Learning Helicopter Model Through “Examples”

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Abstract: **-** In this paper, a neuro-fuzzy system identification using measured input and output data are carried out. A model-free learning from “examples” methodology is developed to train a neuro-fuzzy model of a small-size helicopter. The helicopter model is obtained and tuned using training data gathered while a teacher operates the helicopter. Behavior-based model architecture is used, with each behavior implemented as a hybrid neuro-fuzzy model. The neural network structure learns the parameters of the fuzzy membership functions and finally the fuzzy-based model works alone. The neuro-fuzzy architecture and the helicopter hardware system used to measure the sensors and command data are also described. The methodology has been successfully applied in the behavior-based model of a radio control model helicopter. The identified behavior model can be used in the position control also based on the neuro-fuzzy theory.

Key-Words: **-** neuro-fuzzy modeling, learning from examples, helicopter, behavior-based model, avionics box.

1 Introduction

Recently, unmanned helicopters have been expected in the observation field namely for fire detection, rescuing and aerial photograph. For these monotonous or dangerous tasks, an autonomous flight control of the helicopter offers a major advantage over the airplane. With a suitable combination of sensors, the helicopter can move to a GPS waypoint and hover there for a long period of time, while an airplane must continue to fly in a pattern around the waypoint avoiding any obstacles that may be presented. However, the flight control of the helicopter involves some difficulties [1], and constant corrective control inputs are necessary to maintain a stable desired flight path. The use of an aerial robot in your work is motivated by challenges and opportunities associated with the autonomous control of an unmanned helicopter.

Helicopter characteristics makes difficult to automate the helicopters behavior and control with the conventional theory. For example, the helicopter environmental sensibility and with the increasing system complexity, a completely and accurately mathematical model becomes more difficult. An additional problem, common to both model-based and model-free behavior and control approaches, is related with the system parameters that can be time-varying. If these parameters are ignored the system behavior-based model or control may present inaccuracies and instabilities [2].

To control this system, it is not needed to explicitly model it. Through interaction with the system and observation of its movements, a human is able to learn his behavior and how to control it during its operation. In your approach, the helicopter behavior-based model is generated using training data gathered while a human teacher controls the aerial vehicle. A basic assumption of your approach is that we have access to a human capable of controlling the system movements for which we want to produce a behavior-based model.

Several unmanned helicopters have been developed [3-4], or are under development throughout the world. However, a complete autonomous flight control system has not yet been realized.

The goal of the research is to design an autonomous flight control system of a small-scale unmanned helicopter. The authors carry out the system identification experiments of the small-scale helicopter to derive the behavior-based model using a supervised neuro-fuzzy algorithm. It was developed an avionics box and a terrain data acquisition system to measure the input and output data of the helicopter dynamics. The identified behavior model will be used in the position control also based on the neuro-fuzzy theory for the autonomous flight.

2 Behavior-Based Model

The proposed behavior-based model architecture, converts this modeling problem into a set of coupled computing modules (behaviors). Each behavior is responsible for a specific task and they act in parallel to achieve a specific helicopter motion. Figure 1 shows the behavior-based architecture adapted from our work.

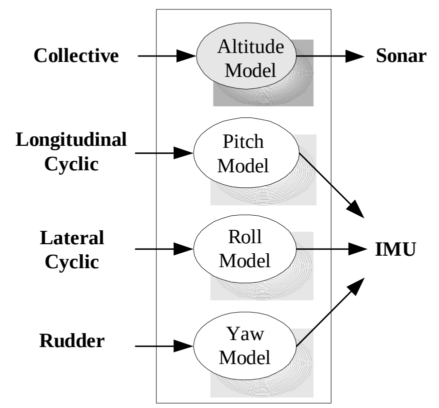

Fig. 1 Behavior-Based Helicopter Model.

To model the helicopter behavior, a neuro-fuzzy model with a hybrid learning algorithm is used [5]. This hybrid learning algorithm is composed by the Levenberg-Marquardt algorithm and with the Least Squares Estimate. In the described method, the neuro-fuzzy system learns off-line with the training data set derived from the helicopter behavior. After the neuro-fuzzy model is trained, his architecture is simplified reducing the number of rules.

The altitude model use the collective command input to control the collective pitch angle of the main rotor blades and the thrust.

2.1 Neuro-fuzzy architecture

Figure 2 shows the six-layered architecture for the neural network based fuzzy inference model. This connectionist structure performs the fuzzy inference with some minor restrictions. For the altitude model there are 2 nodes in layer 1 representing the collective pitch and the throttle input commands and $2.B$ nodes in layer 2 corresponding to the number of linguistic terms used in the universes of discourses of the two input variables. In the layers 3 and 4 there are I nodes each one that corresponds to the number of inference rules. There are two nodes in layer 5 and only one node in layer 6 that corresponds to the output layer.

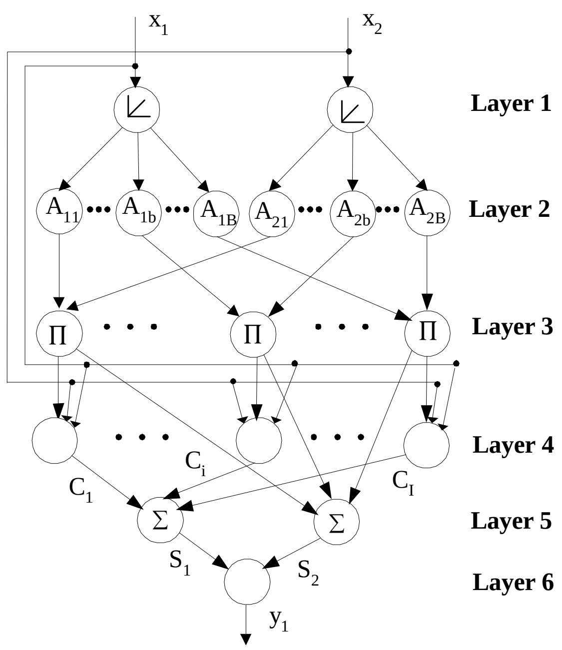

Fig. 2 Neuro-Fuzzy Architecture.

The first layer, the input layer, consists in the input of the data values derived from the two input variables. The layer 2 contains the membership functions associated to each universe of discourse. Each membership functions correspond to a linguistic term. The antecedent and consequent parts of each inference rule is represented in the layer 3 and 4, respectively. The number of nodes in this layers is the same as the number of rules in the fuzzy inference system.

The output of each node in the layer 3, $T_i(x_n)$ is given by the following equation:

$$T_i = \prod_{n=1}^{2} LX_{ni}(x_n) \tag{1}$$

where the firing strength of i^{th} rule is obtained by taking the product of the membership functions, LX_{ni}, in the antecedent parts.

To increase the degrees of freedom in the learning stage it is used a membership function with a varying shape where the corresponding parameters of the position of the function in the universe of discourse, c_{ni}, of the membership function shape, l_{ni}, and his left and right bandwidths, eq_{ni} and dr_{ni}, are tuned using the Levenberg-Marquardt algorithm [6]. With this type of membership function definition the shape of the functions can be asymmetric with respect to his center.

The output of each node in the layer 4, C_i is given by the following equation:

$$C_i = T_i \,.\, f_i = T_i \,.\, (p_i \,.\, x_1 + q_i \,.\, x_2 + k_i), \tag{2}$$

where f_i corresponds to the first order Sugeno model [7]. The parameters $\{p_i, q_i, k_i\}$, $i = 1, \cdots, I$ are tuned using the Least Square Estimate algorithm.

In the layer 5 are two different summation nodes. The first node, S_1, sums the activation of each rule and is given by (3). The other node, sums the activation of each antecedent part given by (4).

$$S_1 = \sum_{i=1}^{I} C_i. \tag{3}$$

$$S_2 = \sum_{i=1}^{I} T_i. \tag{4}$$

The output layer, layer 6, consists in a division of the signal provided by the nodes in the antecedent layer (5).

$$y = \frac{\left(\sum_{i=1}^{I} \left(\prod_{n=1}^{2} LX_{ni}(x_n) \right) . f_i \right)}{\sum_{i=1}^{I} \left(\prod_{n=1}^{2} LX_{ni}(x_n) \right)}. \tag{5}$$

This network architecture is functionally equivalent to a type-3 fuzzy inference system (Takagi and Sugeno fuzzy if-then rules).

The initial identification structure of the neuro-fuzzy model is obtained using the an iterative grid partition method that define the number of membership functions for the universe of discourse of the input variables [8]. This method also defines the position of each function in the input space, the type of function (triangular, bell-shape, …, etc.), and the left and right bandwidths.

2.2 Learning algorithms

In the learning stage of the neuro-fuzzy model it is applied a hybrid algorithm based on the Levenberg-Marquardt and Least Square estimate algorithms. The antecedent parameters, $\{c_{ni}, l_{ni}, eq_{ni}, dr_{ni}\}$, are tuned by the Levenberg-Marquardt algorithm while the consequent parameters, $\{p_i, q_i, k_i\}$, are tuned by the Least Square estimate algorithm.

The least square estimate of the set of consequent parameters used the recursive formulas widely adopted in the literature [9] and make the algorithm more efficient.

Table 1 summarizes the activities in each pass of the hybrid-learning algorithm. Each epoch of the hybrid learning procedure is composed of a forward pass and a backward pass.

	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	Levenberg-Marquardt
Consequent Parameters	Least Squares Estimate	Fixed

Table 1. Passes in the Hybrid Learning Procedure.

3 Helicopter Hardware System

This work was realized with the Kyosho Concept 60, a relatively inexpensive RC helicopter, as the platform for the unmanned flying vehicle (figure 3). The Concept 60 was powered by an O.S. 91 size nitro-methane fueled two stroke engine. The Concept 60 has a main rotor diameter of 1.80 meters.

It has four control inputs: rudder, lateral cyclic, longitudinal cyclic and collective. In the Concept 60 helicopter, throttle and the collective pitch are mixed into a single collective control. The first three inputs controlled yaw, roll and pitch of the helicopter while the single collective command controls the main rotor collective pitch and the throttle to vary engine RPM.

Fig. 3 Concept 60 helicopter.

For telemetered control of the helicopter, it is used a set of sensors to measure twelve state variables:

- gyroscopes and accelerometers for roll, pitch and yaw velocities ($\dot{\phi}, \dot{\theta}, \dot{\psi}$); and rectilinear accelerations ($\ddot{X}, \ddot{Y}, \ddot{Z}$).
- Global Positioning System (GPS) for horizontal position (X, Y); and rectilinear velocities ($\dot{X}, \dot{Y}, \dot{Z}$).
- sonar for the altitude (Z).

The GPS measures positions once every second. However, the sampling period of our control system is 140 milliseconds, so more frequently sampled position data is needed. As a result, the GPS output data was interpolated by integrating twice the sensor acceleration data to obtain position data every 70 milliseconds.

3.1 Avionics box

An avionics box that transmits the measured state variables of the helicopter to a ground station was designed. Figure 4 shows the on-board hardware inside the avionics box.

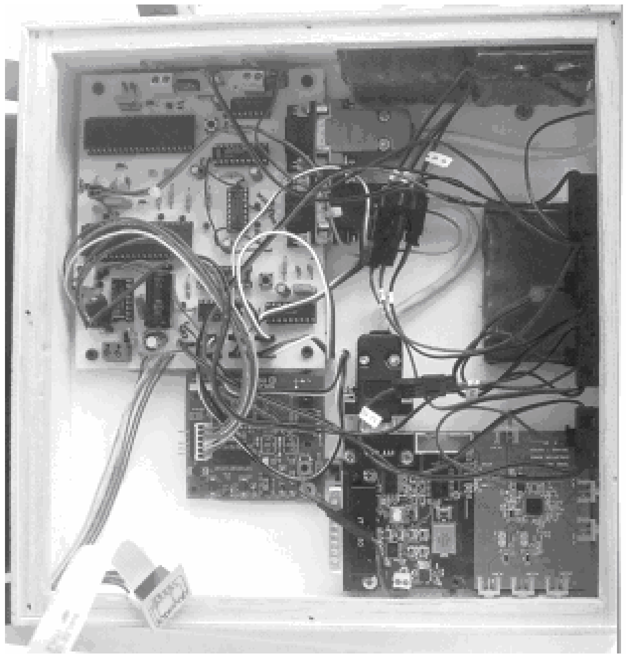

Fig. 4 Inside the avionics box.

It is equipped with a two-axial accelerometer board, a wireless board and a main board with a Microchip 18F458 microcontroller that receives the data from all sensors and sends them to the ground station via wireless link. The microcontroller run at 40MHz and communicates with the wireless board at 19200 baud serial link. The GPS, the three gyroscopes and the sonar are located outside the avionic box. The accelerometers and the gyroscopes form the inertial measurement unit (IMU) of the unmanned aerial vehicle.

3.2 Ground station

To model the helicopter behavior using examples it is needed to know the helicopter commands that corresponds to the measured helicopter state variables. Therefore, in the ground station was developed a terrain data acquisition system that receives the command data from the hand-held radio controller and transmits for a personal computer (PC). Figures 5 show the terrain data acquisition system. Figure 6 show the hand-held radio controller.

The terrain system is based on a 16F877 microcontroller running at 20MHz that reads radio controller commands and sends to a PC via serial link also at 19200 baud. In the ground station there also exist a wireless board that receives the data from the avionics box and sends them to the PC at same communication velocity described above.

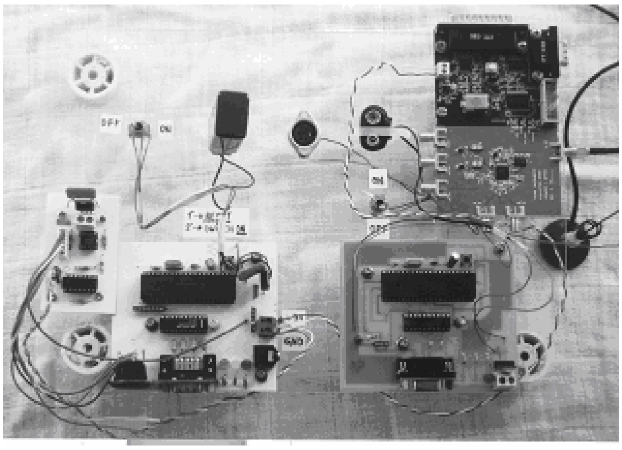

Fig. 5 Terrain data acquisition system.

Fig. 6 Helicopter radio controller.

Finally it is possible to obtain an example used to learning the neuro-fuzzy model of the helicopter.

3.3 Vibration isolation

Electronic circuits and sensors can be affected by harmful vibration from the engine and rotors. In particular, the IMU, GPS and the sonar altimeter are likely to produce faulty readings with inadequate vibration isolation.

The avionics box is supported by four elastomeric shock absorbers at its corners, which can be seen in figure 7 pointed by arrows.

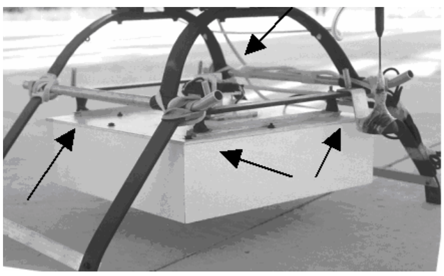

Fig. 7 Avionics box.

As the GPS is mounted beneath the helicopter engine it needs separate protection from harmful vibration. By using short pieces of rubber to connect the GPS to the helicopter, it should be effectively decoupled from the engine and main rotor vibrations.

4 Experimental Results

Experimental results were obtained and stored in a PC using the developed avionic box and the terrain data acquisition system. Figure 8 shows the avionic box and the GPS mounted in the helicopter and the ground station with the PC to receive the measured data. The different examples correspond to helicopter movements between different altitudes.

Fig. 8 Helicopter data acquisition system.

Each training data vector used in the learning process as four elements: three inputs and one output. One of those input elements is the previous helicopter height. Since a variation in the collective command changes the helicopter height then it is necessary to know the previous height to determine the current one. The training data vector is represented in (6).

$$\left\{ \delta_{cp}, \delta_t, w_{k-1}, w_k \right\}. \qquad (6)$$

The first vector element, δ_{cp}, corresponds to the main rotor collective pitch, δ_t and w_{k-1} are the throttle and the previous helicopter height, respectively. The actual helicopter height is denoted by w_k. In fact, the neuro-fuzzy-based altitude model has three inputs and one output. Figures 9 shows the first two command inputs applied to the altitude model. Figure 10 shows the actual output model and the desired output for the applied input commands.

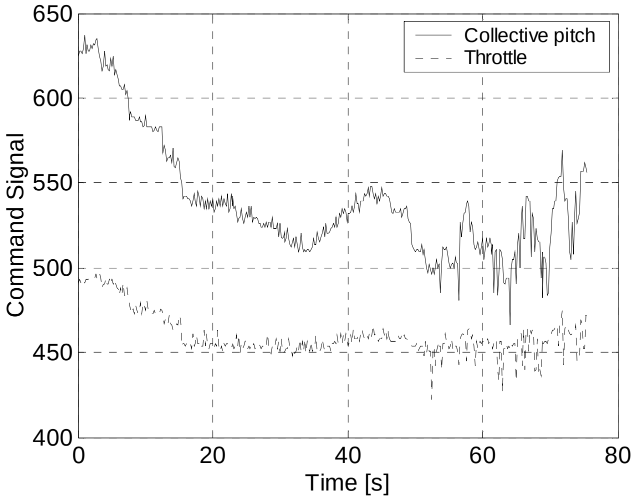

Fig. 9 Input command data.

As stated before, throw figure 9 it can be seen that the collective pitch and throttle commands have identical curves because they are mixed into a single collective control.

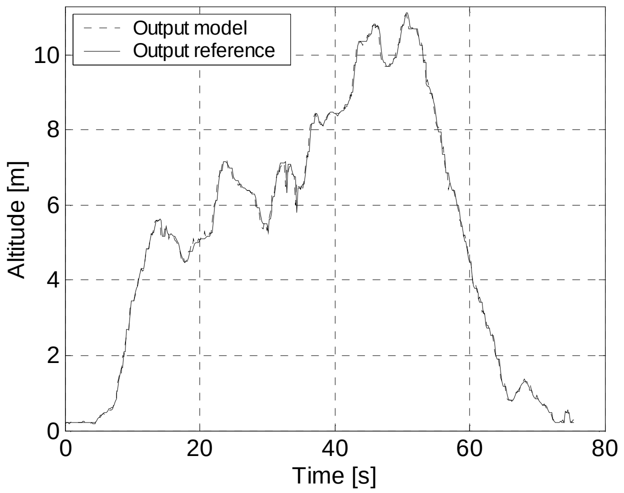

Fig. 10 Helicopter altitude model response.

The initial parameter identification of the altitude model is obtained using the iterative grid partition method described in [8].

The objective function used in the supervised learning process is the root mean square training errors that represents the difference between the output of the altitude model and the training data output at each epoch.

The altitude model has 3 membership functions for each input. Figures 11, 12 and 13 shows the input membership functions obtained after the learning stage. The output surface of the altitude model is represented in figure 14. The error of each training epoch is showed in figure 15.

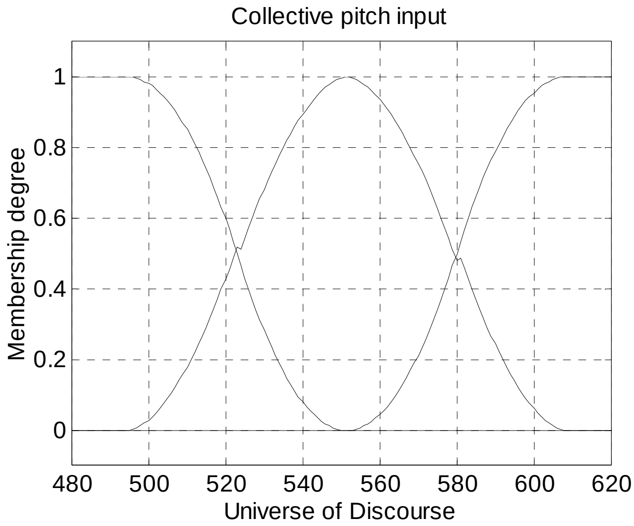

Fig. 11 Collective Pitch membership functions.

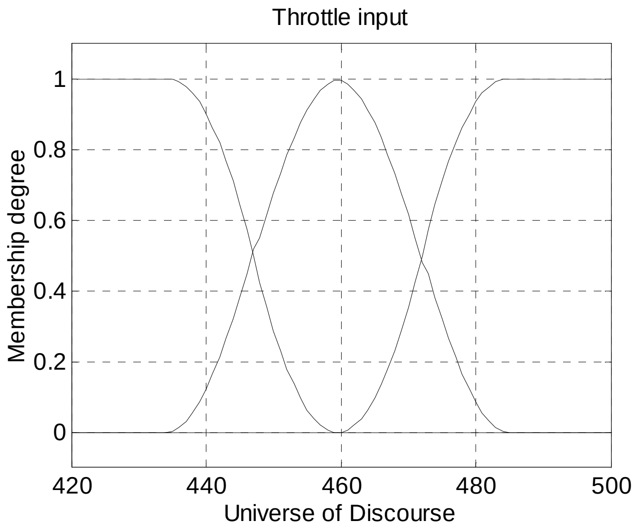

Fig. 12 Throttle membership functions.

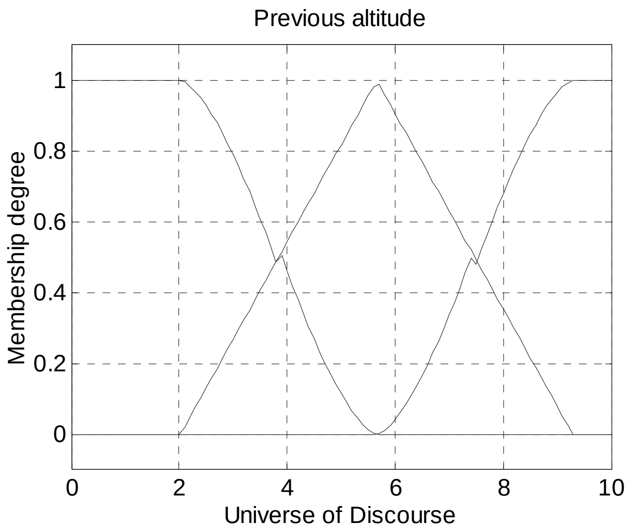

Fig. 13 Previous altitude membership functions.

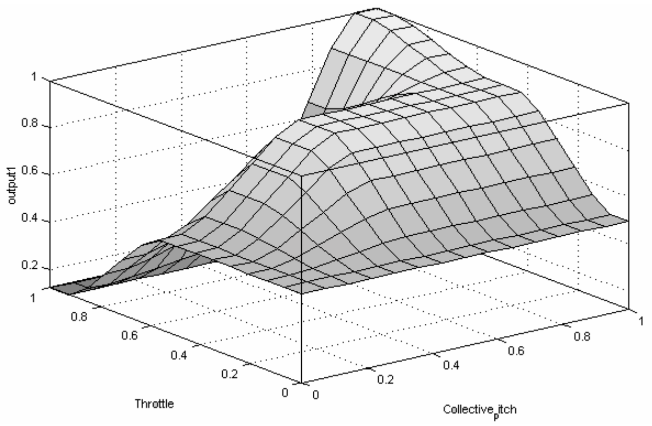

Fig. 14 Output surface of the altitude model.

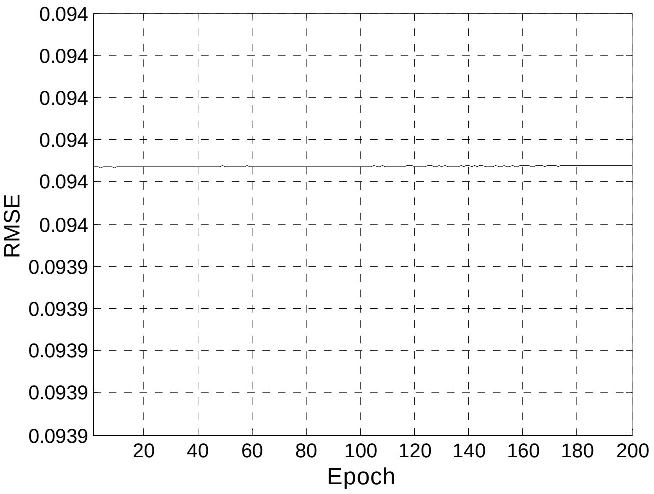

Fig. 15 RMSE using the proposed neuro-fuzzy architecture.

The results are compared with the ANFIS method implemented in the Matlab and developed by [10]. In the ANFIS method it was used 3 membership function for each of the three inputs with a generalized bell curve. The corresponding root mean square error is represented in figure 16. Comparing the RMSE obtained by the two methods it can be seen that the proposed neuro-fuzzy method has a better performance. For 200 epochs, the error between the output model and the desired output model was higher in the ANFIS method. The RMSE after 200 epochs are equal to 0.124 and 0.094 for the ANFIS and the proposed neuro-fuzzy architecture, respectively.

In figure 15, the initial RMSE value is small because the used structure identification method that permits to minimize the initial error in the learning stage.

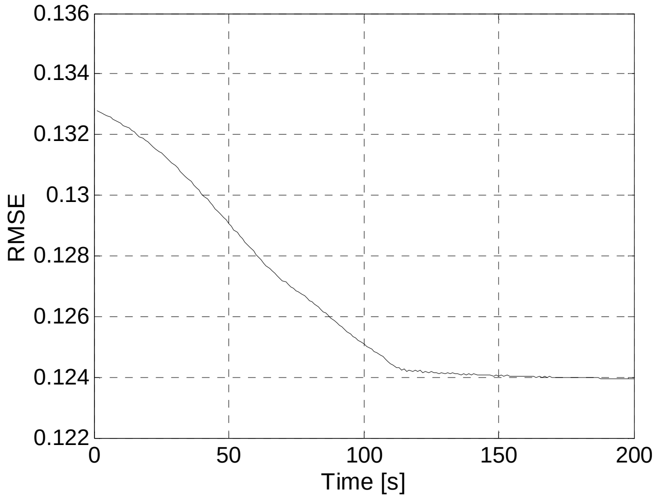

Fig. 16 RMSE using the ANFIS method.

5 Conclusion

In this paper was proposed a helicopter behavior-based model using a supervised neuro-fuzzy architecture. The training data was obtained throw the development of an avionics box and a terrain data acquisition system. Experimental results and comparisons with the ANFIS method show the effectiveness of the proposed method.

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