DESIGN AND DEVELOPMENT OF AN OPTIMAL INTELLIGENT FUZZY LOGIC CONTROLLER FOR LASER TRACKING SYSTEM

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ABSTRACT

This paper presents the design and development of an optimal fuzzy logic controller (FLC) for a laser tracking system. An optimal intelligent fuzzy logic controller was founded on integral criterion of the fuzzy models and three-dimensional fuzzy control. Research had been also concentrated on the methods for multivariable fuzzy models for the purposes of real-time process. Simulation results have shown remarkable tracking performance of this fuzzy PID controller.

1.0 INTRODUCTION

There have been numerous conventional approaches in the literature to the control of various laser tracking systems, including robust control methods [1]. However, despite the significant improvement of the fuzzy PID controller, it is noted that these fuzzy PID controllers do not meet specific optimality criteria for a laser tracking system [2]. The constant control gains of these controllers are tuned manually, so generally they do not achieve their best possible performance due to the lack of optimization [3]. As we know, a two-dimensional fuzzy controller has its advantages in various applications, but for the tracking system the number of parameter increases would cause dominant problems for the search precision. Therefore, it is reasonable to consider that a three-dimensional fuzzy controller could be provided an optimal structure for a nonlinear fuzzy PID controller [4]. The parameters of a three-dimensional fuzzy controller with fuzzy models may well represent a solution for the design of an optimal fuzzy logic controller.

In this paper, we concentrated on the methods for multivariable fuzzy models in three-dimensional fuzzy controller for the laser tracking system.

2.0 DESIGN OF FUZZY CONTROL SYSTEM

There was a general procedure for the research that we used to design a fuzzy control system (Figure 1).

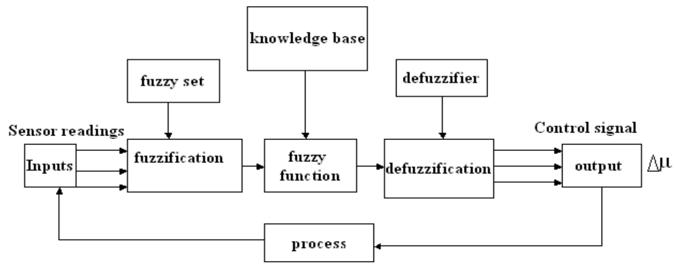

Figure 1. Structure of a fuzzy logic controller

First, we had to identify the process input and output variables that needed to be considered. Thus, we had to have a good knowledge on the system to be controlled. To determine input and output variables, we also set the variables according to the system requirements. Next, we needed to determine on the number of fuzzy partitions for the input and output linguistic variables. The number of fuzzy partitions of the input-output spaces needed to be large enough to provide an adequate approximation and small enough to save memory space. This number had an essential effect on how fine a control could be obtained. In the third step, the research had to choose the membership functions for the input and output fuzzy variables, and to assign fuzzy sets to variables, and then define membership functions. To establish the fuzzy logic controller, it was necessary to interpret control rules that generated the output values corresponding to the input signal.

A good alternative of the fuzzy PID controller was to use a three-dimensional table (lookup table) to establish a fuzzy PD controller, and to add the integral part to the control path without fuzzification. It looked at the current value of the error, the integral of the error over a recent time interval, and the current derivative of the error signal to determine the correction in Figure 2.

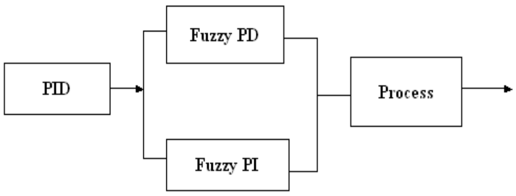

Figure 2. Optimal Fuzzy PID Controller

Nonlinearities that existed in the laser tracking system included transfer function of the quadrant detector, plant model, and dead-zone. For some applications, an accurate and fine control was needed to achieve the objectives of high tracking speed and small steady-state error. The following diagram of the fuzzy logic controller was used in the control system in Figure 3.

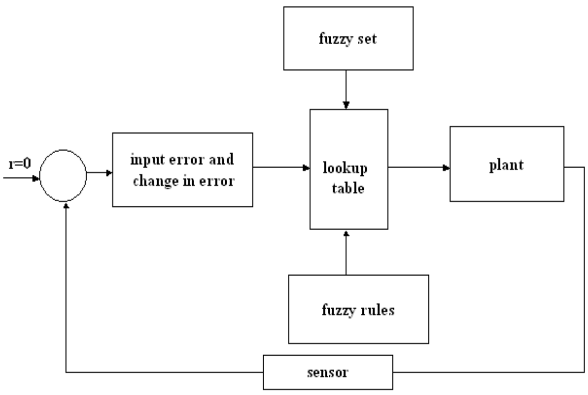

Figure 3. Block diagram of the FLC

The lookup table was derived from the membership function and control rules in the actual laser tracking system. Different tunings may be needed to obtain the optimal lookup table based on the laser tracking system.

3.0 OPTIMAL FLC DESIGN

3.1 Nonlinear Three-Dimensional FLC

The three-dimensional fuzzy logic controller was composed of fuzzification, knowledge based rule, and defuzzification. A fuzzy logic distinctive feature was the use of a linguistic variable instead of the numerical variables. These were defined as sentences in a nature language and can be represented by fuzzy sets. The fuzzy logic controller had three basic steps to process: fuzzification, control rule evaluation and defuzzification in Figure 4.

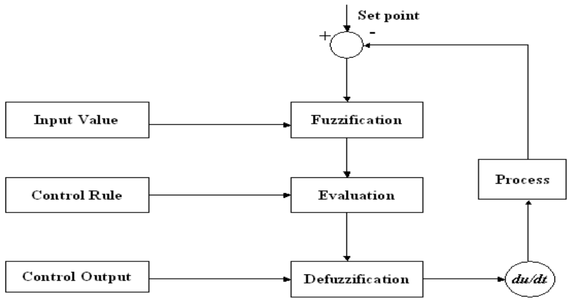

Figure 4. Fuzzy logic control system architecture.

The control variables were divided into a set of fuzzy sets, which were given nature names: big positive (BP), medium positive (MP), small positive (SP), zero (Z), small negative (SN), medium negative (MN) and big negative (BN). We supposed that all variables were selected within the closed interval [SN, BP]. Each of these fuzzy sets had two members. The linear fuzzification algorithm was for output with fuzzy set five members. We started to use a triangular shape function to express the knowledge-based rule in following equations:

$$K_p(\mathbf{e}) = \tfrac{1}{2}(BP)\ [X_e \times e(nT) + BP],\ \ K_n(e) = \tfrac{1}{2}(BP)[BP - X_e \times e(nT)]$$

$$K_p(\mathbf{r}) = \tfrac{1}{2}(BP)\ [X_r \times r(nT) + BP],\ \ K_n(r) = \tfrac{1}{2}(BP)[BP - X_r \times r(nT)]$$

$$K_p(\mathbf{p}) = \tfrac{1}{2}(BP)\ [X_p \times p(nT) + BP],\ \ K_n(p) = \tfrac{1}{2}(BP)[BP - X_p \times p(nT)]$$

where $\boldsymbol{e}$, $\boldsymbol{r}$, and $\boldsymbol{p}$ were denoted as error, change in error and control process output in a three-dimensional fuzzy control system. $\boldsymbol{T}$ denotes sampling time. These fuzzy sets were calculated during the fuzzification process. Assuming a resolution of 13 points in each universe, the table held 2197 elements. It would be a tremendous task to fill these in manually, but it is manageable with control rules. A three-dimensional table can be represented using relational representation. The table can be rearranged into three columns for each of the three inputs ($\boldsymbol{e}_1$, $\boldsymbol{e}_2$, $\boldsymbol{e}_3$), ($\boldsymbol{r}_1$, $\boldsymbol{r}_2$, $\boldsymbol{r}_3$) and one for the output ($\boldsymbol{p}$). Each input took five values, and the lookup table corresponded to the output value.

In the fuzzification step, two inputs were employed: the error signal $\boldsymbol{e}$ and change in error signal $\Delta\boldsymbol{e}$, and the control output $\boldsymbol{p}$ as the input to the process being controlled. The inputs to the fuzzy PID controller have to be fuzzified before being fed into the controller. The membership functions for the two inputs and the output had similar shape but different peak values and standard deviation. These values of constant were chosen according to the range of values received in the tracking system. The control signal for fuzzy PID was easily computed by combining its P and D coefficients. This can be converted into fuzzy rules. The fuzzy rules were applied to each joint of the tracking system. The fuzzy proportional controller has a different set of rules applied to each joint. This was derived from the performance of the tracking system.

3.2 Fuzzy Controller Models

Fuzzy models had excellent capabilities to use in a given system. A fuzzy model of a non-linear system consists of a set of implication rules, which were used to express control statements. We used an input system with m inputs (x_1, x_2, …, $x_{\mathbf{m}}$) and a single output y. In principle, the fuzzy model of such a system consists of a rule base with n fuzzy implication rules. The $\boldsymbol{i}$-th rule $R^{\boldsymbol{i}}$ ($\boldsymbol{i}$ = 1, 2, … , n) had the following general equation.

$\boldsymbol{R^i}$: if $\boldsymbol{f}$(x_1 is $A^{\boldsymbol{i}}_{\mathbf{1}}$, $x_{\mathbf{2}}$ is $A^{\boldsymbol{i}}_{\mathbf{2}}$, …, $x_{\boldsymbol{m}}$ is $A^{\mathbf{i}}_{\boldsymbol{m}}$) then $y^{\boldsymbol{i}}$ = $g^{\boldsymbol{i}}$(x_1, x_2, … , x_m)

where $y^{\boldsymbol{i}}$ inferred a variable of the consequence of the $\boldsymbol{i}$-th rule. The final output y of the system is a combination of all y^i ($\boldsymbol{i}$= 1, 2, … , n). $\boldsymbol{f}$ is a connective function that joins the propositions in the premise, and $g^{\boldsymbol{i}}$ is the function that implies $y^{\boldsymbol{i}}$ when the x_1, x_2, …, $x_{\boldsymbol{m}}$ satisfies the promise.

If $\boldsymbol{f}$ is the "and" connective function and g^i is a linear function of the form $a^i_0 + a^i_1x_1+\ldots+ a^i_mx_m$ the $\boldsymbol{i}$-th fuzzy implication rule became:

$\mathbf{R^i}$: if x_1 is A^i_1 and x_2 was A^i_2 and … x_m is $A^{\boldsymbol{i}}_m$ then $y^{\boldsymbol{i}} = a^{\boldsymbol{i}}_0 + a^{\boldsymbol{i}}_1x_1 + \ldots+ a^{\boldsymbol{i}}_mx_m$

The truth-value of the conjunction between propositions in the premise was estimated by the minimum of their membership values. That is, the truth value of (x is A and y is B) was estimated as ***min***(A(x), B(y)), where A(x) and B(y) was the membership values. Assume some input variables and some initial premise parameters. Consequent parameters were optimally adjusted with respect to the premise parameters and then the premise parameters were readjusted. This was accomplished by a complex algorithm, which was based on a non-linear optimization method. The optimal fuzzy model was achieved by using a set of sample data (input and output). The parameter identification was concerned with the determination of the fuzzy set for the reference signal. This was done by dividing the input space of each variable into fuzzy subspaces, provided that variables were chosen. The reference signal was included to get better response for big changes in the reference signal. For the plant in Figure 5, the controller first requires model identification. The number of the linear models needed depends on behavior of the nonlinearity of the plant.

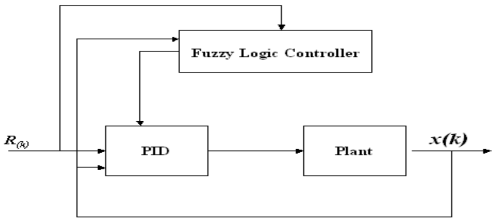

Figure 5. The reference signal.

The modeling was performed collecting input and output data from the simulation and using some parameter estimation algorithm. During the simulation, the data value of the plant output was selected as the operating point of the model. The parameters of the fuzzy PID controller were determined based on the models. If strong nonlinearities occurred in the control parameters, more models were estimated where required to obtain more accurate approximation of the controller parameters with the fuzzy logic.

The plant output had the same number of fuzzy sets as the number of the models. The points of parameters in the models were estimated. The fuzzy sets and the membership functions of the reference signal were identified with the plant output. The plant was stable, but its dynamics change dramatically over the operation range, which can be easily seen from the open loop step responses. The optimal fuzzy PID could be computed from the linearized model. The model parameters had been estimated from input and output data with sampling interval.

3.3 Optimal Fuzzy Logic Controller for Laser Tracking System

Figure 6 was based on the error derived from the difference between the desired input and the actual measured output fed back for PID control loop.

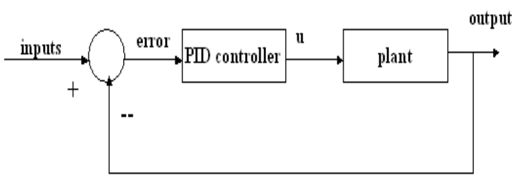

Figure 6. PID control loop

Therefore, the equation for the activation *u* is given by equation. $u(t) = K_p e(t) + K_i \int e(t)dt + K_d$ de/dt where $e(t)$ is the error input to the PID controller. When K_d was zero, there were two gain parameters to set K_p and K_i. The proportional gain K_p was usually set first with $K_i = 0$, then K_i was increased to achieve good steady-state response. Setting the PI controller aside for the research, we needed to design the fuzzy part of the system. We assigned error and change in error as the variables to meet the name that the PD controller indicated. The error was pointed out as the digital signal that converted from the analog output, which represented the offset of the laser spot from the control point. This error signal also represented the displacement in the mirror by the target moving in the target. Error change equals the previous error minus the error from the last sampling. It was supposed that the error is "zero" in an imprecise way. Then the error had a membership value given by the functional value shown below in Figure 7.

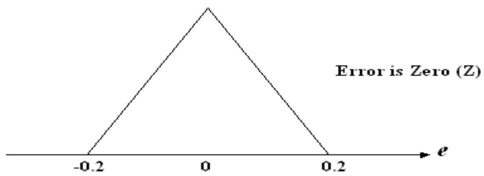

Figure 7. Small negative that error is zero

If the error was zero and the change in error was small positive, then the control input was small negative. If the error was small positive and the error change was small positive, then the control input was small medium positive. Thus, if the error was actually 0.1, its membership in Z would be 0.5, and the value of the triangular function was at that point. We collected all the IF-THEN rules together and formed a decision table (lookup table) for the fuzzy controller that was much more concise and easier to manipulate. Continuing with the research, the linguistic values of the error were taken to be negative (N), zero (Z) and positive (P) with the following membership functions in Figure 8.

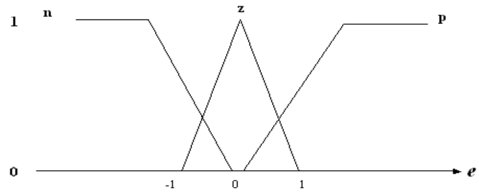

Figure 8. Error derivative

We constructed different rules, corresponding to the possible combination of the error and the error derivative. The fuzzy set, or membership functions, and control rule were combined together to form the lookup table, and the outcome of the step was a fuzzy variable. From the research, the method was used to obtain the lookup table. The method was to use the input error and change in error, combined with the membership function, to calculate the output in real time. This method was accurate and smooth for the control output.

4.0 Simulation

In the simulation results, we presented the effectiveness and special features of the proposed control method using the fuzzy PID controller. Plots of the system output with the optimal PID gains that achieved the best results by error and change in error where P = K_p, I = K_i, D = K_d, and K_{upd} and K_{ui} were fuzzy gains. The parameters for the fuzzy PID controller gains were found such that there were only little overshot, no oscillations, and a good tracking performance with respect to the given set point. With the speed of 760 r/min, the fuzzy PID controller kept the speed of the motor within a ± 1.2% band of the set point. The results were shown and the significant feature of tracking performance was much better because of the smaller overshot and smaller rise-time. As the speed decreased, there was an increasing non-linear loading effect and the performance of the controller went down. The number of the membership function was tested in models by using three membership functions per variable. It was found that with these fuzzy models, two variable models also better on the checking data.

The input values were normalized by dividing the set point for the controllers. The error and change in error value were between the intervals [0, 0.015]. The system automatically generated the input variables, their linguistic types, initial rule base and the output variable. The value may be used as a way for structural learning of the fuzzy model. Using the value we could limit the size of the rule base. Fuzzy clustering was to identify natural groupings of data from a large data. Each data point may partially belong to more than one cluster with a degree specified by a membership function in Figure 9.

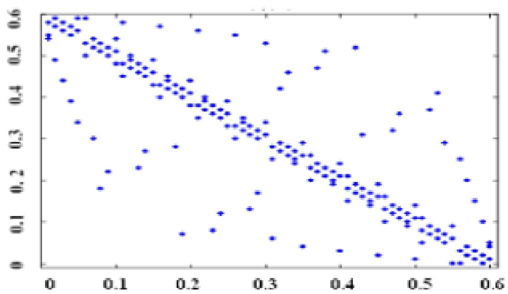

Figure 9. Fuzzy PID Cluster

The cluster center locations and iteratively updates the cluster centers and the membership functions for each data point based on minimizing a cost function. Two input variable models and five membership functions per variable turned out the lowest error, about 0.017 for the checking data. However, the differences between the outputs were not very large. We analytically derived the structure of the fuzzy controller modes and related the resulting structure to nonlinear PI control as well as gained scheduling control. We analyzed the characteristics of the gains. Based on the derived models structure, we analyzed the performance stability of the optimal fuzzy control systems using the fuzzy models theorem. In order to visualize error and change in error, we provided three-dimensional plots of K_p(e, r) in three different typical settings. It could handle inputs and an output. However, the size of the fuzzy table was grown exponentially with each input added. The maximum and minimum of K_p(e, r) was 8 and 5, respectively. This demonstrated that we could obtain different characteristics of the gain variation by using different parameter values. According to the derived fuzzy model structure, as well as the explicit expression of the gain variation, the optimal fuzzy controllers were closely related to the concept of gain scheduling. A three-dimensional fuzzy controller, using three six bits input (6x6x6) and (2x2x2) fuzzy lookup tables, were used each having 216 and 8 values, respectively. The system used three inputs, the upper three bits of each input were used for addressing the exact position of the nearest data point in the lookup table, and the rest of the input was the information about the membership function. The required point was obtained using 32 points, 10 in each dimension. These points were used to calculate one point for each dimension to find out the required point. Using this method there was a lot of reduction in error and change in error, which reduced computational complexities and made the system precision of the tracking performance in Figure 10.

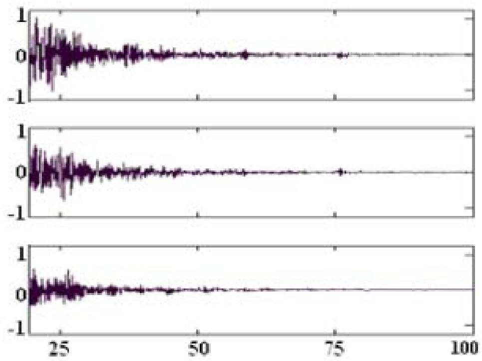

Figure 10. The Responses of Tracking Performance with Optimal Fuzzy PID Controller.

Figure 10 showed that the tracking performance had smaller errors during the simulation. The fuzzy model scheme had been tested thoroughly on different conditions, and satisfied results were obtained. Although a rule for choosing the fuzzy model range for K_p and K_d was obtained by the simulation, it was still possible to make further performance improvement by fine tuning the ranges, as well as by modifying the tuning rules. In the Figure 10, the responses were at time t= 100 using the optimized PID values, whereas at time t = 25 for starting values. The method was also a more scientific and logical approach to a difficult problem of tuning the PID controller. The obtained values could be directly to the results of the responses of the tracking system.

5.0 Conclusion

All the simulation results indicated that the optimal fuzzy logic controller was superior to the fuzzy PID controller for the tracking system. Nevertheless, based on the satisfactory performance of the optimal fuzzy PID controller, we believe that the optimal fuzzy PID controller is suitable and potential for the control of nonlinear plants in various industrial applications.

6.0 References

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