Hexacopter Trajectory Control using a Neural Network

ARTICLE · OCTOBER 2013

DOI: 10.1063/1.4825729

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Abstract. The modern flight control systems are complex due to their non-linear nature. In fact, modern aerospace vehicles are expected to have non-conventional flight envelopes and, then, they must guarantee a high level of robustness and adaptability in order to operate in uncertain environments. Neural Networks (NN), with real-time learning capability, for flight control can be used in applications with manned or unmanned aerial vehicles. Indeed, using proven lower level control algorithms with adaptive elements that exhibit long term learning could help in achieving better adaptation performance while performing aggressive maneuvers. In this paper we show a mathematical modeling and a Neural Network for a hexacopter dynamics in order to develop proper methods for stabilization and trajectory control.

Keywords: flight control, hexacopter, neural network, mathematical model.

INTRODUCTION

The development of the flight control methodologies has been dominated by classical control techniques that have produced several highly reliable and effective control systems. On the contrary, in recent years there has been a growing interest for applications based on robust, nonlinear and adaptive control theory. In this paper two approaches for flight control of a hexacopter will be shown, a mathematical one and another related to soft computing. The commonly used configuration of a hexacopter is treated, whose six rotors are equidistant from the center of gravity and the propulsion system consists of three pairs of counter rotating fixed pitch blades. The hexacopter is assumed as a rigid body in order to describe its dynamical behavior. Because of classical Euler parameterization leads to gimbal-lock, Newton-Euler equations are derived in terms of quaternions, [1]. A relevant feature in flight management of the drone is the trajectory control strategy that allows to reach automatically a desired position maintaining a specific orientation. The control law presented here is a Proportional-Derivative control (PD control) law that works by adjusting the angular velocities of the rotors, as shown in [2]. In particular, it differs from the classical approaches, such as Lyapunov method or least square estimations, [3,4,5], due to the linearity of the quaternion error. Soft computing techniques seek to evaluate, decide, monitor and measure in a unclear and vague field emulating and using humans ability to perform the above activities on the basis of experiences. Soft computing approaches are used in various fields [6, 13, 17] and in recent years they found also several applications in aerospace. In fact, NN controllers have been applied in several aerospace industry applications. A NN, based on adaptive flight controller for uncertain, dynamic and non-linear systems, reduces or even eliminates the need for offline gain tuning and scheduling methodologies. In addition, it reduces the economic costs and the effort needed to identify and model system dynamics. NN have online adaptability, which can be used to design control laws in order to handle uncertainties and non-linearity in system and environment dynamics. Therefore, considering this aspect and that they can be implemented with certain simplicity, NN controllers are the natural choice for the control systems of Unmanned Aerial Vehicle (UAV). Using a NN for adaptive flight controllers in UAV control systems design also reduces the effort required in flight system modeling and flight platform identification.

Neural Networks for Flight Control

Neural Networks controllers are becoming increasingly popular in everyday life. Home automation [7], health [8], industry [9] and Intelligent Transportation System [10] are some examples of application fields. In recent decades several studies focused on flight control. In [11] a stability and convergence analysis of a neural net adaptive flight control is presented. The learning rate effects of the neural network have been studied by authors through a deep analysis and it is validated by several simulations. The authors of present several thoughts on the verification and validation approaches as an enabling technology that will enable adaptive flight control to be realized in future missions. A neural-network-based adaptive control law is proposed in [12] considering that the dynamics in the system are not precisely known. The proposed control scheme combines a conventional back-stepping controller with neural network in order to guarantee the stability and the robustness of closed-loop system under the condition of control surface damage. The authors of [14] introduce a neutral network based adaptive dynamic inversion flight control system. The proposed approach is based on online learning neural networks that are implemented in order to compensate inversion errors due to modeling error or actuator faults. In [15] the authors propose an approach to adaptive control, through a neural network, which uses the current or the online information as well as stored or background information for adaptation. Through the proposed approach it is possible to overcome the rank one limitation on the adaptive law resulting in faster adaptation to the unknown dynamics. An adaptive controller based on neural networks, used to compensate the effects of the aerodynamic modeling errors, is proposed in [16]. The neural networks' parameters are adjusted to offset the error term. The closed-loop stability of the error states and the parameters of the neural networks are deep examined by authors.

Hexacopter Model and Control

The dynamics of the hexacopter is described by the Newton-Euler equations that govern both linear and angular motion. Taking into account all the influences acting on the drone and balancing forces and moments, the dynamical model with respect to the inertial frame is provided by the following equations:

$$\begin{gathered} m\ddot{\boldsymbol{\xi}}+\boldsymbol{A}\dot{\boldsymbol{\xi}}=\boldsymbol{F}_g+\boldsymbol{Q}\,\boldsymbol{T}_B \\ \boldsymbol{I}\,\dot{\boldsymbol{\nu}}+\boldsymbol{\nu}\times(\boldsymbol{I}\,\boldsymbol{\nu})+\boldsymbol{\Gamma}=\boldsymbol{\tau}_B \\ \ddot{\boldsymbol{q}}=\dot{\boldsymbol{S}}\,\boldsymbol{\nu}+\boldsymbol{S}\,\dot{\boldsymbol{\nu}} \end{gathered}$$

where m is the mass, $\boldsymbol{\xi}$ is the inertial position vector, $\boldsymbol{A}$ is the aerodynamic coefficient matrix, $\boldsymbol{F}_g$ is the gravitational force, $\boldsymbol{T}_B$ is the total thrust, $\boldsymbol{Q}$ represents the orthogonal transformation matrix from the body frame to the inertial one, $\boldsymbol{I}$ is the diagonal inertial matrix, $\boldsymbol{\nu}$ is the angular velocity, $\boldsymbol{\Gamma}$ represents the gyroscopic effects, $\boldsymbol{\tau}_B$ is the moment torque, $\boldsymbol{q}$ is the quaternion vector and $\boldsymbol{S}$ is the transformation matrix concerning the velocity.

Let us observe that the torques are balanced due to the pair of counter-rotating fixed pitch blades that realize the propulsion system and the inertial matrix $\boldsymbol{I}$ is diagonal because of the geometrical symmetry of the hexacopter in the body reference frame. Once the mathematical model is defined, a control system is implemented to manage and stabilize the drone flight. The general form of the PD control is

$$u(t)=K_P(x_d(t)-x(t))+K_D(\dot{x}_d(t)-\dot{x}(t))$$

where $u(t)$ is the control input, $x_d(t)$ is the desired target, $x(t)$ is the present state and K_P, K_D are the proportional and derivative constants of the controller respectively. In this case, the desired target corresponds to a desired position and orientation that have to be reached by the drone. Thus, the constants K_P, K_D are determined by minimizing the error that measures the actual distance of the drone with respect to the target. Control inputs are adopted to compute angular velocities that have to be assigned to each rotor in order to manage the flight and to reach the desired configuration. The PD controller could be integrated by adding the quantity $K_{DD}\ddot{e}(t)$ in the control input.

Neural Network Controller for Hexacopter Position

The proposed approach involves the use of a neural network for hexacopter positioning. Since the neural network is a soft computing mechanism, the proposed approach can be implemented on appropriate electronics prototyping platform, for example Arduino, which receive several inputs and can affect its surroundings by controlling actuators.

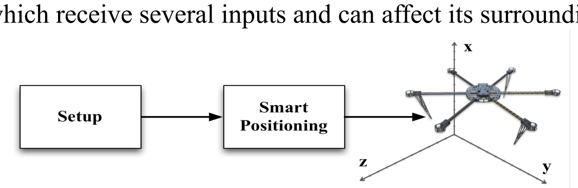

FIGURE 1. Neural Network Controller procedures.

The proposed Neural Network Controller for Hexacopter Position (NNCHP) is characterized by an algorithm based on the following procedures (Figure 1):

- Setup: the NNCHP takes as input several setup information, in order to initialize the smart positioning process, such as a table that contains the quaternions and the positions.
- Smart Positioning: by using these setup information, the controller trains a Non Linear Autoregressive with External Input (NARX) neural network component; the neural network, shown in Figure 2, is composed by 10 hidden neurons and number of delays equal to 2.

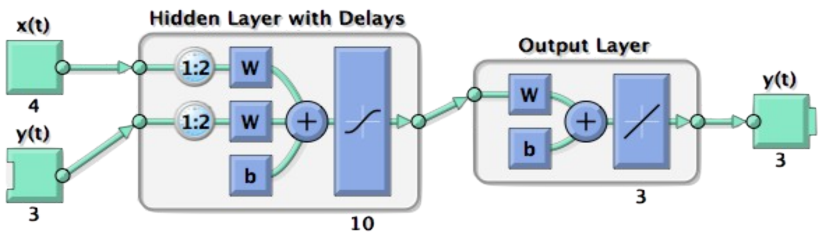

FIGURE 2. The NARX neural network used.

Through this mechanism, the NNCHP evaluates the estimated coordinates (x, y, z) of hexacopter by using a neural network taking the quaternions as input. Moreover, the results are stored in a local database, containing an historical of previous positions and used for neural network training in order to increase performance.

Neural Network Performance

In order to prove the validity of the proposed approach a testbed scenario, using Matlab Toolbox, has been deployed. The neural network has been set to have a 60% of training, a 20% of testing and the remaining 20% of validation. The duration of each simulation was 40 seconds with a time step of 1ms. Figure 3 shows the trend of hexacopter coordinates under the desired positions $x_d = 2$, $y_d = 2$ and $z_d = 1$ and considering the predicted coordinates by neural network controller. As it is possible to see, the trend of the predicted coordinates by neural network is almost equal to the desired ones. In fact, the Mean Squared Error (MSE) returned by neural network is $1.62903*10^{-10}$; lower values are better while zero mean no error.

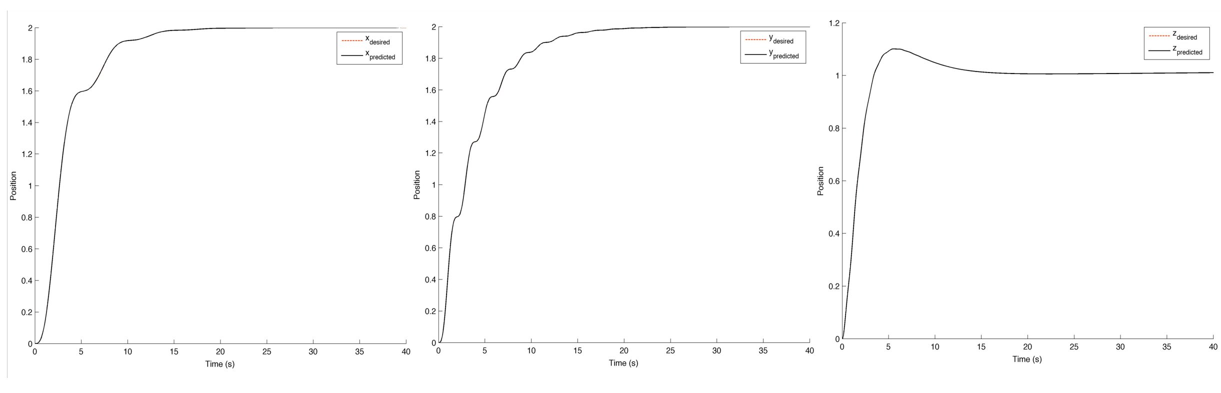

FIGURE 3. Hexacopter coordinates considering both desired and predicted coordinates; x (left), y (center) and z (right).

Approaches Comparison

A comparison between the mathematical approach and the neural network is provided in this section. Figure 4 shows the behavior of the hexacopter under the mathematical approach (left) and considering the predicted coordinates by NNCHP (right). Using as input the quaternions and through the training, the neural network returns the hexacopter coordinates that are almost equal to those of the mathematical approach. The neural network predicts positions that are almost equal to those of the mathematical approach.

CONCLUSIONS

In this paper a Neural Network approach has been presented in order to develop proper methods for stabilization and trajectory control of a hexacopter. The rapid response of this technique and the high quality of data approximation compared with a mathematical solution have been shown and simulations results are very promising. So, the next step will be the integration of the whole dynamical system, considering the forces and the moments acting on the drone, in order to obtain the position and the orientation of the drone together. This method will be implemented on hardware for real flight simulations.

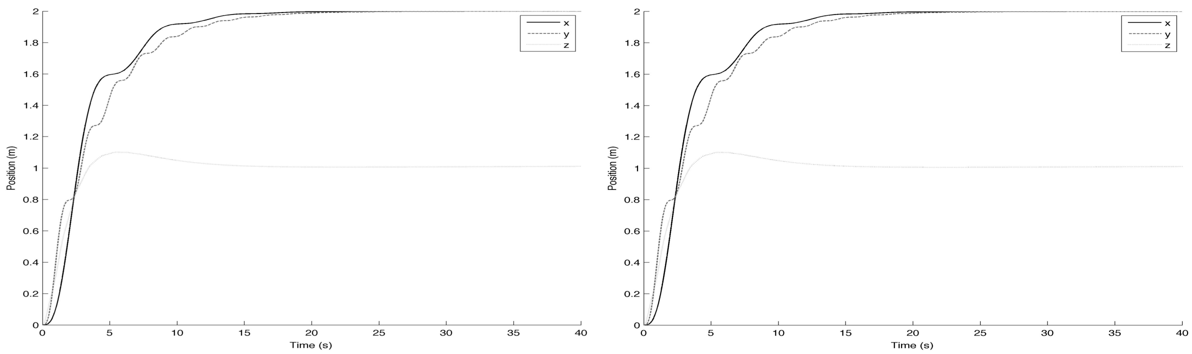

FIGURE 4. Hexacopter position: mathematical approach (left) and NNCHP (right).

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