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An adaptive trajectory control for UAV using a real-time architecture

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***Abstract*—Multirotor helicopter have generated much interest in recent years as a powerful tool both for civil and military applications. The trajectory of the aircraft is controlled by modifying the angular velocity of the rotors. Among different control techniques the PID controller finds great application due to its simplicity. It uses proportional, integral and derivative regulator to control one or more input signal. In this paper a novel real-time system, based on a real-time Neural Network, is presented to propose an alternative control technique to the PID. In order to prove the validity of the proposed approach simulations are performed through a real experimental test-bed.**

I. Introduction

The Unmanned Aerial Vehicles (UAVs) are motorized aircraft without crew on board. They can fly autonomously or piloted remotely and can carry weapons or monitoring equipment (sensors, cameras). The main advantage of UAVs, compared to piloted aircraft, is the absence of the pilot on board the aircraft. This feature allows to use them in dangerous and risky missions for the safety and the lives of pilots. These missions are traditionally called 3D missions [2]. In addition to military contexts, in recent years, UAVs are also used in civilian missions [3] normally reserved for piloted aircraft, such as remote sensing (meteorology, scientific research, aerial photography) or surveillance (monitoring of territorial boundaries, traffic monitoring, rescue). The UAVs as reconnaissance and surveillance platforms, also involve advantages over satellites. The latter, unlike the UAVs, have a high launching cost and a high cost associated with the in orbit repositioning and, in many cases, their payload can not be changed during their life cycle. On the contrary, UAVs can be reprogrammed quickly and can change the payload in accordance with the mission to be performed. Moreover, they can operate closer to the Earth than satellites, and then can withdraw more precise images using the same sensor. A significant advantage is their ability to fly over a particular area, monitoring a specific position, for long periods. The absence of the pilot on board also has implications on the design of the aircraft. In fact, it is possible to develop an aircraft without particular regard for the human physical dimensions. In fact, UAVs can be designed in such a way to load higher payload and greater amounts. However, in harsh environments failure situations can arise [4] and in these cases the control system of the UAV should be able to detect and counteract these failures preventing the aircraft from

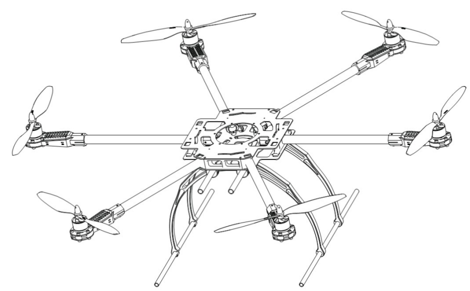

Figure 1. Hexacopter

crashing. It is clear that the development of a self-learning and self-adaptive flight controller system is a primary step in the UAVs, in order to manage the aircraft when flight conditions change.

A. The Proposed Approach

In this paper a novel flight control technique, based on a Neural Network, for a hexacopter (depicted in Figure 1) will be shown. Moreover, a deep analysis will be carried out in order to identify the appropriate software/hardware architecture and the main components characterizing the flight controller. Through the results of this analysis, a development on a real embedded prototyping board will be presented. In order to check the validity of the proposed approach, the errors which affect the NN will be analysed and measured.

In Section II main related works regarding to flight controllers of UAVs are shown. In Section III the proposed system architecture is described, showing both the flight controller and the real-time scheduling modules. The modelling and a kind of control of the hexacopter are introduced in Section IV and in Section V while in Section VI the NN controller is presented. Finally, in Section VII the performance obtained with the proposed approach are shown and in Section VIII is summarized the paper reporting conclusions.

II. Flight Control System of UAVs

The control of an aircraft requires a mathematical model that consider all flight characteristics associated with the motions of the aircraft. A deep analysis of the aircraft requires

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the study of complex phenomena such as lift, deviance, vectored thrust, air resistance, wind and even the surfaces of the aircraft. In recent years, several nonlinear control methods, such as the Lyapunov function [5] [6], back-stepping [7] [8] and non-linear dynamic inversion [9] [10], have been applied in flight control systems for small UAVs. The above methods improve the attitude and trajectory control performance of UAVs, however they are complex both to design and to implement.

Several new approaches are based on soft computing techniques whose objective is to evaluate, decide and monitor in a unclear and vague field emulating humans ability to perform the above activities on the basis of experiences. In recent years, novel soft computing techniques are applied in various fields and they found applications in aerospace [11] [12]. Among soft computing techniques, Neural Network controllers have been applied in several flight control applications [13] [14] [15] [16]. In fact, an adaptive flight controller based on an NN can reduce or even eliminate the need for off-line gain tuning and scheduling methodologies. An NN is also characterized by on-line adaptability, which can be used to design real-time control laws in order to handle uncertainties and non-linearity in system and environment dynamics [13], [15]. Considering these advantages and that an NN can be implemented with certain simplicity, NN controllers can be the right choice for the control systems of Unmanned Aerial Vehicles. Furthermore, through an NN controller for flight control it is possible to overcome the limitations of other non-linear control methods.

A. Flight Controllers based on Neural Network

Several studies focused on flight control deal with the use of neural networks. In [13], an approach based on neural network to control the trajectory of an UAV is presented. The chosen UAV is a hexacopter and the authors present it through a mathematical modelling. The proposed NN controller evaluates the estimated coordinates (x, y, z) of the UAV taking as input the quaternions. Moreover, the NN controller stores the results in a local database, containing an historical of previous positions, and uses them for training in order to increase performance. The authors compare a mathematical approach with the neural network and the results underline that the NN has a rapid response and a high quality of data approximation.

The authors of [14] presents a neural adaptive flight controller for ducted fan UAVs. The non-linear dynamics of the ducted fan UAV is decoupled using adaptive back-stepping (an adaptive feedback control law of the aircraft's state) and individual controllers are developed for pitch, roll and yaw axis as an attitude command altitude hold system. The performance of the proposed approach is evaluated using the 6-DOF model and the results indicate that the proposed control approach provides necessary stability and tracking performance.

In [16] a RBF (radial basis function) neural network is used to real-time update the PID parameters on line by its learning function for achieving the longitudinal channel control of an UAV. The RBF neural network control algorithm has good global search optimization features, which can approximate any non-linear function, and it is fast and easy to operate so that it is more adapted to the UAV flight control system. The simulation results show that the neural network is more efficient and has higher adaptability than the traditional PID control algorithm. Moreover, it would be useful to make a comparison between the approach proposed in [16] and the one proposed in this work. But, although the two approaches refer to a PID and to a neural network, they have different aims. Therefore, they can not be compared directly.

Another application of neural network on flight control is presented in [17]. The analysis presented by authors wants to demonstrate that a neural network can be applied in flight control applications. It is underlined that the NN software architecture can be integrated with any conventional flight controller configuration. This feature offers significant cost savings, especially for retrofit additions to existing controller configurations. For these reasons, it is clear that NN can be suitable for the adaptive flight control applications where system dynamics are dominated by the unknown non-linearities.

The authors of [18] introduce an NN based adaptive dynamic inversion flight control system. An online learning neural network characterizes the proposed approach. Simulations results show that the limitation of needing accurate mathematical model in dynamic inversion method is overcome through adaptive compensating inversion error by neural networks.

A stability and convergence analysis of an NN adaptive flight control is presented in [19]. The learning rate effects of the neural network have been studied by authors through a deep analysis and it is validated by several simulations. Results show that a high-gain learning can become unstable and so the authors propose an improvement that avoid high frequency oscillations. The paper shows also several thoughts on the verification and validation approaches as an enabling technology that will enable adaptive flight control to be realized in future works.

After analysing these works that propose NN-based approaches for flight control, it is clear that more and adequate research works about flight controller based on neural networks are needed.

III. The Proposed System Architecture

In order to develop a suitable system architecture for flight control, it is necessary to identify an appropriate and valid set of timing requirements for a real-time system. In fact, any failures can lead to dangerous behaviour. Over the years, several researches [20] [21] on real-time systems have proposed techniques which provide greater scheduling flexibility and providing a means for guaranteeing the timing requirements. In the development of a system for flight control it is necessary to realize a suitable environment, based on appropriate technologies, in order to ensure the timely

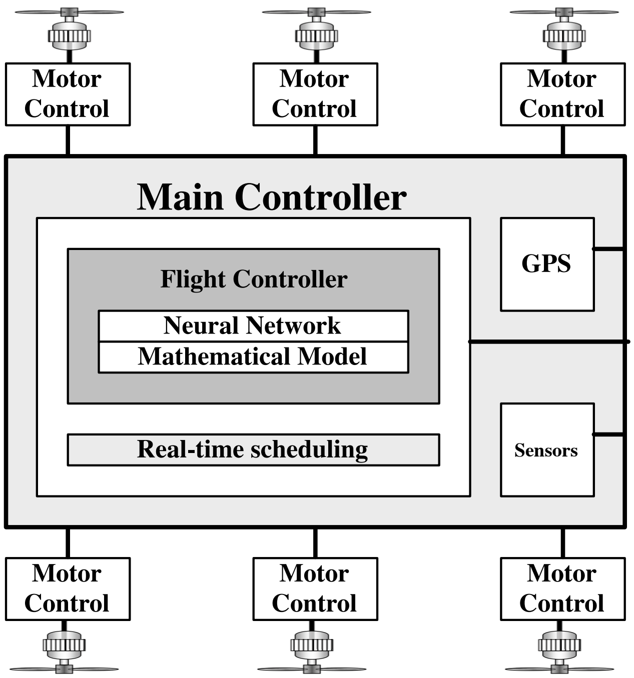

Figure 2. System Architecture

processing of information. This environment must guarantee several requirements including:

- real-time communication;
- real-time scheduling of tasks;
- performance predictability;
- prevention and reaction to critical situations.

In the design of a flight control system several constraints must be taken into account, such as light weight, small size, low energy consumption, small memory usage, and sufficient computational power for performing real-time navigation and sensory processing. The proposed real-time embedded system is characterized by an architecture shown in Figure 2. The main objective is to control the flight of an UAV, specifically the chosen UAV is a hexacopter. The control of the hexacopter can be realized on the basis of on-board measurements that are performed by sensors placed on the vehicle. An efficient, accurate and inexpensive solution for measuring the state of the hexacopter can be based upon MEMS-based inertial sensors including accelerometers and angular rate sensors (gyroscopes). Moreover, in order to have absolute position measurements, a positioning system is needed. In outdoor environments the GPS system is suitable to determine absolute position and it is possible to combine these positions with the inertial measurements in order to avoid problems arisen from the sparse time-scale and availability of GPS. The sensory acquisition is performed by the on-board system architecture that uses such data to trigger the motors for speed and direction control during autonomous flight.

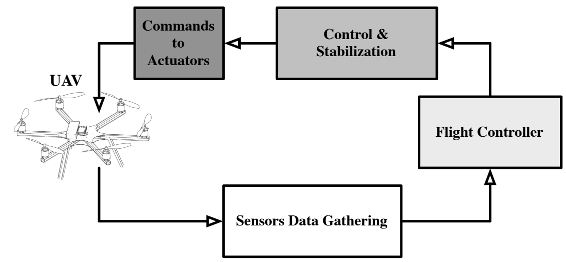

Figure 3. Block diagram of the flight control application

In this paper a real test-bed scenario has been deployed in order to validate the proposed flight controller. The used processing unit is the Microchip PIC24FJ256GB108 micro-controller [22], which integrates the control features of a Micro-Controller Unit (MCU) with the processing and throughput capabilities of a Digital Signal Processor (DSP). It is a 16-bit micro-controller ideal for low power (<100nA standby current) and connectivity applications that benefit from the availability of multiple serial ports and ¡independent timers. Moreover, it is suitable for embedded control and monitoring applications due to large amounts of RAM (16kB) memory for buffering and large (up to 256kB) Enhanced Flash program memory. The proposed approach has not been implemented on a real hexacopter but has been tested on the prototyping board just described. Whereby, both the sensing and the GPS modules have not been implemented and so used. Their description has been carried out in order to show, in a complete way, the system architecture of the hexacopter.

A. *Flight Controller*

In Figure 3, the proposed flight control application is depicted. It runs on the micro-controller and consists of a closed loop where the information captured by on-board sensors is used to control the UAV direction and orientation. Referring to the block diagram of the flight control application shown in Figure 3, the Sensor Data Gathering block is responsible for collecting data from sensors, the Control & Stabilization block stabilizes the UAV and controls its direction/speed, while the Commands to Actuators block drives the actuators. The major innovation proposed in this paper is represented by the Flight Controller block. In fact, it allows to manage the flight of UAV with a Neural Network. In the deployed test-bed scenario, the micro-controller takes the input values of the NN in the programming phase while the output values are both shown through an LCD display connected to the processing unit and sent to a computer through a programming cable. In section IV and section VI details on the mathematical modelling of the hexacopter and on the NN are presented.

B. *Real-time scheduling*

In modern control systems, the control algorithm is normally implemented with several periodic/aperiodic tasks performing activities such as sensory sampling, control signal calculation, state updating, and actuation. The period of periodic tasks is typically derived in accordance with the traditional discrete-time control theory, which analyzes the system behaviour and guarantees stability based on the periodicity assumption. In order to realize the autonomous flight behaviour of an UAV, an appropriate control system, based on hardware and software components, must be developed. In this system, the tasks running on the micro-controller are subject to stringent timing constraints [23], which must be enforced by the operating system in order to guarantee the desired performance level. Several real-time constraints, such as deadlines, response times, activation periods, input-output delays and jitter, must be met. The timing behaviour of the application strictly depends on task scheduling, interrupt handling, synchronization protocols, and resource management algorithms. For this reason, the application performance are closely linked to the operating system.

At present, several real-time operating systems are available in the market [24], however only few of them are suitable for small embedded micro-controllers with limited processing resources. The ERIKA (Embedded Real tIme Kernel Architecture) Enterprise real-time operating system [25] is specifically designed for minimal embedded systems with limited on-board resources. For this reason, the real-time scheduling module, proposed in this work, is based on ERIKA Enterprise real-time kernel because it is configurable both in terms of services and kernel objects (tasks, resources, and events) and supports advanced scheduling mechanisms, as for example the Earliest Deadline First (EDF) [26] algorithm.

The flight control application consists of three grouped concurrent tasks (hard real-time, soft real-time and non-real-time) and these run concurrently and are managed through the EDF algorithm. The deadline of the hard real-time tasks should be guaranteed explicitly in order to prevent any critical situation. During scheduling, real-time tasks have higher priority than other tasks. For example, flight control tasks have the highest priority since they are labelled as hard real-time. On the contrary, during flight, a set of periodic real-time tasks is used to monitor the UAV position and direction. The period of these tasks is related to the sensor sampling rate. Finally, the non-real time tasks are executed after the completion of real time tasks.

IV. Dynamical Model

In this paper a hexacopter is taken into account. This UAV is an aircraft with supporting structure equipped of six electric motor located on the vertices of the hexagon shaped structure. The dynamical model, described ignoring aerodynamic effects and starting from Newton-Euler equations of motion, yield the following system of the airframe:

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

$$\mathbf{I}\,\dot{\boldsymbol{\nu}} + \boldsymbol{\nu} \times (\mathbf{I}\,\boldsymbol{\nu}) + \boldsymbol{\Gamma} = \boldsymbol{\tau}_B \tag{2}$$

$$\ddot{\mathbf{q}} = \frac{d}{d\,t}(\mathbf{S}\,\boldsymbol{\nu}) \tag{3}$$

Table I
Constants used for the PID controller.

i	$\mathbf{K_{i,P}}$	$\mathbf{K_{i,I}}$	$\mathbf{K_{d,I}}$
x	0.23	0.0255	1.6
y	0.7	0.09	4
z	10	10	5

in which m is the mass, $\mathbf{F_g}$ and $\mathbf{T_B}$ are the gravitational force and the total thrust respectively, $\mathbf{Q}$ the orthogonal transformation matrix from the body frame to the inertial one, $\boldsymbol{\nu}$ is the angular velocity, $\boldsymbol{\Gamma}$ represents the gyroscopic effects $\boldsymbol{\tau}_B$ the external torque, $\mathbf{S}$ is the velocity transformation matrix, $\mathbf{I}$ is the diagonal inertia matrix. All the parameters and variables involved in the dynamical system are defined as in [27].

The state variable are the UAV position with respect to the inertial frame $\boldsymbol{\xi} = (x\ ,y\ ,z\ )$ and the UAV orientation described by means of quaternion formalism $\boldsymbol{q} = (q_0\ ,q_1\ ,q_2\ ,q_3\ )$, whose component satisfies the normality condition $\sum_{i=0}^{3} q_i^2 = 1$, [28].

V. PID controller scheme

The Proportional - Integral - Derivative , commonly abbreviated as PID , is a negative feedback system widely used in control strategy. This is a very versatile technique because the response to the error can be modified. The controller acquires some data as input by a process and compares them with reference or target values. The difference between acquired and target quantity, known as error, is then used to compute the output variable of the controller.

The PID adjusts the output based on the value of the error signal (proportional gain), the past values of the error (integral gain), and the rate of change of the error (proportional gain). The general scheme of a PID controller is:

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

where $u(t)$ is the generated signal through PID and $e(t) = x_d(t) - x(t)$ is the error, while K_P, K_I, K_D represent the *proportional*, *integrative* and *derivative* constants, tuned experimentally, [29]. In the present work, the controller is applied to attitude and orientation in order to compute the angular velocity of the six rotors and to reach the desired position and the optimal values of PID parameters are chosen as in I

The PID controller associated to the dynamical system is often sufficient for trajectory control, but contains an intrinsic limit as the inability of changing the parameters of the process. For this reason, in this paper an adaptive control technique is presented.

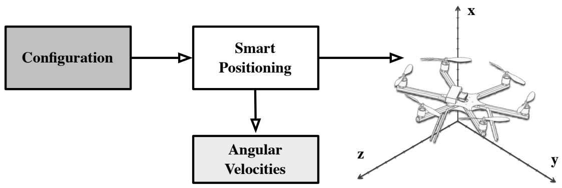

Figure 4. Controller procedures of the Neural Network

VI. Neural Network Model

The proposed approach is based on a Neural Network in order to manage the flight of a hexacopter. The NN is implemented on a micro-controller [22] whose control application is developed on top of the ERIKA Enterprise real-time kernel [25]. The controller procedures characterizing the proposed NN are shown in Figure 4 and they are:

- Configuration: the controller of the Neural Network takes as input several configuration, in order to initialize the smart positioning process and the mathematical processing (tables that contain angular velocities, positions and quaternions);
- Smart Positioning: the controller trains a Non Linear Autoregressive with External Input (NARX) NN component by using the information from Configuration block.

Taking as input the estimated coordinates (x, y, z) of hexacopter the NN controller evaluates the angular velocities $(\omega_1, \omega_2, \omega_3, \omega_4, \omega_5, \omega_6)$. The results obtained with the Neural Network are stored in a database in order to increase performance. Moreover, the proposed NN differs from the one proposed in [13] because the inputs and outputs of the neural network are different. In fact, the NN used in [13] takes the quaternions as input and give the coordinates of the UAV as output through Matlab simulations. On the contrary, in the approach proposed in this work the NN takes the estimated coordinates as input and evaluates the angular velocities as output. Moreover, it is implemented in a prototyping board. These characteristics represent the novelty of our approach compared to other in the literature. The predictor associated with the proposed NARX model, proposed in this work, is presented as following [30]:

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

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 NN 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 NN is composed by 10 hidden neurons (trained using the Levenberg-Marquardt algorithm [31] [32]), number of delays equal to 2 and it uses a symmetric sigmoid transfer function. The Neural Network is created and trained in open loop form so that it is supplied with correct past outputs during training in order to produce the correct current outputs.

Table II
Error measures used to assess the forecasting performance of the NARX model

Error measure	Formula
MSE	$mean(e_i^2)$
$RMSE$	$\sqrt{MSE}$
MAE	$mean(\|e_i\|)$
$MdAE$	$median(\|e_i\|)$
$MASE$	$mean(\|b_i\|)$
$MAPE$	$mean(\|p_i\|)$
$MdAPE$	$median(\|p_i\|)$
$NMAPE$	$\frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\|Y_i-\hat{Y}_i\|}{max_{i=1}^{N_t}(Y_i)}$
$sMAPE$	$\frac{1}{N_t}\sum_{i=1}^{N_t}\frac{\|Y_i-\hat{Y}_i\|}{(\|Y_i\|+\|\hat{Y}_i\|)/2}$
R_0	$\frac{1}{N_t\sigma_{pred}\sigma_{test}}\sum_{i=1}^{N_t}(\hat{Y}_i-\bar{\hat{Y}})(Y_i-\bar{Y})$

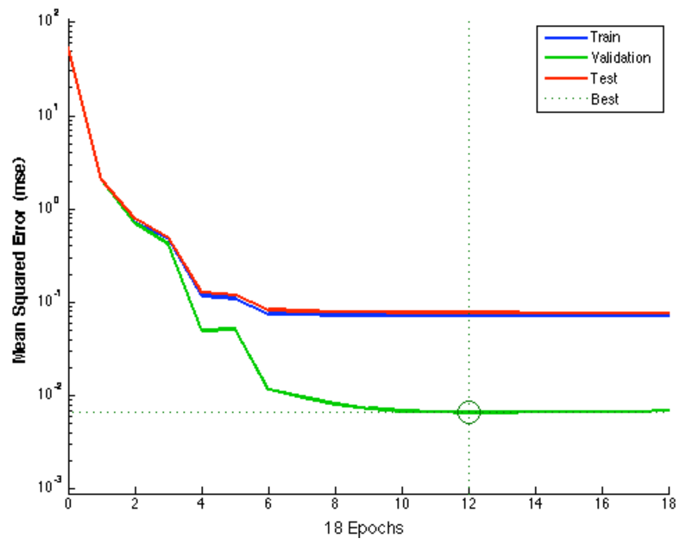

Figure 5. Best validation performance (MSE) of the Neural Network

VII. Neural Network Performance

A real test-bed scenario has been deployed in order to prove the validity of the proposed approach. The coordinates, representing the inputs of the Neural Network, refer to a hexagonal path at fixed altitude ($z = 1$). In details, the way points are

$$(1,0,1), (2,0,1), (2.5,1,1),$$
$$(2,2,1), (1,2,1), (0.5,1,1), (1,0,1)$$

In order to calculate and plot the performance of the NN, the micro-controller continuously sends the output data to a computer through a serial cable. To guarantee good generalization performance to the model and prevent the risk of over-fitting the training data the early stopping technique has been used. In fact, the entire dataset available 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 Mean Sqared Error (MSE), and updating the network weights. The training is stopped when the validation error increases for a specified number of iterations, and the network's weights at the minimum of the validation error are returned. In the used NARX model 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. It is useful to note that the training set of the data should be greater than 50% in order to achieve good results. The performance of the NN has been validated using the following error measures:

- Mean Squared Error (MSE);
- Root Square Mean Error ($RMSE$);
- Mean Absolute Error (MAE);
- Median Absolute Error ($MdAE$);
- Mean Absolute Scaled Error ($MASE$);
- Mean Absolute Percentage Error ($MAPE$);
- Normalized Mean Absolute Percentage Error ($NMAPE$);
- Median Absolute Percentage Error ($MdAPE$);
- Symmetric Mean Absolute Percentage Error ($sMAPE$);
- Determination Coefficient (R_0).

The formulas of the errors are shown in Table II, where Y_i is the value of the i-th actual observation, $\hat{Y}_i$ is its forecasted value, σ_{pred} is the standard deviation of the predictions obtained on the test set data and σ_{test} is the standard deviation of the test set data. 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:

$$b_i = \frac{e_i}{\frac{1}{N_{t-1}} \sum_{i=2}^{N_t} |Y_i - \hat{Y}_i|} \tag{8}$$

The validation performance and the training state of the NN are depicted in Figure 5 and Figure 6, where mu is the Marquardt adjustment parameter [31] [32] and $valfail$ represents the number of iterations for which the validation error continuously increased after the last decrease. Lower values of MSE are better while zero means no error. The Figure 5 highlights that the best validation performance (lowest MSE value, that is 0.007) is obtained at epoch 12 while the Figure 6 shows that the NN reaches six validation checks at epoch 18. So, in these 18 epochs, the neural network get the best results in the epoch 12. Moreover, the results obtained with the NARX model on the test set data are shown in Table III and it is clear that errors values are considerably lower and this means excellent performance of the Neural Network.

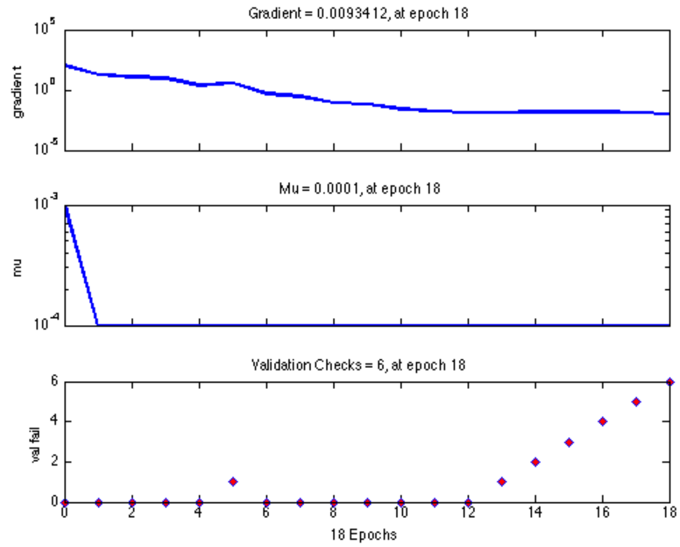

Figure 6. Training state of the Neural Network

Table III
PERFORMANCE MEASURES (TRAINING EPOCHS = 18)

Error measure	Value
MSE	0.007
$RMSE$	0.084
MAE	0.006
$MdAE$	0.071
$MASE$	0.003
$MAPE$	0.095
$MdAPE$	0.082
$NMAPE$	0.079
$sMAPE$	0.067
R_0	0.034

An additional test to prove the validity of the NN controller is to use the results obtained through the NN in the dynamical system directly. In details, the NN produces the angular velocities of the six rotors after the training phase; these angular velocities are passed as input to the system (1)-(3) and then positions x, y, z are compared with the trajectory obtained though the PID controller. In Figure 7 this comparison is depicted, in which it is possible to deduce the reached target positions. The figure emphasizes the good agreement between the target hexagon position and the (x, y, z) coordinates obtained by through the PID and the NN controllers. According to obtained results, it is clear that the on-line adaptability of the NN can be used to design real-time control laws in order to handle uncertainties and non-linearity in system and environment dynamics rather than a PID controller.

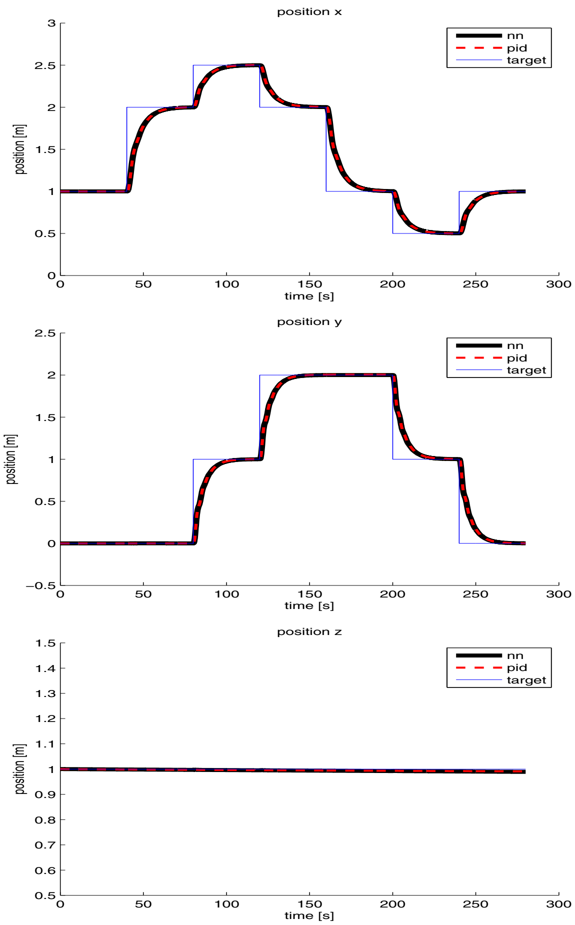

Figure 7. x, y, z components of target position and the obtained ones through the NN and the PID

VIII. Conclusions

In this paper a novel real-time system for flight control, based on a Neural Network model, has been presented to develop proper methods for stabilization and trajectory control of a hexacopter. The rapid response of the NN and the high quality of data approximation have been shown. Experimental results, obtained through a prototyping board, are very promising in terms of error measures and reconstruction of the hexacopter dynamics through its angular velocities. Moreover, the output of the NN have been compared with a PID controller and results show that there is a good agreement between the controllers.

In the next step the proposed approach must be improved in terms of neural network optimization. And also future works are related to the use of the trained NN in order to compute proper angular velocities to reach different desired trajectories under a specific orientation.

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Answer to reviewers on the paper

An adaptive trajectory control for UAV using a real-time architecture
by Valeria Artale, Mario Collotta, Cristina Milazzo, Giovanni Pau, Angela Ricciardello submitted to ICUAS 14.

We are grateful to the Editor and the Reviewers for their precious suggestions that allowed us to improve the quality of our paper. According to received suggestions and comments, we properly modified the paper. In the following, we would like to emphasize the principal changes. We indicate in italics Reviewer's suggestions and in plain text our answers.

Reviewer 1

1. *TITLE should mention Multi-rotor UAV/helicopter rather than just UAV.*
The title can not be changed.
2. *Introduction section describes UAVs in too much detail; it should focus on the multi-rotor UAV instead. On page 1 most of the information described is well known by the UAV community.*
In the introduction we have tried to provide an overview of the main characteristics of the UAV. Following the suggestion, the introduction has been streamlined.
3. *Please provide a picture/diagram of hexacopter because it is of more interest and also check its spelling.*
An illustrative and schematic figure of the hexacopter has been inserted.
4. *You mentioned that it's a novel flight control technique; it's helpful if you could highlight its novelty. Why it's different from the similar work done in the past.*
In the approach proposed in this work the NN takes the estimated coordinates as input and evaluates the angular velocities as output. Moreover, it is implemented in a prototyping board. These characteristics represent the novelty of our approach compared to other in the literature.

5a. *The non-linear control techniques used in the literature are complex to design or complex to implement?*
They are complex both to design and to implement.

5b. *Can you provide an example of how NN have been used to handle uncertainties and non-linearity? Why traditional controls have failed to do so?*
Two literature works have been reported in the paper.

5c. *A reference is given to [13] that describe an NN controller. Can you please describe in more detail and also how your technique is different from the one described in the literature.*
The proposed NN differs from the one proposed in [13] because the inputs and outputs of the neural network are different. In fact, the NN used in [13] takes the quaternions as input and give the coordinates of the UAV as output through Matlab simulations. On the contrary, in the approach proposed in this work the NN takes the estimated coordinates as input and evaluates the angular velocities as output.

5d. *What is adaptive back-stepping?*
It is an adaptive feedback control law of the aircraft?s state.

5e. *How effective is your control strategy in comparison with an RBF controller [16].*
It would be useful to make a comparison between the approach proposed in [16] and the one proposed in this work. But, although the two approaches refer to a PID and to a neural network, they have different aims. Therefore, they can not be compared directly.

6. *No description of hexacopter properties? Its dimensions, weight, size, drag coefficient etc.*
The proposed approach has not been implemented on a real hexacopter but has been tested on a prototyping board.
7. *The validation, performance and the training state of the NN are depicted in Figure 4 and 5 but the figures are not clear and also they are not explained in a sufficient detail. For example it's says mu is the Marquardt adjustment parameter but it does not tell what it is and how these values are obtained.*
The results depicted in the Figures have been discussed in more depth.
8. *Sensor noise: No information provided on sensor noise of GPS and MEMS based sensors. How much GPS lag was encountered and how were the timing issues resolved?*
Both the sensing and the GPS modules have not been implemented and so used. Their description has been carried out in order to show, in a complete way, the system architecture of the hexacopter.
9. *No mention of test trajectories that have been used? How many different scenarios were used?*
The coordinates, representing the inputs of the Neural Network, refer to a hexagonal path at fixed altitude ($z = 1$). In details, the way points are
$$(1,0,1),(2,0,1),(2.5,1,1),$$
$$(2,2,1),(1,2,1),(0.5,1,1),(1,0,1)$$
10. *Figure 6 compares the performance of the NN and a PID controller. However I cannot see the PID tracking performance of the plots. All I see is dark lines and a blue dashed line representing NN. Again it will be helpful to describe the trajectory that has been used for testing purpose. This Figure only shows the results of one of the test scenarios and what about the outcomes of other tests?*
Figure 6 has been modified by making more visible the trajectories obtained by means of PID. From the Figure 6 it is possible to deduce the target points reached by the hexacopter through NN and PID controllers.

11. *How large diversity of training is required for NN to produce good results?*
    It is useful to note that the training set of the data should be greater than 50% in order to achieve good results.
12. *What are key benefits of using NN in comparison with a PID controller? Can you quantify the improvements achieved in the performance?*
14. *In conclusion it says there is a good agreement between the two controllers but then where is the advantage of using this particular technique?*
    Answer to questions 12 and 14: according to obtained results, it is clear that the on-line adaptability of the NN can be used to design real-time control laws in order to handle uncertainties and non-linearity in system and environment dynamics rather than a PID controller.
13. *Not sure what the novelty of this technique is? It's not been communicated clearly. Need to clearly identify what makes this technique novel as many other researcher have used similar techniques as described in the paper.*
    The proposed NN differs from other proposed in the literature because takes the estimated coordinates as input and evaluates the angular velocities of the UAV as output. Moreover, it is implemented in a prototyping board. These characteristics represent the novelty of our approach compared to other in the literature.

Reviewer 3

1a. *It is stated that "The major innovation proposed in this paper is represented by the Flight Controller block." However, there are no any details in the paper concern with the structure or parameters of discussed Flight Controller that is based on a Neural Network.*
    The proposed approach is based on a Neural Network in order to manage the flight of a hexacopter. Regarding to the flight control, the parameters taken into account are the angular velocities of the UAV and the estimated coordinates. In fact, in the proposed approach, taking as input the estimated coordinates of hexacopter the NN controller evaluates the angular velocities. In future work we will use other parameters, such as the quaternions and the GPS coordinates.
1b. *Dependence of structure and parameters of Flight Controller on structure and parameters of the mathematical model given by equations (1)-(3) does not disclosed.*
    This dependence can be seen in the definition of the error $e(t) = x_d(t) - x(t)$ in the PID controller, in which $x(t)$ is solution of the dynamical system.
2a. *The parameters of the mathematical model given by equations (1)-(3) are not defined in the paper.*
    The set of variables that are available for measurement are not defined in the paper as well.
    All the parameters and variables involved in the dynamical system are defined as in [27].
3. *There are no any details in the paper concern with the structure or parameters of PID Controller.*
    Dependence of structure and parameters of PID Controller on structure and parameters of the mathematical model given by equations (1)-(3) does not disclosed.
    What is the way to the tuning of PID Controller?
    What are the values of PID Controller parameters during computer simulations?
    The parameters have been introduced in the paper in section V.
4. *The simulation results on Figure 6 can not be verified by reason of lack of any data about the actual parameters in (1)-(3) as well as due to lack of data about the actual parameters Flight Controller and PID Controller.*
    Data about parameters and trajectory have been presented in details in sections IV, V and VII. Figure has been modified by making more visible the trajectories obtained by means of PID. From the Figure it is possible to deduce the target points reached by the hexacopter through NN and PID controllers.

Reviewer 4

1. *a NN should be an NN*
2. *"In [14] is presented an approach.." should be "In [14], an approach is presented.."*
3. *"The analysis presented by authors want.." should be "The analysis presented by authors wants .."*
4. *"performances" is better written as "performance"*

5. *In statistics, "Coefficient of correlation" is in fact the "determination coefficient"*

All typos have been corrected as suggested.