Hybrid Adaptive Control of a Dragonfly Model

Micael S. Couceiro*, N. M. Fonseca Ferreira**
J. A. Tenreiro Machado ***

**Institute of Systems and Robotics, University of Coimbra*
Pólo II, 3030-290 Coimbra, Portugal
(e-mail: micaelcouceiro@isr.uc.pt)
***Department of Electrical Engineering, Institute of Engineering of Coimbra*
Rua Pedro Nunes, 3031-601 Coimbra, Portugal
(e-mail: nunomig@isec.pt)
****Institute of Engineering of Porto*
Rua Dr. António Bernardino de Almeida, 4200-072 Porto, Portugal
(e-mail: jtm@isep.ipp.pt)

Abstract: Dragonflies demonstrate unique and superior flight performances than most of the other insect species and birds. They are equipped with two pairs of independently controlled wings granting an unmatchable flying performance and robustness.
In this paper, it is presented an adaptive scheme controlling a nonlinear model inspired in the dragonfly-like robot. It is proposed a hybrid adaptive (HA) law for adjusting the parameters analyzing the tracking error. The performance analysis proves the superiority of the HA law over the direct adaptive (DA) method in terms of faster and improved tracking and parameter convergence.

Keywords**:** control, robot, fuzzy, dragonfly, adaptive, hybrid.

1. INTRODUCTION

In the last few years, there were significant advances in robotics, artificial intelligence and other fields allowing the implementation of biologically inspired robots (Couceiro *et al.*, 2009a) (Bar-Cohen and Breazeal, 2003) having as one of the major challenges the controllability of those systems since they are nonlinear or even chaotic.

The study of dynamic models based on insects is becoming an area of active research and shows results that can be considered very close to the real systems (Schenato *et al.*, 2001) and (Wang, 2005). The dragonfly has been one of the systems under study (Tamai *et al.*, 2007) because it is considered one of the major challenges in the field of aerodynamics. Recent studies show that the aerodynamics of dragonflies is unstable because they use it to fly one way radically different from the steady flight of aircrafts and large birds (Kesel, 2000). The unsteady aerodynamics has not had proper attention due to the level of inherent complexity.

Fuzzy controllers (*FC*) are supposed to work in situations where there is a large uncertainty or unknown variation in plant parameters and structures (Wang, 1996). Fuzzy logic systems (*FLS*) provide nonlinear mappings from an input data vector space into a scalar output space, that are general enough to perform any nonlinear control or identification actions (Wang, 1993), for the control and identification of linear and nonlinear systems. However, in order to maintain consistent performance, fuzzy controllers should be equipped with appropriate online adaptive algorithms to form adaptive fuzzy controllers. In (Wang, 1993) it was presented a "direct fuzzy controller" based on *FC* rules, and an "indirect fuzzy controller" based on fuzzy modeling rules. Generally, the basic objective of adaptive control is to maintain consistent performance of a system in the presence of uncertainties.

The controller considered in this paper is constructed from fuzzy modeling rules based on (Hojati *et al.*, 2002). For adjusting the parameters, the author proposed a hybrid adaptive scheme, combining adaptive fuzzy identification and adaptive fuzzy control. In the hybrid scheme, the adaptive algorithm utilizes a combination of two types of error for adjustment. We will apply and compare the performance analysis of the direct and the hybrid adaptive *FC* to control the nonlinear mathematical model based on the dragonfly dynamics implemented in *MatLab* / *Simulink* (Couceiro *et al.*, 2009b).

The paper is organized as follows. In the section two we present the adaptive *FC* implemented. Section three shows the architecture control of the dragonfly robot. In section four we compare the performance of both the direct adaptive and the hybrid adaptive *FC*. Finally, section five outlines the main conclusions in.

2. ADAPTIVE FUZZY CONTROL

PID methods are useful with linear processes but, in practice, most processes are nonlinear.

The basic configuration of an adaptive fuzzy control system is shown in Fig. 1. The Reference Model is used to specify the ideal response that the *FC* system should follow. The Plant is assumed to contain unknown components. The Fuzzy Controller is contrasted from fuzzy systems whose parameters θ are adjustable. The Adaptation Law adjusts the parameters θ online such that the plant output $y(t)$ tracks the reference model output $y_m(t)$.

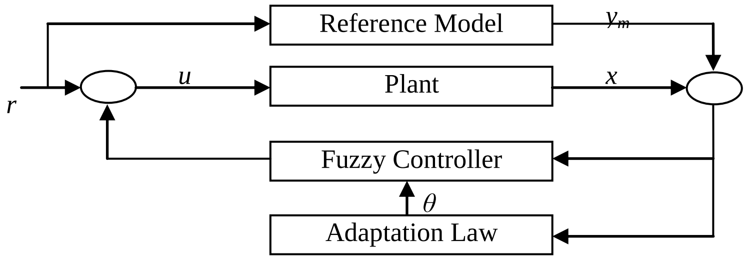

Fig. 1. Basic configuration of the adaptive fuzzy control system.

During real-time operation the adaptation law (*AL*) adjusts the *FC* parameters leading to a better performance. We can classify the adaptive *FC* into three categories (Wang, 1996): direct, indirect, and combined direct/indirect (hybrid) schemes.

One of the main approaches for constructing adaptive controllers is the self-tuning method (Astrom and Wittenmark, 1989) (Sastry and Bodson, 1989). In this strategy, first a design method (for known plants) is used to provide a controller structure and a relationship between plant and controller parameters. The plant parameters are estimated using an online parameter identification algorithm. The controller parameters are then obtained from the estimates of the plant parameters as if these were the true plant parameters. This idea is often called the certainty equivalence principle.

Consider the n^{th}-order nonlinear system of the controllability canonical form (Isidori, 1989):

$$\begin{cases} x^{(n)} = f\left(x, \dot{x}, \dots, x^{(n-1)}\right) + g\left(x, \dot{x}, \dots, x^{(n-1)}\right)u \\ y = x \end{cases} \tag{1}$$

where f and g are unknown real continuous functions, u and y are the input and output of the system, respectively, and $\bar{x} = \left(x, \dot{x}, \dots, x^{(n-1)}\right)^T$ is the state vector of the system which is assumed to be available for measurement. The controllability of (1) requires that $g(\bar{x}) \neq 0$ for all $\bar{x}$ in a certain controllability region $U_c \subset \Re^n$. The control objective is to find a feedback control law $u = u(\bar{x}, t)$ such that to make the state $\bar{x}(t)$ track a given desired bounded reference trajectory $\bar{y}_m(t) = \left(y_m, \dot{y}_m, \dots, y_m^{(n-1)}\right)^T$.

We assume the following collection of *If-Then* rules that describe the input-output behavior of *f(x)* and *g(x)*:

$$\begin{aligned} &If\ x_1\ is\ A_1^r\ and\ \dots\ and\ x_n\ is\ A_n^r\ , \\ &Then\ f(\bar{x})\ is\ C^r \end{aligned} \tag{2}$$

$$\begin{aligned} &If\ x_1\ is\ B_1^s\ and\ \dots\ and\ x_n\ is\ B_n^s\ , \\ &Then\ g(\bar{x})\ is\ D^s \end{aligned} \tag{3}$$

respectively, where A_i^r's and B_i^s's are fuzzy sets in $\Re$, C^r and D^s are fuzzy sets in $\Re$ which achieve membership value one at some point, $r = 1,2, \dots, N_f$, and $s = 1,2, \dots, N_g$.

If the plant model is not known, it is intuitively reasonable to replace it by an estimated model and use this model for designing the controller. This is the basic idea of a self-tuning adaptive controller, in which the controller is designed based on an estimated model of the plant (assuming this model is the true model of the plant) and the estimated model parameters are updated by an online algorithm.

Now consider the problem of controlling the system (1). If the plant dynamics is known, *i.e.*, the functions *f* and *g* are known, we can solve the control problem stated above by the so-called feedback linearization method. In this method, the functions *f* and *g* are used to construct the following feedback control law:

$$u = u(\bar{x}, t) = \frac{1}{g(\bar{x})}\left[-f(\bar{x}) + y_m^{(n)}(t) + \bar{k}^T\bar{e}\right] \tag{4}$$

where $e = y_m(t) - y(t)$ is tracking error, $\bar{e} = \left(e, \dot{e}, \dots, e^{(n-1)}\right)^T$, and $\bar{k} = (k_n, \dots, k_2, k_1)^T$ is chosen such that all roots of the polynomial $h(s) = s^n + k_1 s^{n-1} + \cdots + k_n$ are in the open left-half of the complex plane. Applying the control law (2) to the system (1) results in the following error dynamics:

$$e^{(n)} + k_1 e^{(n-1)} + \cdots + k_n e = 0 \tag{5}$$

This implies that starting from any initial conditions, we have $\lim_{n\to\infty}|\bar{e}(t)| = 0$, *i.e.*, tracking of the reference trajectory is asymptotically achieved. However, since f and g are unknown, we cannot use them for constructing the control law (4). Therefore, we replace them by their estimates $\hat{f}$ and $\hat{g}$ to construct a self-tuning controller:

$$u_c = \frac{1}{\hat{g}(\bar{x}|\bar{\theta}_g)}\left[-\hat{f}(\bar{x}|\bar{\theta}_f) + y_m^{(n)}(t) + \bar{k}^T\bar{e}\right] \tag{6}$$

where $\bar{\theta}_f$ and $\bar{\theta}_g > \delta$ are parameters of the approximating systems $\hat{f}$ and $\hat{g}$, respectively.

The following hybrid adaptive law was proposed by Hojati in (Hojati and Gazor, 2002) in order to adjust the parameters:

$$\begin{cases} \dot{\bar{\theta}}_f = -\gamma_1 \left[\gamma \varepsilon + \bar{e}^T P \bar{b}_c \right] \bar{\xi}(\bar{x}) \\ \dot{\bar{\theta}}_g = -\gamma_2 \left[\gamma \varepsilon + \bar{e}^T P \bar{b}_c \right] \bar{\xi}(\bar{x}) u_c \end{cases} \quad (7)$$

where $\bar{\xi}(\bar{x})$ is the vector of fuzzy basis functions, γ_1, γ_2 and γ are positive constants, ε is the modeling error defined in (8), P is a matrix that satisfies the Lyapunov equation [9](Hojati *et al*, 2002) and $\bar{b}_c = (0, \dots, 0, 1)^T$.

The modeling error can be written as:

$$\varepsilon = \left[\bar{\phi}_f + \bar{\phi}_f u_c \right]^T \bar{\xi}(\bar{x}) + w \quad (8)$$

where $\bar{\phi}_f = \bar{\theta}_f - \bar{\theta}_f^{\,*}$, $\bar{\phi}_g = \bar{\theta}_g - \bar{\theta}_g^{\,*}$ and $w = (\hat{f} - f) + (\hat{g} - g) u_c$.

3. DRAGONFLY ARCHITECTURE

The mathematical model of the dragonfly system is the same analyzed in (Couceiro *et al.*, 2009b) with the support of (Couceiro *et al.*, 2009c) and the *MSc* thesis (Couceiro, 2010). The following control diagram in Fig. 2 depicts the dragonfly system.

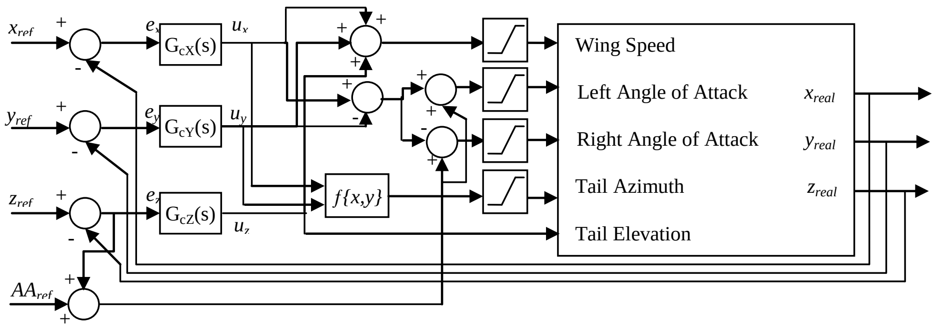

Fig. 2. Control Diagram of the dragonfly system.

In order to analyze the previous control diagram we need to understand the behavior of our system for certain variations of the error (in this case, the position error).

As we can see the wing speed inevitably depends on the sum of the position errors in *x*, *y* and *z*-axis being limited to a minimum and maximum saturation which in turn is associated to the simulated model. Based on what we see in nature the dragonfly model the wing speed is limited between 0 cycles/s and 10 cycles/s. The Left (wing) and Right (wing) Angle of Attack will allow the execution of different maneuvers (*e.g.*, turn/change direction, spin on its axis) and will depend on the position error in the *xy*-plane, *i.e.*, the difference between the position error in *x* and the position error in *y*. In this perspective, we add two references: a reference value (AA_{ref}) being the value considered to be ideal for the model to follow a path without deviation from the *xy*-plane (straight path) and the position error in the *z*-axis error (elevation) to ensure that the model follows the desired trajectory (*e.g.*, going up while changing direction). The Tail Azimuth angle will depend on a function *f*(*errorX*, *errorY*) which depends on the position error in *x*-axis and in the *y*-axis. This angle is only intended to assist the rotation maneuvers (regardless on the model in question, although the dynamics inherent in the use of the tail is different). The nonlinear function *f*(*errorX*, *errorY*) will systematically adjust the angle of azimuth of the tail in order to adjust the actual position on the *xy*-plane. For example, if you wish to turn left (*i.e.*, if the *xy*-plane error starts to increase), it will result in an incremental azimuth angle of the tail to the left (negative spin along the *z*-axis) until the error decreases. The Tail Elevation angle depends only on the position error in the *z*-axis (elevation).

4. CONTROLLER PERFORMANCES

We choose $\delta = 0.4$, $\gamma_1 = 2$, $\gamma_2 = 1$ and $\gamma = 4$ for the hybrid adaptive fuzzy controller and defined ten fuzzy sets over each axis and the following membership functions for $i = 1{,}2$:

$$\begin{cases} \mu_{F_i^1}(x_i) = 1/\left[1 + e^{5(x_i+4)}\right] \\ \mu_{F_i^2}(x_i) = e^{-(x_i+3.5)^2} \\ \mu_{F_i^2}(x_i) = e^{-(x_i+2.5)^2} \\ \mu_{F_i^2}(x_i) = e^{-(x_i+1.5)^2} \\ \mu_{F_i^3}(x_i) = e^{-(x_i+0.5)^2} \\ \mu_{F_i^4}(x_i) = e^{-(x_i-0.5)^2} \\ \mu_{F_i^5}(x_i) = e^{-(x_i-1.5)^2} \\ \mu_{F_i^5}(x_i) = e^{-(x_i-2.5)^2} \\ \mu_{F_i^5}(x_i) = e^{-(x_i-3.5)^2} \\ \mu_{F_i^6}(x_i) = 1/\left[1 + e^{-5(x_i-4)}\right] \end{cases} \quad (9)$$

The initial conditions $\bar{\theta}_f(0)$ and $\bar{\theta}_g(0)$ were chosen randomly in the intervals [-30;30] and [δ;30], respectively.

The signal $x_1(t)$ and $x_2(t)$ represents the velocity and the acceleration in the *x*-axis (horizontal axis), respectively and the initial conditions are $x_1(0) = 2$ and $x_2(0) = 0$. The reference trajectory is

$$\bar{y}_m(t) = \left(\left(1/2\right)\sin\left(1/2\, t\right), \left(1/4\right)\cos\left(1/2\, t\right)\right)^T.$$

Fig. 3 and 4 depict the response of the system under the action of the direct and hybrid adaptive fuzzy control, respectively.

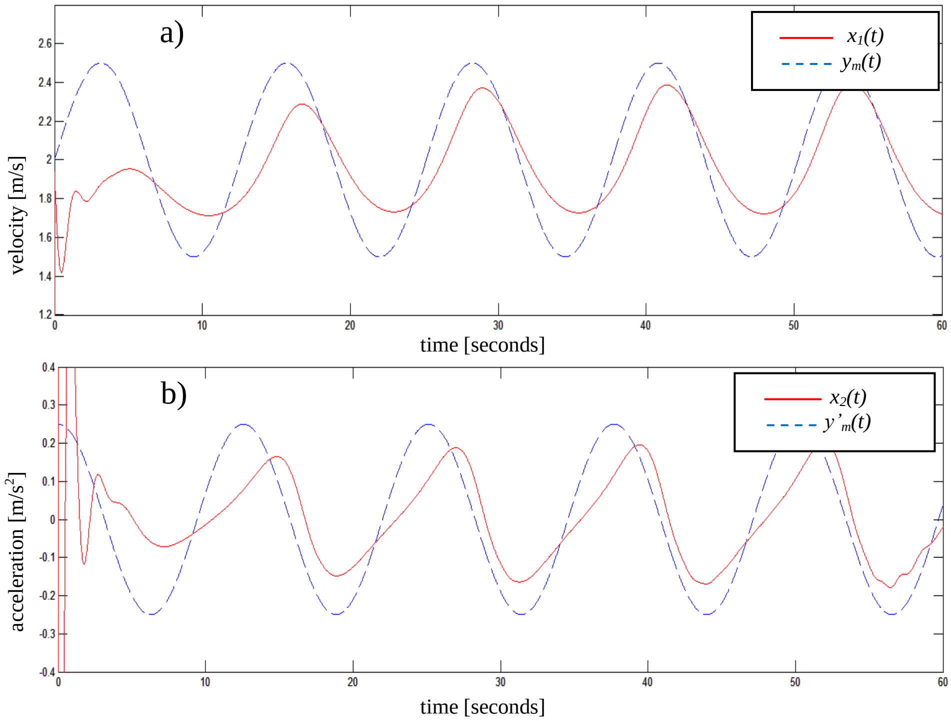

Fig. 3. Time response of the dragonfly system under the action of the direct adaptive fuzzy controller. a) x_1 signal; b) x_2 signal;

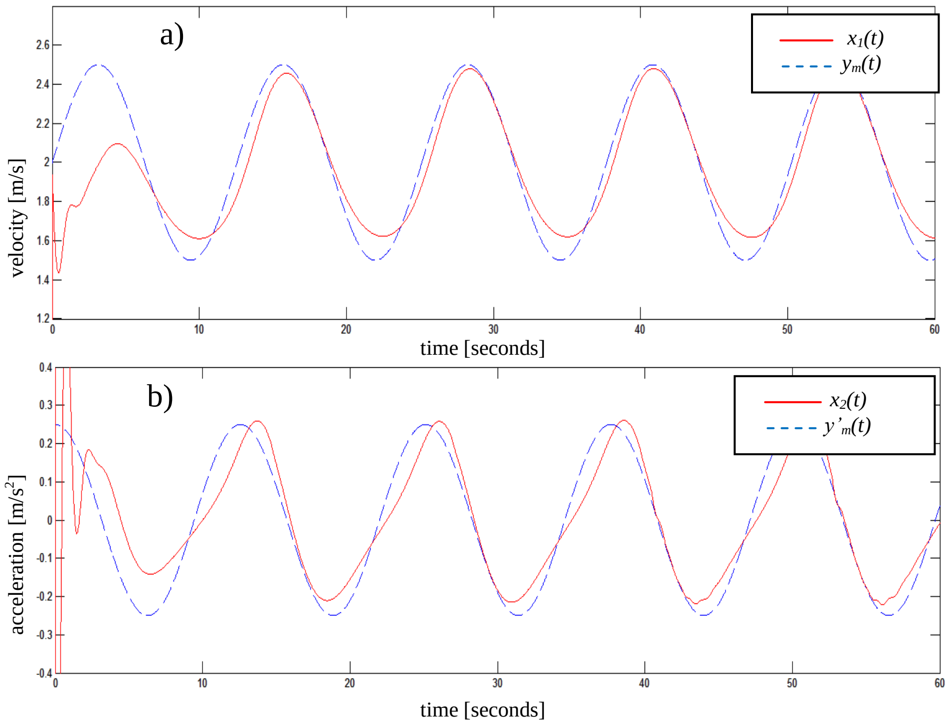

Fig. 4. Time response of the dragonfly system under the action of the hybrid adaptive fuzzy controller. a) x_1 signal; b) x_2 signal;

Fig. 5 depicts the norm of the tracking error vector versus time in the logarithmic scale $|e(t)| = \sqrt{e^2(t) + \dot{e}^2(t)} = \sqrt{(y_m(t) - x_1(t))^2 + (\dot{y}_m(t) - x_2(t))^2}$ for the direct adaptive law and the hybrid adaptive law where we can see the superiority of this last one.

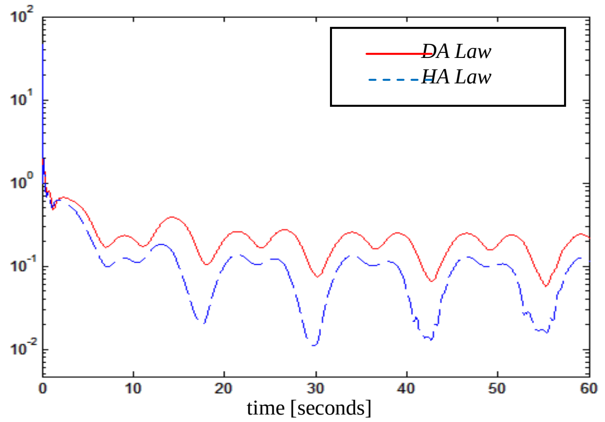

Fig. 5. Norm of tracking error vector in controlling the dragonfly system using the direct adaptive fuzzy controller (dashed line), and the hybrid adaptive fuzzy controller (solid line);

We can clearly see the advantages of the hybrid adaptive controller providing a faster tracking convergence with lower initial overshoots.

5. CONCLUSIONS

In this paper we developed a hybrid combined direct and indirect adaptive fuzzy controller to control the nonlinear mathematical model based on the dragonfly dynamics. In direct adaptive control, the controller parameters are directly adjusted and no effort is made for identifying the plant parameters while that in indirect adaptive control, the controller parameters are based on the estimated model parameters.

The simulation results confirm the superiority of the *HA* law (fast tracking error convergence, fast and improved parameter convergence). They also show that the hybrid adaptive fuzzy controller could perform successful control without incorporating any linguistic description into the design.

REFERENCES

Couceiro, M.S., Carlos M. Figueiredo, N. M. Fonseca Ferreira, J. A. Tenreiro Machado (2009a). Biological inspired flying robot. In: *Proceedings of IDETC/CIE 2009 ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference* August 30 - September 2, San Diego.

Bar-Cohen Y., C. Breazeal (2003). Biologically-Inspired Intelligente Robots. In: *SPIE Press*, **Vol. PM122**, May.

Schenato, L., X. Deng, W.C. Wu, S. Sastry (2001). Virtual Insect Flight Simulator (VIFS): A Software Testbed for Insect Flight. In: *IEEE Int. Conf. Robotics and Automation*, Seoul, Korea, May.

Jane, Z., Wang (2005). Dissecting Insect Flight. In: *Annu. Rev. Fluid Mech*, 183-210.

Tamai, M., Zhijian Wang, Ganesh Rajagopalan, Hui Hu (2007). Aerodynamic Performance of a Corrugated Dragonfly Airfoil Compared with Smooth Airfoils at Low Reynolds Numbers. In: *45th AIAA Aerospace Sciences Meeting and Exhibit*, Reno, Nevada, Jan.

Kesel, Antonia B. (2000). Aerodynamic Characteristics of Dragonfly Wing Sections Compared with Technical Aerofoils. In: *Journal of Experimental Biology*, **Vol 203**, Issue 20 3125-3135.

Wang, Li-Xin (1996). A course in fuzzy systems and control. In: *Prentice-Hall*, Inc., Upper Saddle River, NJ.

Wang, Li-Xin (1993). Stable adaptive fuzzy control of nonlinear systems. In: *IEEE Trans. Fuzzy Syst.*, **vol. 1**, pp. 146–155, April.

Hojati, M. and Gazor, S. (2002). Hybrid Adaptive Fuzzy Identification and Control of Nonlinear Systems. In: *IEEE Transactions on Fuzzy Systems*, **vol. 10**, no 2, pg. 198–210, April.

Couceiro, M.S., N. M. Fonseca Ferreira and J. A. Tenreiro Machado (2009b). Analysis and Control of a Dragonfly-Inspired Robot. In: *International Symposium on Computational Intelligence for Engineering Systems*, November 18-19, Porto.

Astrom, K. J. and B. Wittenmark (1989). Adaptive Control. In: *Reading, MA:* Addison-Wesley.

Sastry, S. and M. Bodson (1989). Adaptive Control: Stability, Convergence, and Robustness. In: *Upper Saddle River*, NJ: Prentice-Hall.

Isidori, A. (1989). Nonlinear Control Systems. In: *New York: Springer-Verlag*.

Couceiro, M.S., Carlos M. Figueiredo, N. M. Fonseca Ferreira and J. A. Tenreiro Machado (2009c). The Dynamic Modeling of a Bird Robot. In: *9th Conference on Autonomous Robot Systems and Competitions, Robotica 2009*, Castelo Branco, Portugal, 07 May.

Couceiro, M.S. (2010). Desenvolvimento e Controlo de Robôs Voadores Biologicamente Inspirados. In: *MSc Thesis at the Institute of Engineering of Coimbra*.