Improvement of the stability performance of a quad-copter helicopter by a fuzzy controller Trajectory Tracking of a Quad-copter Using Neurone network Controllers

Djalal Baladji «baladji.djalal@gmail.com», *Kheireddine Lamamra «l_kheir@yahoo.fr», Farida Batat «f_batat@yahoo.fr»*

Department of Electrical Engineering, University of Oum El Bouaghi, Algeria.

Abstract—*The quadri-rotor helicopter has recently attracted attention because of its excellent quality, flexibility, and ability to perform various aerial missions, even under difficult conditions. The quad-rotor helicopter can adopt a variety of flight attitudes, which is attributed to the effective engine speed controller with about four propellers. In order to allow the four-rotor helicopter to better fulfill its flight mission, flight stability is of particular importance. A neural network control algorithm is proposed in this article to ensure stability performance of the quad-rotor helicopter. The proposed algorithm is based on a neural network, which preserves the possibility of self-organization and self-control. It uses the strong learning capacity of knowledge as well as the neural network. The proposed control scheme aims to implement good capabilities such as qualitative knowledge description, a robust control mechanism and the direct processing of quantitative data from the quad-rotor helicopter. In the practical flight process of the four-rotor helicopter, the gap between position and attitude information becomes more important. Our control is adopted to shorten the go-around and installation times. On the other hand, if the position and attitude deviation becomes relatively smaller, the PID command will be used to limit this error. Experimental results indicate that the proposed neural network algorithm offers good performance in the flight process of the quad-rotor helicopter.*

1. INTRODUCTION

In recent years, some current research has focused on the fuzzy and neural network; for example, Qu et al (2011) has addressed the design of an autopilot for an autonomous UAV using a draft genetic algorithm for an evolution on the rules of fuzzy limb functions. Roopashree et al (2012) explained the design of a compact, accurate and economical system. Fuzzy logic controllers (FLC) and fuzzy inference systems (FIS), which estimated the attitude of drones. Sabo and Cohen (2012) proposed a methodology for two-dimensional data management[1][2][3]. In order to improve the system's performance characterization, a recurrent online neural network modeling for the dynamic uncertainty of the four-rotor unmanned aerial (QUAV) was used to develop an under-operated sliding mode control based on a recurrent neural network (Hwang, 2012) [4] [5]. A new adaptive neural control scheme for stabilizing quadcopter helicopters in the presence of sinusoidal turbulence has been proposed (Boudjedir et al., 2012) [6][7][8]. Due to the excellent performance of the fuzzy system and the neural network, fuzzy control of the neural network has been used in several areas; for example, He and Dong (2017) conducted research for adaptive control of the neural fuzzy network (NN) by learning[9] [10] [11].

The above control strategies, with the aim of suggesting a flexible control scheme based on piloting errors, which uses the advantages of the ANFIS system, so that regulation is effective on the four rotors of the four helicopter quad-copters

2. Quad-copter

Four-screw helicopters are four-engine quad-copters mounted on a cross, usually made of carbon fibre, hence their name quad-copters. Examples are shown in **fig.1**.

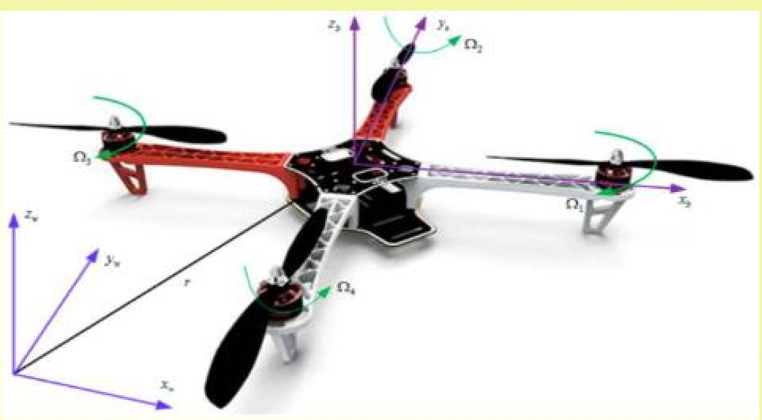

fig .1: Four-propeller helicopters

In a quad-copter, the front and rear engines rotate clockwise while the right and left engines rotate counter-clockwise. The propellers used are fixed-pitch. The pitch is obtained by a difference in the rotational speed of the front and rear rotors[12][13]. The roll is obtained in a similar way with the speed difference of the lateral engines. Yaw is achieved by increasing the speed of the front and rear engines while reducing the speed of the side engines.

3. Model of the quad-copter

To evaluate the mathematical model of the quad-copter, two benchmarks are used, a fixed benchmark linked to the ground Rb and another mobile Rm. The passage between the moving reference frame and the fixed reference frame is given by a matrix called transformation matrix T which contains the orientation and position of the moving reference frame with respect to the fixed reference frame.

The following axis convention is chosen:

$$T = \begin{bmatrix} R & \xi \\ 0 & 1 \end{bmatrix}$$

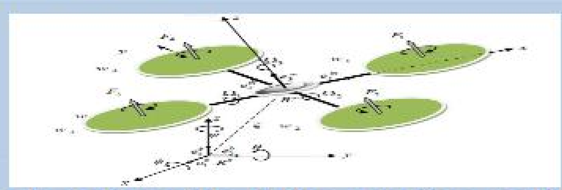

fig.2: Géométrie du quad-copter with R the rotation matrix (describes the orientation of the moving object), $\zeta = [x\ y\ z]^T$ is the position vector. To determine the elements of the rotation matrix R, Euler angles are used.

A. Euler's Angles:

At the beginning the moving reference mark is coincident with the fixed reference mark, after the moving reference mark makes a rotational movement about the x-axis by a roll angle ($-\pi/2 < \phi < \pi/2$), followed by rotation about the y-axis at a pitch angle ($-\pi/2 < \phi < \pi/2$), followed by a rotation about the z axis of angle of ($-\pi < \phi < \pi$)[13].

so we have the formula of the rotation matrix R :

$$R = Rot_z(\psi) + Rot_y(\theta) + Rot_x(\phi)$$

$$= \begin{bmatrix} c\psi & -s\psi & 0 \\ s\psi & c\psi & 0 \\ 0 & 0 & 1 \end{bmatrix} \times \begin{bmatrix} c\theta & 0 & s\theta \\ 0 & 1 & 0 \\ -s\theta & 0 & c\theta \end{bmatrix} \times \begin{bmatrix} 1 & 0 & 0 \\ 0 & c\phi & -s\phi \\ 0 & s\phi & c\phi \end{bmatrix}$$

$$R = \begin{bmatrix} c\psi c\theta & s\phi s\theta c\psi - s\psi c\phi & c\phi s\theta c\psi + s\psi s\phi \\ s\psi c\phi & s\phi s\theta s\psi + c\psi c\phi & c\phi s\theta s\psi - c\psi s\phi \\ -s\theta & s\phi c\theta & c\phi c\theta \end{bmatrix}$$

with : c= cos and s= sin

B. Angular speeds:

Rotation speeds $\Omega 1, \Omega 2, \Omega 3$ in the fixed reference frame are expressed as a function of the rotation speeds ψ, θ, ϕ in the moving reference frame, we have:

$$V = \begin{bmatrix} V_x^b \\ V_y^b \\ V_z^b \end{bmatrix} = R \times \begin{bmatrix} V_x^m \\ V_y^m \\ V_z^m \end{bmatrix}$$

C. Linear speeds:

Linear speeds V^b_x, V^b_y, V^b_z in the fixed reference mark as a function of linear speeds V^m_x, V^m_y, V^m_z in the moving reference frame are given by:

$$\Omega = \begin{bmatrix} \Omega 1 \\ \Omega 2 \\ \Omega 3 \end{bmatrix} = \begin{bmatrix} \dot\phi \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \dot\theta c\phi \\ -\dot\theta s\phi \end{bmatrix} + \begin{bmatrix} -\dot\psi s\theta \\ \dot\psi s\phi c\theta \\ \dot\psi c\phi c\theta \end{bmatrix} = \begin{bmatrix} \dot\phi - \dot\psi s\theta \\ \dot\phi c\phi - \dot\psi s\phi c\theta \\ \dot\psi c\phi c\theta - \dot\theta s\phi \end{bmatrix}$$

$$\Omega = \begin{bmatrix} 1 & 0 & -s\theta \\ 0 & c\phi & s\phi c\theta \\ 0 & -s\phi & c\phi c\theta \end{bmatrix} \times \begin{bmatrix} \dot\phi \\ \dot\theta \\ \dot\psi \end{bmatrix}$$

4. Application of ANFIS on quad-copter:

The ANFIS controllers are taught along the three axes by the least squares method to estimate the consequent parameters and the gradient descent algorithm to determine the parameters of the premises (adjustment of the parameters related to the belonging functions). This is called "blended learning". The neural network used in this work was programmed by the equivalent neural structure proposed to generate the vertical flight control is presented in **fig.3** we have the same structure for the other two axes: x and y to generate the commands *u2x* and *u2y* respectively.

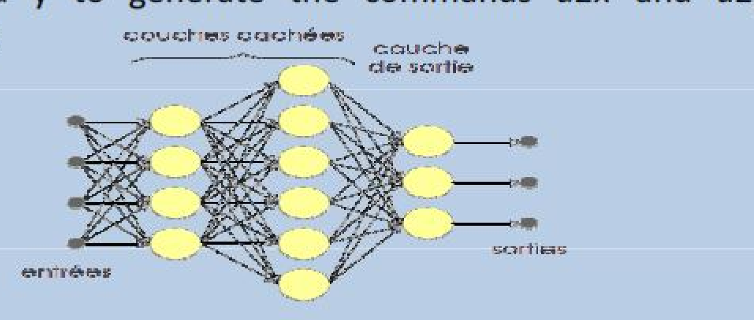

fig.3: Neural structure of the proposed ANFIS controller to generate *u3*.

4. Results

From **fig.4** and **fig.5**, we notice that the error of the ANFIS controller is much smaller than that of the fuzzy PD controller but nevertheless the control by the neural network controller presents oscillations which increases with the increase in drag force which can disturb the drone.

We notice that the errors tend towards zero so the desired position is reached.

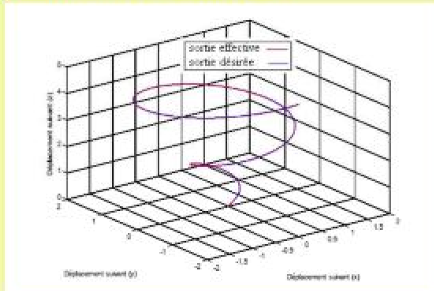

fig.5: Realization of a cone by the A neural network controller.

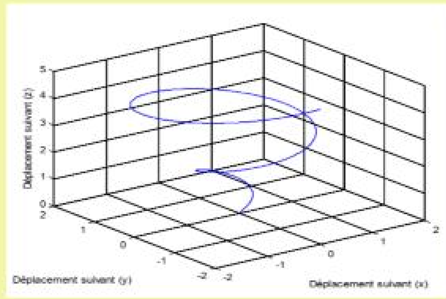

fig.4 : Cone ascent.

5. CONCLUSIONS

From this work it can be seen that the use of an architecture called a neural network **is a simple and effective way to obtain, on learning, a powerful controller whose behavior can be interpreted in the form of decision rules. We found that using a simplified structure allowed us to obtain effective control law through e-learning.**

The controller results used show the validity of our approach to controlling our system. These techniques have therefore been successfully applied to the design of control algorithms that move the drone from an initial position to a desired equilibrium position. The results of the simulation confirmed the controller performance used.

REFERENCES

[1]M. S. Ali, N. Gunasekaran, and Q. Zhu, "State estimation of T–S fuzzy delayed neural networks with Markovian jumping parameters using sampled-data control," *Fuzzy Sets Syst.*, vol. 306, pp. 87–104, 2017.
[2]W. He and Y. Dong, "Adaptive fuzzy neural network control for a constrained robot using impedance learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 4, pp. 1174–1186, 2017.
[3]Z. Jin, J. Chen, Y. Sheng, and X. Liu, "Neural network based adaptive fuzzy PID-type sliding mode attitude control for a reentry vehicle," *Int. J. Control Autom. Syst.*, vol. 15, no. 1, pp. 404–415, 2017.
[4]B. Mi and D. Liu, "A fuzzy neural approach for vehicle guidance in real–time," *Intell. Autom. Soft Comput.*, vol. 23, no. 1, pp. 13–19, 2017.
[5]D.-J. Zhao and D.-G. Yang, "Model-free control of quad-rotor vehicle via finite-time convergent extended state observer," *Int. J. Control Autom. Syst.*, vol. 14, no. 1, pp. 242–254, 2016.
[6]B. O. Mushage, J. C. Chedjou, and K. Kyamakya, "Fuzzy neural network and observer-based fault-tolerant adaptive nonlinear control of uncertain 5-DOF upper-limb exoskeleton robot for passive rehabilitation," *Nonlinear Dyn.*, vol. 87, no. 3, pp. 2021–2037, 2017.
[7]M. Prasad, C.-T. Lin, D.-L. Li, C.-T. Hong, W.-P. Ding, and J.-Y. Chang, "Soft-boosted self-constructing neural fuzzy inference network," *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 47, no. 3, pp. 584–588, 2015.
[8]Y. Qu, S. Pandhiti, K. S. Bullard, W. D. Potter, and K. F. Fezer, "Development of a genetic fuzzy controller for an unmanned aerial vehicle," in *International Conference on Industrial, Engineering and Other Applications of Applied Intelligent Systems*, 2011, pp. 328–335.
.[9]J. Ruan, X. Chen, M. Huang, and T. Zhang, "Application of fuzzy neural networks for modeling of biodegradation and biogas production in a full-scale internal circulation anaerobic reactor," *J. Environ. Sci. Health Part A*, vol. 52, no. 1, pp. 7–14, 2017.
[10]J. Yao, W. Deng, and Z. Jiao, "Adaptive control of hydraulic actuators with LuGre model-based friction compensation," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6469–6477, 2015.
[11]J. Yao, Z. Jiao, D. Ma, and L. Yan, "High-accuracy tracking control of hydraulic rotary actuators with modeling uncertainties," *IEEEASME Trans. Mechatron.*, vol. 19, no. 2, pp. 633–641, 2013.
[12]G. V. Raffo, M. G. Ortega, and F. R. Rubio, "Robust nonlinear control for path tracking of a quad-rotor helicopter," *Asian J. Control*, vol. 17, no. 1, pp. 142–156, 2015
[13]L. Sun and Z. Zuo, "Nonlinear adaptive trajectory tracking control for a quad-rotor with parametric uncertainty," *Proc. Inst. Mech. Eng. Part G J. Aerosp. Eng.*, vol. 229, no. 9, pp. 1709–1721, 2015.

Contact Information

Baladji Djalal

Address

Email:
Baladji.Djalal@Gmail.com