Improvement of Flight Simulator Feeling Using Adaptive Fuzzy Backlash Compensation

Zied AMARA, Joël BORDENEUVE-GUIBE Dept. of Avionics & Systems, ENSICA, 1 place Emile Blouin-31056 Toulouse Cedex 5 - FRANCE zied.amara@ensica.fr

Abstract- In this paper we addressed the problem of improving the control of DC motors used for the specific application of a 3 degrees of freedom moving base flight simulator. Indeed the presence of backlash in DC motors gearboxes induces shocks and naturally limits the flight feeling. In this paper, dynamic inversion with Fuzzy Logic is used to design an adaptive backlash compensator. The classification property of fuzzy logic techniques makes them a natural candidate for the rejection of errors induced by the backlash. A tuning algorithm is given for the fuzzy logic parameters, so that the output backlash compensation scheme becomes adaptive. The fuzzy backlash compensator is first validated using a realistic model of the mechanical system and is actually tested on the real flight simulator.

I. INTRODUCTION

This new kind of simulator, which is developed by the 6Mouv company (www.6mouv.com), is actually the matter of an industry-university partnership between 6Mouv and ENSICA (Fig.2.). Its innovative characteristic relies on a low cost mechanical system (fig.2) that allows the cabin to move around 3, 4 or even 6 degrees of freedom. Basically, in comparison with classical solutions, this one makes use of electrical drives instead of hydraulic actuators.

The first prototype has been extensively used for students training to the PPL (Pilot Private License) and has demonstrated sound benefits. Numerous professional pilots and instructors have also expressed their warm congratulations when testing the prototype.

The cost driven solution leads to the use of 4 to 6 TFT screens in the cabin at the windows place to display both outer



Fig. 1. Interior sight of the simulator cabin.

scene and the aircraft instruments (fig.1). Off the shelf equipments are used for rudders, control stick, and others commands. Several flight simulation software benefiting from large volume of the game industry are possible, and provide a high quality 3D display engine capable of photo realistic terrains and detailed aircraft view, while also permitting formation flying through a network.

The motion based is based on rotary asynchronous AC motors using standard rod-crank systems, which appears to be much robust and cheaper than screw or hydraulic jack's solutions. The output force can be very large when using a high ratio gearbox and a powerful motor.

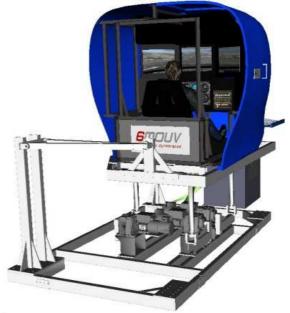


Fig. 2. Total sight of the simulator.

Many technical problems appear when attempting to use such a solution, while maintaining high motion fidelity. The present paper deals with one of these, which has been a major concern: the backlash of the motor gearbox which can be up to 0.25°. Minimizing motors size is an important source of cost reduction and therefore the cabin weight is compensated by springs acting directly between the fixed base and the cranks. But the weight compensation induces an unwanted effect when the motor torque changes its sign and cross the backlash. The effect is an unacceptable perception, corresponding to an

abnormal shock during the flight.

Up to date a provisory solution has been implemented. Basically it consists in under compensating the cabin weight by approximately 30%, preventing the backlash to be crossed, at the expense of bigger electrical motors, leading to heat production and more power consumption.

The two main sources of imprecision in an articulated system are the springiness of the components and the presence of backlash in mechanical organs, and especially in the transmission organs of torque: gearings, couplers... The hysteresis caused by backlash is a well-understood dynamic nonlinearity. Discussions can be found in several control papers such [1]. This backlash can be countered by mechanical processes (brake, auxiliary engine), that is to say to be left free, but taken into account in the command orders in such a way to correct their effects. The present study relates to this last solution. The main idea along this work is, starting from an existing control, to "add" an auxiliary control signal permitting to minimize the backlash. It is thus necessary to find a control law for the reducing gear actuator unit, allowing to cope with the backlash, or at least to minimize its effects.

In the literature several methods are mentioned [2], [3]: by continuously exerting an action on the machine output shaft, contacts between gear's teeth are forced. The contact point being then unknown, the mechanism is in constant thrust, whatever the rotation.

Instead of exerting a force to diminish the backlash, it is also possible to verify if there is indeed contact between the gearbox teeth and to act in consequence. In this case, with this intention, it is needed to detect or to estimate the torque value. Deformation gauges could be set up to this end.

The backlash can also be mechanically coped by adding a second torque, opposed to the main movement, but of lower intensity. In other words, that means placing a secondary motor on the reducers' output shaft and making it turn in opposite direction, thus rendering the final solution "very" expensive.

A spiral spring could also exert a permanent contact action. The drawbacks of such a solution are on one hand that this action - being permanent - causes a useless energy consumption, and on the other hand it remains impossible to adapt or to change the intensity during the run.

The "ideal" solution would be to overlook mechanical systems and to find a way of reaching accurate positioning using only one control law.

For this project, a first solution was first developed by using a neural controller [4]: in this paper we examined the dynamic inversion technique by using an adaptive fuzzy controller, and we showed how to use a fuzzy controller for inverting the backlash nonlinearity.

The paper is organized as follows. Section 2 presents the control system and in Section 3 the controller is developed and derives the control algorithm.

Section 4 reports simulations and conclusions.

II. DESCRIPTION OF THE CONTROL SYSTEM

In this paper, we present a simple iterative learning control scheme, that can be applied for a broad class of nonlinear systems. The tracking capability of the iterative learning process hinges upon the stability of the closed-loop system at each iteration.

The fuzzy controller to be tuned is a feed-forward controller (fig.3). This fuzzy controller can be seen as a one-step-ahead controller which is identical with the inverse process model. In the proposed control architecture the gradient-descent method is used to learn the inverse model of the plant by changing the parameters of the fuzzy part of the inverse model.

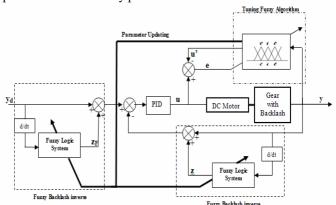


Fig. 3. Fuzzy output backlash compensation.

A. Gradient-descent adaptation

More and more references to "fuzzy neural networks" or "neuro-fuzzy systems" can be found in the literature. A few of them really use neural networks initialized by a fuzzy rule base. Examples can be found in [5], [6], [7] and [8], where a fuzzy system is first translated into a neural network and then used to learn a model. Most of the publications on fuzzy neural networks address the adaptation of fuzzy systems based on a gradient-descent adaptation method for optimization [9]. However, the gradient-descent adaptation technique is not specific to neural networks. Several authors have applied gradient-descent adaptation methods to fuzzy systems. What those methods have in common is that they minimize a similar objective function E as it is done in case of the learning rules in neural networks, as well as in many other gradient-descent optimization methods:

$$E = \frac{1}{2} (y - y_d)^2 \tag{1}$$

where y_d is the reference for the fuzzy system output y.

B. The adaptation scheme

We consider triangularly-shaped membership functions for the inputs (fig.4), Sugeno rules with constant consequent and the product operator for conjunction. The rules have the following form [10]:

$$L^{i,j}$$
: IF $y(k+1)$ is A_1^i and $y(k)$ is A_2^j THEN $u(k) = b^{i,j}$ (2)

Where $L^{i,j}$ denote the i,j-th implication, $i=1,2,...,N_i$, $j=1,2,...,N_j$ and N_j are the number of the fuzzy sets on the i-th and j-th input domain, respectively; the symbol A_q^i and A_q^j are the membership functions and $b^{i,j}$ are the rule consequent parameters (Fuzzy singleton).

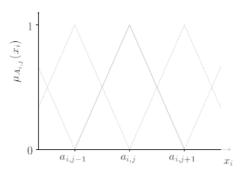


Fig. 4. Membership function used by modified gradient-descent adaptation of fuzzy system.

The learning rules are:

$$\Delta a_{i,j} = \begin{cases} \frac{K_a(y-y_d)}{(a_{i,j}-a_{i,j-1})} \begin{bmatrix} \frac{\mu_{A_{i,j}}(x_i)}{\mu_{A_{i,j-1}}(x_i)} & \sum_{k=1}^{N_{A_{i,j}}-1} \beta_k \cdot (b_k \cdot -y) \\ -\sum_{k=1}^{N_{A_{i,j}}} \beta_k \cdot (b_k \cdot -y) \end{bmatrix}, & \text{if } a_{i,j-1} < x_i < a_{i,j} \\ \frac{K_a(y-y_d)}{(a_{i,j}-a_{i,j+1})} \begin{bmatrix} \frac{\mu_{A_{i,j}}(x_i)}{\mu_{A_{i,j+1}}(x_i)} & \sum_{k=1}^{N_{A_{i,j}}+1} \beta_k \cdot (b_k \cdot -y) \\ -\sum_{k=1}^{N_{A_{i,j}}} \beta_k \cdot (b_k \cdot -y) \\ k = 1 \end{bmatrix}, & \text{if } a_{i,j} < x_i < a_{i,j+1} \end{cases}$$

$$\Delta b^{i,j} = K_b \beta_k (y - y_d) \tag{4}$$

where K_a and K_b are adaptation (learning) factors for the centers $a_{i,j}$ of the membership functions and $b^{i,j}$.

III. THE CONTROL PROBLEM

A fuzzy backlash inverse compensator is designed for the nonsymmetric output backlash nonlinearity. The output backlash example is shown in fig.5. The backlash characteristic $F(\cdot)$ whith input z(t) and output y(t): y(t) = F[z(t)] is described by two parallel straight lines, upward and downward sides of $F(\cdot)$, connected with horizontal line segments. Mathematically, the backlash is modelled as (5), [11]:

$$y = F(y, z, z)$$

$$= \begin{cases} \cdot & \text{if } z(t) > 0 \text{ AND } y(t) = z(t) - d_{+} \\ z(t), & \text{or } z(t) < 0 \text{ AND } y(t) = z(t) - d_{-} \\ 0, & \text{otherwise} \end{cases}$$
(5)

A graphical inverse of the backlash characteristic is shown in fig.6, which contains vertical jumps. The mapping $FI(\cdot)$:

 $y_d(t) \rightarrow z_d(t)$, define the backlash inverse $F(FI(y_d(\tau))) = y_d(\tau) \Rightarrow F(FI(y_d(t))) = y_d(t)$ for any $\tau > t$. Because of the dynamic nature of backlash, the backlash inverse is defined with the initialization $F(FI(y_d(t))) = y_d(\tau)$.

To offset the deleterious effects of backlash, we introduce the idea of the fuzzy backlash inverse scheme in fig.6. A fuzzy backlash inverse compensator using dynamic inversion would be discontinuous and would depend on the region within which

 y_d occurs. It would be naturally described using the rules (6):

$$IF (y_d > 0) \qquad THEN (z_d = y_d + \hat{d}_+)$$

$$IF (y_d = 0) \qquad THEN (z_d = y_d + \hat{d}_0)$$

$$IF (y_d < 0) \qquad THEN (z_d = y_d + \hat{d}_-)$$
(6)

where $\hat{d} = \begin{bmatrix} \hat{d}_+ & \hat{d}_0 & \hat{d}_- \end{bmatrix}^T$ is an estimate of the backlash with

parameter vector $d = \begin{bmatrix} d_+ & d_0 & d_- \end{bmatrix}^T$. d_0 is determined by:

$$\hat{d}_{0} = \hat{d}_{+} \text{ if } \hat{y}(t-1) > 0
\hat{d}_{0} = \hat{d}_{-} \text{ if } \hat{y}(t-1) < 0$$
(7)

To make this intuitive notion (7) mathematically precise for analysis, let's define the membership functions

$$X_{+}(y_{d}) = \begin{cases} 0, & \vdots \\ 0, & y_{d} < 0 \\ \vdots \\ 1, & y_{d} > 0 \end{cases}, X_{0}(y_{d}) = \begin{cases} 0, & \vdots \\ 0, & y_{d} \neq 0 \\ 1, & y_{d} = 0 \end{cases}, X_{-}(y_{d}) = \begin{cases} 0, & \vdots \\ 0, & y_{d} < 0 \\ \vdots \\ 1, & y_{d} > 0 \end{cases}$$

One may write the inverse compensator as

$$z_d = y_d + z_F \tag{8}$$

where z_F is given by the rule base

$$IF (y_d \in X_+(y)) \qquad THEN (z_F = \hat{d}_+)$$

$$IF (y_d \in X_0(y)) \qquad THEN (z_F = \hat{d}_0)$$

$$IF (y_d \in X_-(y)) \qquad THEN (z_d = \hat{d}_-)$$

$$(9)$$

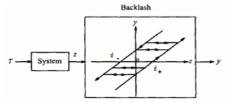


Fig. 5. System with output backlash.

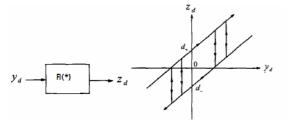


Fig. 6. Backlash inverse.

The output of the fuzzy logic system with this rule base is given by

$$z_{F} = \frac{\hat{d}_{+} X_{+} (y_{d}) + \hat{d}_{0} X_{0} (y_{d}) + \hat{d}_{-} X_{-} (y_{d})}{X_{+} (y_{d}) + X_{0} (y_{d}) + X_{-} (y_{d})}$$
(10)

The estimates $\overset{\wedge}{d_+},\overset{\wedge}{d_0},\overset{\wedge}{d_-}$ are respectively, the control representative value of $X_+(y_d),X_0(y_d)$ and $X_-(y_d)$. This may

be written (note $X_{+}(y_d) + X_{0}(y_d) + X_{-}(y_d) = 1$) as

$$z_F = d^T X(y_d) \tag{11}$$

where the fuzzy logic basis function vector given by

$$X(y_d) = \begin{bmatrix} X_+(y_d) \\ \vdots \\ X_0(y_d) \\ \vdots \\ X_-(y_d) \end{bmatrix}$$
(12)

is easily computed given any value of y_d . It should be noted that the membership functions are the indicator functions and $x(y_d)$ is similar to the regressor.

The fuzzy backlash inverse compensator may be expressed as follows

$$z_d = y_d + z_F = y_d + \hat{d}^T X(\overset{\bullet}{y_d})$$
 (13)

where \hat{d} is the estimated backlash width. Since z(t) is not available, we choose its estimate to be:

$$\bar{z}(t) = y(t) + \bar{z}F = y + d X(y)$$
 (14)

where the fuzzy basis function vector given by

$$X(y) = \begin{bmatrix} X_{+}(y) \\ X_{0}(y) \\ \vdots \\ X_{-}(y) \end{bmatrix}$$

$$(15)$$

is easily computed given any value of y

IV. SIMULATION RESULTS & CONCLUSIONS

The bench (fig. 7) consists in an asynchronous motor (LEROY SOMER) of power P=0.37KW, with a gear ratio R=204, and an angular dead zone distance (0.25°) , identical to the one mounted on the simulator.

The objective of this manipulation is to carry out movements in a quasi real configuration, i.e. ensuring a resistant torque (500N) similar to the one supported by the motor assembled on the simulator. This is why two metallic bars are fixed on the output shaft. Moreover, two loads (around 50kg) are hung at both extremities of the bar. Encoders were mounted on both shafts, but only the motor shaft encoder was used for parameter estimation and control.

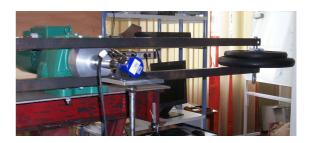
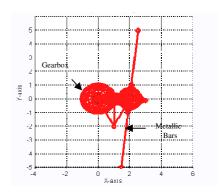


Fig. 7. The test bench.

The simulation of the gearbox and metallic bars respecting (5) were carried out with the SimMechanics library available under Matlab, this model takes into consideration real measurements (metallic bars and loads inertia, damping and stiffness of gear's teeth, backlash region). In order to reduce the gear box model complexity, only one among the two really present gear stages is considered. The model is simulated and successfully validated (fig. 8).



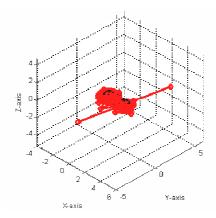


Fig. 8. System overview - Gear & Metallic bars -

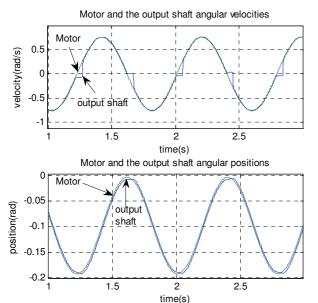


Fig. 9. Backlash effects.

It can be observed (fig. 9) that in the backlash "region", both velocities (shaft and machine) are not so close. The velocity of the shaft becomes zero and stays zero until the shaft gear engages with the machine gear.

When the gear shaft engages with the machine gear, the velocity of the shaft instantaneously starts tracking the motor velocity producing a shock in the mechanical system and follows until the next backlash region.

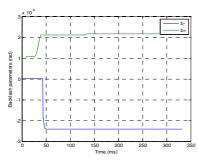


Fig. 10. On-line Identification of backlash parameters.

The simulation result for on-line identification of backlash parameters is shown in (fig. 10) by using (3), (4) and (9).

The result proves the robustness and speed of the Adaptive Fuzzy Algorithm. The Identification parameters are updated online in the Inverse model of the Gear.

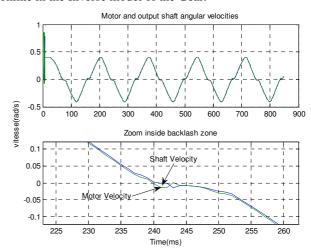


Fig. 11. Inverse backlash model.

The appearing oscillations within the first 10 seconds (Fig. 11.) are related to the backlash parameters identification.

The development of inverse dynamics technique makes it possible to command the machine in the opposite backlash dynamic and thus, minimizing the effects caused by this backlash non-linearities. This approach is actually under evaluation in the test bench described above.

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