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Comparative Study for Different Quad-Rotor Helicopter Feedback Controllers

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Abstract

In this paper, Adaptive Neuro Fuzzy Inference System (ANFIS) is developed for an unmanned quadrotor air vehicle. This controller is compared with conventional fuzzy controller and genetically tuned PID controller from robustness point of view when the plant is subjected to model uncertainty. The robustness with respect to environmental disturbances, especially wind, is also compared since the wind speed magnitude is comparable to the quadrotor speed. Finally; the comparison between the controllers includes the effect of noise measured on the quadrotor output sensors such as gyroscopes and altitude sensor. The simulation results based on the quadrotor model show the superiorities and the drawbacks of each controller.

1. Introduction

Controller design for Unmanned Air Vehicles (UAV), especially a four rotors Vertical Take-Off and Landing (VTOL) aircraft known as the quadrotor, has drawn great attention in recent years.

The controller has to guarantee the accuracy of the tracking path, and the robustness with respect to model uncertainties and environmental disturbances. The controllers also should mitigate the effect of measured noise on plants outputs [1-4].

A control system is robust if it is insensitive to differences between the actual system and the model of the system, which has been used to design the controller. These differences are referred to as model/plant mismatch or model uncertainty [1]. In the robustness study of a system, the uncertainty set must be determined first then robust stability and robust performance can be examined.

The controller must be robust against external environmental disturbances and especially wind. Small UAVs are significantly sensitive to wind disturbance since its magnitude may be comparable to the UAVs speed [5].

The controller is also affected by the noise measured using sensors on the planet output such as gyroscopes and altitude sensor. This effect should be attenuated by the controllers.

In this paper; genetically tuned PID, ANFIS, and fuzzy logic controllers are designed for quadrotor. The three controllers are compared based on robustness to model uncertainties, environmental disturbance rejection, and noise effect attenuation.

PID controller is designed first for the nonlinear system model of the quadrotor. Simplex algorithm is used as a fast optimal tuning technique for the PID controller parameters. Genetic Algorithm (GA) is then used as a fine tuning technique for PID parameters.

Input-output data of the PID controlled system are collected along the whole range of operation. These data are used as learning and checking data for the ANFIS design.

Finally, conventional PID-like fuzzy controller is designed for the quadrotor. The relations between the membership functions of the inputs and the membership functions of the output are developed using if-then rules.

The simulation results obtained using ANFIS, as a nonlinear controller, are compared with those obtained using genetically tuned PID and conventional fuzzy controllers. Following desired trajectory, robustness to model uncertainty, disturbance rejection, and noise effect mitigation are considered as the comparison criteria. These results show the superiorities and the drawbacks of each controller.

2. Quadrotor model and assembly

As mentioned in [6], a quadrotor consists of two fixed pitch clockwise spinning rotors and two counter-clockwise spinning rotors which diagonally oppose each other as shown in Figure 1. This results in the reactive force of each propeller being effectively cancelled out by the diagonally opposite rotor’s reactive component. This eliminates the need for a helicopter tail rotor.

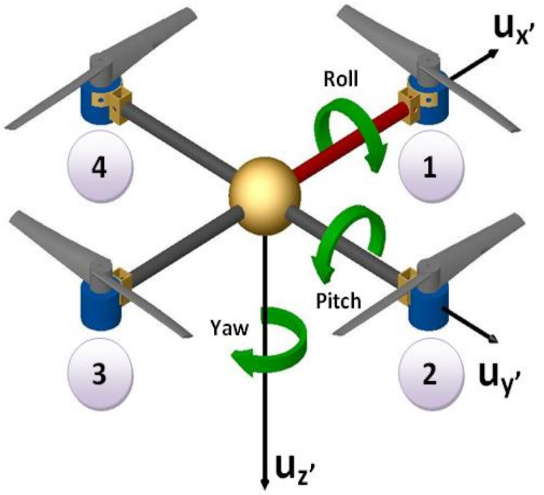

Figure 1: Free body diagram of a quadrotor helicopter.

The quadrotor is an under-actuated system with four inputs (roll, pitch, yaw and throttle). The parameters that determine the characteristics of a flying machine are the flying principle and propulsion mode [7].

The basic quadrotor has a symmetrical design. It consists of four complete rotors attached at equal distance from the central hub. All the rotors are located within the same plane and oriented to generate thrust and torque. Each rotor of the quad-rotor helicopter produces both thrust and torque. Given that the front and rear motors both rotate counter-clockwise (make clockwise torque) and the other two rotate clockwise to balance the total torque of the system. The quad-rotor is controlled by separately adjusting the speed of the four rotors. Let τ_i and υ_i be the thrust and torque for i_{th} rotor respectively, where i = 1,2,3,4. These values are normalized with the moment of inertia and the mass, respectively. Denoting the distance of the rotor from the centre of mass by l, a set of four control inputs u_i can be introduced as function of normalized individual thrusts and torques as in the following equations. The total thrust, the rolling moment, the pitching moment, and the yawing moment are given in (1), (2), (3), and (4) respectively.

$$u_1 = \tau_1 + \tau_2 + \tau_3 + \tau_4 \tag{1}$$

$$u_2 = l(\tau_3 - \tau_4) \tag{2}$$

$$u_3 = l(\tau_1 - \tau_2) \tag{3}$$

$$u_4 = \upsilon_1 + \upsilon_2 - \upsilon_3 - \upsilon_4 \tag{4}$$

The way of modelling the quadrotor differs from the one used for fixed wing vehicle in the fact that the rotational transformations are not made in the same order to go from the earth to body axes. Indeed, the most practical way is to carry out the final rotation of the earth to body transformation along the thrust direction [8]. Thus, for the body to earth transformation, the following direction cosine matrix is considered as given in (5), where:

ϕ, θ, ψ : roll, pitch, and yaw angles respectively; S=Sin, C=Cos.

$$R_{zxy} = \begin{bmatrix} s\theta s\phi s\psi + c\psi c\theta & s\phi s\theta c\psi - c\theta s\psi & s\theta c\phi \\ c\phi s\psi & c\psi c\phi & -s\phi \\ c\theta s\psi s\phi - s\theta c\psi & c\theta s\phi c\psi + s\theta s\psi & c\theta c\phi \end{bmatrix} \tag{5}$$

The development of a suitable attitude controller for the quadrotor prototype required an accurate dynamic model to be developed. A Newtonian modelling method was chosen to define the quadrotor dynamics for control purposes. The Newtonian method is the most popular choice for modelling rigid bodies in six degrees of freedom and has been used extensively for the modelling of traditional helicopters [9,10]. As a result, the Newtonian based equations used to represent a rigid body in six degrees of freedom are well defined and can be found in many texts [10-12]. The dynamics of a rigid body under external forces applied to the centre of mass and expressed in the body fixed frame are in Newton-Euler formalism given in (6) [13]:

$$\begin{aligned} m\dot{v}^b + \omega^b \times mv^b &= F^b \\ I\dot{\omega}^b + \omega^b \times I\omega^b &= \tau^b \end{aligned} \tag{6}$$

Let us consider an earth-fixed frame E and a body-fixed frame B as seen in Figure 2. Using Euler angles parameterization, the airframe orientation in space is given by a rotation R from B to E, where R∈SO3 is the rotation matrix. The frame system shown in Figure 2 is in conformity with the N, E, D (North, East, Down) standard.

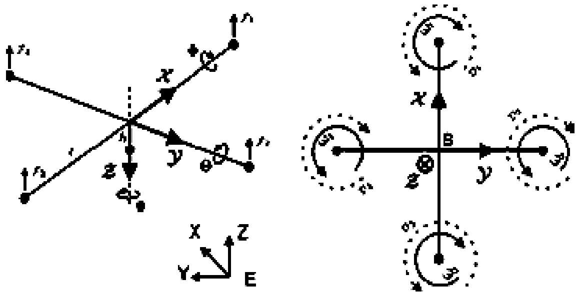

Figure 2: Quadrotor configuration, frame system with a body fixed frame B and the inertial frame E.

The equations can be summarised in (7) where:

ϕ, θ, ψ : roll, pitch, and yaw angles respectively;

I_{xx}, I_{yy}, I_{zz} : body moment of inertia;

Ω_r : rotor speed;

J_r : rotor moment of inertia.

$$\begin{cases} I_{xx}\ddot{\phi} = \dot{\theta}\dot{\psi}\left(I_{yy} - I_{zz}\right) + J_r\dot{\theta}\Omega_r + l\left(-T_2 + T_4\right) - h\sum_{i=1}^{4} H_{yi} + \left(-1\right)^{i+1}\sum_{i=1}^{4} R_{mxi} \\ I_{yy}\ddot{\theta} = \dot{\phi}\dot{\psi}\left(I_{zz} - I_{xx}\right) + J_r\dot{\phi}\Omega_r + l\left(T_1 - T_3\right) + h\sum_{i=1}^{4} H_{xi} + \left(-1\right)^{i+1}\sum_{i=1}^{4} R_{myi} \\ I_{zz}\ddot{\psi} = \dot{\phi}\dot{\theta}\left(I_{xx} - I_{yy}\right) + J_r\Omega_r + \left(-1\right)^{i}\sum_{i=1}^{4} Q_i + l\left(H_{x2} - H_{x4}\right) + l\left(-H_{y1} + H_{y3}\right) \\ m\ddot{z} = mg - \left(c\phi c\psi\right)\sum_{i=1}^{4} T_i \\ m\ddot{x} = \left(c\psi s\theta c\phi + s\psi s\phi\right)\sum_{i=1}^{4} T_i - \sum_{i=1}^{4} H_{xi} - \tfrac{1}{2}C_x A_c \rho\dot{x}\left|\dot{x}\right| \\ m\ddot{y} = \left(s\psi s\theta c\phi - c\psi s\phi\right)\sum_{i=1}^{4} T_i - \sum_{i=1}^{4} H_{yi} - \tfrac{1}{2}C_y A_c \rho\dot{y}\left|\dot{y}\right| \end{cases} \tag{7}$$

As described in [6], the actual prototype is assembled as shown in Figure 3. It consists of two sets of counter-rotating blades driven by Brushless DC motors. Arduino Mega 2560 module was chosen as the hardware controller. Arduino IDE was used to program the Arduino Mega 2560 module with the control laws. Directional cosine matrix is implemented in this environment to observe the craft attitude. Arduino IDE software was also able to configure the required inputs and outputs of the system.

Figure 3: The complete quadrotor assembly.

To reduce system wiring and sensor alignments a custom designed Arduino Mega 2560 module is fixed at the centre of the craft. Arduino Mega 2560 module contains nine degree of freedom IMU chip with tri-axial accelerometer, tri-axial gyroscopes, and tri-axial magnetometer. These sensors can be considered as the source of measurement noise to the feedback control system. DC power cables are running from a power distribution board to each one of the four speed controllers that attached to the four brushless motors. A control signal cable from Arduino Mega 2560 is assigned to each one of the speed controllers. A lithium polymer high discharge rate battery is acting as a DC power supply to the craft. Flight control directions and commands coming from handheld remote control transmitter are bypassed to the flight controller via a directly attached receiver module.

The speed controllers utilized were constructed based upon a fan controller circuit [14]. An op-amp based triangular oscillator is set to produce a wave between 0 and 5V. This wave is compared with the output of the Arduino Mega 2560 to produce a Pulse Width Modulated (PWM) signal of controllable duty cycle. This PWM signal is then used to drive the motor. The IMU system is an Ienvensense MPU 6000 chip containing a digital motion processor and uses I2C serial bus.

As discussed in [6] the major challenge of the current quadrotor prototype is the motor control system. The motor controllers are not linear across the entire range of operation and caused erroneous motor speeds. The dynamic response of the motors also has a large impact on the controllability of the system. This has been proven by dealing as in system identification to identify experimentally the relation between the input and the output of the black box system. The motor driving circuit (electronic speed controller), the motor, and the rotors are considered as a black box in this case. The input to this black box is voltage to the motor driving circuit and the output is the thrust produced out of the rotor. It was found experimentally that the relation between the input voltage to the motor driving circuit and the motor output speed measured in Revolution Per Minute (RPM) is linear with time delay involved. The relation between the motor speed and the thrust is deduced through a flight test. The procedure of flight test in this paper is typically started by taking the remote controller to a hovering condition after taking-off gradually and measure experimentally the relation between the thrust force and the motor speed in RPM. The experimental set up can be seen in Figure 4. From the experiment, the relation between the thrust and the motor speed in RPM is obtained as in Figure 5. The quadratic approximation used is shown also in the same figure. These approximations can be considered as a source of model uncertainty.

The total thrust force imparted on the body attached frame can be defined mathematically from the experimental results to be as in (8), where:

T: is the total thrust of the quadrotor,

F_i: is the force produced by rotor i,
ω_i: is the motor speed in RPM.

$$T=\sum_{i=1}^{4} F_i = b\sum_{i=1}^{4}\omega_i^2 \qquad (8)$$

Figure 4: Motor test setup for thrust calculation.

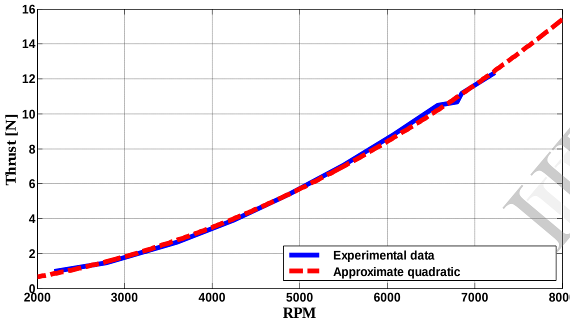

Figure 5: Experimental and approximate relations between thrust and motor speed.

4. Controller design

Controller design for quadrotor has drawn great attention in recent years. The controller has to guarantee the accuracy of the tracking path, and the robustness with respect to model uncertainties, and environmental disturbances. The controller also should mitigate the effect of measured noise on plants outputs [1-4].

Figure 6 shows the simple one degree of freedom negative feedback structure. The input to the controller $K(s)$ is $r-y_m$, where y_m is the measured output, and r is the reference value (set point) for the output. The measured output can be defined as: $y_m = y+n$, where n is the measured noise and y is the actual output. Thus the input to the plant can be described as in (9).

$$u = K(s)(r-y-n) \qquad (9)$$

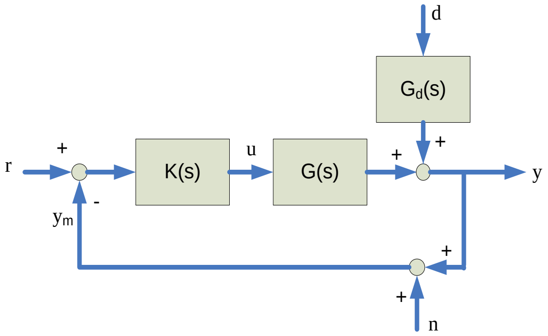

Figure 6: The simple one degree of freedom negative feedback structure

The objective of controller design is to manipulate u such that the control error e remains small in spite of disturbances d. The control error is given in (10).

$$e = y - r \qquad (10)$$

The output y can be written as in (11).

$$y = G(s)u + G_d(s)d \qquad (11)$$

Substituting from (9) in (11) the following equation can be obtained.

$$y = G(s)K(s)(r-y-n) + G_d(s)d \qquad (12)$$

Hence the closed loop response is given in (13).

$$y = (I+GK)^{-1}GKr + (I+GK)^{-1}G_d(s)d - (I+GK)^{-1}GKn \qquad (13)$$

Defining the loop transfer function L, sensitivity function S, and the complementary sensitivity function T as in (14).

$$L = GK$$
$$S = (I+GK)^{-1} = (I+L)^{-1} \qquad (14)$$
$$T = (I+GK)^{-1}GK = (I+L)^{-1}L$$

As a result equation (13) can be simplified to be as in (15).

$$y = Tr + SG_d d - Tn \qquad (15)$$

The most important design objectives of a controller, which necessitate trade-offs in feedback control, are summarized as below [1]:

- Good disturbance rejection which needs large controller gains, i.e. L large.
- Good command following: L large.
- Mitigation of measurement noise on plant output: L small.
- Robust stability of model uncertainty: L small.

Fortunately, the conflicts in design objectives are generally at different frequency ranges. Most of objectives can be met by using large loop gain at low frequencies below crossover, and small loop gain at high frequencies above crossover [1,2].

In this paper, ANFIS is developed for an unmanned quadrotor air vehicle. This controller is compared with conventional fuzzy logic controller and genetically tuned PID.

In this section; genetically tuned PID, ANFIS, and fuzzy controllers are designed for quadrotor. The three controllers are compared in the following sections. The comparison criteria considered are; following desired trajectory, robustness to model uncertainty, disturbance rejection, and noise mitigation.

4.1 Genetically tuned PID controller

A PID controller is designed for each channel of the system as described in [6]. As the four channels are coupled, the tuning of the four PID controller parameters need to be optimized. The optimization algorithm should minimize the coupling effect and the error signal between the desired and actual measured values in each channel.

Simplex algorithm is used at extreme condition of flight as a fast optimizer. PID control parameters obtained from simplex fast algorithm is used as initial acceptable parameters for genetic algorithm. Fine tuning of PID parameters is obtained using genetic algorithm. The PID parameters obtained, using genetic algorithm, are used to study the robustness of the PID controller at different operating points [6].

The implementation of the controller deviated from normal PID controller implementation due to the feedback information available.

Proportional compensation was provided for the Euler based attitude estimate with a derivative term being used to provide compensation for the angular velocities. The use of the actual angles of roll, pitch and yaw as feedback into the controller allowed for attitude set points to be used to enable the craft to be manoeuvred.

As the angular velocity of the craft is calculated using on-board gyroscopes the derivative term of the controller is available in real-time and does not have to be calculated based on previous attitude samples.

For the traditional implementation the output of the controller *y(t)* can be defined as in (16).

$$y(t) = K_P e(t) + K_I \int_0^t e(\tau) d\tau + K_D \frac{de(t)}{dt} \qquad (16)$$

where K_P is proportional gain, K_I is integral gain, K_D is derivative gain, and *e(t)* is the difference between the desired value and the actual controlled variable value. The quadrotor controller will be targeted at forcing the attitude angles to desired set points. As a result *e(t)* can be defined as in (17).

$$\begin{aligned} e_{Roll}(t) &= \text{set point- measured roll} \\ e_{Pitch}(t) &= \text{set point- measured Pitch} \\ e_{Yaw}(t) &= \text{set point- measured yaw} \end{aligned} \qquad (17)$$

The proportional component of the controller can be implemented once *e(t)* is defined. The integral and derivative components are normally need more computations. By utilizing the craft angular velocity estimate the derivative control component can be simply and efficiently calculated. The craft angular velocity can be considered to be the derivative of the attitude angle measurement and the control set point can be considered as a constant value. This can be described in (18).

$$\begin{aligned} \frac{de(t)}{dt} &= \frac{d}{dt}(\text{set point-Attitude angle}) \\ &= \frac{d}{dt}(\text{Const.}) - \text{craft angular velocity} \\ &= -\text{craft angular velocity} \end{aligned} \qquad (18)$$

The Quadrotor Prototype was able to achieve stable flight under the influence of the Arduino Mega 2560 controller. The prototype was also able to maintain desired angles of pitch and roll under different conditions. The results obtained from the flight experiments show that the designed PID controller is capable of controlling the prototype quadrotor aircraft both for level and attitude set-points [6].

4.2 Adaptive neuro-fuzzy inference system based controller

The architecture and learning procedure underlying ANFIS implemented in the framework of adaptive networks. By using a hybrid learning procedure, the proposed ANFIS can construct an input-output mapping based on both human knowledge in the form of fuzzy if-then rules, and input-output data pairs. In the simulation, the ANFIS architecture is employed to model nonlinear functions, identify nonlinear components on-line in a control system, and predict a chaotic time series, all yielding remarkable results [15].

In this paper, as the system is nonlinear ANFIS can be used as a nonlinear controller. The input–output data of the PID controlled system at different operating points are used as training and checking data sets for ANFIS. Half of these data are used as a training data and the other half as a checking data. Training the FIS is started using hybrid optimization method after generating the initial FIS structure. In the case studied, a sixty training Epochs with zero tolerance error are used in the system training. Validation of the model obtained is performed then the generated FIS is successfully used as a controller of the system in the Simulink model [6].

4.3 Fuzzy logic controller

Fuzzy Logic Controller (FLC) is designed as a controller to be compared with ANFIS and genetically tuned PID controllers. FLC is one of the artificial intelligence methods for control that has a nonlinear and rule-based nature. The FLC provides an algorithm, which converts the linguistic control based on expert knowledge into an automatic control strategy. Therefore, the fuzzy logic algorithm is much closer in spirit to human thinking than traditional logical systems [16].

In this subsection, the PD-like fuzzy controller is designed for each channel (roll, pitch, yaw, and altitude). It is required to reduce the coupling effect between the channels and to achieve the desired trajectory tracking with acceptable performance speed and quality. Seven triangular membership functions for the altitude channel inputs (the error, and rate of error), and the altitude channel output are used. Forty nine if-then rules relating the inputs and the output are established based on expert knowledge. For the remaining channels (roll, pitch, and yaw), five triangular membership functions are used for the inputs (the error, and rate of error) and the output. Twenty five if-then rules relating the inputs and the output are established based on expert knowledge.

5. Comparison between controllers based on desired trajectory tracking

In this section, the desired trajectory tracking is considered as the comparison criterion between the three controllers. Figure 7 shows the output responses for the four channels (roll, pitch, yaw, and altitude). The quadrotor initially started at 2m altitude; and at 0.3 rad for roll, pitch, and yaw angles. It is required for the controlled system to maintain the same altitude and to reach zero rad for roll, pitch, and yaw angles.

It can be seen that the output responses for roll, pitch, and yaw obtained by ANFIS and genetically tuned PID are identical. They are better than the output responses obtained by FLC. The output response obtained by ANFIS controller is the best response for the altitude channel. There is a steady state error for the FLC. There is also a small steady state error for the genetically tuned PID in addition to the overshoot obtained.

As a result the ANFIS controller is the best controller for desired trajectory tracking from performance speed and performance quality points of view.

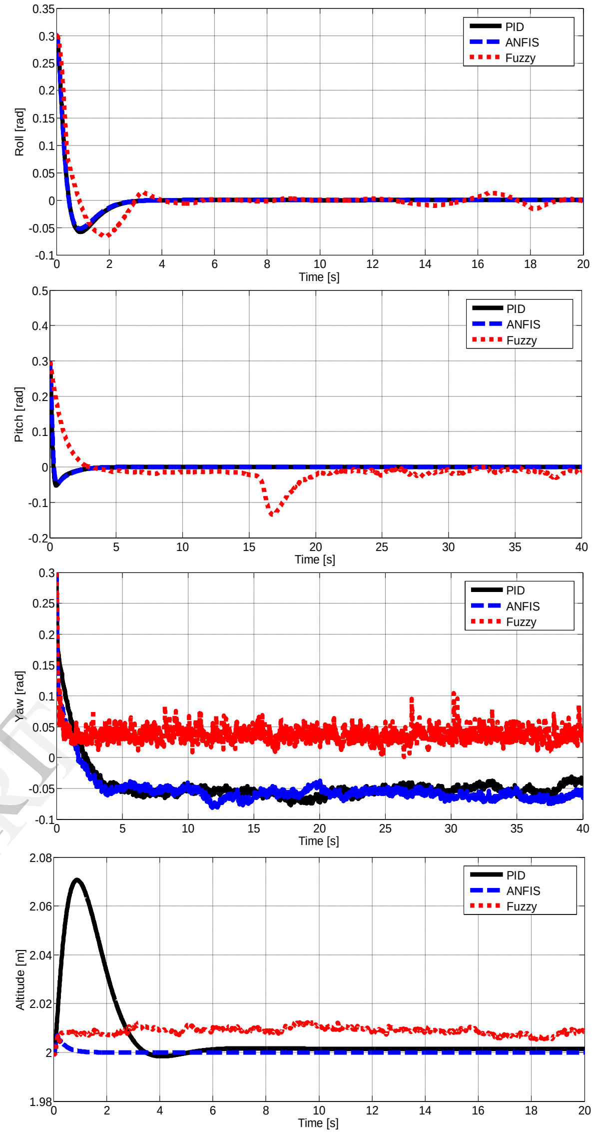

Figure 7: Output responses of the desired trajectory tracking

6. Comparison between controllers based on robustness to model uncertainty

Uncertainty in the plant model may have several origins [1]:

- There are always parameters in the linear model, which are only known approximately or incorrectly.
- The parameters in the linear model may vary due to nonlinearities or changes in the operating conditions.
- Measurement devices have imperfections.
- At high frequencies, the uncertainty will always exceed 100% at some frequencies.
- Even when a very detailed model is available, a simpler (reduced order) model may be chosen to represent the system and the neglected dynamics are considered as uncertainty.

- Finally, the controller implemented may differ from the one obtained by solving the integrated problem. In this case, uncertainty may be included to represent the effect of controller order reduction and implementation inaccuracies.

These various sources of model uncertainty may be grouped into two main classes:

- Parametric uncertainty: in which the structure of the model, including the model order, is known, but some of the parameters (such as: gain, time constant, etc.) are uncertain.
- Neglected and unmodelled dynamics uncertainty: in which the model is incorrect because of missing dynamics, usually at high frequencies, either through deliberate neglect or because of a lack of understanding of the physical process. Any model of a real system will contain this source of uncertainty.

A combination of the previous two main classes can be represented in what is called lumped uncertainty. In most cases it is preferable to lump the uncertainty into a multiplicative uncertainty as shown in Figure 8.

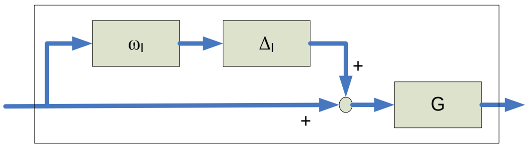

Figure 8: Plant with multiplicative uncertainty

The multiplicative uncertainty shown can be represented as in (19).

$$G_p(s) = G(s)(1+\omega_I(s)\Delta_I(s)); \left|\Delta_I(j\omega)\right| \le 1 \forall \omega \qquad (19)$$

where:

$G(s)$ is the nominal plant model (without uncertainty),

$G_p(s)$ is a particular perturbed plant model,

$\omega(s)$ is a scalar weight,

$\Delta_I(s)$ is the normalized perturbation which can be represented by any stable transfer function which at any frequency is less than or equal to one in magnitude.

In this section, a comparison between the different types of controllers designed section 4 is performed from robust stability and robust performance points of view, when the plant is subjected to model uncertainty.

The model uncertainty in this paper is concerned with the four motors of the quadrotor. Three cases can be considered according to the chosen motor/motors to be uncertain.

6.1 The first case

In this case, the model of two opposite motors such as motor 1, and motor 3 in Figure 1 are considered to be uncertain. The efficiency of these motors is considered to be less than one. Simulation results are used to examine the robust stability and performance of each controller. Figure 9 shows the output responses of the controlled system using the three types of controllers when the system is subjected to model uncertainty. The efficiency of the considered motors in this figure is 70%.

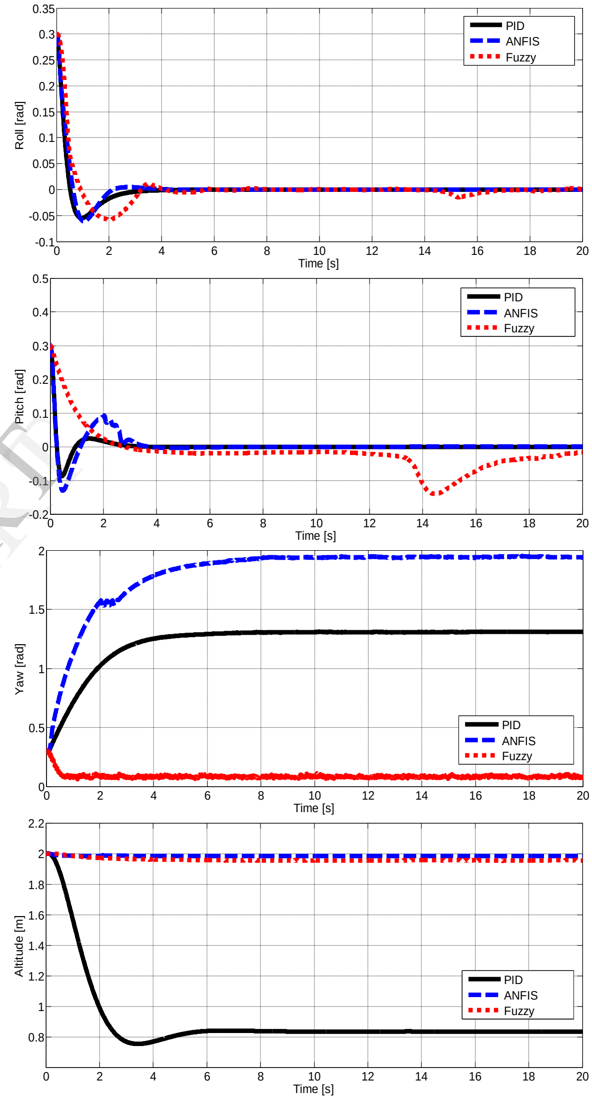

Figure 9: The output performance when the system is subjected to model uncertainty (Efficiency of motor 1, 3 is 70%)

From robust performance point of view, it can be seen from this figure that the required altitude is achieved using ANFIS and FLC. The system controlled using genetically tuned PID couldn't reach the desired altitude in this case of model uncertainty. It can be seen also that the performance of the system controlled using ANFIS controller is better than the system controlled using FLC in roll and pitch channels, whereas the system controlled using FLC is better than that controlled using ANFIS in yaw channel.

From robust stability point of view in this case, it was found that the system controlled using ANFIS or FLC is stable to model uncertainty limit of 48%. The system controlled using genetically tuned PID is stable to model uncertainty limit of only 59%.

As a result of this study, we can say that the quadrotor controlled using ANFIS or FLC is better than that controlled using genetically tuned PID.

6.2 The second case

In this case, the model of two adjacent motors such as motor 1, and motor 2 in Figure 1 are considered to be uncertain. The efficiency of these motors is considered to be less than one. Simulation results are used to examine the robust stability and performance of each controller. Figure 10 shows the output responses of the controlled system using the three types of controllers when the system is subjected to model uncertainty. The efficiency of the considered motors in this figure is 84%.

From robust performance point of view, it can be seen from this figure that the required altitude is achieved using ANFIS and FLC. The performance of the altitude channel of the system controlled using ANFIS is better than that controlled using FLC. The system controlled using genetically tuned PID couldn't reach the required altitude in this case of model uncertainty. It can be seen also that the performance of the system controlled using ANFIS controller is better than the system controlled using FLC in pitch channels.

From robust stability point of view based on the simulation results, it was found that the system controlled using ANFIS is stable to model uncertainty limit of 68% whereas the system controlled using FLC is stable to model uncertainty limit of only 84%. The system controlled using genetically tuned PID is stable to model uncertainty limit of 59% but with unacceptable performance.

Based on the simulation results obtained in this case of model uncertainty, the ANFIS controller can be considered as the best controller for the quadrotor.

6.3 The third case

In this case, the models of the four motors are considered to be uncertain. The efficiency of these motors is considered to be less than one.

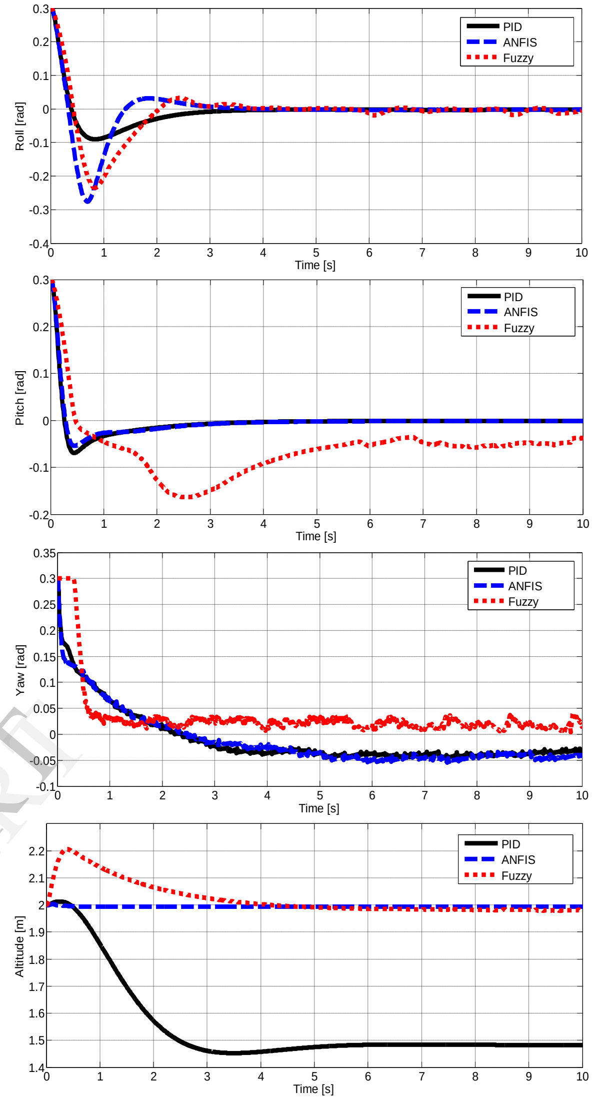

Figure 10: The output performance when the system is subjected to model uncertainty (Efficiency of motor 1, 2 is 84%)

Simulation results are used to examine the robust stability and the robust performance of each controller. Figure 11 shows the output responses of the controlled system using the three types of controllers when the system is subjected to model uncertainty. The efficiency of the considered motors in this figure is 80%.

From robust performance point of view, it can be seen from this figure that the required altitude is achieved with the same performance quality using ANFIS and FLC. The system controlled using genetically tuned PID couldn't reach the desired altitude in this case of model uncertainty. It can be seen also that the performance of the system controlled using FLC controller is better than the system controlled using ANFIS in roll, pitch, and yaw channels.

From robust stability point of view based on the simulation results, it was found that the system controlled using ANFIS is stable to model uncertainty limit of 34% and the system controlled using FLC is stable to model uncertainty limit of 30%. The system controlled using genetically tuned PID is stable to model uncertainty limit of only 75%.

Based on the simulation results obtained in this case of model uncertainty, the FLC controller can be considered as the best controller for the quadrotor. The ANFIS can be considered also as an acceptable controller for the quadrotor in this case.

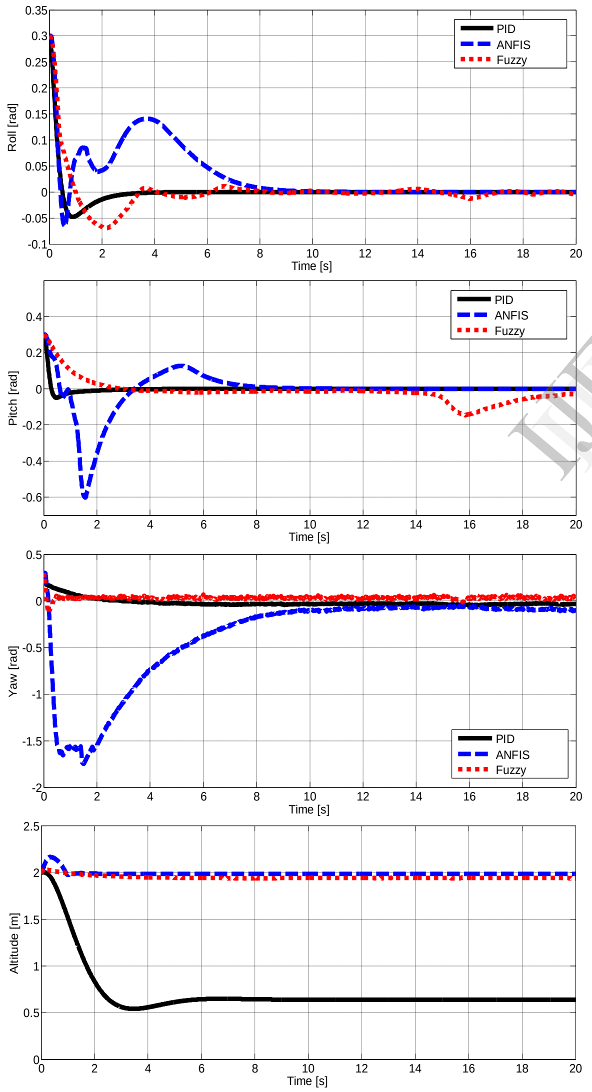

Figure 11: The output performance when the system is subjected to model uncertainty (Efficiency of all motors is 80%)

7. Comparison between controllers based on disturbance rejection

The effect of cross wind disturbance in X-Y plane is studied in this section. The quadrotor is subjected to crosswind disturbance in the X-Y plane. The X and Y components of the wind speed are identical and can be seen in Figure 12. A desired altitude of 1m and zero rad for roll, pitch, and yaw angles are to be maintained in presence of wind disturbance. Figure 13 shows the output responses of the fuzzy controlled system. It can be seen from the altitude curve that the quadrotor fall down causing crash. This means that the disturbance rejection couldn’t be achieved using FLC for this wind speed.

The ANFIS and the genetically tuned PID are compared when the system is subjected to cross wind disturbance of higher amplitude. The X and Y components of the wind speed are identical and can be seen in Figure 14. The output responses of the controlled system when subjected to this cross wind disturbance are shown in Figure 15. It can be seen that the altitude response of the system controlled by ANFIS is better than that of the system controlled by genetically tuned PID.

It is clear from this section that the ANFIS controlled system is the best when dealing with external wind disturbance.

8. Comparison between controllers based on measurement noise effect attenuation

The output sensors such as gyroscopes and altitude sensor are the sources of measurement noise. They are used for the feedback control to be compared with the desired inputs. A drawback with feedback is that the controller feeds measurement noise into the system. It is important that the control actions generated by measurement noise are not too large. Since measurement noise typically has high frequencies, the controller should achieve small loop transfer function for high frequencies. This property is called high frequency roll off [2].

For the case studied, the three gyroscopes and the altitude sensor are considered as the source of measurement noise. In simulation, these noise are considered to be white noise.

Figure 16 shows the output responses of the controlled system when the measurement noise is considered. For roll and pitch angles, the output responses of the three controllers are similar. For the output responses of yaw angle and altitude, it is clear that the FLC and the genetically tuned PID are better than the ANFIS.

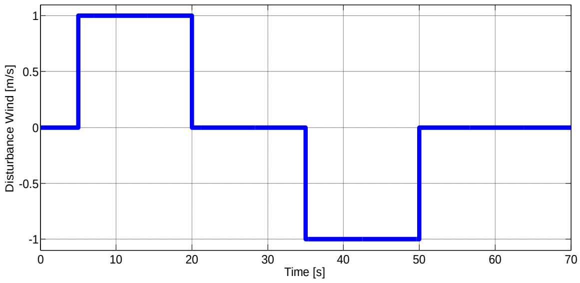

Figure 12: The X and Y components of the wind disturbance

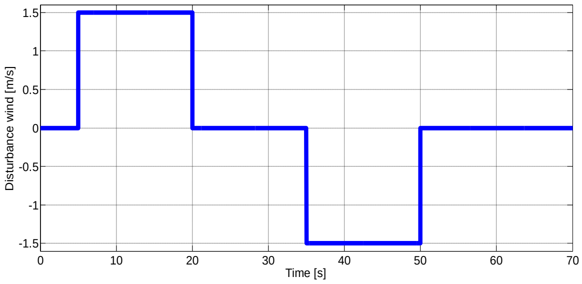

Figure 14: The X and Y components of the wind disturbance

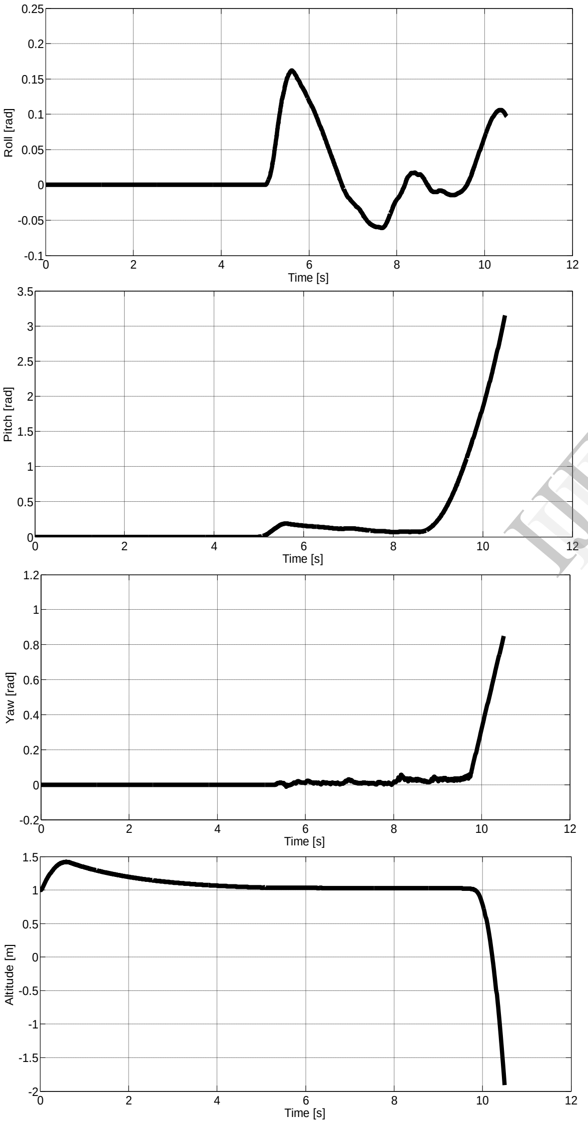

Figure 13: The output responses of the fuzzy controlled system when the system is subjected to external wind disturbance

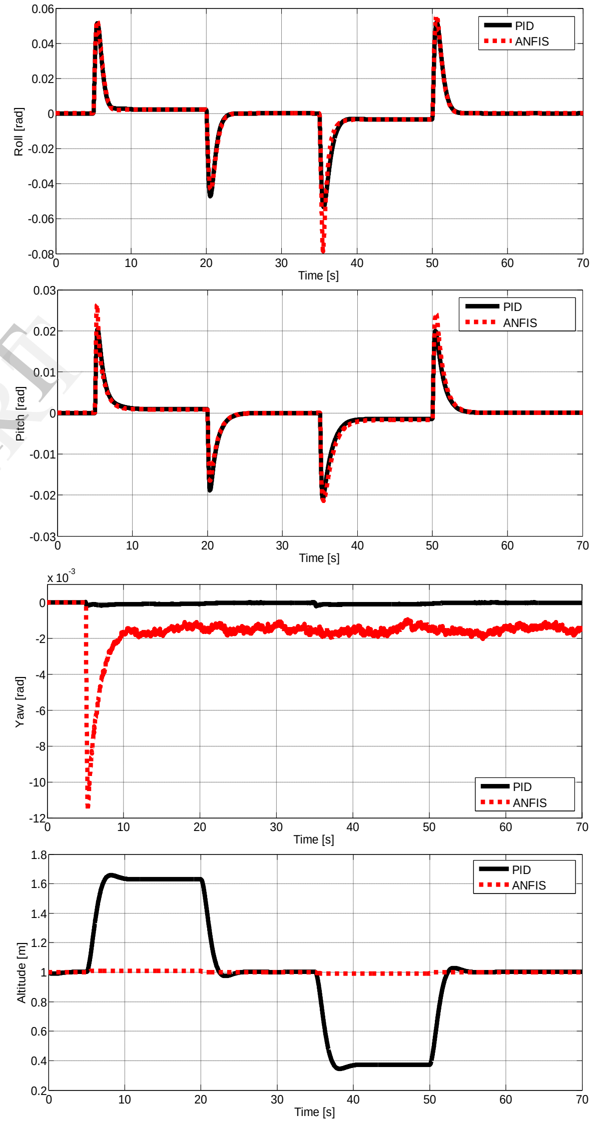

Figure 15: The output responses of the ANFIS and genetically tuned PID controlled system when the system is subjected to external wind disturbance

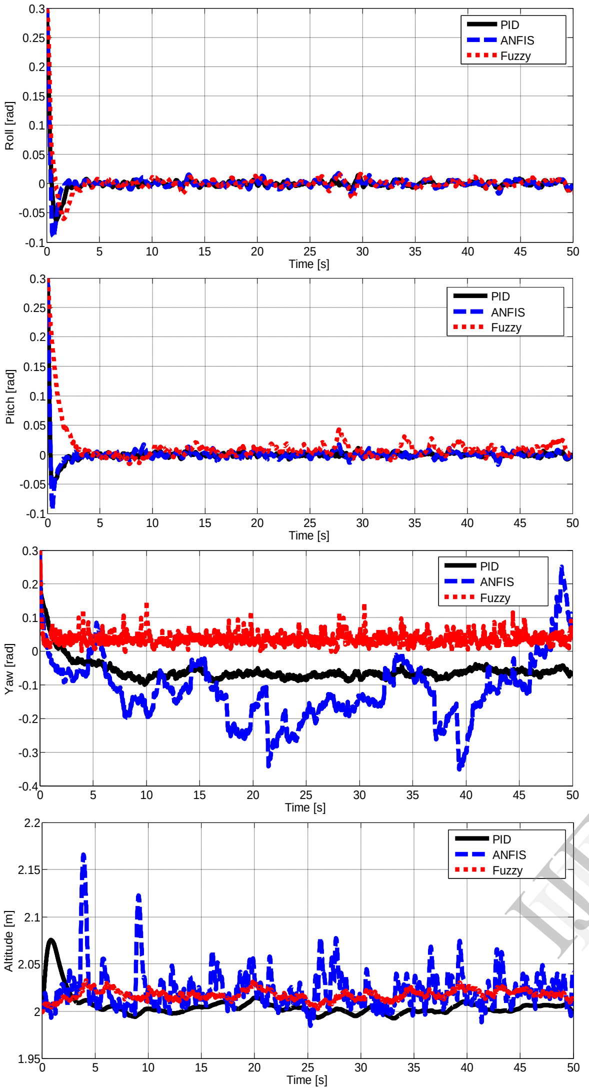

Figure 16: The output responses of the controlled system when the measurement noise is considered.

9. Conclusions

Three types of controllers have been designed for an unmanned quadrotor aerial vehicle. The designed controllers are ANFIS, genetically tuned PID, and conventional FLC. These controllers are compared based on accuracy of tracking path, and robustness with respect to model uncertainty and environmental disturbances. The controllers also compared with respect to measurement noise on the quadrotor output sensors. The comparison is achieved using simulation results obtained from controlled quadrotor model.

From accuracy of tracking path point of view, it was found that the output responses of the quadrotor controlled using ANFIS controller have the best performance speed and quality over the system controlled using the other two controllers.

From robust stability and robust performance points of view when the system is subjected to model uncertainty, it was found that the best controller performance is the ANFIS followed by the FLC. The worst performance was the genetically tuned PID.

From robustness to environmental disturbances point of view, it was found that the best controller was the ANFIS controller. The performance of the genetically tuned PID was unacceptable. The worst controller in this case is the FLC which considered robustly unstable in this case.

With respect to the measurement noise on the quadrotor output sensors, the best performance achieved using FLC followed by genetically tuned PID. The worst performance in this case is the ANFIS but it is still acceptable.

Considering the superiorities and the drawbacks of each controller in this case studied, ANFIS can be chosen as the best controller for the quadrotor.

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