

A Genetic Algorithm-Based Neuro-Fuzzy Controller for Unmanned Aerial Vehicle Control

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ABSTRACT

In this paper, a self-tuning adaptive neuro-fuzzy inference system (ANFIS) controller by genetic algorithm (GA) applied to trajectory tracking task of unmanned aerial vehicle (UAV) is studied. The quadrotor was chosen due to its simple mechanical structure; nevertheless, these types of aircraft are highly nonlinear. A model of a nonlinear closed-loop dynamic model of three degrees of freedom (3-DOF) quadrotor is developed and implemented. Intelligent control such as fuzzy logic is a suitable choice for controlling nonlinear systems. The ANFIS controller is used to reproduce the desired trajectory of the quadrotor in 2-D vertical plane, and the GA algorithm aims to facilitate convergence to the ANFIS's optimal parameters in order to reduce learning errors and improve the quality of the controller. The performance of the ANFIS-GA controller is compared with a ANFIS and a conventional PID controller. Simulation results confirm the advantages of the proposed controller and approve better performance.

KEYWORDS

Adaptive Neuro-Fuzzy Inference System, Genetic Algorithm, Intelligent Control, Optimization, Unmanned Aerial Vehicle

1. INTRODUCTION

Unmanned Vehicles (UAVs) are the most suitable platforms for surveillance, rescue and search in confined environments due to their high flexibility and superior mobility. In such missions, it is essential that agents be able to explore and navigate autonomously in various environments. UAVs are capable of performing a mission more or less autonomously (Mostafa et al, 2017). Autonomous navigation in complex environments gives rise to engineering challenges. These problems require an integrated approach for perception, estimation, planning, control and high-level situational awareness.

Research on UAVs has deserved increasing interest in recent years, due to the variety of tasks these robots can perform. UAVs will continue to be applied in various areas such as traffic monitoring (Wang et al, 2015), logistics (Murray & Chu, 2015), road construction and urban development (Siebert & Teizer, 2014), integration to smart cities and cooperative networks (Mohammed et al, 2014), Safety and security (European Aviation Safety Agency, 2016), agriculture (Puri et al, 2017), search and rescue in disasters management (Erdelj et al, 2017), and many other applications. Its use is increasing in most areas due to their ease of deployment, high mobility and hovering ability.

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Soft computing techniques are known as the essential tools capable for developing intelligent machines and solving nonlinear and mathematically system problems. Their applications include the design of intelligent autonomous systems/controllers and handling of complex systems with unknown parameters such as prediction of world economy, industrial process control and prediction of geological changes within the earth ecosystems. These paradigms have shown an ability to process information, adapt to changing environmental conditions, and learn from the environment.

The major soft computing techniques are following.

- (a) Neural networks (NNs) modeling has a history dating back to the 1950s, but only received an increasing amount of attention in the 1980s, with the emergence of the back-propagation algorithm (Rumelhart & McClelland, 1986), and have gained widespread recognition and approval. Their ability to learn and approximate functions has been the subject of considerable researchers' interest and scientific inquiry. One only has to look at the many related industrial applications from the 1990s onwards and consult the abundant scientific literature on the subject to be convinced of this.
- (b) Fuzzy logic (FL) introduced by Zadeh (Zadeh, 1965) in the 1960s, is a powerful tool that permits the treatment of vague, imprecise, uncertain and ill-defined knowledge and concept. Its use in the field of control (fuzzy control) was one of the first applications of this theory in industry with the work of Mamdani and Assilian (Mamdani & Assilian, 1975). Since then, the applications of FL have increased greatly to reach very diverse fields.

The use of fuzzy control (Milanés et al, 2012; Mon & Lin, 2012; David et al, 2013; Pinto et al, 2013; Ibrahim et al, 2014) is particularly interesting when there is no precise or even non-existent mathematical model of the system to be controlled or when the latter has strong non-linearity. Unlike traditional approaches to automation, which are largely based on a mathematical model, fuzzy logic control is based on a collection of linguistic rules in the form "If ... Then" that reflect a human operator's control strategy.

- (c) Genetic algorithms are stochastic methods based on an analogy with biological systems. They are based on the coding of variables organized as chromosomal structures and are based on the principles of Darwin's natural evolution to determine an optimal solution to the problem under consideration. They were introduced by Holland (Holland, 1992) for complex optimization problems. Unlike traditional optimization methods, these algorithms are characterized by high robustness and have the ability to avoid local minima to perform a global search. Moreover, these algorithms do not obey the differentiability assumptions that constrain many traditional methods designed to address real problems.

Several hybridizations have been proposed of these techniques, of which the most encountered are: Genetic Algorithm with Fuzzy Controller (GA-FC) (Cheong & Lai, 2000; Larbes et al, 2009; Martinez-Soto et al, 2010; Zhou et al, 2013; Torkzadeh et al, 2014; Chen et al, 2016; Syed & Ram, 2016) and Neural Network with Fuzzy Controller (NN-FC) (Hui, et al, 2006; Selma & Chouraqui, 2013; Barman et al, 2016; Asif et al, 2016; de Souza et al, 2019).

The objective of this paper is the optimization of the parameters of the membership functions (MFs) by GA to improve the performance of the neuro-fuzzy system. Therefore, for best results, there should be an encoding that simultaneously supports input and output membership functions parameters. Because of one part of a very large search space and on the other hand the use of a chromosome initialization procedure often based on a random process, the proposed methods require usually a significant number of generations. It is within this framework that our motivations and interests lie in the design of fuzzy controllers by genetic algorithms.

Neural Networks (NNs) are augmented with FL-based schemes in order to enhance artificial intelligence of automatic control systems. Such combinations exhibit reasoning ability, adaptation and learning, the combination of these techniques will produce a robust nonlinear controller known as a Genetic-Neuro-fuzzy Inference System (ANFIS-GA).

The tracking performance using tuned fuzzy neural network parameters with GA (ANFIS-GA) of a quadrotor unmanned vehicle is investigated in this study.

The computer simulation results depict that the proposed optimized fuzzy ANFIS-GA controller performance outperforms the PID and ANFIS controllers. Several reference signals were tested to evaluate the tracking performance where the outcomes demonstrate that the proposed ANFIS-GA controller was able to minimize the error and bring the quadrotor to the desired trajectory and reached to a steady state in short time period. In addition, RMSE error was reduced significantly using the proposed controller.

Through this study which was based on the development and the application of artificial intelligence techniques in nonlinear systems control, it is showed that:

- Neuro-fuzzy networks like ANFIS present a powerful tool in the control of non-linear systems.
- The GA is dedicated to the optimization of the ANFIS parameters and represents a precise intelligent solution.
- The correct choice of the parameters of the ANFIS algorithm, GA is subject to the robustness of the laws based on last.

2. RELATED WORKS

Various design methods have been widely described in the literature, that allow to specify the different parameters of a fuzzy controller. They are mainly based on a learning process, which iteratively defines the best set of parameters for a given fuzzy controller structure. Currently, researchers have focused in particular on the following approaches: (a) Optimization of MFs, (b) Optimization of fuzzy rules, (c) Simultaneous optimization of MFs and fuzzy rules.

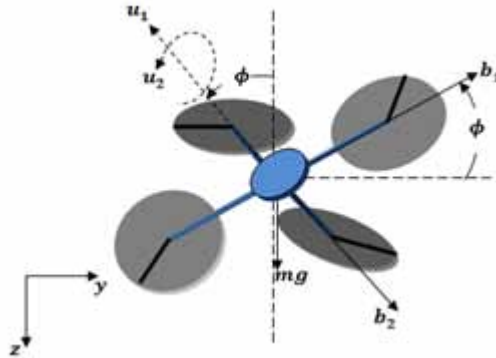
Several researches have been carried out on the optimization of the fuzzy controller MFs using Genetic Algorithms (GAs) (Thrift, 1991; Karr & Gentry, 1993; Michael & Takagi, 1993; Liska & Melsheimer, 1994; Herrera et al, 1995; Shimojima et al, 1995; Homaifar & McCormick, 1995; Chen & Wong, 2002; Belarbi et al, 2005; Refoufi & Benmahammed, 2018). Thrift is the first to introduce a method of optimization of fuzzy rules by GA, he used three bits to encode each rule (Michael & Takagi, 1993). In 1993, Lee and Takagi proposed a method for simultaneous optimization of MFs and fuzzy rules (Homaifar & McCormick, 1995). Several methods on the same concept were used in these works (Chen & Wong, 2002; Belarbi et al, 2005; Refoufi & Benmahammed, 2018). Other optimization techniques of tuning fuzzy systems using swarm intelligence (Juang & Chang, 2010; Talbi & Belarbi, 2011; Talbi & Belarbi, 2013; Castillo et al, 2015; Premkumar & Manikandan, 2015; Caraveo et al, 2016; Lagunes et al, 2018; Selma et al, 2020; Selma et al, 2021).

This paper is organized as follows. The description of the UAV model and the problem formulation are given in section 2. The purpose of section 3 is to present ANFIS system with its architecture and learning algorithm, the GA that will later be used for the optimization of ANFIS parameters, and details the proposed control design and strategy. In section 4, comparisons and numerical simulations results are given in order to demonstrate the optimal effectiveness of the proposed controller. Section 5 gives the conclusions.

3. MODELING OF A QUADROTOR AND PROBLEM FORMULATION

The 3-DOF quadrotor considered in this work can be described as rigid body using a simplified dynamic model via affine parameterization for a multivariable nonlinear UAV modeled to fly in two-dimensional (2D) space and is modeled analytically, based on dynamic and kinematic equations based in Newton-Euler method.

Figure 1. Quadrotor configuration scheme



3.1. Dynamical Model

It is primordial to introduce the reference coordinates to describe the full structure, before describing the mathematical model of the quadrotor. The motion of a rigid body is described by the motion of a body-fixed frame $FB = (OB, \{b_1, b_2\})$ with respect to an inertial reference frame $FI = (OI, \{y, z\})$, as shown in Figure 1. The origin located in the center of the UAV. The Euler angle defined as the roll angle ϕ about the horizontal axis represent the orientation of the UAV.

The quadrotor is modeled to fly in 2 dimensions $y - z$ plane with an angle ϕ as shown in Figure 1, therefore the state of the quadrotor is $[y, z, \phi]^T$. The two inputs u_1 and u_2 are the thrust and the moment about the x-axis respectively.

The equations describing the movement are written by the following system;

$$\ddot{y} = \frac{u_1}{m} \sin(\phi) \quad (1)$$

$$\ddot{z} = g - \frac{u_1}{m} \cos(\phi) \quad (2)$$

$$\ddot{\phi} = \frac{u_2}{I_{xx}} \quad (3)$$

Where m , g and I_{xx} are the mass, the intensity of gravity and the moment of inertia of the drone, respectively.

The equations of motion have been rewriting as follows;

$$\begin{bmatrix} \ddot{y} \\ \ddot{z} \\ \ddot{\varphi} \end{bmatrix} = \begin{bmatrix} 0 \\ g \\ 0 \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \sin\phi & 0 \\ -\frac{1}{m} \cos\phi & 0 \\ 0 & \frac{1}{I_{zz}} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (4)$$

The state space description of the quadrotor;

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} y \\ z \\ \varphi \\ \dot{y} \\ \dot{z} \\ \dot{\varphi} \end{bmatrix} \quad (5)$$

So, the first derivative of the state vector is expressed in equation (6). The first three parameters of the x vector represent velocities and the last three parameters represent accelerations.

$$\dot{x} = \begin{bmatrix} \dot{y} \\ \dot{z} \\ \dot{\varphi} \\ 0 \\ g \\ 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ \frac{1}{m} \sin\phi & 0 \\ -\frac{1}{m} \cos\phi & 0 \\ 0 & \frac{1}{I_{zz}} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \end{bmatrix} \quad (6)$$

The vector $[u_1, u_2]$ is the input signals that can drive the dynamical system, by specifying the properties of u_1 and u_2 ; it can change the state of the quadrotor.

4. CONTROLLER DESIGN

4.1. Structure of the Neuro-Fuzzy Controller

The neural network and fuzzy system are combined in a homogeneous architecture. It can be interpreted as a special NN with fuzzy parameters or as a fuzzy system implemented in a distributed and parallel form. Several architectures implementing this hybrid approach are described in the literature (Jang,

1993). Adaptive Neural Fuzzy Inference System (ANFIS) is one of the widely used neuro-fuzzy architecture.

ANFIS is composed of a set of interconnected neurons by direct connections. Each neuron models a parameterized function. The ANFIS structure contains five layers; two inputs x and y and one output f .

Figure 2. ANFIS Architecture

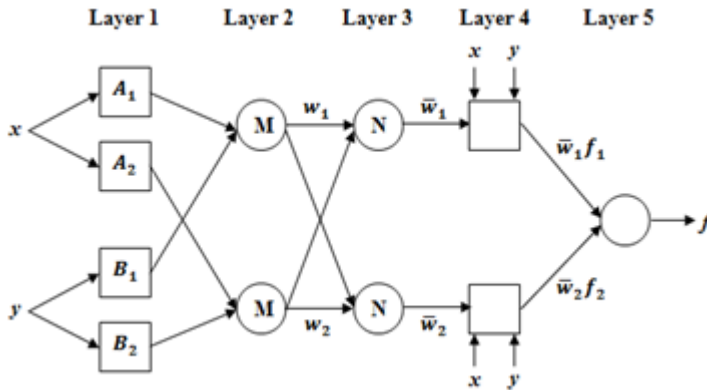
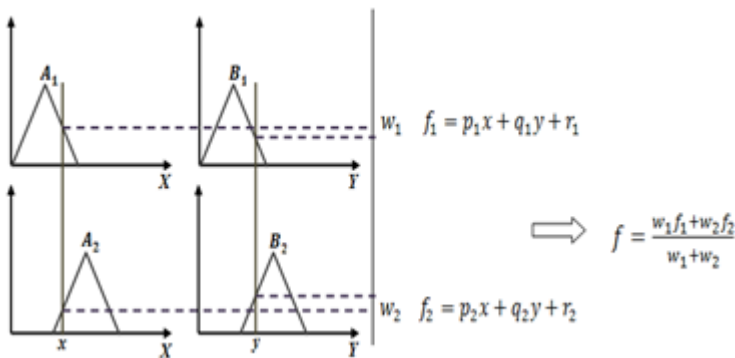


Figure 2 shows the architecture of an ANFIS based on Takagi and Sugeno’s first-order reasoning model, two inputs, one output and a rule base consisting of two fuzzy if/then rules which are expressed by:

$$\text{Rule}_1 : \text{if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1$$

$$\text{Rule}_2 : \text{if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2$$

Figure 3. The equivalent typical ANFIS architecture



Layer 1 (fuzzification): This layer contains adaptive nodes. The outputs are the fuzzy membership grade of the inputs, which are given by:

$$f_i^1 = \mu_{A_i}(x) \quad (7)$$

$$O_i^1 = \mu_{A_i}(x) \quad i = 1, 2 \quad (8)$$

$$O_j^1 = \mu_{B_j}(y) \quad j = 1, 2 \quad (9)$$

Fuzzifying the inputs is conducted by MF such as Piecewise linear, triangular, trapezoidal, gaussian and singleton. Among the abovementioned MFs, this paper has used the gaussian function because of its smooth and concise notation. Therefore, as $\mu_{A_i}(x)$, given that

$$\text{Triangular: } \mu_{A_i}(x) = \max \left(\min \left(\frac{x - a_i}{b_i - a_i}, \frac{c_i - x}{c_i - b_i} \right), 0 \right), \quad i = 1, 2 \quad (10)$$

$$\text{Trapezoidal: } \mu_{A_i}(x) = \max \left(\min \left(\frac{x - a_i}{b_i - a_i}, 1, \frac{d_i - x}{d_i - c_i} \right), 0 \right), \quad i = 1, 2 \quad (11)$$

$$\text{Gaussian: } \mu_{A_i}(x) = \exp \left(- \frac{(x - c_i)^2}{\sigma_i^2} \right) \quad (12)$$

Where a_i , b_i , c_i and σ_i are the premise parameters.

Layer 2 (Weighting of fuzzy rules): The symbol M shows every fixed node in this layer. This layer calculates the firing strength w_i by using membership values computed in fuzzification layer, and the outputs are computed as the following:

$$O_i^2 = w_i = \mu_{A_i}(x) * \mu_{B_j}(y), \quad i, j = 1, 2 \quad (13)$$

Layer 3 (normalization): Every node is fixed node and called by N. Each node obtains the normalization by calculating the ratio of the k^{th} rule's firing strength (truth values) to the sum of all rules firing strength. The output O_i^3 at this step is given by:

$$O_i^3 = \overline{w_i} = \frac{w_i}{\sum w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \quad (14)$$

Layer 4 (defuzzification): Weighted consequent values of rules are calculated in each node of this layer as given in (15).

$$O_i^4 = \overline{w_i} f_i = \overline{w_i} (p_i x + q_i y + r_i), \quad i = 1, 2 \quad (15)$$

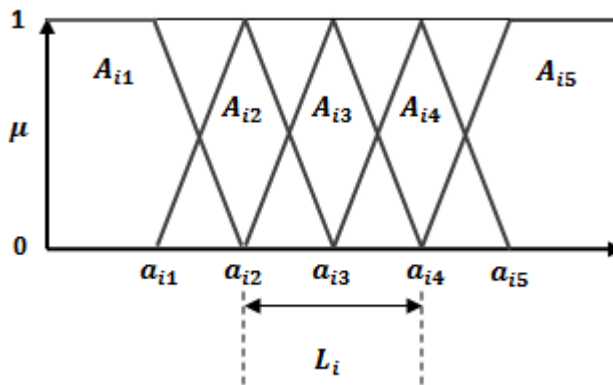
Where w_k represents the output of the third layer, and $\{p_i, q_i, r_i\}$ are consequent parameters.

Layer 5 (summation): The actual output is obtained by summing the outputs of all incoming signals that coming from the defuzzification layer to produce the overall ANFIS output as shown in Figure 3.

$$O_i^5 = \sum_{k=1}^2 \overline{w_i} f_i = \frac{\sum_{i=1}^2 w_i * f_i}{w_1 + w_2} \quad (16)$$

In order to ensure completeness and distinguishability of the fuzzy partitions, symmetrical triangular membership functions are considered (Figure 4).

Figure 4. Symmetrical triangular partition of the discourse universe (with 5 fuzzy subsets)



In a neuro-fuzzy system, each linguistic variable is defined by a set of membership functions of the language terms, and fuzzy rules are applied to linguistic terms. These terms, which qualify a linguistic variable, are defined through membership functions. As shown in Figure 4.

The membership function is defined by parameters like the triangular one as shown in Figure 4, it is defined by five parameters a_{i1} , a_{i2} , a_{i3} , a_{i4} and a_{i5} which take their values in the interval $[a, b]$. The Figure 4, illustrates an example of fuzzy partitioning with 5 triangular membership functions A_{i1} , A_{i2} , A_{i3} , A_{i4} and A_{i5} .

4.2. Genetic Algorithm

The GAs developed by John Holland (Holland, 1992), are meta-heuristic computational methods, which are part of evolutionary algorithms family. GAs are robust stochastic search methods based on the mechanism of the natural genetic variation and natural selection. Unlike conventional search methods, they do not evaluate and improve a single solution but start with an initial set of random solutions called population satisfying system constraints and/or boundary value problem. In the population each individual is called a chromosome, which represents a solution to a given problem. Chromosome is a string of a binary bit but other encodings are also possible as string of symbols. The chromosome evolves over successive iterations called generations. To evaluate a chromosome during each generation, a function is used called fitness function. The next generation of the population is generated from the most successful individuals in the current generation. The offspring are chromosomes, created by the three standard genetic operators of crossover and mutation applied to the individuals (parents). A new generation of the same size is formed by selecting some parents and some offspring, based on the fitness values. Chromosomes with high fitness scores have more chances of being selected for reproduction. After termination condition has been reached, the algorithm converges to the best individual, which represents the optimal or near-optimal solution.

4.2.1. General Structure Of GA

In general, a GA for a particular problem has five basic components, as summarized by Michalewicz (Michalewicz, 1994):

- Genetic representation of solutions (chromosomes) to the problem.
- Create an initial set of potential solutions (population).
- Evaluation function assessing solutions according to their fitness.
- Genetic operators (crossover, mutation, selection) to alter the genetic composition of offspring (children).
- Parameters values (population size, probability of mutation and probability of crossover, etc.).

Figure 5 describes the general structure of GA. In current generation t , $P(t)$ and $C(t)$ represent parents and offspring, respectively.

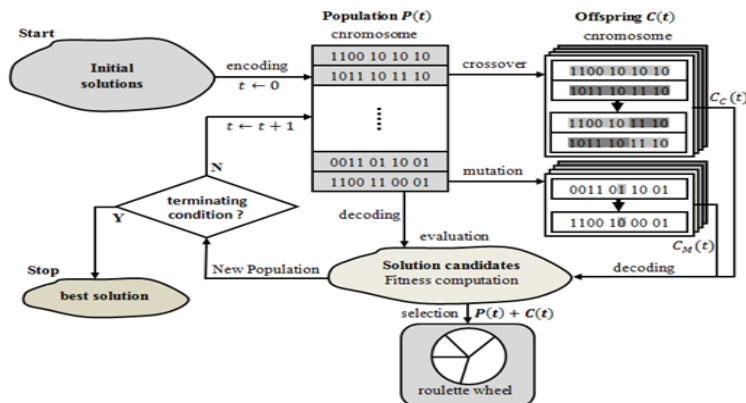


Figure 5. The general structure of genetic algorithms

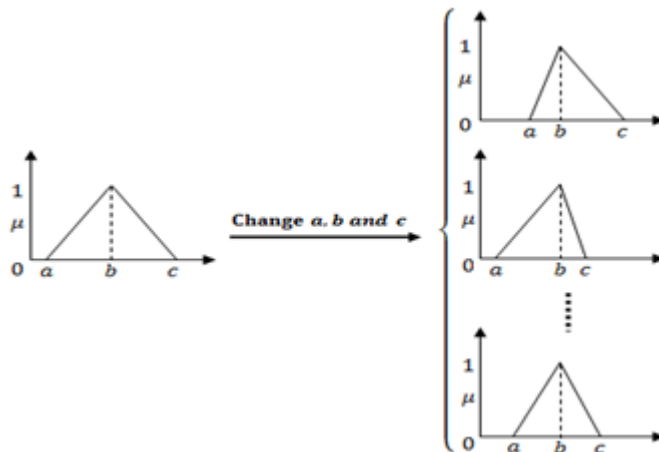
4.3. ANFIS-GA Controller

The essential point of designing a neuro-fuzzy controller lies in the selection of high-performance MFs that represent human expert interpretation of linguistic variables, because well-parametered (well-distributed) membership function determines the extent to which the rules affect the action and hence the performance.

The application of GAs to neuro-fuzzy controllers holds a great deal of promise. GA's robustness allows it to cover a complex search space to be explored and providing an optimal or near-optimal solution in a relatively short period of time. Due to the capability GA's are a natural match for neuro-fuzzy controllers.

The GA is used to determine all the parameters of the membership functions of the ANFIS controller. GA can impact the selection of the optimal parameters of MF practicality during training process. A MF adjust parameters is shown in Figure 6.

Figure 6. Possibilities of parametric changes of a MF after optimization



4.3.1. GA Representation of Solutions

The neuro-fuzzy control is composed by many input and output membership functions. So for this problem it is necessary to use the chromosome concept.

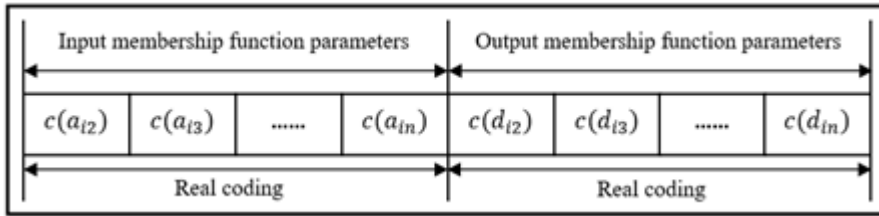
The solution for a problem is associated with a population of chromosomes composed $p = \{p_1, p_2, p_3, \dots, p_n\}$, where each component p_i represents a chromosome. Each chromosome represents one possible solution.

However, each chromosome is composed by the membership functions parameters for the antecedents and consequents.

The size of the population, i.e., the number of chromosomes will have, this will depend on the number of membership functions defined by user.

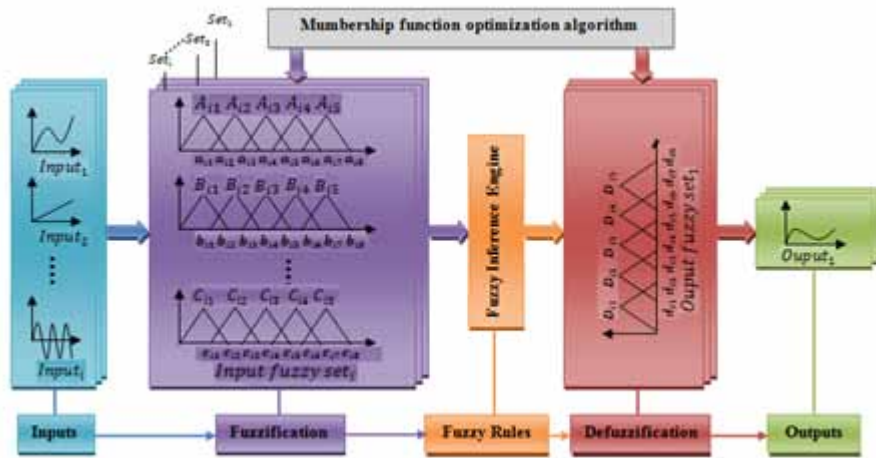
The chromosome thus obtained is divided into two parts coded in real numbers, representing the input and output parameters of the membership functions respectively. This structure is represented by Figure 7.

Figure 7. Framework of the ANFIS controller



This controller design is adapted to the tuning of membership functions. Using GA to optimize both input and output fuzzy membership functions automatically as shown in Figure 8.

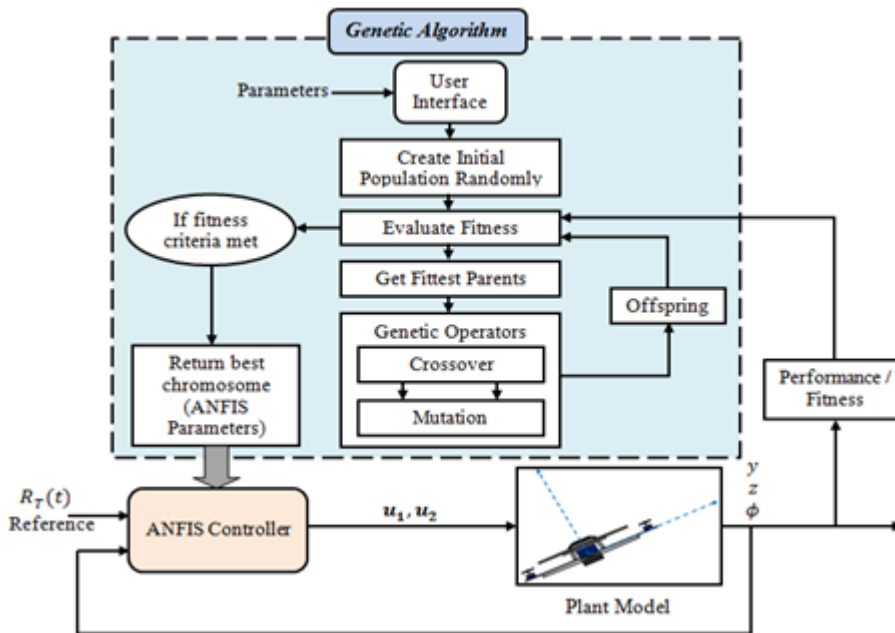
Figure 8. Framework of the ANFIS controller



4.3.2. Controller Design

The proposed system introduces the uses of the GA for optimizing the parameters of the neuro-fuzzy controller as shown in Figure 8. So, the proposed system can improve the performance of the UAV. It has applied for trajectory tracking task of an UAV. Its results are compared with other traditional controller systems as described in section 4.

Figure 9. ANFIS-GA controller design



In order to improve the performance of the ANFIS controller and to achieve the desired level of robustness, the exact tuning of the MFs is very important. This work intends to apply GA in order to dynamically adjust the MFs of our model and design optimal neuro-fuzzy controllers. The approach of using a GA for control MFs tuning in ANFIS is shown in Figure 9. The proposed real time GA algorithm is expressed by the sequential steps that are executed at each time step which are cited in above section.

To validate the suggested Neuro-Fuzzy controller trained by GA, we carried out simulations for the adaptive control of a 3-DOF UAV robot moving along a specified trajectory, whose model parameters are estimated by three ANFIS networks. The adjustment of the network parameters is performed by a GA to obtain the optimal objective value. The UAV is commanded to follow a reference trajectory defined as a function of time described by $y(t)$ and $z(t)$.

The objective function is to minimize the error $e(t)$ between the output of the system and the desired output. This objective can be defined by several numerical indices. In our remarks, we have opted for the minimization of the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

4.3.3. GA Implementation Procedure

According to the UAV modeling in Section 2, and to the feedback control system, initialize the plant, i.e., trajectory information including the coordinates of the two dimensions $y - z$ plane and the roll angle ϕ .

Being N the GA iteration, P the population, $[a, b]$ the input space is referred as the universe of discourse of each fuzzy set. The algorithm shown below generates as a start the vector global best solution with N positions to store the best chromosome result.

The detailed implementation procedure of GA can be described as follows.

- Step 1: initialize parameters of GA, such as solution space dimension D , population size N , probability of mutation and probability of crossover, and the number of iteration T .
- Step 2: generate initial population P randomly with chromosomes in the interval $[a, b]$.
- Step 3: compare the fitness of each chromosome, and find the current best solution.
- Step 4: operate genetic operators; crossover, mutation and selection to alter the genetic composition of offspring (children). Then we compare the fitness values of all chromosomes and find the new best solution.
- Step 5: if complete in iteration number T , stop, and output the results. If not, go to Step 4.

5. SIMULATION RESULTS

The main objective of this Section is to test the robustness of the proposed controller for handling the model uncertainties. The proposed system is an intelligent controller. It uses GA to optimize the parameters of the ANFIS controller. It has been applied for UAV that can fly in 2 dimensions (yz) plane. Table (1) shows parameters of the UAV used in the simulations. The simulation was done with MATLAB (R2018b). The simulation results are obtained with a vertical trajectory in 2D space. The desired trajectory input is defined as:

$$y_d(t) = 2\sin(t) \quad (17)$$

$$z_d(t) = 5\sin(t) \quad (18)$$

Table 1. Parameters of quadrotor.

| Symbol | Value |
|----------|------------------------|
| m | 0.2kg |
| I_{xx} | 0.1kg.m ² |
| g | 9.81m / s ² |

After initializing the architectures, the type of MFs and fuzzy rules of the ANFIS networks and the parameters of the GA algorithm. In this approach the estimated UAV parameters by GA are injected into the calculated trajectory command using the ANFIS system. (Figure 8) shows the structure of the adaptive control used in our application.

In this study, all membership functions have been chosen to be Gaussian-shaped. During the learning of ANFIS, the experimental data sets were used to perform 100 training cycles.

A comparison of the ANFIS system optimized by GA was carried out with a PID and ANFIS. As can be seen from the results given bellow, the ANFIS-GA produces better results than both of the PID and ANFIS controllers and provides more robust control performance and ensures good disturbance rejection.

Figure 10. Measured $z(t)$ trajectory with PID controller

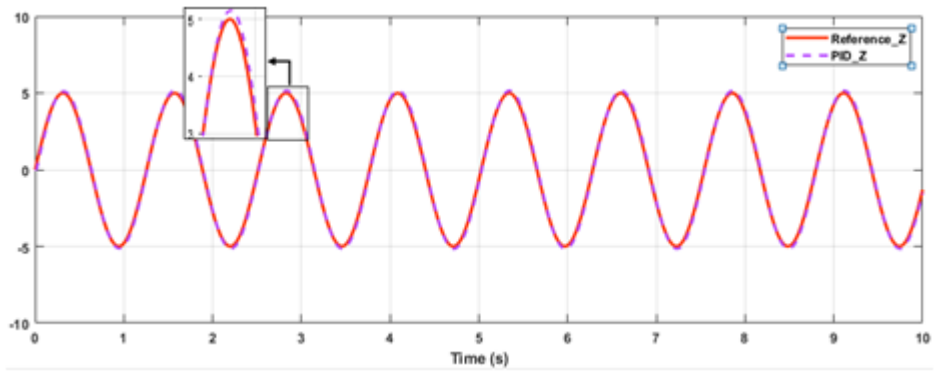


Figure 11. Measured $y(t)$ trajectory with PID controller

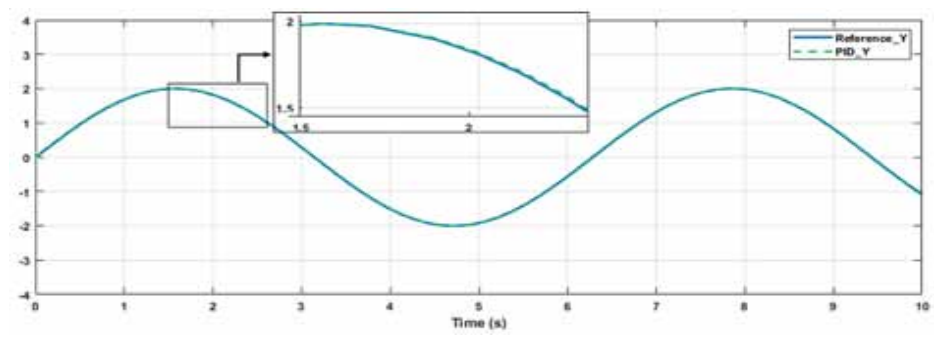


Figure 12. Measured $\phi(t)$ trajectory with PID controller

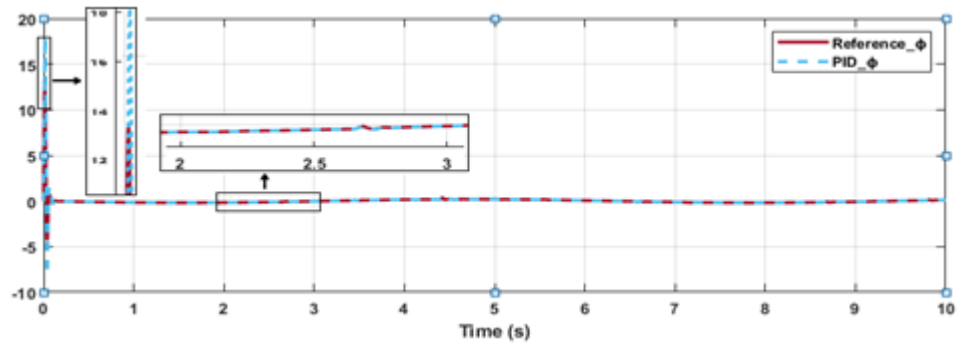


Figure 13. Measured Trajectory with PID Controller

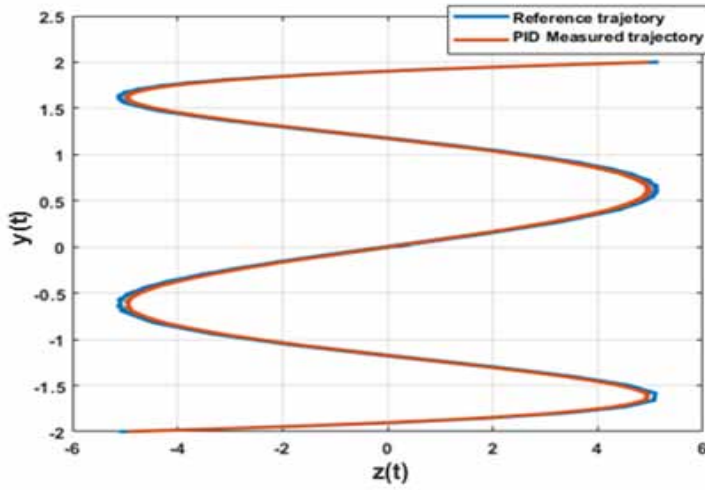


Figure 14. Measured $z(t)$ trajectory with ANFIS controller

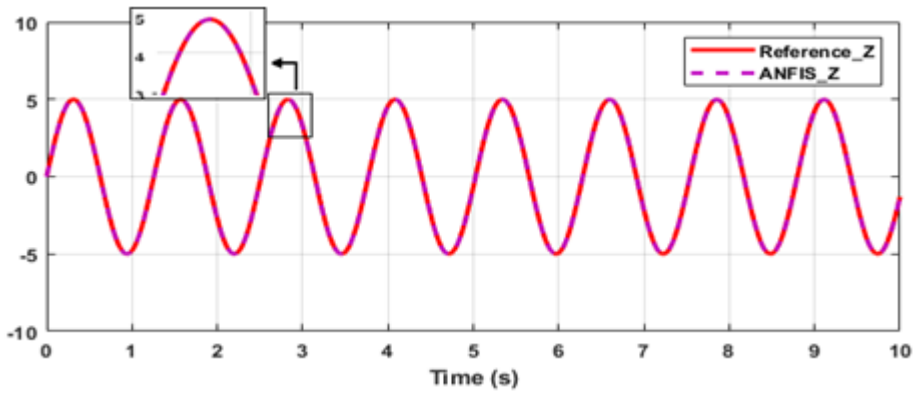


Figure 15. Measured $y(t)$ trajectory with ANFIS controller

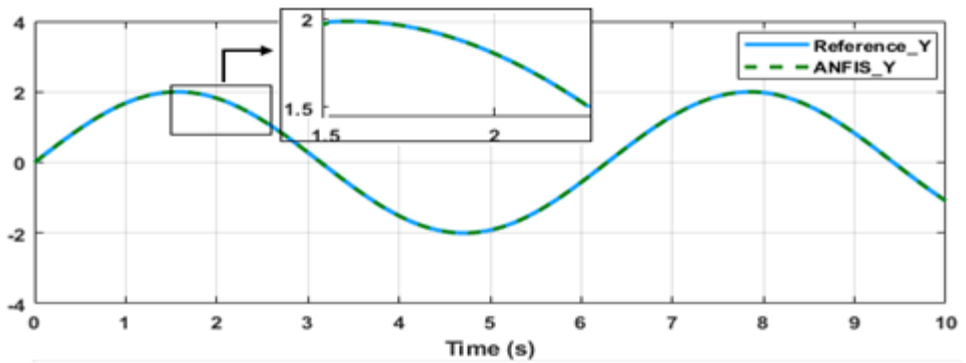


Figure 16. Measured $\phi(t)$ trajectory with ANFIS controller

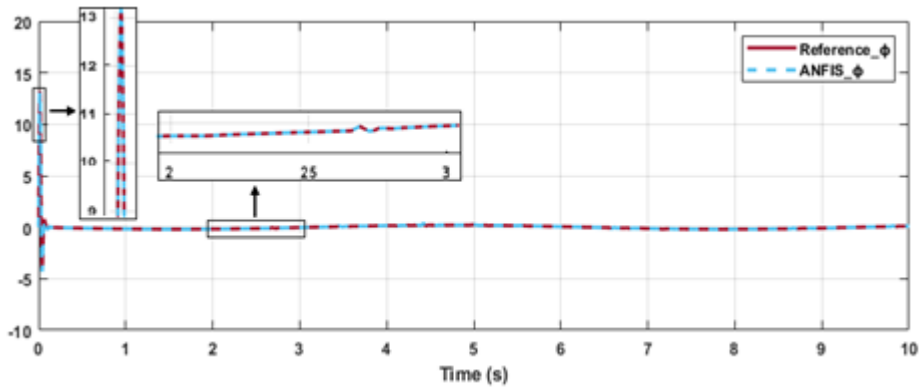


Figure 17. Measured Trajectory with ANFIS Controller

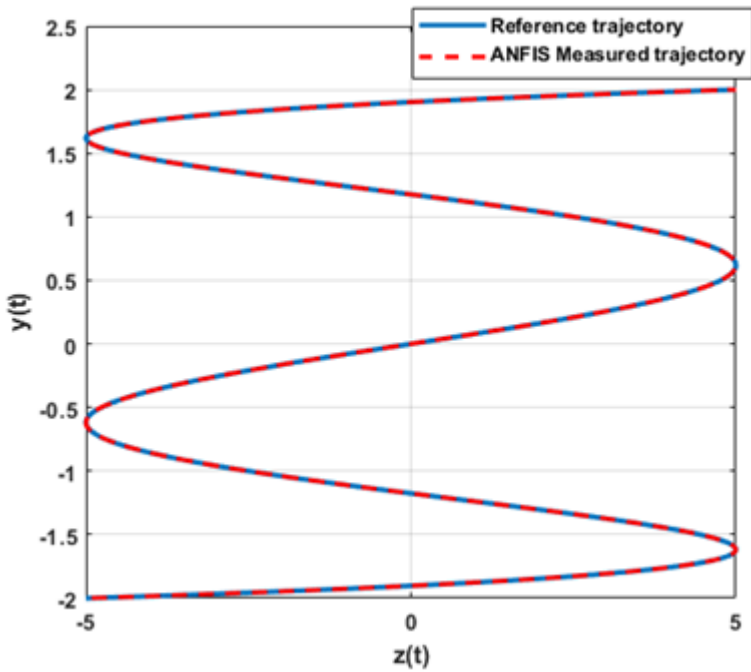


Figure 18. Measured $z(t)$ trajectory with ANFIS-GA controller

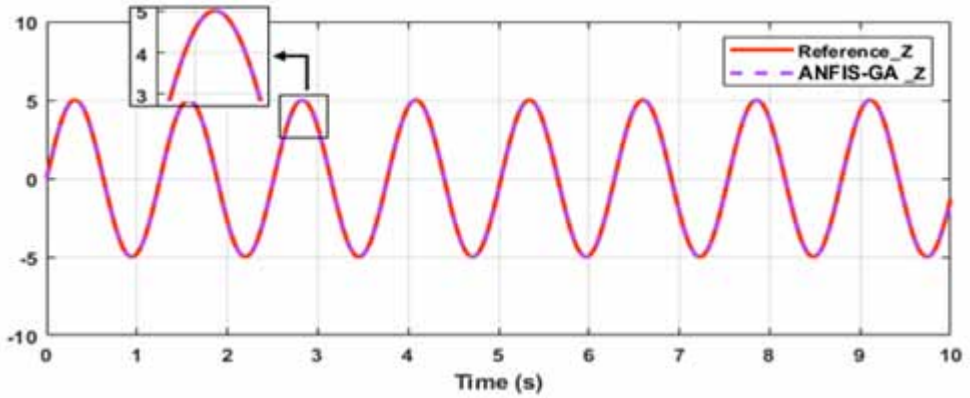


Figure 19. Error of parameter z

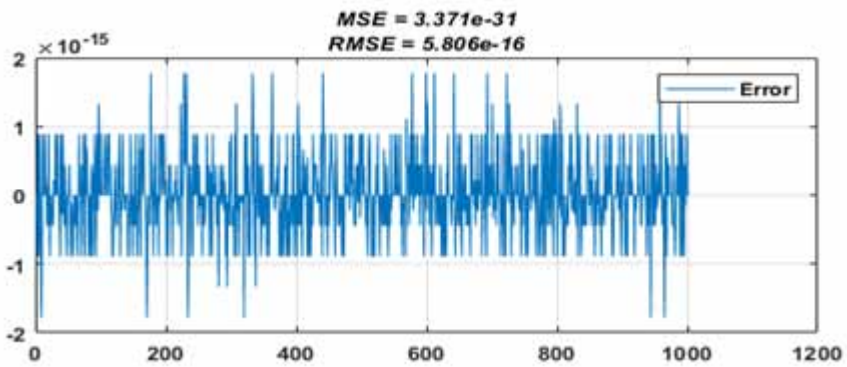


Figure 20. Measured $y(t)$ trajectory with ANFIS-GA controller

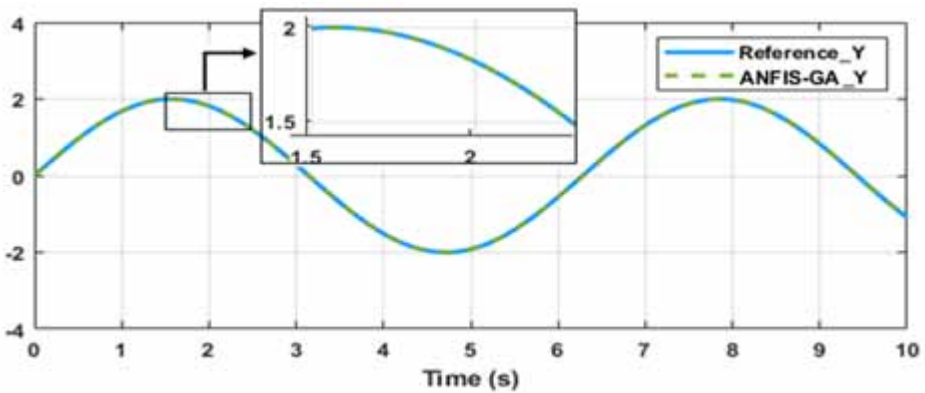


Figure 21. Error of parameter γ

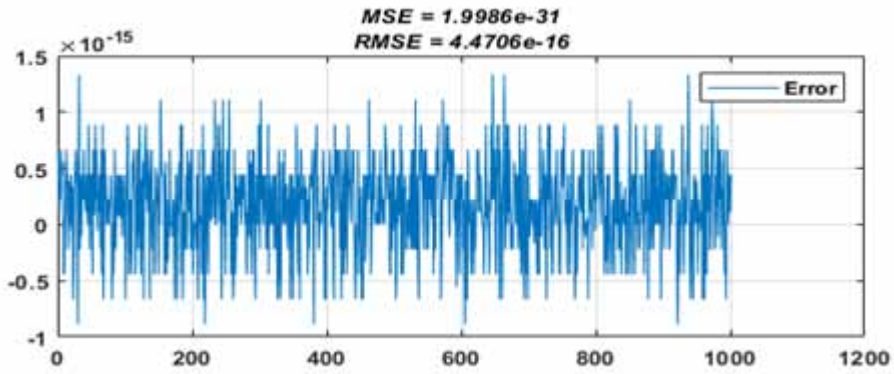


Figure 22. Measured $\phi(t)$ trajectory with ANFIS-GA controller

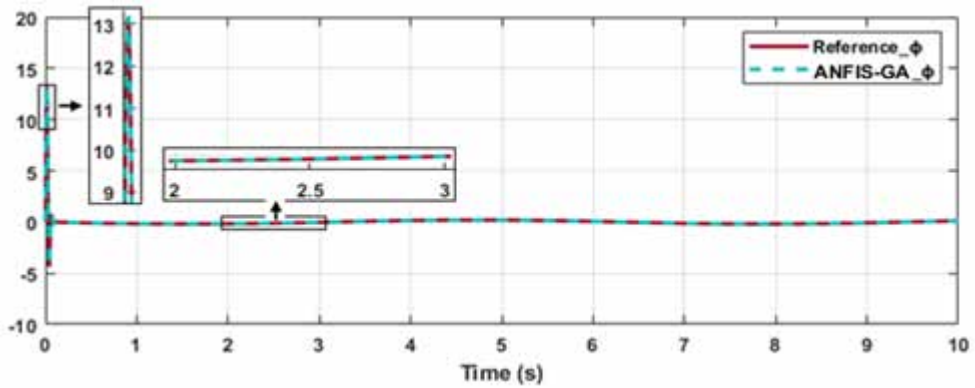


Figure 23. Error of parameter ϕ

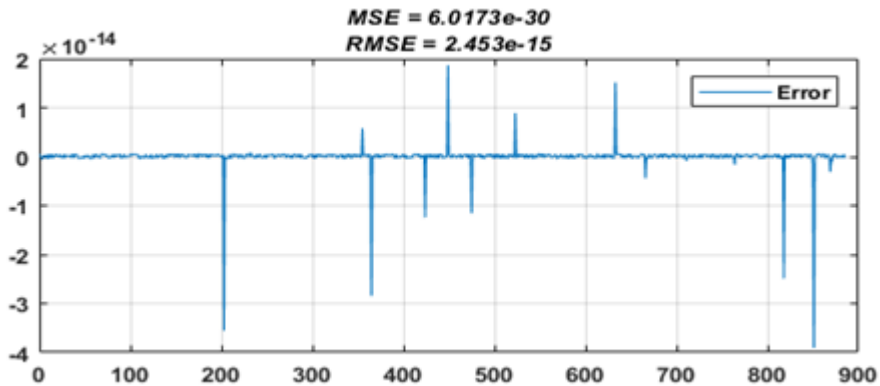
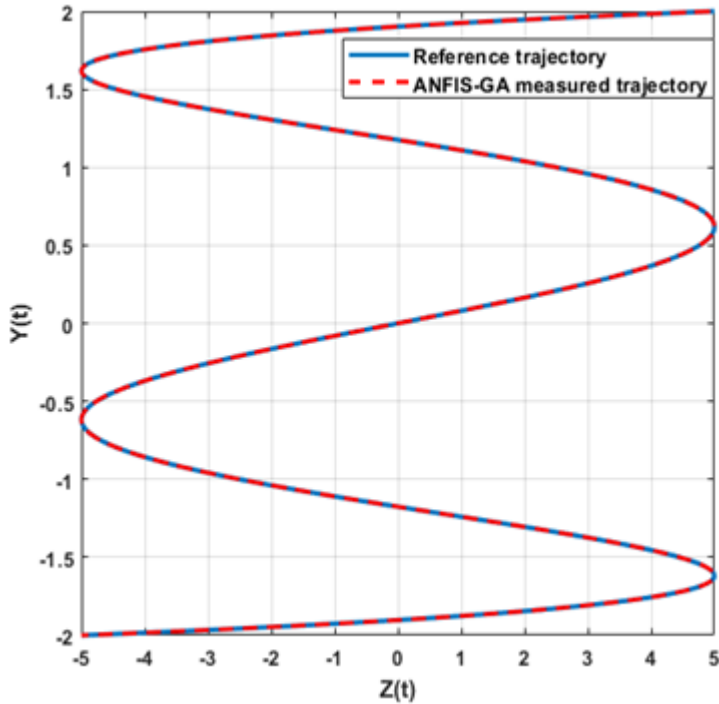


Figure 24. Measured Trajectory with ANFIS-GA Controller



The ANFIS controller performed better than conventional PID controller. However, the performance of ANFIS-GA controller was better than ANFIS for trajectory tracking. This work also proves the suitability of GA for the controller tuning of the UAV positions and orientation.

As a way to keep the facts brief, the graphs for the trajectory tracking performance, controller output, path tracked, y , z and ϕ versus time variations and positions errors for PID, ANFIS, and ANFIS-GA are presented in Figure 10-24. The optimization of the control of the parameters y , z and ϕ has improved the performance of the quadrotor. GA optimization is a search optimization method that aims to improve the efficiency of neuro-fuzzy controllers. It therefore allows exploring the controller definition space, by comparing their performance using cost functions. Cost functions therefore make it possible to measure the overall effectiveness of controllers.

The PID-based control was used to control the UAV robot for a control purpose. The desired positions and the calculated positions are presented in Figure 10, Figure 11. Figure 12 shows the desired and calculated roll angles. The calculated trajectory is compared with the desired one as shown in Figure 13. It can be seen that the PID makes an approximation of the system with an error $MSE = 6.42 \cdot 10^{-2}$ and $RMSE = 0.25$. There one can see that both the position and velocity errors are closer to zero.

The control by ANFIS has proved its worth. The results obtained clearly justify the use of artificial intelligence techniques, of which ANFIS is a part.

Based on the simulation results obtained in Figure 14, Figure 15, Figure 16 and Figure 17. We can see that they are very satisfactory because the error of the trajectory tracking is about $1e10^{-5}$, which explains the robustness of the control law based on the ANFIS system.

In ANFIS, some parameters must be decided in advance according to the problems considered. They include the width and number of partitions of membership functions, as well as the definition of fuzzy rules.

From this study we are faced with a constraint that implies the optimization of the parameters of the proposed approach in an automatic way in order to complete the optimization of the ANFIS parameters, whose goal is to have robust control law that gives maximum system performance.

To make easier to visualize the decrease in the control errors, Figure 19, Figure 21 and Figure 23 present the evolution of the global position (altitude-latitude) and the roll angle errors, respectively, along time. As one can see from the results presented, the adaptive control system is able to decrease the errors in trajectory tracking caused by a bad identification of the model parameters. The plots of error distribution presented in Figure 19, Figure 21 and Figure 23 effectively show that the variance and the dispersion of the errors decrease, getting to 0. From these Figures, it is inferred that ANFIS-GA controller is better than other controllers with Mean error of $1,05014 \cdot 10^{-16}$. In addition, the tracking errors in Y-axis, Z-axis, and ϕ -angle tend to 0.

From Figure 24, the ANFIS-GA controller has more robust stability and performance characteristics than the ANFIS controller. The optimization approach works well. The obtained results clearly explain the impact of the GA algorithm to obtain the best optimal values of membership functions that lead to a robust and efficient state of the controlled system.

6. CONCLUSION

In this paper an adaptive dynamic controller was designed for a UAV trajectory tracking task based on ANFIS. In order to tune the MFs and compensate for parametrization errors or non-modeled dynamic effects i.e., to achieve minimum deviation and reproduce the desired trajectory, we have used an evolutionary method which is genetic algorithm. Although the model used to represent the UAV is simpler than others presented in the literature, the UAV position is controlled in two dimensional space (altitude, and latitude positions), the obtained results allows to claim that the proposed adaptive controller is able to deal with uncertainties in the model parameters or non-modeled effects. Moreover, the parameters of the input and output MFs are directly updated during navigation, configuring a directly updated self-tuning regulator with input error, aiming to reduce the tracking errors, and, therefore, also to improve the system performance in trajectory tracking task accomplishment.

According to the results, the presented controller has more robust stability and performance. Moreover, using the parameters updating law does not require precise model identification in advance. In the simulations presented here, the initial values of the ANFIS parameters were adjusted by GA.

A comparative study of the proposed controller has also been carried out with other two potential controllers are conventional PID and ANFIS controllers. In addition, the robustness testing of the mentioned controllers for model uncertainties has also been investigated. From the most robust results obtained, it can be concluded that ANFIS-GA controller comes out to be robust among all studied controllers with superior trajectory tracking. Moreover, the proposed ANFIS-GA controller has more robust stability and performance characteristics than other controllers applied to UAV trajectory control. As a result of the simulations presented in the paper one can conclude that the strategy of adapting the controller parameters improves the performance of the UAV during the task accomplishment. To synthesize the conclusions, the results presented here allow claiming that the proposed intelligent controller works to reduce control errors and improving navigation performance.

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