IEEE/RSJ International Workshop on Intelligent
Robots and Systems IROS '91, Nov. 3-5, 1991,
Osaka, Japan. IEEE Cat. No. 91TH0375-6

FUZZY INTERNAL MODELS IN VISION SYSTEMS MODELLING

P. Lefèvre[1,2] M. De Neyer[1,2] R. Gorez[1] J. Barreto[1,2]

[1]Lab. of Control Systems & [2]Lab. of Neurophysiology, Université Catholique de Louvain
Place du Levant, 3, B-1348 LOUVAIN-LA-NEUVE (Belgium)
E-Mail: lefevre@buclln11.bitnet

ABSTRACT

The aim of this paper is to study internal-model representations in the framework of control theory and of visual system modelling. It will be shown that the control of rapid orienting movements of the visual axis in space (saccadic system) can be modelled as a control system based on internal models. Moreover, fuzzy approach is found to be very well adapted for the modelling of some parts of the saccadic system (related to highly nonlinear sensors and/or internal representations). Classical properties of this control structure such as robustness and disturbance rejection are met.

1. INTRODUCTION

In some process control applications an explicit model of the plant to be controlled is used for control purposes. One of those control schemes is Internal Model Control (IMC), which is known from a long time (see e.g. Smith's predictor in the fifties) and has been revisited over the last ten years [10] because of its nice properties of robustness and disturbance rejection. Such a control structure is valid whatever the implementation of the model or of the controller may be. Several different paradigms of internal models are possible: quantitative models using differential or difference equations, qualitative models based on fuzzy representation [1], etc. Here fuzzy models are considered [3,4].

Independently some researchers in the field of physiology [5,8] have developed models of the oculomotor system of living beings, using a so-called "efference copy" which can be related to an internal model. This new approach is progressively replacing the classical "inverse model" technique, because it seems to be closer to the way that real physiological systems operate. In experiments on eye movements two observations are noteworthy. The first one is that retinal sensor on one hand, internal collicular representation on the other hand, are highly nonlinear. The second observation concerns saccadic eye movements which occur when the eye is tracking a target in space. We can explain this type of motion as the result of a discrete-time correcting process based on an internal model.

In this paper a fuzzy internal model representation is used in the position control of a vision system. The case of coordinated movements of the eye and head in living beings is considered. The study is performed by a simulation analysis. Considering well established properties of control systems based on fuzzy logic [2,6,7,9,13], particular emphasis is put on robustness aspects: sensitivity to changes in dynamic parameters. Possible auto-adaptation of the model is also discussed as a way of taking into account learning processes; this would open the way to further investigations into the interaction of vision with proprioceptive feedback loops.

The interest of this particular study is mainly in the robotic field. The position control and tracking possibilities of orientation and coordination of vision sensors in robots can be designed using several different techniques. Here the functioning of living beings is the starting point to the design, using the concept of efference copy mentioned above. As a collateral interest, important from the physiological viewpoint, a control system based on physiological data helps getting a better understanding of the physiological mechanism.

Preliminary investigations have shown the viability of this approach. This is probably even stronger than initially thought, because internal model representation can take place at different levels inside the complete gaze control system (optokinetic system, premotor level, ...). Control of more complex peripheral limb movements could probably be modelled by equivalent techniques.

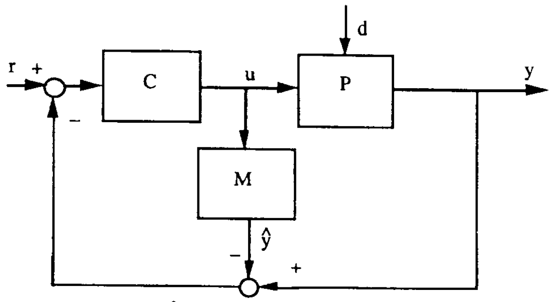
This paper is organized as follows:
- Section 2 describes a control system based on an internal model of the process,
- Section 3 presents the process to be controlled and the fuzzy linguistic computation,
- Section 4 shows the simulation results,
- Section 5 discusses these results and
- Section 6 gives conclusions.

2. INTERNAL MODEL CONTROL

Basic structure

The structure of an Internal Model Control system (IMC) [10] is presented in Figure 1. This control scheme has two nice properties:
- it does not change the nominal tracking dynamics of the compensated process,
- it allows full rejection of external disturbances.

Accurate modelling of the process is not necessary since internal model control is fairly robust [11]. In many cases, if the process gain has been precompensated by an inverse gain, an approximate model giving roughly the settling time of the process can be satisfactory. Moreover, if the sampling period is at least equal to the settling time of the process, the process transient response can be neglected such that the simplest model is a one-step ahead shift operator, predicting the expected steady-state value of the process output. If this is not satisfactory, the transient response of the process can approximately be taken into account by means of a first-order predictor. This would allow to have smaller sampling intervals and to improve the performances of the control system. In this study, the model used was the one-step ahead shift operator.



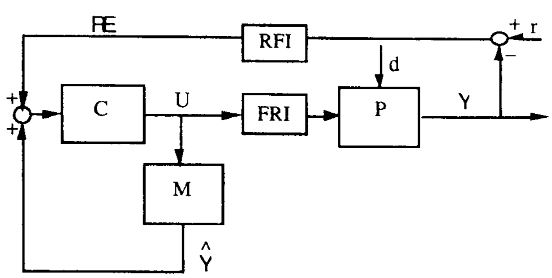
r = reference u = control variable
d = disturbance
y = output $\hat{y}$ = model output
M = model C = controller P = process

Figure 1: Internal Model Control System

Fuzzy implementation

Several implementations of the internal model control system can be considered. We mainly distinguish two types of implementation representing different parts of the control system either by quantitative numerical or by qualitative implementations using fuzzy data. Hybrid implementations using both types of representations are also possible. Here the control system will be implemented using a fuzzy internal model of the system to be controlled. The fuzzy values of the output of this model and of the error signal (retinal sensor) are added before being applied to a controller whose output is defuzzified.

The choice of the fuzzy representation is motivated by the use of approximate reasoning and calculation, and by some nonlinear features of the retinal sensor and of the internal representation. The handling of fuzzy data in control of a real process implies two interfaces performing complementary tasks. Figure 2 represents a fuzzy version of an Internal Model Control system.



RFI: Real to Fuzzy Interface - FRI: Fuzzy to Real Interface
RE: retinal error

Figure 2: Fuzzy implementation of an internal model control system.

The simplest model introduced in the previous section, namely a one-step ahead shift operator with a sampling period at least equal to the process settling time is used. This can be seen as the representation of a "wait and see" strategy resulting in progressive updatings of the control variable.

Its quantitative implementation would be described by $\hat{y}(k) = u(k-1)$ where k refers to the current sampling time. The qualitative translation of this model is $\hat{Y}(k) = U(k-1)$ where $\hat{Y}$ and U are fuzzy variables, respectively the current (updated) model output and the last control input (calculated at the preceding sampling time). Fuzzy addition is characterized by a set of fuzzy rules relating the two terms, RE and $\hat{Y}$, and the sum. Here for simplicity in this implementation, the compensator will not be considered.

3. APPLICATION

Description of the process

The process that will be modelled is the human saccadic system, which is involved in the orientation of the visual axis in space. The input of the process is a command u, yielding the new desired position of the visual axis in space (gaze). The process output y is the position of the gaze in space. In this study, the process has been simulated using the model proposed by Guitton et al. [5], adapted to man. In the simulation, the retinal error (sensory signal coming from the retina) is reconstructed by subtracting the output y (eye position in space) from the reference r (target position in space).

Often large amplitude movements include several saccades (fast combined eye-head orienting movement in space) The occurrence of these saccades obviously depends on the accuracy of the initial saccadic movement. It may be related to the precision of the internal model or to the resolution of the sensor in the periphery of the retina (RFI) combined with the effects of the fuzzy addition.

Two experimental observations are noteworthy and can be directly related to this study and to the proposed model (Figure 2)

- for larger saccades (bigger RE=retinal error), the eye undershoot is bigger and seems to be roughly proportional to the saccade amplitude (10% undershoot in man [12]).
- the absolute scatter about the mean is greater for larger saccadic movements.

The first observation seems to indicate that M is a good estimator of S. The fact that the relative undershoot is constant shows that the approximation of M and P by linear models is sound. Moreover, for physiologists an 'undershoot strategy' has clear functional advantages like the use of the same premotor and motor pathways for a correcting saccade in the same direction as the initial one.

The second observation indicates that the scatter about the mean depends on movement amplitude. This can be related to the 'fuzziness' of the retinal sensor and/or of the internal collicular representation (non-homogeneity of the retinal sensors, nonlinear spatial collicular representation). This behaviour can be related to the RFI.

Fuzzy computation

1) RFI

A scaling factor of 20 is applied between the Real and the Fuzzy part of the control structure, in order to use classical universes of discourse (40 degrees corresponds to 2, the center of the class Positive Medium).

The Real to Fuzzy Interface (RFI in Figure 2) takes into account the higher resolution of the retina in its foveal (central) part, the retinal sensor having much more numerous cells in its central part. This internal organization makes much sense in giving more attention (details) to the perifoveal zone, the visual axis being a priori assumed to be pointing at the most interesting part of the space.

However, it is worth noting that internal collicular

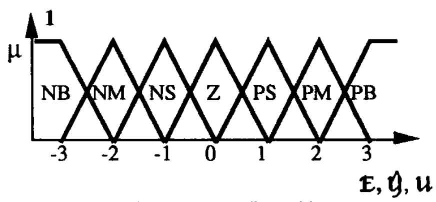
representation is highly nonlinear (log-like) . The non-homogeneity in the density of retinal sensors is similar to the nonlinear spatial representation in the colliculus. These two nonlinear characteristics are experimentally observed. Indeed, the scatter about the mean is significantly more important for larger saccadic movements.
The RFI has been designed as follows: each real number defines a triangular membership function half the width of which is proportional to the amplitude of the number (normalized threshold of 0.5, maximum half width of 0.5 for an input of 3). A scaling factor of 20 is applied between the Real and the Fuzzy part of the control structure, in order to use classical universes of discourse (40 degrees corresponds to 2, the center of the class Positive Medium).

2) Fuzzy internal model

The fuzzy linguistic model selected is a one-step ahead shift operator, described above. It does not involve calculations except a time shift. The addition of the model output and the error signal is also qualitative. It is described by a set of rules having the following form:

If (RE is A_i and $\hat{Y}$ is B_i)*then* set U to C_i .

where A_i, B_i and C_i are linguistic values of E, $\hat{Y}$, U. They are labels of fuzzy sets characterized by their membership functions μ defined on their respective "universes of discourse", $\mathcal{E}, \mathcal{Y}, \mathcal{U}$. Membership functions of the linguistic values of E, $\hat{Y}$, U are represented in Figure 3.



N: negative P: positive
Z: zero S: small
M: medium B: big

Figure 3: Membership functions (E, $\hat{Y}$, U).

Table 1 summarizes the rules of this fuzzy addition. It must be interpreted as:

If (RE is Negative Medium and $\hat{Y}$ is Zero)
then U equals Negative Small.

Table 1: Qualitative addition of the error signal and the model output.

RE \ $\hat{Y}$	NB	NM	NS	Z	PS	PM	PB
NB	NB	NB	NM	NM	NS	NS	Z
NM	NB	NB	NM	NS	NS	Z	PS
NS	NB	NB	NM	NS	Z	PS	PM
Z	NB	NM	NS	Z	PS	PM	PB
PS	NM	NS	Z	PS	PM	PB	PB
PM	NS	Z	PS	PS	PM	PB	PB
PB	Z	PS	PS	PM	PM	PB	PB

Given an actual situation, "RE = A' " and "$\hat{Y}$ = B' ", one can infer from the i-th rule a value of U represented by the fuzzy set C':

$$\mu_{C'_i}(z) = \min \{\max_x \min\{\mu_{A'}(x),\mu_{A_i}(x)\}, \max_y \min\{\mu_{B'}(y), \mu_{B_i}(y)\}, \mu_{C_i}(z)\},$$

All the rule contributions are gathered in a global value C' using the maximum operator:

$$\mu_{C'}(z) = \max_i \mu_{C'_i}(z)$$

3) FRI

The Fuzzy to Real Interface (FRI in Figure 2) extracts a real command from a fuzzy signal (U), using the center of gravity law:

$$y_s = \frac{\sum_z z * \mu_{C'}(z)}{\sum_z \mu_{C'}(z)}$$

where $z \in \mathcal{U}$.

4. SIMULATION RESULTS

Two sets of simulation results are presented:
- responses of the nominal process to steps of different amplitude in the reference signal or in external disturbance; the analysis of responses to different values of the input signals is motivated by the fact that a fuzzy control system is nonlinear;
- responses to one mean value of reference signal or disturbance for several combinations of plant parameters or different sampling periods of the fuzzy model, with a view of checking the sensitivity to uncertainties in the process parameters.

First, Figure 4 presents a typical simulation result. A 30 degrees reference step is attained after one correcting saccade. Eye, head and gaze trajectories are plotted versus time.

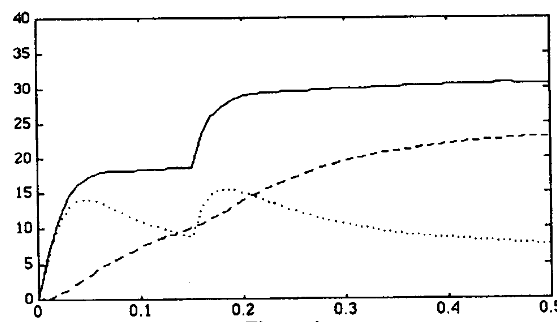


Figure 4.
Output of the process in degrees: Gaze (=Y) solid line, Eye = dotted line, Head = dashed line, versus Time in seconds. Reference step = 30 degrees.

Other simulation results give the position error (in degrees) in function of time (in seconds). The solid line corresponds to the nominal value of the parameters, the dotted line to a selected parameter twice smaller and the dashed line to the same parameter twice bigger.
Figure 5a gives step responses for three different values of the reference (R=10, 30, 50 degrees), Figure 5b responses to three

different values of disturbance (D= 10, 30, 50 degrees). It can be seen that responses for the largest R and D have a steady-state error due to the limited range of the output of the fuzzy adder.

The model used in the control system is based on the assumptions that the process has a unit static gain and a settling time of 0.1 s. The sensitivity to parameters that influence those characteristics has been investigated: gain of the process G, time constant of the head plant Th, perturbation on the head during the movement. The influence of the sampling period T has also been studied.

The effects of variations of the process gain G are shown on Figure 6 for a mean reference input (Figure 6a) and a mean disturbance input (Figure 6b). As expected, the responses become more oscillatory when G increases.

Figure 7 corresponds to variations of the time constant of the head plant: Th (second order system with one double time constant). Responses to the reference and to the disturbance are similar, faster and with an overshoot when the time constant is smaller. Variation of the time constant would correspond to a change in the inertia of the head platform for instance to the application of an external load.

The influence of the sampling period T is analysed in Figure 8. The responses to these three values of sampling period are very similar. Small periods (0.075 s) do not lead to oscillatory responses, because they are of the same order as the settling time of the process (0.1 s); but smaller values would lead to oscillations.

Finally, Figure 9 presents responses to transient perturbations on the physical head plant (velocity pulses). It can be shown that one sampling period is sufficient to compensate for a positive or a negative perturbation (head tapping).

From all the responses to disturbances it appears that the fuzzy IMC structure is able to reject disturbances. However, as expected it must be remarked that the control system with fuzzy model is unable to cope with large reference or disturbance steps. This is due to limitations on input and output variables of the fuzzy adder.

5. DISCUSSION OF SIMULATION RESULTS

In this study, a link is made between internal model representation and the modelling of the saccadic system. The process that has been considered involved the Superior Colliculus and all the structures downstream to it (premotor level).

However, it is worth noting that this link with the internal model representation could as well have been done at the motor level (upstream to the motoneurons), all the more as there is no clear experimental evidence of any U signal (Figure 2) in the brain, excepted at very high cortical level. The system seems to work only with error signals instead of position in space signals.

Indeed, the model proposed by Guitton, Munoz and Galiana

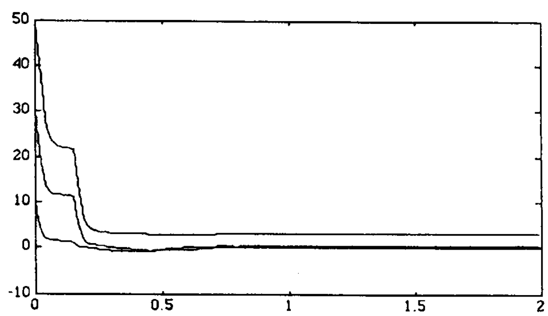


Figure 5a

Position error (degrees) versus time (s) for three references: 10, 30 and 50 degrees. Nominal parameter values: head plant time constant Th=0.3 s, process gain G=1, sampling period T=0.15 s

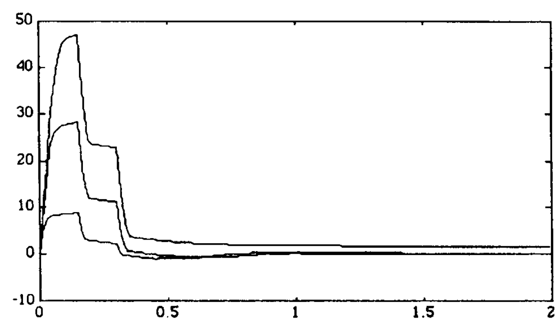


Figure 5b

Responses to disturbances in the nominal case. Disturbance steps: 10, 30 and 50 degrees. Nominal parameter values: head plant time constant Th=0.3 s, process gain G=1, sampling period T=0.15 s.

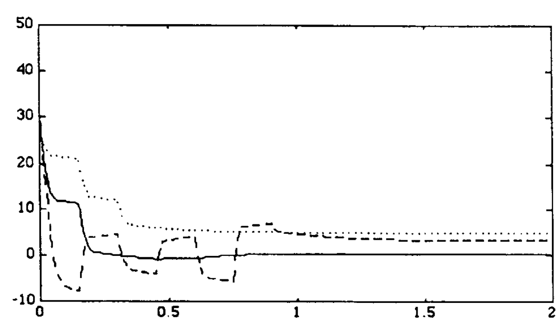


Figure 6a

Influence of the process gain G on the response to a mean reference input (R=30 degrees). G = 0.5, 1 and 2.

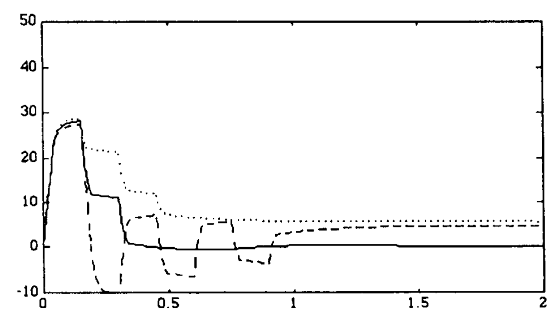


Figure 6b

Influence of the process gain G on the the response to a mean disturbance input (D=30 degrees). G = 0.5, 1 and 2.

assumes that the oculomotor itself is controlled by a feedback loop based on internal models [5].
This is particularly interesting, because it shows that the link made between the saccadic system and the internal models is probably even stronger than initially proposed. It could take place at multiple nested levels.

As a corollary of this study, a link can be clearly done with the optokinetic system, which could be pretty well modelled on the basis of internal model representation. In this case, the eyes try to follow a target which is moving in space (tracking), and the signal coming from the retina is assumed to give an estimate of target velocity.

Even if the eyes nearly always undershoot the target in space, it happens for some subjects and/or some particular experimental paradigms that the target is overshot. The model gives good predictions in that case too, a correcting saccade in the opposite direction being triggered when the visual feedback loop is closed (next sample).

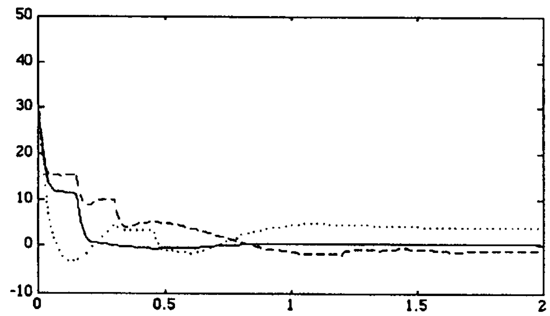


Figure 7a
Effect of the time constant of the head plant Th on the response to a mean reference input (R=30 degrees). Th = 0.15, 0.3, 0.6 s.

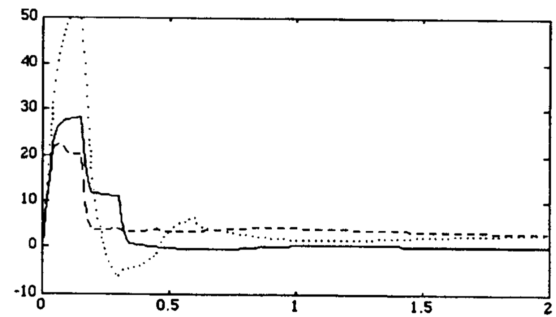


Figure 7b
Effect of the time constant of the head plant Th on the response to a mean disturbance input (D=30 degrees). Th = 0.15, 0.3, 0.6 s.

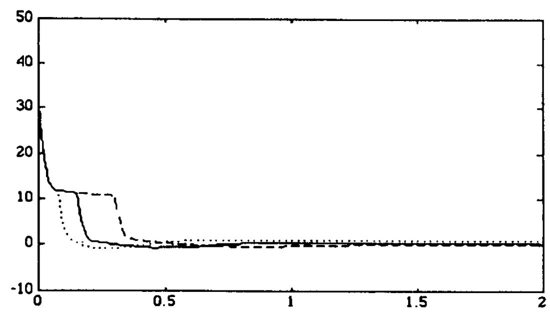


Figure 8a
Influence of the sampling period T on the response to a mean reference input (R=30 degrees). T = 0.075, 0.15, 0.3 s.

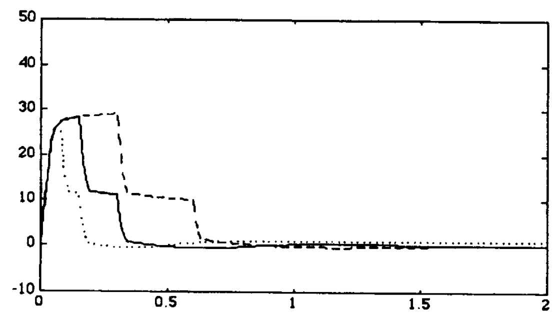


Figure 8b
Influence of the sampling period T on the response to a mean disturbance input (D=30 degrees). T = 0.075, 0.15, 0.3 s.

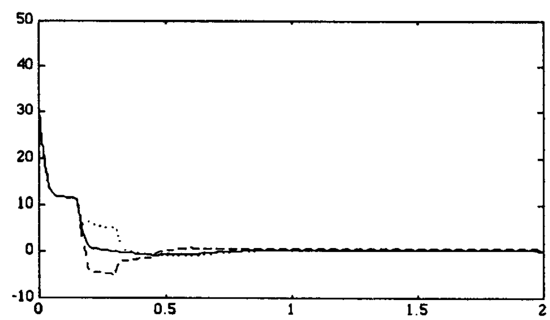


Figure 9a
Effect of a pulse of perturbation on the head plant to a mean reference input (R=30 degrees). Perturbation = pulse in velocity, applied at time t = 0.16 s, duration = 0.025 s, amplitude = -200 (dotted) or 200 °/s (dashed).

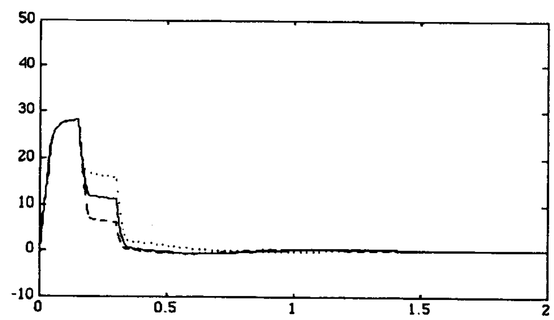


Figure 9b
Effect of a pulse of perturbation on the head plant to a mean disturbance input (D=30 degrees). Perturbation = pulse in velocity, applied at time t = 0.16 s, duration = 0.025 s, amplitude = -200 (dotted) or 200 °/s (dashed).

In this study, we did not talk about how the internal model had been built and how it could eventually be adapted. The learning would be a very important way to investigate further (proprioceptive feedback loops interacting with vision...).
Noteworthy, the control of more complex peripheral limb movements could probably be modelled by equivalent techniques (role of the cerebellum...).

6. CONCLUSIONS

The above simulation analysis illustrates nice properties of internal models control systems: robustness to changes in dynamic parameters and rejection of disturbances. These performances are retained in fuzzy implementations of IMC systems.
The link between this control structure and biological systems is probably even stronger than described in this study. Indeed, the use of internal models could take place at multiple nested levels.
Moreover, the proposed control scheme could most probably apply to other biological systems related to vision (optokinetic system) or to motion (peripheral limb movement).

ACKNOWLEDGMENTS

This research is supported by the Belgian National incentive-program for fundamental research in Artificial Intelligence, Prime Minister's Office - Science Policy Programming. The scientific responsibility is assumed by its authors.

REFERENCES

[1] J. Barreto, M. De Neyer, P. Lefèvre, R. Gorez, "Qualitative physics versus fuzzy sets theory in modeling and control". To be presented at *IECON 1991, International conference on industrial electronics, control and instrumentation,* Kobe, Japan.

[2] M. De Neyer, R. Gorez and J. Barreto. "Disturbance rejection based on fuzzy models". *Proc. IMACS Workshop on Decision Support Systems and Qualitative Reasoning*, (in press) Toulouse, France, 1991.

[3] M. De Neyer, R. Gorez and J. Barreto. "Fuzzy controllers using internal models". *Proc. IMACS - IFAC Symposium on Modelling and Control of Technological Systems*, Lille, France, **1**, pp 726-731, 1991.

[4] R. Gorez, M. De Neyer, J. Barreto. "Model based fuzzy control systems". To be presented at *13 th IMACS World Congress on Computation and Applied Mathematics*, Dublin, Ireland, 1991.

[5] D. Guitton, D. P. Munoz and H. L Galiana, "Gaze control in the cat: studies and modeling of the coupling between orienting eye and head movements in different behavioral tasks". *Journal of Neurophysiology,* 64, pp. 509-531, 1990.

[6] W.J.M. Kickert and H.R. van Nauta Lemke, "Application of a fuzzy controller in a warm water plant", *Automatica*, Vol.12,pp.301-308, 1976.

[7] P.J. King and E.H. Mamdani, "The application of fuzzy control systems to industrial processes", *Automatica*, vol.13, pp.235-242, 1977.

[8] V. P. Laurutis and D. A. Robinson, "The vestibulo-ocular reflex during human saccadic eye movements". *Journal of Physiology,* 373, pp. 209-233, 1986.

[9] E.H. Mamdani, "Application of fuzzy algorithms for the control of a dynamic plant. In *Proc. I.E.E.*, 121, pp 1585-1588, 1974.

[10] M. Morari and E. Zafiriou. Robust process control. Prentice-Hall, Englewood Cliffs, N. Y., 1989.

[11] M. Morari, C. E. Garcia and D. M. Prett. "Model predictive control: theory and practice".*Proc. IFAC Workshop on Model Based Process Control,* Atlanta, Ge, USA, pp 1-12, 1989.

[12] A. Smit, J. van Gisbergen, L. Cools, "A parametric analysis of human saccades in different experimental paradigms'. *Vision Research*, 57, pp. 1745-1762, 1987.

[13] R. Tanscheit and E.M. Scharf, Experiments with the use of a rule-based SOC for robotic applications, *Fuzzy sets and systems*, n°26,pp.195-214, 1988.