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NEURO-FUZZY CONTROL IS SOMETIMES BETTER THAN CRISP CONTROL

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Abstract. The objective of this work is to present some results concerning the neuro-fuzzy control synthesis as applied to electrohydraulic servomechanisms actuating primary flight controls. This represents a remarkable control strategy, with antisaturating and antichattering properties, which is in fact independent of mathematical model of the system, thus achieving certain robustness and reducing complexity. Thus, the paper's title is thought as a paraphrase to a recent sentence of Professor Michael Athans (MIT, Cambridge, USA): Crisp control is always better than fuzzy control (see: http://fuzzy.iau.dtu.dk/download/athans99/sld001.htm).

2000 *Mathematics Subject Classification*: 93C42 – fuzzy control, 93C95 – control applications.

1. INTRODUCTION

This work addresses the problem of laboratory test validation for an electrohydraulic motion control system (EHMCS) based on neuro-fuzzy synthesis. The fuzzy supervised neurocontrol (FSNC) of an analogous electrohydraulic servomechanism was previously illustrated in a theoretical framework, with only numerical validation, in recent works of the authors [1]-[3]. A LabView implementation of the algorithm was performed. The experimental results indicate the effectiveness of the neuro-fuzzy control versus the classical approaches PID, LQG etc.

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Figure 1: Partial view of the EHCMS

2. CONTROL PROBLEM. CLASSICAL VERSUS ARTIFICIAL INTELLIGENCE APPROACH

The EHMCS Figure 1 consists firstly of a double effect hydraulic cylinder with $S = 3 \times 10^{-4} m^2$ piston area and $9.1 \times 10^{-2} m$ half of piston stroke and an ORSTA TGL33649 electrohydraulic (servo)valve. The valve is a direct valve, in which a linear motor drives the spool directly according to the input current. The valve has a nominal flow of $40 \times 10^{-3} m^3/60s$, at the nominal pressure drop of 70 bar. Secondly, a PC with dual processor Pentium 4 2x3.0 GHz and 1 GB of RAM controls the system through a DAQ PCI 6040E National Instruments. Thirdly, an inductive position transducer Penny Gilles and two Hottinger Baldwin Messtechnik (HBM) pressure transducers provide the measurement input for DAQ. Finally, the inertial load is simulated by an inertial load simulator and the hydraulic power is supplied by a hydrostatic generator.

The EHMCS is in fact a tracking system. Therefore, for this system the aim of control synthesis is to have a good tracking by the piston position of the specified desired position references introduced as electrical signals by PC. When this control problem is treated in classical manner, a mathematical model of the system must be firstly performed. Secondly, a mathematical procedure of control synthesis must be developed. But, in classical manner, the procedure is dependent of model, and the model is not infallible, and frequently classical control methodologies fail facing to mathematical model complexity. For instance, a non-exhaustive mathematical model of the above described system is the following:

$$m\ \ddot{x} + f\dot{x} + F + F_f = S(p_1 - p_2), x_v = k_{x_v u} u$$

$$\dot{p_1} = \frac{B}{C + Sx}\{cW|x_v|sgn[p_s(1+sgn(x_v))-2p_1]\sqrt{|p_s(1 + sgn(x_v)) - 2p_1|/\rho}-S\dot{x}\}$$

$$\dot{p_2} = \frac{B}{C-Sx}\{cW|x_v|sgn[p_s(1-sgn(x_v))-2p_2]\sqrt{|p_s(1 - sgn(x_v)) - 2p_1|/\rho}+S\dot{x}\} \quad (1)$$

$$F_f = \sigma_0 x_f + \sigma_1 \dot{x_f} + f_v \dot{x}$$

$$\dot{x_f} = \dot{x} - |\dot{x}| x_f / g(\dot{x})$$

$$g(\dot{x}) = [F_c + (F_s - F_c)e^{-\frac{\dot{x}}{v_s}}]$$

Given this EHMCS mathematical embodiment, classical solutions of the control problem *"find control variable u such that tracking error* $\epsilon(t) := r(t) - k_p x(t) \longrightarrow 0$ *as* $t \longrightarrow \infty$ *for specifie reference signals* $r(t)$*" have to facing obvious difficulties.*

The nomenclature in equations (1) is given in cited author's references and will not be repeated herein. k_p is the position transducer coefficient $[V/m]$.

3. NEUROCONTROL

Thus, artificial intelligence based new approach in the treatment of control problem concerns principially an **input-output behavioral philosophy of solution**. In fact, the mathematical model (1) will herein serve only as illustration of applying the new strategy. In the on line process variant, the mathematical model is naturally substituted by the physical system.

In this and next Sections, the structure of the proposed FSNC is shortly described. The algorithm is composed of a neurocontrol and a fuzzy logic control supervising neurocontrol. As neurocontrol, an unilayered perceptron architecture was used. For this elementary network, two weighting parameters v_1, v_2 and a linear combiner generate the neurocontrol

$$u_n = v_1 y_1 + v_2 y_2 =: v_1(r - k_p z) + v_2(p_1 - p_2) \quad (2)$$

where $r(t)$ - reference input (command) $[V]$. Worthy noting, from EHMCS behavior view point, the input is u and the output is $y = (y_1, y_2)$. From neurocontrol training viewpoint, the system performance is assessed by the *cost function*, a criterion supposing a trade-off between the first input y_1 - tracking error -, the second input component y_2 and the control u.

$$J = \frac{1}{2n}\sum_{i=1}^{n}(q_1 y_1^2(i) + y_2^2(i) + q_2 u_n^2(i)) := \frac{1}{2n}\sum_{i=1}^{n} J(i) \tag{3}$$

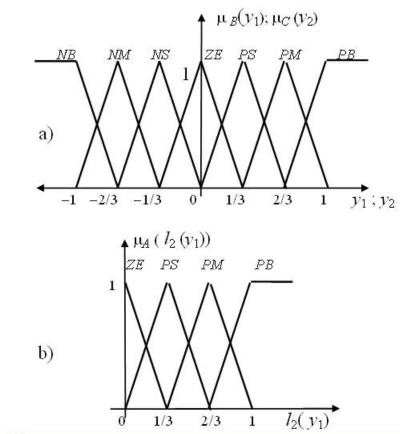

Figure 2: Triangular membership functions for: a)scaled input variables y_1, y_2 and b) $l_2(y_1)$

The weighting vector $v = [v_1, v_2]^T$ is updated online by the gradient descent learning method [6] to reduce the cost J. Consequently, the update is given by the expression

$$\begin{gathered} v(n+1) = v(n) + \Delta v(n) \\ \Delta v(n) := -diag(\delta_1, \delta_2)\frac{\partial J}{\partial v(n)} = \\ -diag(\delta_1, \delta_2)\sum_{i=n-N}^{n}\left(\frac{\partial J(i)}{\partial y(i)}\frac{\partial y(i)}{\partial u(i)} + \frac{\partial J(i)}{\partial u(i)}\right)\frac{\partial u(i)}{\partial v(i)} \end{gathered} \tag{4}$$

where the matrix $diag(\delta_1, \delta_2)$ introduces the learning scale vector, $\Delta v(n)$ is the weight vector update and N marks a back memory (of N time steps). The derivatives in (4) require only input-output information about the system. $\frac{\partial y(i)}{\partial u(i)}$

is online approximated by the relationship

$$(y(i) - y(i-1))/(u(i) - u(i-1))$$

The results obtained using this simple unilayered perceptron are very satisfactory.

4. FUZZY LOGIC CONTROL AND FUZZY SUPERVISED NEUROCONTROL

In many applications, particularly in the field of aerospace engineering, actuator saturation is the principal impediment to achieving significant closed-loop performances [4]. In the learning process with artificial neural networks, the risk of control saturation is real. To counteract this risk and not compromise the learning neural network by harmful phenomena as control's chattering and making worse system's performance, FSNC is herein considered as AW strategy. Thus, the control will have a switching type structure, which will be clarified in the following.

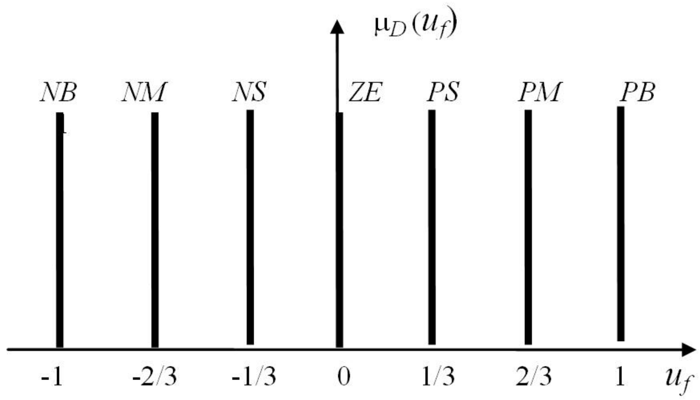

Figure 3: Singleton membership function for scaled fuzzy control u_f

The commonly used Mamdani fuzzy logic control supposes three main components: the fuzzyfier, the fuzzy reasoning, and the defuzzyfier [5]. Herein, the proposed *fuzzyfier* component converts the crisp input signals

$$l_2(y_{1k}) := \sqrt{\sum_{j=k-2}^{k} y_{1k}^2}, y_{1k}, y_{2k}, k = 1, 2, \ldots \quad (5)$$

into their relevant fuzzy variables (or, equivalently, membership functions) using a set of linguistic terms: zero (*ZE*), positive or negative small (*PS, NS*), positive or negative medium (*PM, NM*), positive or negative big (*PB, NB*); thus, fuzzy sets and their pertinent membership functions are produced (for sake of simplicity, triangular and singleton type membership functions are chosen, see Figures(2), (3). The considered l_2 norm computes, over a sliding window with a length of k samples, the maximum variation of the tracking error. The insertion of this crisp signal in the fuzzyfier will result in a reduction of fuzzy control switches due to the effects of spurious noise signals.

The strategy of *fuzzy reasoning* construction embodies herein the idea of a (direct) proportion *between the error signal* y_1 *and the required fuzzy control* u_f. Thus, the fuzzy reasoning engine totals a number of $n = 4 \times 7 \times 7$ IF..., THEN... rules, that is the number of the elements of the Cartesian product $A \times B \times C, A := \{ZE; PS; PM; PB\}, B = C := \{NB; NM; NS; ZE; PS; PM; PB\}$. These sets are associated with the sets of linguistic terms chosen to define the membership functions for the fuzzy variables $l_2(y_1), y_1$ and, respectively, y_2. Consequently, the succession of the n rules is the following:

1. IF $l_2(y_1)$ is *ZE* and y_2 is *PB* and y_1 is PB, THEN u_f is *PB*
2. IF $l_2(y_1)$ is *ZE* and y_2 is *PB* and y_1 is *PM*, THEN u_f is *PM*

⋮

7. IF $l_2(y_1)$ is *ZE* and y_2 is *PB* and y_1 is NB, THEN u_f is *NB*
8. IF $l_2(y_1)$ is *ZE* and y_2 is *PM* and y_1 is PB, THEN u_f is *PB*

⋮

196. IF $l_2(y_1)$ is *PB* and y_2 is *NB* and y_1 is PB, THEN u_f is *NB*

Let τ be the discrete sampling time. Consider the three scaled input crisp variables $l_2(y_{1k}), y1k$ and y_{2k}, at each time step $t_k = k\tau(k = 1, 2, \ldots)$. Taking into account the two ordinates corresponding in Figures (2), (3) to each of the three crisp variables, a number of $M \leq 2^3$ combinations of three ordinates must be investigated. Having in mind these combinations, a number of M IF..., THEN... rules will operate in the form

$$\begin{aligned} &IF\ y_{1k}\ is\ B_i\ and\ y_{2k}\ is\ C_i\ and\ l_2(y_1k)\ is\ A, \\ &\qquad THEN\ u_{fk}\ is\ D_i, i = 1, 2, \ldots, M \end{aligned} \tag{6}$$

(A_i, B_i, C_i, D_i are linguistic terms belonging to the sets $A,\ B,\ C,\ D$ and $D = B = C$, see Figures (2), (3). The *defuzzyfier* concerns just the transforming of these rules into a mathematical formula giving the output control variable u_f. In terms of fuzzy logic, each rule of (6) defines a fuzzy set $A_i \times B_i \times C_i \times D_i$ in the input-output Cartesian product space $R_+ \times R^3$, whose membership function can be defined in the manner

$$\mu = min[\mu_{B_i}(y_{1k}), \mu_{C_i}(y_{2k}), \mu_{A_i}(l_2(y_{1k})), \mu_{D_i}(u)],\ i = 1, \ldots, M\ (k = 1, 2, \ldots) \tag{7}$$

For simplicity, the singleton-type membership function $\mu_D(u)$ of control variable has been preferred; in this case, $\mu_{D_i}(u)$ will be replaced by u_i^0 , the singleton abscissa. Therefore, using 1) the singleton fuzzyfier for u_f, 2) the center-average type defuzzyfier, and 3) the min inference, the M IF..., THEN...rules can be transformed, at each time step $k\tau$, into a formula giving the crisp control u_f [6]:

$$u_f = \sum_{i=1}^{M} \mu_{u_i} u_i^0 / \sum_{i=1}^{M} \mu_{u_i} \tag{8}$$

The FSNC operates as fuzzy logic control in the case when neurocontrol saturated, or so called l_2-norm of tracking error y_1 increased. FSNC switches on neurocontrol whenever u_n is not saturating ($|u_n| \leq u_{n,max}$) and scaled $l_2(y_1) < l_{2,min}$. In the case of fuzzy control operating, the fuzzy neurocontrol u_n is concomitantly updated considering the real acting fuzzy control u_f .

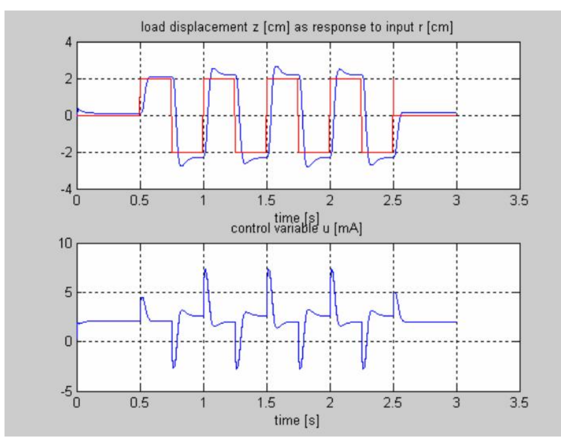

Figure 4: LQG algorithm: response to step reference

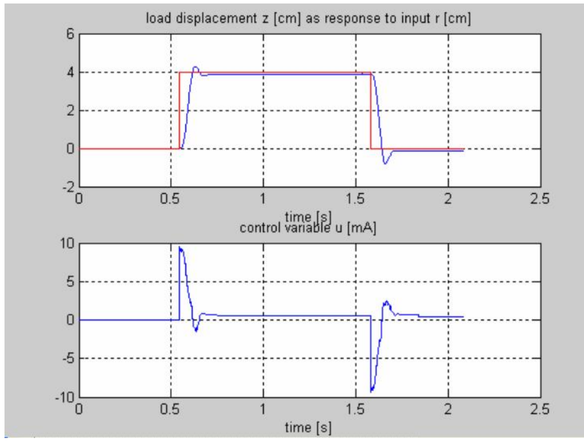

Figure 5: Neuro-fuzzy algorithm: response to step reference

5. EXPERIMENTAL RESULTS

The aforementioned FSNC was applied in simulation studies of the systems similar to (1) [1]–[3]. Despite of such model complexity, the simulation studies performed in the cited references attest good tracking performance, both in the presence of step and sinusoidal combination type signals r.

The present paper report that the FSNC was applied to the system described in Section 2. The detailed in Sections 3, 4 algorithm was implemented using LabView programming language. Alternate classical algorithms P, PI and LQG were also implemented, in order to evaluate and compare the results. Various experimental results were thus collected.

In Figures (4)-(7), representative time responses to step and sinusoidal references are shown, and a comparison LQG versus FSNC is emphasized. The system controlled with FSNC is proved to be better than the corresponding LQG system (see transitory and stationary regime performances), in accordance with simulation studies developed in previous works of the authors. Thus, the above results are very encouraging from viewpoint of development of the intelligent control strategies.

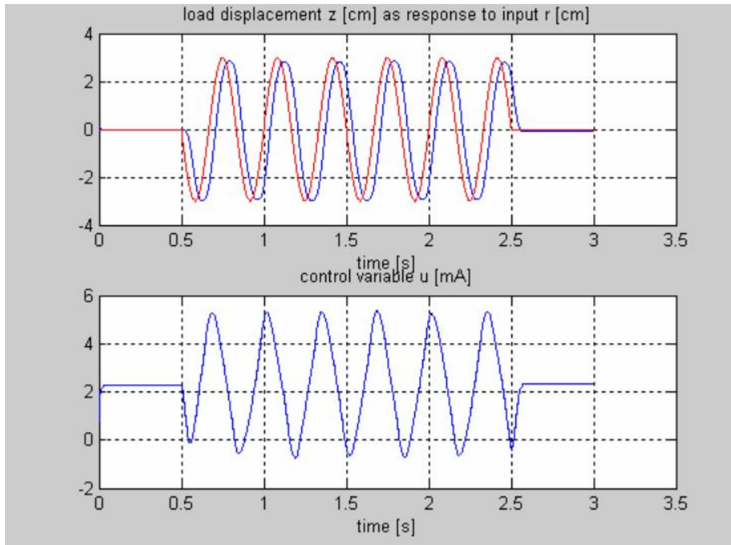

Figure 6: LQG algorithm: response to sinusoidal reference (amplitude 3cm, frequency 3Hz)

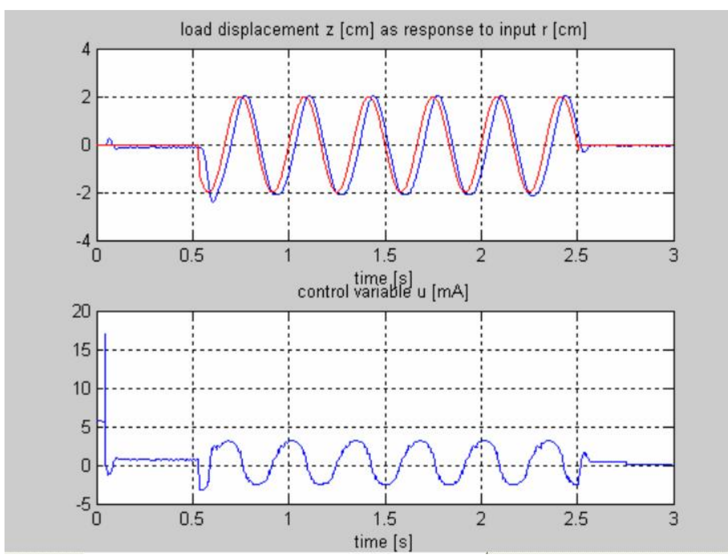

Figure 7: Neuro-fuzzy algorithm: response to sinusoidal reference (amplitude 3cm, frequency 3Hz)

6. CONCLUSIONS

While most of reported results in the literature of the field are categorically favorable to the fuzzy viewpoint, we do not evade that there are many opponents of the fuzzy control; see, for example, the recent tempestuous and radical challenge of Michael Athans, a great name of the classical control. In his exposition titled "Crisp control is always better than fuzzy control" (see fuzzy.iau.dtu.dk, Athans concludes sententiously: "fuzzy control is a parasitic technology". On the contrary, our conclusion is that, in various approaches [1] [3], [7], [8], regarding as applications active and semiactive suspensions and electrohydraulic servo actuating primary flight controls, the fuzzy control worked very well, much better than classical methodologies PID, LQG etc. However, facing with assertions as that of Athans, we consider in principle that even the subjective considerations are necessary and beneficent.

The proposed FSNC is categorically advantageous in comparison with the system presented in [9], since in that approach the synthesis is dependent of a linear model of the controlled system. This new approach of control synthesis accounts for the saturation nonlinearity and provides in addition antichattering and robustness properties to the controlling system. Indeed, the obtained control is robust since it does not demand a model of the system.

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