Applied Mathematics & Information Sciences
An International Journal

http://dx.doi.org/10.18576/amis/100202

Real-Time System based on a Neural Network and PID Flight Control

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Received: 3 Aug. 2015, Revised: 21 Oct. 2015, Accepted: 22 Oct. 2015
Published online: 1 Mar. 2016

Abstract: The modern flight control systems are complex since they have a non-linear nature. Also, modern aerospace vehicles are expected to have non-conventional flight envelopes and, in order to operate in uncertain environments, they must guarantee a high level of robustness and adaptability. A Neural Networks controller can be used in applications with manned or unmanned aerial vehicles. The paper shows the mathematical model for hexacopter dynamics and a comparison between two different technique for stabilization and trajectory control: proportional,integral, derivative controller and real rime system controller based on Neural Networks. Numerical simulations are performed in order to validate both mathematical model and control approaches.

Keywords: Hexacopter, UAV, Flight Control, Real-Time System, Neural Network, PID

1 Introduction

The Unmanned Aerial Vehicles, shortly UAVs and also known as drone, are aircraft characterized by the absence of a pilot on board and represent very promising vehicle for flight in indoor/outdoor environment. Their flight is managed by means of a proper control system, under the supervision of a navigator or pilot on the ground. Anyhow, the flight operations of an UAV must comply with the same rules and procedures of the aircraft with on board pilot and flight crew. In fact, in recent years, the guidelines of flight certification for UAVs are designed to provide an increased reliability, accuracy and safety. UAVs are widely used both in military and civil application such as fire prevention and emergency operations, surveillance, search and rescue. It is clear that the main goal of UAVs consists in avoiding any risk for pilots and aircrew and allowing the execution of "dull, dirty and dangerous" missions, often at a lower cost than conventional aircraft. For this reason, a relevant feature of UAVs is related to flight management and trajectory control strategy with the aim of automatically reaching a desired position under a specific orientation. For as UAVs were conceived, it is crucial define an efficient and accurate control system. UAV could carry expensive instrumentation, such as sensors or cameras, and therefore high demands are set on a well working automatic flight control strategy. These research field is multidisciplinary and involves areas like aeronautics, computer science, mathematics, electronics, mechanics, automatic control, signal processing, and so on. Among UAVs, great interest is produced by hexacopters or hexarotors, which are aircraft with six rotors placed on the vertices of a hexagon-shaped structure. The propulsion system consists of three pairs of counter rotating fixed pitch blades: in details, the blades located on the same arm rotate in opposite direction [1].

In literature there exist a lot of different control technique and traditional methods involve Lyapunov function [2] [3], back-stepping [4] [5] and nonlinear dynamic inversion [6] [7]. Furthermore, in order to manage the dynamics of a quadrotor, the authors in [8] introduce a strategy based on backstepping and proportional, integrative, derivative (PID) action. In [9] attitude control of a quadrotor aircraft has been faced and the strategy introduced can make the attitude error uniformly ultimate bounded. Finally, in [10] the problem of aircraft stabilization is debated.

Recently proposed approaches are based on soft computing techniques [11] [12]. Among these, Neural Network (shortly NN) controllers have been proposed as adaptive controller for nonlinear system applied simply based on observation and experience without a deep knowledge of the dynamical system, [13]. Therefore NNs

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represent a very efficient tool in flight control. In [14] a detailed analysis is carried out in order to validate the use of NNs in flight control applications. The proposed control system satisfies standard conditions for stability and proves that adaptive Neural Network is able to reach the hovering configuration even in presence of failures and damage. In [15] the authors present a stability and convergence analysis of a NN adaptive flight control. Because of the instability related to high-gain learning, a recursive least-squares learning law is presented. Numerical results show that high frequency oscillations, due to unmodeled dynamics, can be avoided by means of this improvement. The authors of [16] introduce an original NN controller for adaptive dynamic inversion flight control systems. The main idea consists in avoiding error caused by mathematical modelling and actuator damages through adaptive NN. The variation of aerodynamic coefficients is proposed in [17], in which on-line learning NNs, based on Lyapunov control theory for weight update rules, are implemented. The proposed approach seems to be more stable than conventional back-stepping controller. Finally, the adaptive NN method presented in [18] evidences that a joint connection between online and background learning methods generates a robust and efficient adaptive flight controller which guarantees good performance even in uncertain environments.

In this paper a comparison between a non adaptive and an adaptive control technique is presented. In details, starting from results proposed [19], the use of NN and PID controller for hexacopter flight management is presented. The NN differs from that presented in [19] since considers different input parameters. Specifically, in the [19] input parameters are quaternions and positions, while in this work are the angular velocities and positions.

2 Dynamical system and non adaptive control strategy

It is assumed that the hexacopter is a rigid body and therefore classical Newton-Euler equations has been chosen in order to deduce the dynamics of the drone. The peculiarity of our model compared to the usual dynamical system consists in parametrizing in terms of quaternions the three dimensional rotations, instead of Euler angles [20]. The dynamics of the hexacopter can be decomposed into translational and rotational component, considering the internal and external influences acting on it. In details, denoting with m the mass of the aircraft, $\boldsymbol{\xi} = (x\ , y\ , z\ )$ its position vector with respect to the inertial frame, $\mathbf{F_g}$ the gravitational force, $\mathbf{T_B}$ the total thrust, $\mathbf{Q}$ the orthogonal transformation matrix from the body frame to the inertial one, the translational component reads:

$$m\,\ddot{\boldsymbol{\xi}} = \mathbf{F}_g + \mathbf{Q}\,\mathbf{T}_B. \tag{1}$$

while the rotational component of the motion is:

$$\ddot{\mathbf{q}} = \frac{d}{d\,t}(\mathbf{S}\,\boldsymbol{\nu}) \tag{2}$$

in which $\boldsymbol{q} = (q_0\ , q_1\ , q_2\ , q_3\ )$ is the quaternion representing the orientation of the hexacopter and $\mathbf{S}$ is the velocity transformation matrix. The angular velocity $\boldsymbol{\nu}$ has to satisfy the following differential equation:

$$\mathbf{I}\,\dot{\boldsymbol{\nu}} + \boldsymbol{\nu} \times (\mathbf{I}\,\boldsymbol{\nu}) + \boldsymbol{\Gamma} = \boldsymbol{\tau}_B \tag{3}$$

where $\mathbf{I}$ is diagonal inertial matrix, $\boldsymbol{\Gamma}$ represents the gyroscopic effects while $\boldsymbol{\tau}_B = [\tau_\phi\ \tau_\theta\ \tau_\psi]^T$ the roll, pitch and yaw moment vector, generated by angular velocity and acceleration of the rotor.
Therefore, equations (1), (2) and (3) with an initial condition, describe the motion and evolution of the drone. Anyhow,the only mathematical model is not sufficient to manage the flight and to stabilize the UAV, then the introduction of a proper control system is necessary. A typical non adaptive controller is the PID (Proportional Integral Derivative) control technique, that is very robust, accurate and performance. The controller PID general structure is based on measurement of error as $e(t) = x_d(t) - x(t)$ between the desired and the actual state of the dynamical system. The control inputs, total thrust and angular moment in our case, are computed as a linear combination of the error, its time integral and its derivative, i.e:

$$u(t) = K_P\,e(t) + \ K_I \int_0^t e(s)ds + \ K_D\,\frac{d}{dt}\,e(t) \tag{4}$$

The three term control in (4) represent the present errors, the accumulation of past errors and a prediction of the future errors, respectively. The coefficients $K_P,\ K_I,\ K_D$ represent the *proportional*, *integrative* and *derivative* gains, and are tuned via trial and error.
The PID controller is applied to the system describing the motion of the hexacopter in order to achieve a target position under a specific orientation, [21]. The hexacopter is controlled by simply modifying the angular velocities of the six rotors.

3 Real-Time System Model

The development of a suitable real-time environment for flight control must fulfill several constraints in order to ensure the timely processing of information. The constraints include the real-time communication, the real-time scheduling of system tasks, the performance predictability and the prevention and the reaction to critical situations. The proposed real-time system for flight control is characterized by the architecture shown in Figure 1and is based on NN.

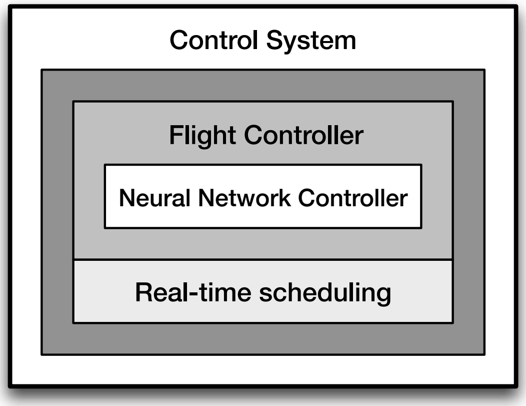

Figure 1: Real-time System Architecture

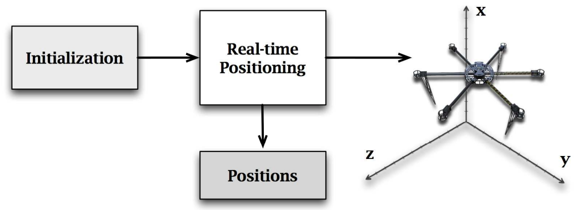

Figure 2: Neural Network Controller procedures

3.1 Real-time scheduling

The hexacopter system consists of hardware and software components and the tasks running on the microcontroller are subject to stringent timing constraints [22], which must be enforced by the operating system in order to guarantee stability and achieve a desired performance level. The dynamics of the system-environment interactions impose real-time constraints, specified by deadlines, response times, activation periods, input-output delays and jitter requirements. For this reason, the application performance are closely linked to the operating system, because the timing behavior strictly depends on task scheduling, interrupt handling, synchronization protocols, and resource management algorithms. In order to enforce timing constraints a static scheduling can be used but this solution is not flexible to changes and is weak under overload conditions. On the contrary, a priority-based kernel is a more suitable choice in order to support dynamic control applications with variable computational requirements [23].

In order to predictably manage concurrent activities with periodic and aperiodic activations and explicit timing constraints, the real-time scheduling, used within the proposed system, is based on ERIKA (Embedded Real tIme Kernel Architecture) Enterprise real-time kernel [24].

Several real-time operating systems are available in the market, however only few of them are suitable for small embedded microcontrollers with limited processing resources. For example, QNX Neutrino [25] , Wind River VxWorks [26] , open source kernels related to Linux, such as RTLinux [27], Linux-RK [28] , are kernels commonly used in real- time control applications but most of them are designed for medium size applications and are not suited for small micro- controllers. On the contrary, the ERIKA Enterprise real-time operating system [24] is specifically designed for minimal embedded systems with limited onboard resources. This real-time kernel is configurable both in terms of services and kernel objects (tasks, resources, and events) and also supports advanced scheduling mechanisms, such as Rate Monotonic (RM) [29] and Earliest Deadline First (EDF) [30] algorithms.

Inside the proposed real-time system, three grouped concurrent tasks (hard real-time, soft real-time and non-real-time) manage the flight control application. In order to prevent any accidental situation, the deadline of the hard real-time tasks should be guaranteed explicitly. The tasks are managed both trough a fixed priority and EDF with preemption thresholds. Real-time tasks have higher priority than other tasks. On the contrary, the non-real time tasks are executed after the completion of real time tasks. Therefore, the real-time scheduling module is able to supports the dynamic reconfiguration of concurrent tasks without loss of any hard deadline of real-time tasks.

3.2 Neural Network Controller

The real-time system is based on a NN controller in order to control hexacopter trajectories. The algorithm that characterizes the proposed neural network is shown in Figure 2 and the procedures on which it is based are:

– Initialization: the neural network controller takes as input several setup information, in order to initialize the real-time positioning process, such as tables that contain angular velocities and positions;
– Real-time Positioning: the controller trains a Non Linear Autoregressive with External Input (NARX) neural network component by using the information from Initialization block.

The neural network controller takes as input the angular velocities of the six rotors ($\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6$) and then evaluates the estimated coordinates (x, y, z). Moreover, the results are stored in a database, containing both historical of previous positions and angular velocities. In fact, these values are used for neural network training in order to increase performance.

The predictor associated with the NARX model [31] is presented according the following equation:

$$\hat{y}(t|\theta) = \hat{y}(t|t-1,\theta) = g(\varphi(t),\theta) \tag{5}$$

where $\hat{y}$ is the value of the variable y at time t predicted by the model; θ is a vector containing the weights of the neural network; g is the function realized by the neural network and $\varphi(t)$ is a vector containing the regressors, given by:

$$\varphi(t) = [y(t-1)...y(t-n_a)u(t-n_k)...u(t-n_a-n_k+1)]^T \tag{6}$$

where u refers to the set of inputs and n_a, n_b and n_k are the parameters defining the order of the regressors.

The proposed neural network, implemented in the micro-controller is composed by 20 hidden neurons (trained using the Levenberg-Marquardt algorithm [32]), number of delays equal to 2 and it uses a symmetric sigmoid transfer function. Furthermore, the network is created and trained in open loop form so it is supplied with correct past outputs during training in order to produce the correct current outputs.

The early stopping technique has been used in order to guarantee good generalization performances to the model and prevent the risk of over-fitting the training data. The entire available dataset is split in three subsets: a training set, a validation set and a test set. The training data set is used for computing the gradient of the cost function, which is a function of the MSE (Mean Squared Error), and updating the network weights. The error on the validation set is monitored during the training process.

In the proposed NN the training set comprises 60% of the data, whereas 20% of the data is used as validation set and the remaining 20% is retained as test set. The forecasting performances of the networks will be assessed using the test set data and against the error measures presented in Table 2, where Y_i is the value of the i-th actual observation and $\hat{Y}_i$ is its forecasted value. The forecast error is calculated as follow:

$$e_i = Y_i - \hat{Y}_i \tag{7}$$

while the scaled error is determined with the following equation:

$$se_i = \frac{e_i}{\left(\sum_{i=2}^{N_t} |Y_i - \hat{Y}_i|\right)/N_{t-1}} \tag{8}$$

4 Numerical Results

This section deals with comparison between the PID controller and a real-time system, based on a NN model. First of all, given a squared path as desired position, the implementation of the PID scheme provides the angular velocities of the six rotors for trajectory control. Then, such velocities are the input of the NN which is trained in order to obtain the target position as output.

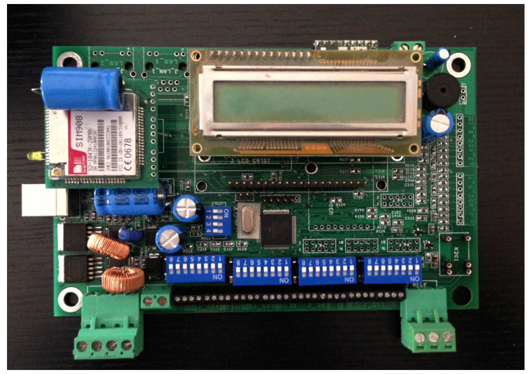

Figure 3: Hardware board

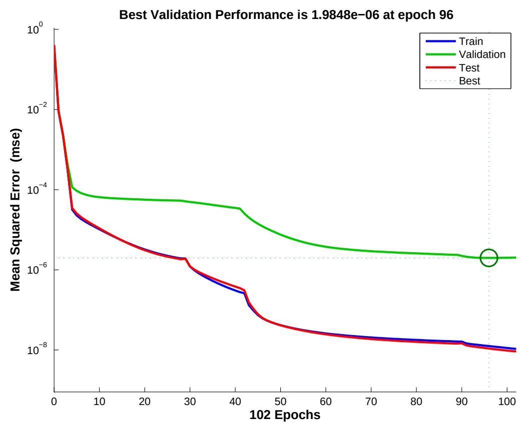

Figure 4: Best validation performance (MSE)

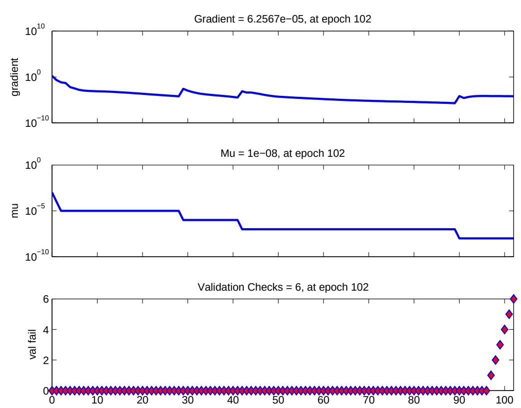

Figure 5: Training state

Table 1: Parameters for numerical simulation

Parameters	Value
k	2.980e-6 [$kg\ m$]
b	1.140e-7 [$kg\ m^2$]
d	0.225 [m]
g	9.81 [m/s^2]
m	0.468 [kg]
I_{xx}	4.856e-3 [$kg\ m^2$]
I_{yy}	4.856e-3 [$kg\ m^2$]
I_{zz}	8.801e-3 [$kg\ m^2$]
I_r	3.357e-5 [$kg\ m^2$]

Table 2: Error measures used to evaluate the performances of the NARX model

Error measure	Formula
Mean Squared Error (MSE)	$mean(e_i^2)$
Root Square Mean Error (RMSE)	$\sqrt{MSE}$
Mean Absolute Error (MAE)	$mean(\|e_i\|)$
Median Absolute Error (MdAE)	$median(\|e_i\|)$
Mean Absolute Scaled Error (MASE)	$mean(\|se_i\|)$

Table 3: Performance measures (Training epochs = 102)

Error measure	Value
MSE	$1.21 * 10^{-8}$
RMSE	$1.34 * 10^{-4}$
MAE	$2.42 * 10^{-8}$
MdAE	$1.01 * 10^{-8}$
MASE	$1.41 * 10^{-4}$

4.1 PID and Neural Network Performance

The model(1), (2) and (3) controlled via PID technique (4) is implemented by choosing parameters listed in Table 1.

As flight controller based on a NN concerns, the processing unit is the Microchip PIC24FJ256GB108 microcontroller [33], which integrates the control features of a Micro-Controller Unit (MCU) with the processing and throughput capabilities of a Digital Signal Processor (DSP). The used prototyping board based on the Microchip PIC24FJ256GB108 microcontroller is shown in Figure 3. In Figure 4 and Figure 5 are depicted the validation performance and training state of the networks respectively, where mu is the Marquardt adjustment parameter and $valfail$ represents the number of iterations for which the validation error continuously increased after the last decrease. It is necessary to note that lower values of MSE are better while zero means no error. Furthermore, the results obtained with the NARX model on the test set data are shown in Table 3. From obtained results it is clear that errors values are considerably lower and this means excellent performance of the neural network.

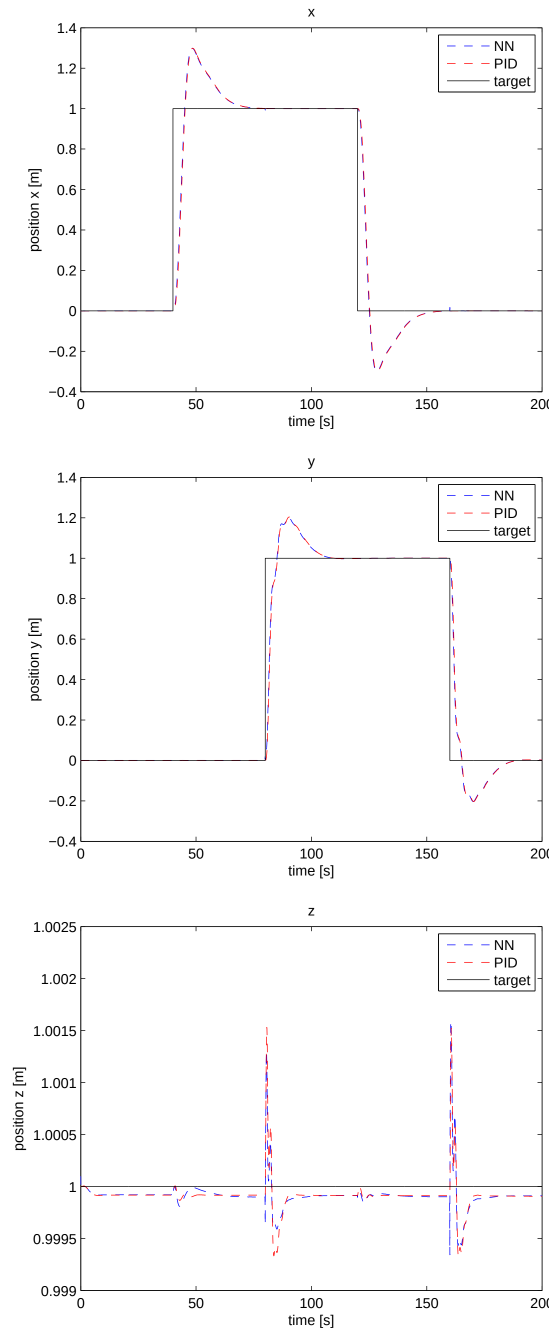

Figure 6: Output of NN and PID compared with desired trajectory

Figure 6 shows the x, y and z coordinates computed through the PID and NN technique. It results a good agreement between two approaches.

5 Conclusions

In this work the dynamical model of a hexarotor is proposed. Two different approaches for drone control has been discussed, comparing the results obtained. Comparison between obtained results show that both of proposed methods are efficient and accurate, showing a good agreement with the given desired trajectory. Future work will concern the optimization both of the neural network and the PID controller in order to maximize their performance even in presence of aerodynamic effects.

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