, it states the membership functions of the input variables are the parameters that need to be optimized. Here we choose to optimize the membership functions of Δw. Since all these functions are of triangular type, the optimization routine will relocate those triangular corners in order to form the optimized functions shape.

Specifically, it can be achieved by altering the parameters of that membership functions which are the 6 corner points of the peaks and bases of the triangles ($x1$ to $x6$) as marked in Figure 6. These points are allow to move within their limits.

The search for optimal solutions are bounded by two constraints. The first is it requires all the concerned membership functions corners lie in their predetermined range on the universe of discourse. The ranges of the movable points are to ensure at all time, all the membership functions can be constructed. Throughout the work, the constraints of corners are as follow; -0.7 $\leq$ x1,x4 $\leq$ -0.3, -0.2 $\leq$ x2,x5 $\leq$ 0.2, and 0.3 $\leq$ x3,x6 $\leq$ 0.7.

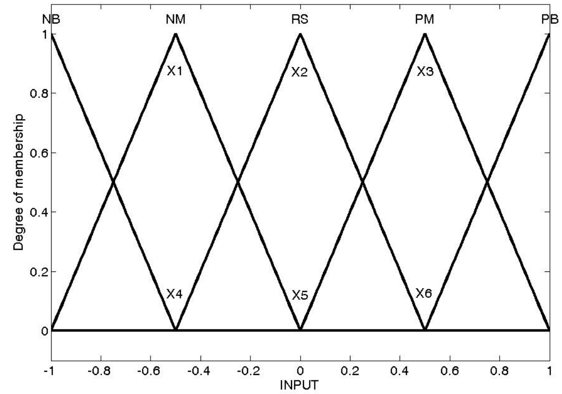

Fig. 6 Optimization points of membership function.

The second constraint is the literal meaning of the linguistic terms should always be consistent. For instance the membership function assigned as NB should be 'zero' on positive universe of discourse and 'non-zero' on negative universe of discourse. The next step is to represent all of the parameters that need to be optimized into chromosomes(strings)form. Each point or the corner of the membership functions is encodes into string, and each string is represented by 4 $bits$, thus resulting in total string length of 6 x 4 $bits$ = 24 $bits$.

4.2 The Fitness Function

The choice of fitness function is directly related to the control system objectives. In this work, it requires the controller to ensure the RUAV is having a smooth and stable vertical flight. The error of the inputs variables are continuously send to the FLC block and this forms an automatic feedback system. In a feedback system, the minimization of sum of the errors, $\sum e$ is clearly being the variable of concerned. The integral of square error shown in Equation 4 normally gives a better performance [2] and was used in this work to evaluate the fitness of each chromosome that representing a particular tuning point for the FLC.

$$f(t) = \int_0^t e^2.dt \tag{4}$$

The simulation of vertical flight control for the RUAV was implemented using *MATLAB, Simulink, Fuzzy Logic Toolbox* and *Genetic Algorithm and Direct Search Toolbox*. Figure 7 depicts the simulation diagram of the GA optimized fuzzy logic control system. The disturbance wind gust was modeled as a impulse function with the magnitude of 10 m/s heading towards north and acted on the RUAV's centre of gravity.

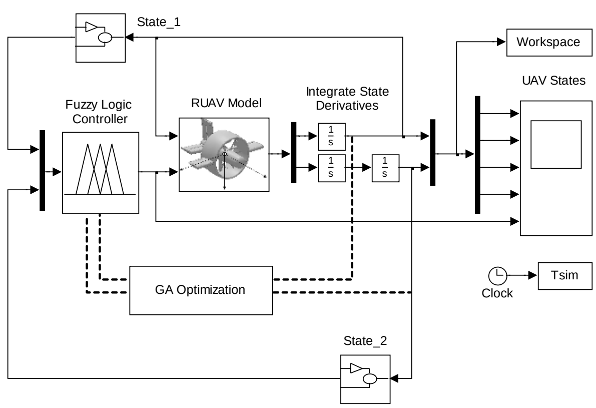

Fig. 7 The RUAV simulation.

5 Results and Discussions

This section will discuss the key simulation results of the UAV control system performance and the effects of optimization on the controller. The comparison between non-optimize FLC and optimized FLC results will be presented. The discussions are based on examining two vehicle states which are north position and vertical pitch angle. The point on the ground that the vertical flight took place was set to zero in north axis. Thus, if the vertical flight was launched in a still air, the north position should always zero. As mentioned before, a wind disturbance has been modeled in the simulation.

The variation plots of the vehicle position in north direction are shown in Figure 8.The effect of the wind can be seen after two seconds of the flight. Here, a 10m/s wind magnitude caused the RUAV to drift away about 1.3m to the north. The FLC responded to this situation which is to bring back the RUAV to the north zero position. In general, the time history of vehicle response to correct its position was in the oscillating manner and the optimized FLC has proved a better response.

The response are quite similar to the second order system response that normally desirable to have a lower overshoot and settling time. The optimized FLC response indicated by the bold plot in Figure 8, caused a smaller overshoot and has a shorter settling time than the response of non optimized FLC.

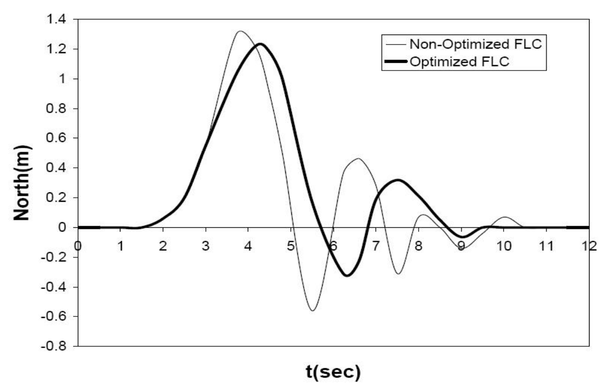

Fig. 8 The north deviation.

The wind disturbance also caused the RUAV to tilted away towards the north. As can be seen in Figure 9, it shows the response of the vehicle to correct itself and in this case, θ_v is the parameter of interest to be monitored. The zero θ_v indicates the RUAV has been corrected from it titled orientation. Similar in the previous discussion, the optimized FLC shows a better response. It was measured in terms of the overshoot and settling time. It was clearly seen in Figure 9 the overshoot was reduced about 5^o for the optimized FLC response.

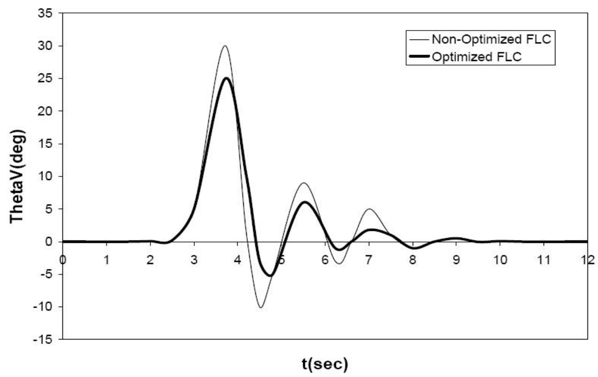

Fig. 9 The vertical theta deviation.

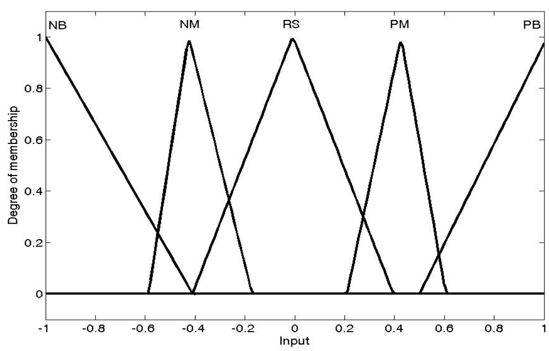

Fig. 10 Optimized membership functions.

The smaller overshoot also indicates the vehicle was having a more stable flight. The optimization algorithm of the FLC that was explained previously has improved the performance of the controller. This is evident from the previous two figures. The corresponding optimal shape of the membership functions for one of the input variable is depicted in Figure 10. This optimized membership functions should be compared to its non optimized shape depicted in Figure 6.

6 Concluding Remarks

This paper has discussed the development and application of fuzzy logic for vertical flight control on a ducted fan VTOL UAV configuration. Some simulation results have been highlighted and discussed. The vehicle response demonstrates a robust and good performance of the proposed control system in a noisy flying environment. It was evident that the UAV is able to correct itself due to the wind disturbance and have a stable vertical flight.

The main issue which is the use of genetic algorithm to optimize fuzzy logic controller has been addressed as well. The observed better performance of the GA optimized FLC in this paper is the evident that the randomness of GA in searching the global space was able to find the optimal solutions. In future, the formulation of the optimization routine for this FLC can be further improved. This may be done in two ways; the coding of the possible solutions and the termination criteria.

7 Copyright Statement

References

[1] Cordon O and et.al. Ten years of genetic fuzzy systems: Current framework and new trends. *Prodeedings of IFSA/NAFIPS*, 2001.

[2] John P. Byrne. Ga optimisation of a fuzzy logic controller. *M.Eng Project Report*, 2003.

[3] L.Doitsidis and K.P.Valavanis. A framework for fuzzy logic based uav navigation and control. pp 4041–4046. EEE International Conference on Robotics and Automation, 2004.

[4] Lin C.-T and Lee C. G. *Neural Fuzzy Systems : A Neuro-Fuzzy Synergism to Intelligent Systems.* Prentice Hall, New Jersey, 1995.

[5] L.Karr C. *Practical Applications of Computational Intelligence for Adaptive Control*. CRC Press, London, 1999.

[6] Negnevitsky M. *Artificial Intelligence, A Guide to Intelligent Systems*. Addison-Wesley, London, 2005.

[7] N.Johnson E and A.Turbe M. Modelling, control, and flight testing of a small ducted fan aircraft. *AIAA Guidance, Navigation, and Control Conference and Exhibit*, 2005.

[8] Omar Z, Bil C, and Hill R. Uav hovering control using intelligent fuzzy technique. *3rd International Conference of Artificial Intelligence in Engineering and Technology*, 2006.