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Fuzzy-Sliding Mode Control of Polishing Robot Based on Genetic Algorithm

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Abstract

This paper shows a self tuning fuzzy inference method by the genetic algorithm in the fuzzy-sliding mode control for a polishing robot. Using this method, the number of inference rules and the shape of membership functions are determined by the genetic algorithm. The fuzzy outputs of the consequent part are derived by the gradient descent method. Also, it is guaranteed that the selected solution become the global optimal solution by optimizing the Akaike's information criterion expressing the quality of the inference rules. It is shown by simulations that the method of fuzzy inference by the genetic algorithm provides better learning capability than the trial and error method.

1 Introduction

To overcome problems related to the unmodeled dynamics in high speed operation of industrial robots, many researchers have used the sliding mode control which is known to be robust against parameter variations and payload changes [6]. However, this algorithm could not completely reduce the inherent chattering which was caused by excessive switching inputs around the sliding surface.

In the our previous study, the fuzzy-sliding mode controller was designed to reduce the inherent chattering of the sliding mode control by the fuzzy rules within a predetermined dead zone. The trajectory tracking experiments showed that the chattering could be reduced prominently by the fuzzy-sliding mode controller and the proposed controller was robust in spite of a change of payload [5]. However, the number of inference rules and the shape of membership functions in the antecedent part should be determined through the trial and error method by an expert who had the knowledge of robot systems. And, because inference rules were determined by the trial and error, it could not be guaranteed whether the selected inference rules were the global optimal solution or not.

This paper shows a self tuning fuzzy inference method by the genetic algorithm. The genetic algorithm is the search algorithm based on the mechanics of natural selection, genetics, and evolution. One of the best advantages of the genetic algorithm is to obtain global optimum because of operators such as crossover and mutation [4]. Using this method, the number of inference rules and the shape of membership functions in the antecedent part are determined by the genetic algorithm and the fuzzy outputs of the consequent part are derived by the gradient descent method. Also, it is guaranteed that the selected inference rules become the global optimal solution by optimizing the Akaike's information criterion [1] expressing the quality of the inference rules. To evaluate the learning performance of the proposed fuzzy-sliding mode control using the genetic algorithm, a trajectory tracking simulation of a polishing robot is carried out.

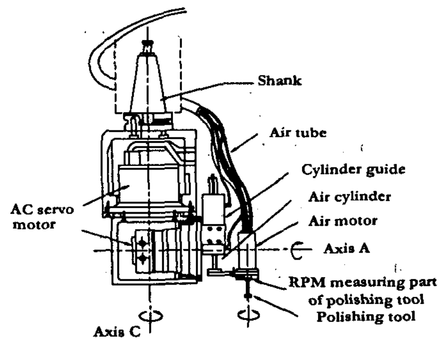

Fig. 1 Polishing robot with two degrees of freedom.

2 Fuzzy-Sliding Mode Control

To automate the polishing process, this study developed the two-axis polishing robot as shown in Fig. 1 [3]. The dynamic equation of the polishing robot is written as follow:

$$J_i \ddot{\theta}_i + B_i \dot{\theta}_i + F_i = k_i u_i \qquad (1)$$

To reduce the inherent chattering of the sliding mode control, in the previous study, the fuzzy-sliding mode control algorithm was proposed [5]. A control input of the fuzzy-sliding mode controller can be easily obtained from the simplified dynamic equation (1). In order to satisfy the existence condition of sliding mode, when the unmodeled nonlinear terms are replaced by disturbances, a control input is proposed as follow:

$$u_i = \psi_{\alpha i} e_i + \psi_{fuzzy} + \psi_{\beta i} \dot{\theta}_{di} + \psi_{\gamma i} \ddot{\theta}_{di} \qquad (2)$$

where $\psi_{\beta i}$ and $\psi_{\gamma i}$ are feed-forward control input terms to satisfy the existence condition of sliding mode against unfavorable effects due to $\dot{\theta}_{di}$ and $\ddot{\theta}_{di}$ on the trajectory tracking. ψ_{fuzzy} is the control input term for compensating disturbances. In equation (2), the limit values of the switching parameter $\psi_{\alpha i}$, $\psi_{\beta i}$, and $\psi_{\gamma i}$ could be derived from the existence condition of sliding mode. And, ψ_{fuzzy} is selected by fuzzy rules within a predetermined dead zone [5].

Fuzzy input variables are the state parameters of a phase plane around the switching line and the change rate of the state value. That is, the fuzzy inputs are s_{fi} and $\dot{s}_{fi}$ which are the fuzzified variables of the state value s_i and the change rate of state value, $\dot{s}_i$, respectively. The fuzzy output variable is u_{fi} which is the fuzzified variable of ψ_{fuzzy} for compensating disturbances. The fuzzy rules are established from a state value and a change rate of state value on phase plane. And, the control input term ψ_{fuzzy} for compensating disturbances is determined by the selected fuzzy rules and defuzzification. Therefore, the fuzzy-sliding mode control algorithm could reduce the inherent chattering because the fuzzy algorithm changed the excessive switching inputs around the sliding surface into small optimal control inputs [5].

However, the number of inference rules and the shape of membership functions in the antecedent part should be determined by an expert who had the knowledge of robot systems. And, because inference rules were determined by the trial and error method, it could not be guaranteed whether the selected inference rules are the global optimal solution or not.

3 A Self Tuning Fuzzy Inference Method by the Genetic Algorithm

3.1 Selection of Individuals and a Fitness Function

In this study, to optimize the number of inference rules and the shape of membership functions in the antecedent part, the genetic algorithm is used. In the genetic algorithm, a solution candidate is expressed by binary coding. Thus, the number and shapes of membership function are expressed in terms of strings consisting of 0 and 1 as shown in Fig. 2. The membership function takes a triangular shape, and the width of each membership function is defined as length between the centers of the neighbored two membership functions. Also, to set the membership functions on both sides of the domain of each fuzzy input variable, the first and last bit of a string are set 1.

The solution candidate expressed by the string is called an individual. A set of individuals is called a population. And, the individuals are determined by uniform random numbers. The fitness value of each individual is calculated by the selected fitness function to determine the selection probability of an individual being acted on three genetic operators: reproduction, crossover, and mutation.

In the genetic algorithm, to evaluate fitness of each individual in the population, the Akaike's information criterion C is employed and the fitness function E is defined as follows:

$$C(S_i) = N_i \log(ERROR) + 2 M_i \tag{3}$$

$$ERROR = \sum_{t=0}^{n} (\theta_i(t) - \theta_{di})^2 \tag{4}$$

$$E(S_i) = \max_j (C(S_i)) - C(S_i) \tag{5}$$

Where N_i is the number of fuzzy input variables, and M_i is the number of membership functions in each individual S_i. ERROR is the summation of the square of trajectory errors of the difference between a desired trajectory θ_{di} and a measured trajectory $\theta_i(t)$. $C(S_i)$ is the information criterion of the *i*th individual S_i and $E(S_i)$ is the fitness value of the

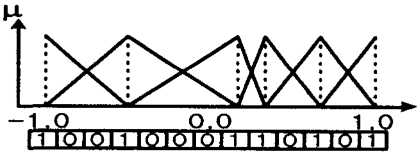

Fig. 2 String and membership function.

S_i. $\max_j(C(S_i))$ is the largest value among all information criteria from the initial generation to the *j*th generation.

The information criterion C shows the overall capability for learning: tracking performance for a desired trajectory and the number of inference rules. The smaller the information criterion is, the better the inference rules and the trajectory tracking performance are. Therefore, the number and positions of membership function maximizing the fitness in a string can be obtained by using the proposed genetic algorithm.

3.2 Learning of the Consequent Part by the Gradient Descent Method

All the universes of discourse of the fuzzified variables have a specified universes which is performed by a fuzzifier. The fuzzifier performs the function of fuzzification which is a subjective valuation to transform measurement data into valuation of a subjective value [2]. In the previous study, the range of variables s, $\dot{s}$, and ψ_{fuzzy} were scaled to fit the universe of discourse of fuzzified variables s_{fi}, $\dot{s}_{fi}$, and u_{fi} with scaling factor K_1, K_2, and K_3, respectively. These scaling factors were selected by an expert who had the knowledge of robot systems [5].

To improve these problems, in this study, the fuzzy outputs of the consequent part are adjusted by using the gradient descent method [2]. In fuzzy logic, the input-output relation of a system is expressed as a collection of fuzzy IF-THEN rules in which the antecedent and consequent part involve fuzzy variables. For example, if x_1 and x_2 are fuzzy input variables and y is the output variable, the relation among x_1, x_2, and y may be expressed as

$$\text{RULE i : If } x_1 \text{ is } A_{i1} \text{ and } x_2 \text{ is } A_{i2}, \text{ then y is } B_i. \tag{6}$$

Where i (i = 1, ···, n) is the number of inference rules. A_{i1} and A_{i2} are the membership function in the antecedent part, B_i is the membership function in the consequent part.

Defuzzification is a mapping from a space of fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy control actions. This process is necessary because in many practical applications crisp control action is required to actuate the control system [2]. Therefore, this study uses the height method for defuzzification [5, 7]. The consequent part is expressed by a real number y_1 and y_2. The defuzzified result is simply derived as follows:

$$\omega_i = A_{i1}(x_1) \wedge A_{i2}(x_2) \tag{7}$$

$$y^{(k)} = \frac{\sum_{i=0}^{n} \omega_i y_i}{\sum_{i=0}^{n} \omega_i} \tag{8}$$

To optimize the real numbers y_i of the consequent part, this study defines a cost function H, which measures the fuzzy inference error by

$$H = \frac{1}{2} (y^{(rk)} - y^{(k)})^2 \tag{9}$$

where $y^{(rk)}$ is a desired fuzzy output for the kth fuzzy inputs, and $y^{(k)}$ is an output of fuzzy inference for the same kth fuzzy inputs. However, in operating a polishing robot, the kth desired fuzzy output $y^{(rk)}$ against parameter variations and payload changes is unknown. Thus, the cost function H is redefined as follow:

$$H \propto H' = \frac{1}{2} (\theta^{(rk)} - \theta^{(k)})^2 \tag{10}$$

Where $\theta^{(rk)}$ is a desired trajectory, and $\theta^{(k)}$ is a measured trajectory. Intuitively, if $\theta^{(k)}$ approaches to $\theta^{(rk)}$, $y^{(k)}$ approaches to a desired fuzzy output $y^{(rk)}$.

Using a gradient descent method, the real number y_i of the consequent parts is adjusted by an amount Δy_i to be proportional to the negative gradient H at the current location:

$$\begin{aligned} y_i(n'+1) &= y_i(n') + \Delta y_i \\ &= y_i(n') - K\frac{\partial H}{\partial y_i} \\ &= y_i(n') - K\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(y^{(k)} - y^{(rk)}) \end{aligned} \tag{11}$$

$$\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(y^{(k)} - y^{(rk)}) \propto \frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(\theta^{(k)} - \theta^{(rk)}) \tag{12}$$

$$y_i(n'+1) = y_i(n') - K\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(\theta^{(k)} - \theta^{(rk)}) \tag{13}$$

where n' is the number of iteration of learning and K is a positive number called the learning constant which determines the rate of learning.

3.3 A learning procedure of the genetic algorithm

The learning procedures of the genetic algorithm consist of the following steps:

[step 1] Establish a base population of individuals: The individuals which constitute a base population are determined by uniform random numbers. The individual is expressed in terms of strings consisting of 0 and 1 as shown in Fig. 2. To set the membership functions on both sides of the domain of each input variable, the first and the last bit of a string are set 1. The number and shapes of membership function in the antecedent part are determined according to the string of each individual.

[step 2] Determine the fitness value of each individual: To evaluate the fitness value of all individuals of a current population, the trajectory tracking simulation of the polishing robot is carried out by the proposed fuzzy-sliding mode control. These procedures can be implemented according to [step 2-1] to [step 2-4].

[step 2-1] The simulation is carried out with an individual selected in the current population. To determine the fuzzy control output ψ_{fuzzy} for compensating disturbances, the membership grades and the output of the fuzzy inference are obtained by using Equation (7) and (8), respectively.

[step 2-2] During the simulation, the real number y_i of the consequent part is updated by using equation (13). And, this step is continued until the following condition is achieved.

$$| \text{ERROR}(n') - \text{ERROR}(n'-1) | < \delta \tag{14}$$

where δ is a threshold value to judge the convergence of the tracking error ERROR as shown in equation (4).

[step 2-3] If equation (14) is satisfied, the fitness E is calculated from the value of the converged tracking error ERROR and the information criterion of the selected individual using equation (3) and (4).

[step 2-4] [step 2] has to be applied to all individuals in a current generation.

[step 3] The fitness value of each individual is used to determine the selection probability P.

[step 4] A pair of mates is selected from the population according to the selection probability P of the selected individual by roulette wheel selection.

[step 5] To generate the new individuals, reproduction, crossover, and mutation are used. Reproduction directs the search toward the best existing individuals. Crossover creates new individuals by mating current individuals. Mutation introduces any new information into the population at the bit level. These three genetic operators are applied repeatedly until the new individuals take over the entire population.

[step 6] The new population is produced by [step 4] and [step 5].

[step 7] The processes from [step 2] to [step 6] are repeated until the number of generation exceeds the predetermined value.

Therefore, as these steps are repeated, individuals of the new population has higher fitness than those of the previous generation.

4 Simulation

To evaluate the learning performance of the proposed fuzzy-sliding mode control based on the genetic algorithm, a trajectory tracking simulation of the polishing robot is carried out.

First, the simulation is carried out by the fuzzy sliding mode control proposed in the previous study. The number of inference rules and the shape of membership functions in the antecedent part are determined through the trial and error by an expert who had the knowledge of robot systems. By using the trial and error method, the selected inference rules are listed in Table 1 and the selected membership function is shown in Fig. 3. The selected scaling factors are K_1 = 40, K_2 = 30, K_3 = 0.2 for axis C and K_1 = 45, K_2 = 35, K_3 = 0.15 for axis A. The simulation results are shown in Fig. 4.

Secondly, the trajectory tracking simulation is carried out by the fuzzy-sliding mode control with a self tuning fuzzy inference method based on the genetic algorithm. The initial conditions for the genetic algorithm are listed in Table 2. By using a learning procedure of the genetic algorithm in Section 3.3, the number of inference rules and the shape of membership functions in the antecedent part are determined as shown in Fig. 5. And, the simulation results are shown in Fig. 6.

Comparing Fig. 4 with Fig. 6, it is known that the tracking performance of the fuzzy-sliding mode control with the trial and error method is similar that of the fuzzy-sliding mode control with the genetic algorithm. Therefore, it is shown by simulations that the method of the fuzzy inference by the genetic algorithm without an expert who has the knowledge of robot systems provides better learning capability than the trial and error method.

5 Conclusion

This study proposes the fuzzy-sliding mode controller using a self tuning fuzzy inference method based on the genetic algorithm. Using this method, the number of inference rules and the shape of membership functions in the antecedent part are determined by the genetic algorithm and the fuzzy outputs of the consequent part are derived by the gradient descent method. Also, it was guaranteed that the selected inference rules become the global optimal solution by optimizing the Akaike's information criterion expressing the quality of the inference rules. To evaluate the learning performance of the proposed fuzzy-sliding mode control based on the genetic algorithm, the trajectory tracking simulation of the polishing robot was carried out. These simulation results showed that the tracking performance of the fuzzy-sliding mode control with the trial and error method is similar that of the fuzzy-sliding mode control with the genetic algorithm. And, it was shown by simulations that the method of fuzzy inference by the genetic algorithm without an expert who has the knowledge of robot systems provides better learning capability than the trial and error method.

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Table 1 Fuzzy rules determined by the trial and error method.

S_{fi} \ $\dot{S}_{fi}$	PB	PM	ZO	NM	NB
PB	NB	NB	NM	NS	ZO
PM	NB	NM	NS	ZO	PS
ZO	NM	NS	ZO	PS	PM
NM	NS	ZO	PS	PM	PB
NB	ZO	PS	PM	PB	PB

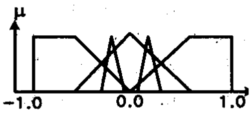

Fig. 3 Membership function determined by the trial and error method.

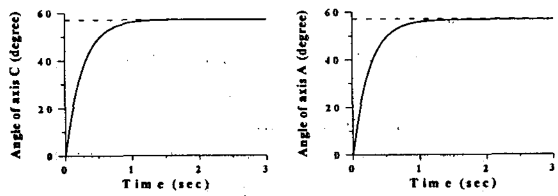

Fig. 4. Angles of axis C and A by the fuzzy-sliding mode control based on the trial and error method.

Table 2 Initial conditions for the genetic algorithm.

Initial conditions	Value
Total number of individuals	20
Length of individual	13
Mutation probability	0.01
Crossover probability	0.65
Number of generation	25
Threshold value	0.00001

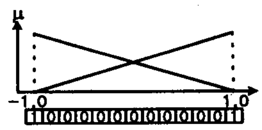

Fig. 5 Membership function determined by the genetic algorithm.

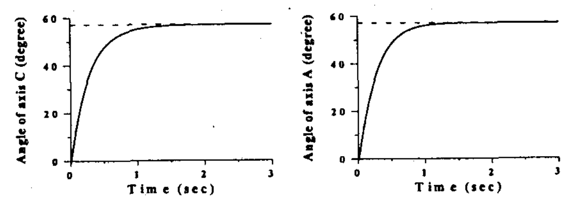

Fig. 6 Angles of axis C and A by the fuzzy-sliding mode control based on the genetic algorithm.

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