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ADAPTIVE TIME OPTIMAL FUZZY CONTROL

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ABSTRACT - **The paper shows how techniques of artificial intelligence and fuzzy reasoning could be used to implement time optimal control policy when exact mathematical model of the process is not known.**

The controller has simple knowledge base with the knowledge about control policy for different starting errors, but it has adaptive and self learning properties, too. After each run the controller adjust itself using simple meta rules in order to improve process response.

Theoretical foundations are illustrated by results of laboratory experiments with two-degree of freedom mechanical system.

1 Introduction

Fuzzy control had its origins in fuzzy set theory, with the first publication appearing in the early 1970's. Since then, the field has maturated considerably, with applications and theoretical work being reported from all over the world. In the last couple of years there are two main streams in the field of fuzzy control. The first one is orientated toward commercialization of simple fuzzy control and its industrial application, and the second one deals with theoretical and experimental development of more sophisticated form of fuzzy control, as for example self-organizing fuzzy control, self - learning fuzzy control, adaptive fuzzy control, optimal fuzzy control etc. This paper belongs to the second group and deals with theoretical development and experimental verification of newly introduced Adaptive Time Optimal Fuzzy Control.

The main idea is the same as in conventional time optimal control whose main objective is to drive process output from an initial steady state to a final steady state in minimal time. This task could be optimally solved using bang-bang control policy which involves switching the control input alternatively from one extreme value to another in pre calculated switching times.

These switching times could be easily find if an exact mathematical model of the process is known, but usually it is almost impossible to obtain an exact mathematical model. To solve the problem of time optimal control also in these cases, an approach based on artificial intelligence and fuzzy set theory has been proposed.

2 Time optimal control policy

The main control objective in time optimal control is to drive process output from an initial steady state to a final steady state in a minimal time. The process is in open loop, so there is no influence of feedback information on control signal. Well known optimal control theory [1] gives methodology, usually known as bang-bang control, which could satisfied this control objective. It involves switching the control input alternatively from one extreme value to another in pre calculated switching times.

The 2-nd order control algorithm could satisfied most practical cases.

It involves two control input switching between the extremes. Fig.1. shows the typical situation when it is necessary to drive process from the initial steady state to a higher final steady state when there is a positive correlation between control signal and the process output.

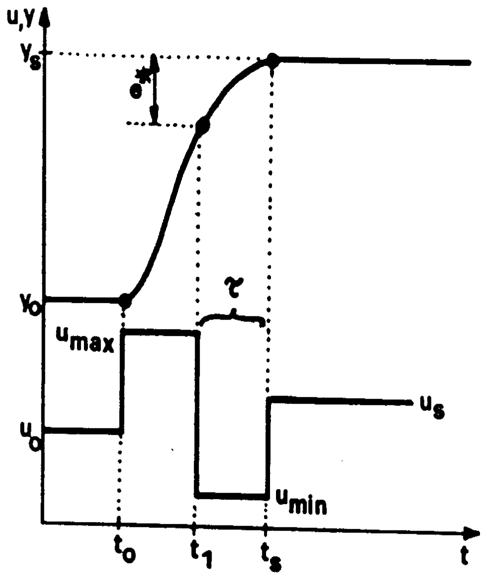

Figure 1: 2-nd order time optimal control

At the beginning the control signal is switched from its current value u_o to maximal positive control u_{max} and kept at this value until the error (difference between final steady-state output and actual output $e(t)=y_s-y(t)$) is equal to pre defined error value e^*. Then the control is switched to minimal value u_{min} and maintained there for some time τ. If parameters e^* and τ are correct, process output would settle exactly to desired steady state value as Figure 1 shows.

Switching parameters e^* and τ could be easily find if an exact model of the process is known. But sometimes it is not possible to find a mathematical model of the process, so switching parameters have to be defined and adjusted heuristically.

In [2] such an approach based on the observed process response is described. It use the simple meta- knowledge about dependence of switching parameters and process response. For e^* it can be simple stated as follows:

"If e^* is too small, then the process output would overshoot the set point and if e^* is too large, then the output would undershoot the set point."

e^* was adjusted using the simple fuzzy rule base algorithm when the step size Δe is calculated taking into account overshoot or undershoot values.

In the next section an alternative, more sophisticated self-learning algorithm of time optimal control also based on fuzzy set theory will be introduced and described.

3 Adaptive time optimal control

Adaptive time optimal controller is conceived as a hierarchical controller with three layers: an ordinary, deterministic 2-nd order time optimal controller, a rule-based module for pre calculation of switching parameters and a modifying module which modifies elements of the module for pre calculation of switching parameters. This third module is also a rule-based and it uses the meta knowledge for modification of switching parameters.

2-nd order time optimal controller needs two switching parameters e^* and τ, so generally both parameters have to be calculated before control. In experiments which will be described in the next chapter τ was fixed and determinate experimentally by a series of trials and only e^* was calculated before each run and modified after each run. In the rest of this paper we will describe this simple control algorithm, but it could be easily improves on a way that both switching parameters e^* and τ are calculated and modified from the observed process response. Control algorithm is shown on Figure 2.

Switching parameter e^* is calculated using equation

$$e^* = k\, e^*_R \qquad (1)$$

where k is a parameter dependent of the starting error e_o (difference between final and initial steady-state values). The value of this parameter could be any one from the interval $[1/k_M, k_M]$

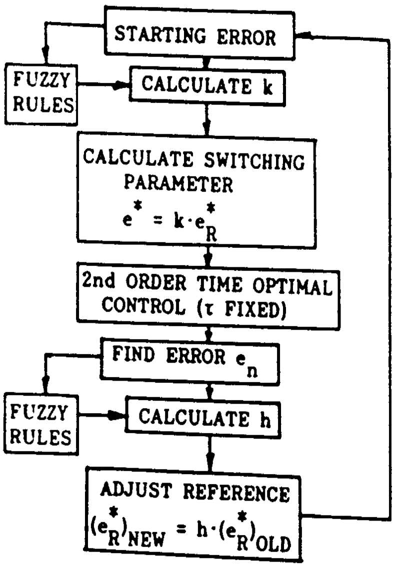

Figure 2: Control algorithm of adaptive time optimal control

where k_M is some pre defined maximal positive value bigger then one. k is calculated using fuzzy algorithm and simple linguistic rules:

(i) If e_o is SMALL then k DECREASE.

(ii) If e_o is MEDIUM then k NIL.

(iii) If e_o is LARGE then k INCREASE.

SMALL, MEDIUM, LARGE, DECREASE, NIL and *INCREASE* are fuzzy propositions characterized by user-specified membership function. In fuzzy algorithm a trapezoidal rule and max-min composition [3] is used.

e_R^* is the average value of switching parameter. At the beginning it is determinate heuristically for some medium value of initial error. For example in experiments described in the next section possible values of error where between 0^o and 180^o, so e_R^* was heuristically defined for starting error of 90^o. Corresponding value of k was 1 ,and fuzzy algorithm and linguistic rules give k bigger then 1, $k \in (1,k_M]$, for e_o bigger than 90^o and smaller then 1, $k \in [1/k_M,1)$, for e_o smaller then 90^o.

After each run, when the process reach new steady-state e_R^* is subjected to modifications and adjusted in order to improve process response. Steady-state error e_n (difference between desired and realized final steady- state value) is calculated and used as an input parameter to modification procedure. New e_R^* is calculated using equation

$$(e_R^*)_{NEW} = h\ (e_R^*)_{OLD} \qquad (2)$$

where h is a parameter taking value in interval $[1/h_M,h_M]$ and h_M is some pre defined maximal positive value bigger then 1. Calculation procedure is similar to calculation of switching parameter e^*. Fuzzy algorithm based on trapezoidal rule and max-min composition [3] is used with linguistic rule base of the form:

(i) If e_n OVERSHOOT then h DECREASE.

(ii) If e_n NO SHOOT then h NIL.

(iii) If e_n UNDERSHOOT then h INCREASE.

OVERSHOOT, NO SHOOT, UNDERSHOOT, NIL, DECREASE and *INCREASE* are fuzzy propositions characterized by user-specified membership functions.

In the next run switching parameter e^* is calculated using equation (1), but this time with the new value of e_R^*.

4 Experimental research

In order to verify and illustrate theoretical foundations a series of experiments were performed using a laboratory model of two-degree of freedom mechanical helicopter. Figure 3 is a schematic diagram of the experimental equipment.

The controller was implemented, in BASIC and ASSEMBLER, on microcomputer and interfaced to a system using a custom made interface. The mechanical helicopter model is highly nonlinear system and quite difficult to model mathematically. Experiments with adaptive time optimal fuzzy control were performed using only one degree of freedom (angle 2) and the second one (angle 1) was rotating freely. Figure 4

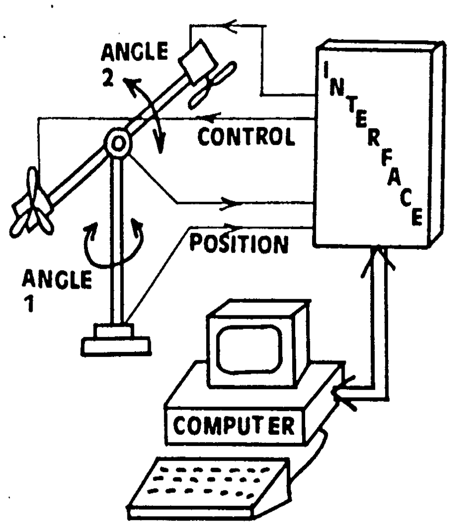

Figure 3: Schematic diagram of the equipment used in experiments

shows typical responses for the same initial error $e_o = 150^o$ (final steady-state was 0^o) and different switching parameters which give undershoot, overshoot and correct response.

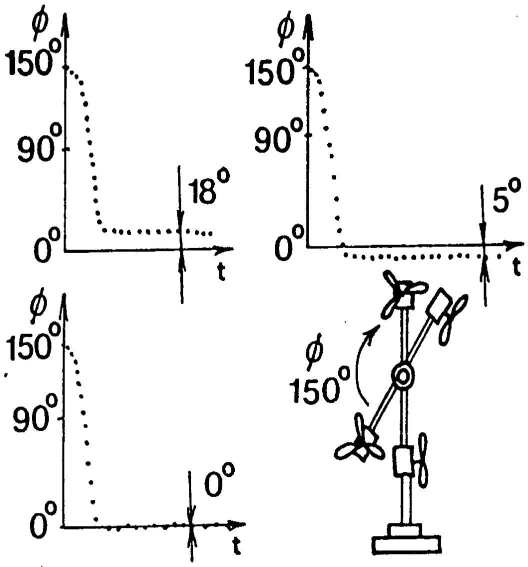

Figure 4: Typical experimental responses - a) undershoot, b) overshoot and c) no shoot

Optimally adjusted e^* was 57^o. In all cases τ was fixed and equal to 0.53 seconds. Starting and final control signal was 0V, maximal control was +5V and minimal control was -5V. Table 1 gives optimal values of e^* for different initial errors and value of k calculated by fuzzy algorithm.

Table 1: Optimal values of switching parameter e^* and k for different initial errors e_o and final value 0^o

e_o	150^o	120^o	90^o	60^o	30^o
e^*	57^o	50^o	40^o	33^o	18^o
k	1.59	1.26	1	0.79	0.56

Other results were quite satisfactory, too, although some problems with accuracy were reported, mostly because mechanical model was not preciously build. After a number of runs determinate switching parameter e^* were no more optimal one, but thanks to its adaptive features the controller was capable to adjust itself and to find new optimal e^* (of course after some learning time).

5 Conclusion

The paper shows how ideas of time optimal control could be applied also in the cases when a precise mathematical model if the system under control is not known, so when it is not possible to find preciously the switching parameters. To solve this task the methodology of artificial intelligence and particularly fuzzy reasoning was used.

The proposed controller has three levels: an ordinary 2nd order time optimal controller, rule-based module for pre calculation of switching parameters for different starting errors and rule-based module for modification of previous module in order to improve process response. Experimental results have shown that ideas are worth of further investigations.

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