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

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This paper proposes a fuzzy-sliding mode control which is designed by a self tuning fuzzy inference method based on a genetic algorithm. Using the method, the number of inference rules and the shape of the membership functions of the proposed fuzzy-sliding mode control are optimized without the aid of an expert in robotics. The fuzzy outputs of the consequent part are updated by the gradient descent method. It is further guaranteed that the selected solution becomes the global optimal solution by optimizing Akaike's information criterion expressing the quality of the inference rules. In order to evaluate the learning performance of the proposed fuzzy-sliding mode control based on a genetic algorithm, a trajectory tracking simulation of the polishing robot is carried out. Simulation results show that the optimal fuzzy inference rules are automatically selected by the genetic algorithm and the trajectory control result is similar to the result of the fuzzy-sliding mode control which is selected through trial error by an expert. Therefore, a designer who does not have expert knowledge of robot systems can design the fuzzy-sliding mode controller using the proposed self tuning fuzzy inference method based on the genetic algorithm.

Key Words : Self Tuning Fuzzy Inference Method, Genetic Algorithm, Fuzzy-Sliding Mode Control, Gradient Descent Method, Akaike's Information Criterion, Polishing Robot

1. Introduction

To overcome the problems of tracking error related to unmodeled dynamics involved in the operation of industrial robots, many researchers have used sliding mode control, which is robust against parameter variations and payload changes (Dong and Shifan, 1996; Fruta and Tomiyama, 1996; Harashima, et al., 1986; Hashimoto, et al., 1987; Lee and Aoshima, 1993; Slotine, 1985; Young, 1978). Lee and Aoshima (1993) proposed a sliding mode control algorithm in which nonlinear and unmodeled dynamic terms were considered as external disturbances. A sliding mode control algorithm with two dead zones was proposed to reduce chattering (Lee and Shin, 1997; Lee, et al., 1998). However, these algorithms could not completely reduce the inherent chattering which was caused by excessive switching inputs around the sliding surface.

In a previous study, a fuzzy-sliding mode controller was designed to reduce inherent chattering of sliding mode control by fuzzy rules within a pre-determined dead zone (Lee and Go, 1997).

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Trajectory tracking experiments showed that chattering could be reduced prominently by the fuzzy-sliding mode controller, and that the proposed controller was robust to changes in payload. However, the number of inference rules and the shape of the membership functions of the fuzzy-sliding mode controller were necessarily determined through trial and error by an expert in robot systems. Also, it could not be guaranteed whether the selected inference rules were the global optimal solution, since the expert used trial and error to determine the inference rules.

This paper proposes a self tuning fuzzy inference method using a genetic algorithm. A genetic algorithm is a search algorithm based on the mechanics of natural selection, genetics, and evolution. One of the main advantages of genetic algorithm is its ability to obtain a global optimal solution using operators such as crossover and mutation (Goldberg, 1989). Using a genetic algorithm, the number of inference rules and the shape of membership functions of the fuzzy-sliding mode controller are optimized without an expert in robotics. Also, the fuzzy outputs are updated by a gradient descent method. It is also guaranteed that the selected inference rules become the global optimal solution by optimizing Akaike's information criterion (Akaike, 1974; Lin and Lee, 1996) expressing the quality of the inference rules. In order to evaluate the learning ability and trajectory tracking performance of the proposed fuzzy-sliding mode controller using a genetic algorithm, a trajectory tracking simulation of a polishing robot is carried out, and the controller is compared with a fuzzy-sliding mode controller using the trial and error method as proposed in previous studies. To evaluate the tracking performance in the event of payload changes, the trajectory tracking simulation of the polishing robot under a change of payload is carried out by the proposed fuzzy-sliding mode control.

2. Fuzzy-Sliding Mode Control

In a previous study, a two-axis polishing robot to automate the polishing process was developed

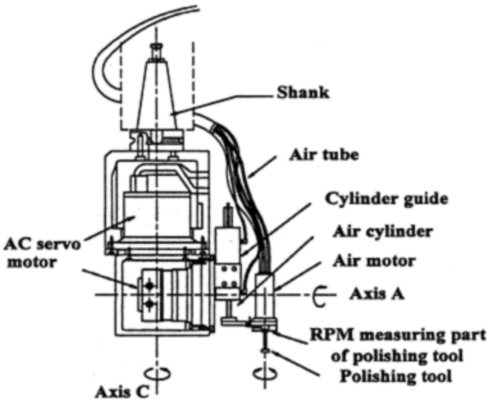

Fig. 1 Polishing robot with two degrees of freedom

as shown in Fig. 1 (Go and Lee, 1998; Lee, et al., 1999a; 1999b; 2000). The simplified dynamic equations of the polishing robot can be written as follows (Go and Lee, 2000; Go, et al., 1999):

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

J_i is the summation of all linear terms in the moment of inertia of link i and the driving motor. B_i is the equivalent damping coefficient from the motor, reduction gears, and the viscous friction of link i. The disturbance term F_i is the summation of the nonlinear terms: the inertia moments, the Coriolis and centrifugal forces, the gravity force, and the Coulomb friction force. k_i is a constant to be determined from the motor torque coefficient, the reduction rate of gears, and the armature resistance. u_i is the control input voltage.

In order to reduce the inherent chattering of the sliding mode control, a fuzzy-sliding mode control algorithm was proposed (Lee and Go, 1997). A control input for the fuzzy-sliding mode controller can be easily obtained from the simplified dynamic Eq. (1). In order to satisfy the existence condition of a sliding mode, when the unmodeled nonlinear terms are replaced by disturbances, a control input is proposed as follows (Lee and Go, 1997):

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

$$\psi_{\alpha i} = \begin{cases} \alpha_{1i} & \text{if } s_i e_i > 0 \\ \alpha_{2i} & \text{if } s_i e_i < 0 \end{cases}$$

$$\psi_{\beta i} = \begin{cases} \beta_{1i} & \text{if } s_i \dot{\theta}_{di} > 0 \\ \beta_{2i} & \text{if } s_i \dot{\theta}_{di} < 0 \end{cases}$$

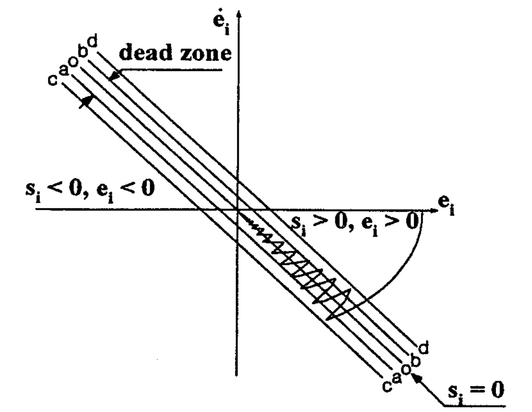

Fig. 2 Phase plane with a pre-determined dead zone around the switching line

$$\psi_{\gamma i}=\begin{cases}\gamma_{1i} & \text{if } s_i\ddot{\theta}_{di}>0\\ \gamma_{2i} & \text{if } s_i\ddot{\theta}_{di}<0\end{cases}$$

where $\psi_{\beta i}$ and $\psi_{\gamma i}$ are feed-forward control input terms which ensure the existence condition of a sliding mode, to compensate for unfavorable effects due to the desired angular velocity $\dot{\theta}_{di}$ and the angular acceleration $\ddot{\theta}_{di}$ for trajectory tracking. ψ_{fuzzy} is the control input term for compensating disturbances. In Eq. (2), the limit values of the switching parameter $\psi_{\alpha i}$, $\psi_{\beta i}$, and $\psi_{\gamma i}$ can be derived from the existence condition of a sliding mode. ψ_{fuzzy} is selected by fuzzy rules within a pre-determined dead zone as shown in Fig. 2.

The selected fuzzy input variables are the state value in the phase plane and its rate of change around the switching line. 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 of the 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 the state value on the phase plane. The control input term ψ_{fuzzy} for compensating disturbances is determined by the selected fuzzy rules and defuzzification (Lee and Go, 1997). Therefore, the fuzzy-sliding mode controller can reduce inherent chattering because the controller transforms the excessive switching input around the sliding surface into a small optimal control input.

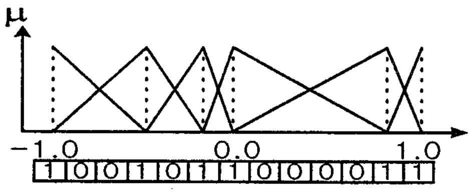

Fig. 3 String and membership function

However, the number of inference rules and the shape of the membership functions of the fuzzy-sliding mode controller should be determined only through trial and error by an expert in robotics. In that case, it cannot be guaranteed whether the selected inference rules are the global optimal solution or not.

3. Self Tuning Fuzzy Inference Method by the Genetic Algorithm

3.1 Selection of individuals and a fitness function

In order to optimize the number of inference rules and the shape of the membership functions of the fuzzy-sliding mode controller, a self tuning fuzzy inference method using a genetic algorithm is proposed in this study. In the genetic algorithm, a solution candidate is expressed by binary coding. Thus, the number and shape of the membership functions are expressed in terms of a string consisting of 0's and 1's as shown in Fig. 3. In Fig. 3, if a bit of the string is 1, this bit has a membership function, and the bit becomes the center position of the membership function. If a bit of the string is 0, this bit does not have a membership function. Therefore, the width of each membership function is defined as the length between the centers of the neighboring two membership functions. To set the membership functions on both sides of the universe of discourse of fuzzy input variables, the first and last bits of a string are set to 1.

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

In the genetic algorithm, to evaluate the fitness of each individual in the population, Akaike's information criterion function AIC (Akaike, 1974; Lin and Lee, 1996) is employed, and the fitness function FIT is defined as follows (Go and Lee, 2000; Go, et al., 1999):

$$AIC(V_i)=N_i\log(ERROR)+2M_i \quad (3)$$

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

$$FIT(V_i)=\max_j(AIC(V_i))-AIC(V_i) \quad (5)$$

where N_i is the number of fuzzy input variables, and M_i is the number of membership functions in each individual V_i. $AIC(V_i)$ is the information criterion of the ith individual V_i. $ERROR$ is the summation of the square of trajectory errors of the difference between a desired trajectory θ_{di} and a measured trajectory $\theta_i(t)$. $FIT(V_i)$ is the fitness value of the V_i. $\max_j(AIC(V_i))$ is the largest value among all information criteria from the initial generation to the jth generation.

The information criterion function $AIC(V_i)$ shows the overall capability for learning, i.e., the tracking performance for a desired trajectory and the number of inference rules. The smaller the information criterion is, the smaller the number of the inference rules and the trajectory tracking error are. Therefore, the number and shape of the membership function maximizing the fitness in a string can be obtained by using the proposed self tuning fuzzy inference method.

3.2 Learning of the consequent part by the gradient descent method

In fuzzy logic, the input-output relation of a system is expressed as a collection of 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

RULE i : If x_1 is A_{i1} and x_2 is A_{i2}, then y is B_i.

where $i(i=1, , n)$ is the number of inference

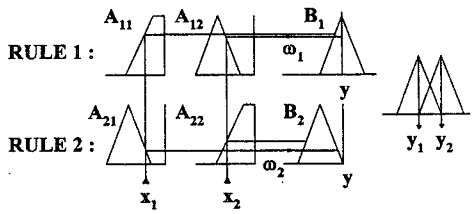

Fig. 4 Height method

rules. A_{i1} and A_{i2} are the membership function in the antecedent part, while B_i is the membership function in the consequent part.

Defuzzification is a mapping from a space of the fuzzy control actions defined over an output universe of discourse into a space of nonfuzzy control actions (Lin and Lee, 1996; Mohammad, et al., 1993; Robot, 1994). This process is necessary because in many practical applications crisp control action is required to actuate the control system. This study uses the height method for defuzzification because it is simpler than the center of gravity method commonly used as technique for defuzzification (Go and Lee, 2000; Lee and Go, 1997; Li and Lau, 1989; Mohammad, et al., 1993; Robot, 1994). The defuzzification process is shown in Fig. 4. A membership grade ω_1 and ω_2 are determined by RULE 1 and RULE 2, respectively. The consequent part is expressed by a real number y_1 and y_2. The defuzzified result is simply derived as follows:

$$\omega_i=A_{i1}(x_1)\wedge A_{i2}(x_2) \quad (6)$$

$$y^{(k)}=\frac{\sum_{i=0}^{n}\omega_i y_i}{\sum_{i=0}^{n}\omega_i} \quad (7)$$

All the universes of discourse of the fuzzified variables have specified universes which are performed by a fuzzifier (Lin and Lee, 1996). The fuzzifier performs the function of fuzzification, which is a subjective valuation to transform measurement data into valuation of a subjective value. Hence, it can be defined as a mapping from an observed input space to labels of fuzzy sets in a specified input universe of discourse. The range of variables s_i, $\dot{s}_i$, and ψ_{fuzzy} are scaled to fit the universe of discourse of fuzzified variables s_{fi}, $\dot{s}_{fi}$, and u_{fi} by using the scaling factor K_1, K_2, and K_3,

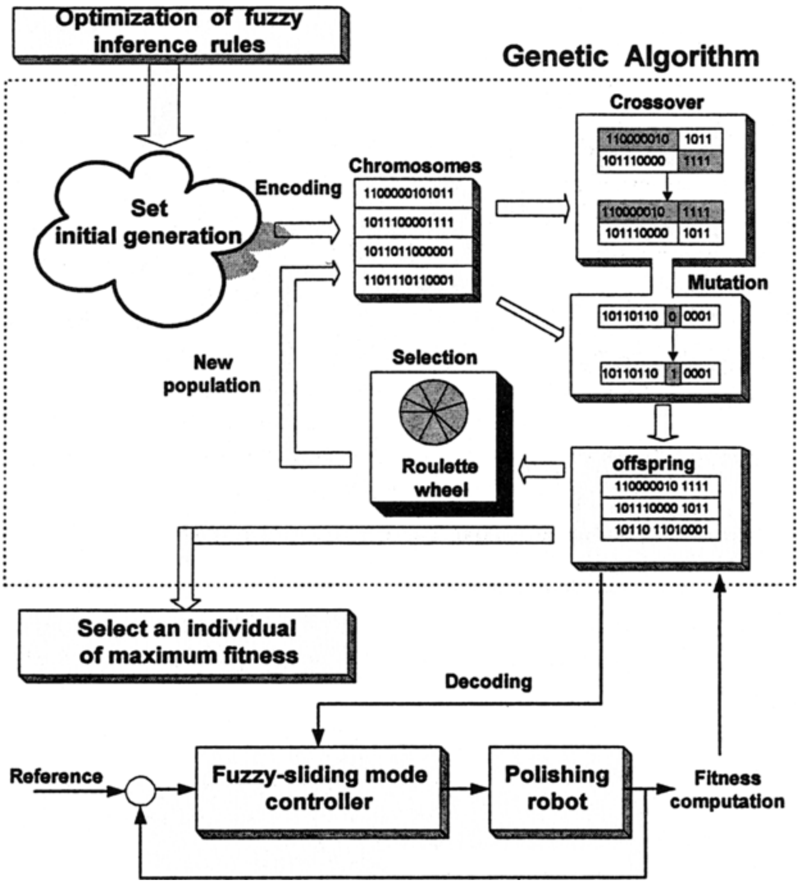

Fig. 5 Flow chart of selection of fuzzy rules using genetic algorithm

respectively (Hwang and Lin, 1992; Lee, 1990; Lee and Go, 1997). However, these scaling factors are determined only through trial and error by an expert in robot systems. In order to solve this problem, this study uses the gradient descent method (Lin and Lee, 1996). The fuzzy outputs of the consequent part are adjusted by the updating law derived from the gradient descent method.

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

$$H=\frac{1}{2}(y^{(rk)}-y^{(k)})^2 \tag{8}$$

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. Therefore, the cost function H is redefined as follows:

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

where $\theta^{(rk)}$ is a desired trajectory, and $\theta^{(k)}$ is a measured trajectory. If $\theta^{(k)}$ approaches $\theta^{(rk)}$, $y^{(k)}$ approaches a desired fuzzy output $y^{(rk)}$.

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

$$\begin{aligned} y_i(t+1)&=y_i(t)+\Delta y_i=y_i(t)-\beta\frac{\partial H}{\partial y_i} \\ &=y_i(t)-\beta\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(y^{(k)}-y^{(rk)}) \end{aligned} \tag{10}$$

$$\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(y^{(k)}-y^{(rk)}) \propto \frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(\theta^{(k)}-\theta^{(rk)}) \tag{11}$$

Table 1 System parameters of the polishing robot

	ω_{ni}(rad/sec)	ξ_i	J_i(Kg m^2)	B_i(Kg m^2/s)
Axis A	12	0.4	0.0114	0.10944
Axis C	12	0.1	0.0991	0.23784

Table 2 Limit values of switching parameters by using the signal compression method

	Axis C	Axis A
c_i	$c_1=4$ ($c_1<5.4$)	$c_2=4$ ($c_2<7.52$)
α_i	$\alpha_{11}<-9.333$, $s_1e_1>0$ $\alpha_{21}<-9.333$, $s_1e_1<0$	$\alpha_{12}<-13.2$, $s_2e_2>0$ $\alpha_{22}>-13.2$, $s_2e_s<0$
β_i	$\beta_{11}<9.0$, $s_1\dot{\theta}_1>0$ $\beta_{21}>9.0$, $s_1\dot{\theta}_1<0$	$\beta_{12}<7.05$, $s_2\dot{\theta}_2>0$ $\beta_{22}>7.05$, $s_2\dot{\theta}_2<0$
γ_i	$\gamma_{11}<1.667$, $s_1\ddot{\theta}_1>0$ $\gamma_{21}>1.667$, $s_1\ddot{\theta}_1<0$	$\gamma_{12}<0.9375$, $s_2\ddot{\theta}_2>0$ $\gamma_{22}>0.9375$, $s_2\ddot{\theta}_2<0$

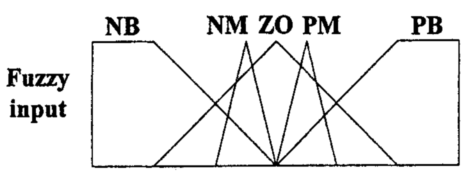

Fig. 6 Membership function determined by trial and error

$$y_i(t+1)=y_i(t)-\eta\frac{\omega_i}{\sum_{i=1}^{n}\omega_i}(\theta^{(k)}-\theta^{(rk)}) \quad (12)$$

where t is the number of iterations of learning and η is a positive number called the learning constant which determines the rate of learning.

3.3 Learning procedure for the genetic algorithm

The learning procedure of the genetic algorithm consists of the following steps as shown in Fig. 5:

[step 1] Establish a base population of individuals: The individuals that constitute a base population are determined by uniform random numbers. The individual is expressed in terms of strings consisting of 0's and 1's as shown in Fig. 3. To set the membership functions on both sides of the universe of discourse of each input variable, the first and the last bit of a string are set to 1. The number and shapes of the membership function in the antecedent part are determined according to the string of each individual.

[step 2] Determine the fitness value of each individual using Eq. (5): To evaluate the fitness value of all individuals of a current population, a trajectory tracking simulation of the polishing robot is carried out by the proposed fuzzy-sliding mode control. These procedures can be implemented according to the steps from [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 Eqs. (6) and (7), respectively.

[step 2-2] During the simulation, the real number y_i of the consequent part is updated by using Eq. (12). This step is continued until the following condition is achieved:

$$|ERROR(t)-ERROR(t-1)|<\delta \quad (13)$$

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

[step 2-3] If Eq. (13) is satisfied, the information criterion of the selected individual is calculated by using Eqs. (3) and (4). The fitness value of the selected individual is calculated from the calculated information criterion by using Eq. (5).

[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 probability of selection.

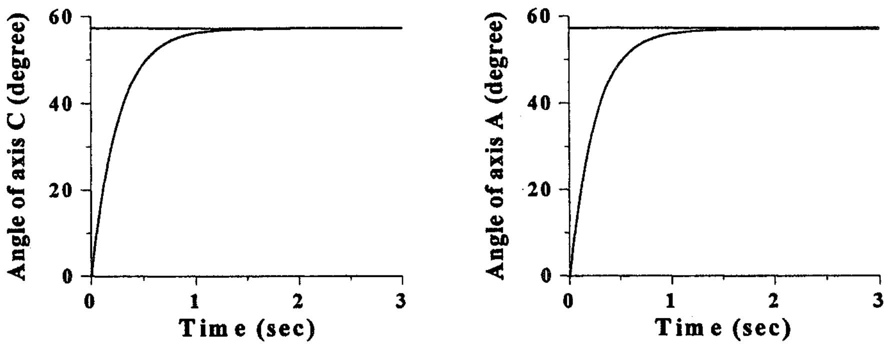

Fig. 7 Angles of axis C and A by the fuzzy-sliding mode control based on trial and error

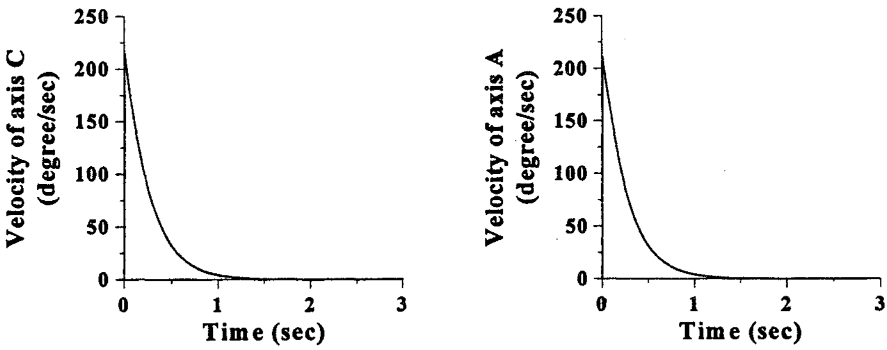

Fig. 8 Velocity of axis C and A by the fuzzy-sliding mode control based on trial and error

[step 4] A pair of mates is selected from the population according to the probability of selection 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 have a higher fitness than those of the previous generation. The flow chart for selecting fuzzy rules using the genetic algorithm is shown in Fig. 5.

4. Simulation

4.1 Evaluation of the learning performance

The developed polishing robot always has large contact force changes due to removal of tool marks and chattering as a result of rotating a polishing tool (Go and Lee, 1998; Lee, et al., 1999a; 2000). Therefore, unless these disturbances of the polishing robot are compensated for properly, control performance cannot be expected to be satisfied. The proposed fuzzy-sliding mode controller using the genetic algorithm can compensate for these disturbances. In order to evaluate the learning ability and trajectory tracking performance of this controller, a trajectory tracking simulation of the polishing robot is carried out. The proposed controller is also compared with the fuzzy-sliding mode controller

Table 3 Fuzzy rules determined by trial and error

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

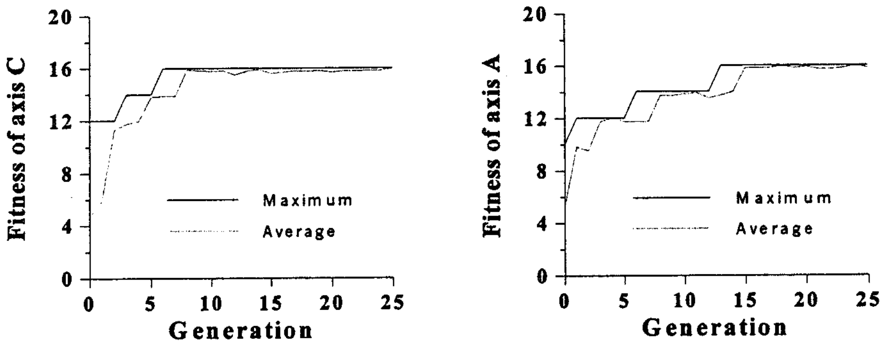

Fig. 9 Fitness value of each generation

Table 4 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

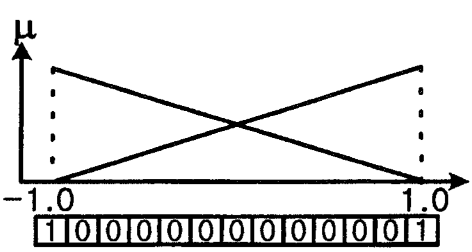

Fig. 10 Membership function determined by the genetic algorithm

using trial and error that was proposed in a previous study.

First, the trajectory tracking simulation is carried out by the fuzzy-sliding mode controller proposed in the previous study. To determine the switching parameters $\psi_{\alpha i}$, $\psi_{\beta i}$, and $\psi_{\gamma i}$ in Eq. (2), the values of the inertia J_i and the damping coefficient B_i of a robot system are estimated by the signal compression method which identifies unknown parameters of a system (Lee and Aoshima, 1989). By using the signal compression method, the unknown parameters of the polishing robot are estimated as listed in Table 1 (Lee, et al., 1999a; 2000). When the slopes of the switching line are $c_1=4$ and $c_2=4$, the limit values of the switching parameters that satisfy the sliding mode existence condition are derived as listed in Table 2. The number of inference rules and the shape of the membership functions in the antecedent part are determined through trial and error by an expert in robot systems. The selected inference rules are listed in Table 3 and the selected membership function is shown in Fig. 6. 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 Figs. 7 and 8.

Second, the trajectory tracking simulation is carried out by the fuzzy-sliding mode control

Table 5 Fitness of total individuals of entire generations

Individual		Fitness E		Criterion C	
Axis C	Axis A	Axis C	Axis A	Axis C	Axis A
1000000000001		22.00	22.08	14.46	13.81
1000000000011		20.00	20.08	16.46	15.81
1000000000101		19.98	20.08	14.48	15.81
...		...	...	...	...
1000001000001		20.01	20.09	16.45	15.80
...		...	...	...	...
1111111111011		2.00	2.00	34.46	33.89
1111111111101		2.00	2.00	34.46	33.89
1111111111111		0.00	0.00	36.46	35.89

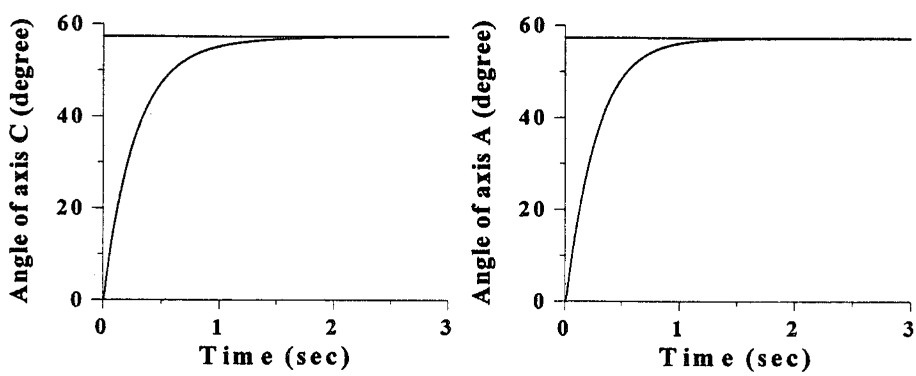

Fig. 11 Angles of axis C and A by the fuzzy-sliding mode control based on the genetic algorithm

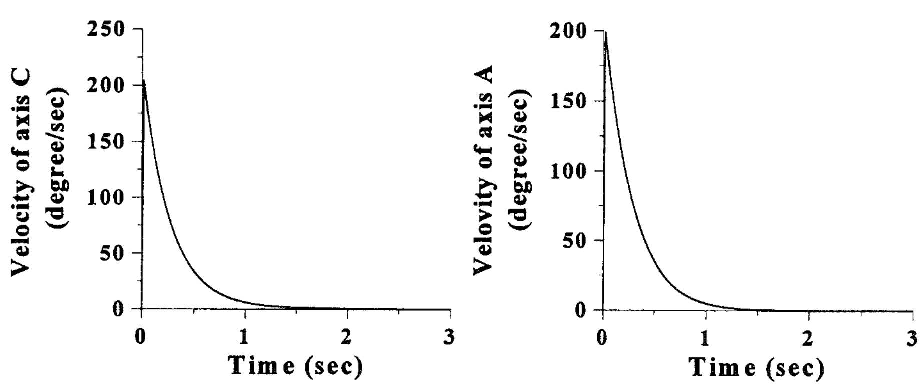

Fig. 12 Velocity of axis C and A by the fuzzy-sliding mode control based on the genetic algorithm

with a self tuning fuzzy inference method based on the genetic algorithm. The initial conditions for the genetic algorithm are listed in Table 4. In order to determine the number of inference rules and the shape of the membership functions for the fuzzy-sliding mode controller, the learning procedure described in Section 3.3 is used. Figure 9 shows the fitness value according to the progress of each generation and also shows that individuals of the new population have higher fitness than those of the previous generation as the learning steps are repeated. The shape of the

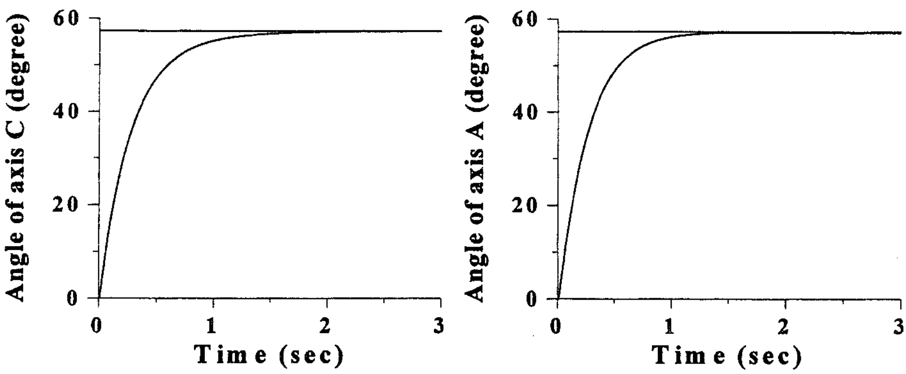

Fig. 13 Angles of axis C and A by the proposed fuzzy-sliding mode control with 40N-polishing force

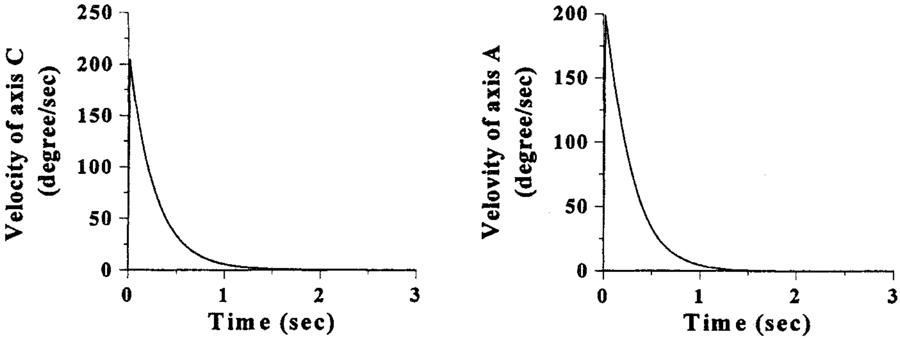

Fig. 14 Velocity of axis C and A by the proposed fuzzy-sliding mode control with 40N-polishing force

membership function determined by the learning procedure is shown in Fig. 10. The selected inference rules become the global optimal solution by optimizing Akaike's information criterion.

In order to prove that the fuzzy rules determined by the genetic algorithm converge to a global optimal solution, total individuals of entire generations are simulated as listed in Table 5. The total number of individuals of each axis are 2^{11} and the optimal solution obtained by the total search is the same as that obtained by the genetic algorithm. Therefore, it is guaranteed that the selected inference rules become the global optimal solution.

The simulation results of the proposed algorithm are shown in Figs. 11 and 12. Comparing Fig. 11 with Fig. 7, the trajectory tracking simulation shows that the optimal fuzzy inference rules are automatically selected by the genetic algorithm and the trajectory control result is similar to the result of the fuzzy-sliding mode control which is selected through trial and error by an expert. Therefore, a designer without expert knowledge of robot systems can design the fuzzy-sliding mode controller using the proposed self tuning fuzzy inference method based on the genetic algorithm.

4.2 Robustness

In the polishing process, the magnitude of the polishing force changes according to the mesh of a polishing sheet and the state of the polished die surface. Generally, it is known that the proper polishing force is 10 N to 20 N (Lee, et al., 1999a). The polishing force according to the state of the polishing progress may be changed. Therefore, the controller should be robust against changes in the polishing force.

To evaluate the robustness of the proposed controller, the trajectory tracking simulation of the polishing robot with a 40 N-polishing force is carried out by the proposed fuzzy-sliding mode control based on the genetic algorithm.

The polishing tool of axis A is equipped with a 40 N payload. The simulation results are shown in Figs. 13 and 14. It is shown that the results are almost the same as Figs. 11 and 12. Therefore, it is proved that the proposed algorithm is robust to changes in payload.

5. Conclusion

This study proposed a fuzzy-sliding mode controller using a self tuning fuzzy inference method based on a genetic algorithm. Using this method, the number of inference rules and the shapes of the membership functions were optimized without an expert in robotics. The fuzzy outputs of the consequent part were updated by the gradient descent method. Also, it was guaranteed that the selected inference rules become the global optimal solution by optimizing Akaike's information criterion expressing the quality of the inference rules. To investigate the learning ability and trajectory tracking performance of the proposed fuzzy-sliding mode controller using the genetic algorithm, a trajectory tracking simulation of a polishing robot was carried out, and the controller was compared with the fuzzy-sliding mode controller using trial and error. Trajectory tracking simulations showed that the optimal fuzzy inference rules were automatically selected by the genetic algorithm, and that the trajectory control result was similar to the result of the fuzzy-sliding mode control which is selected through trial and error by an expert. Therefore, a designer without expert knowledge of robot systems can design the fuzzy-sliding mode controller by using the proposed self tuning fuzzy inference method based on the genetic algorithm. Also, to evaluate the tracking performance under payload changes, the trajectory tracking simulation of the polishing robot with a polishing force of 40 N was carried out by the proposed fuzzy-sliding mode control based on the genetic algorithm. These simulation results showed that the proposed algorithm can provide reliable and robust tracking performance.

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