Design of Fuzzy-Sliding Mode Control with the Self Tuning Fuzzy Inference Based on Genetic Algorithm and Its Application

Seok-Jo Go, Min-Cheol Lee, and Min-Kyu Park

Abstract: This paper proposes a self tuning fuzzy inference method by the genetic algorithm in the fuzzy-sliding mode control for a robot. Using this method, the number of inference rules and the shape of membership functions are optimized without an expert in robotics. The fuzzy outputs of the consequent part are updated by the gradient descent method. And, 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. The trajectory tracking simulation and experiment of the polishing robot show that the optimal fuzzy inference rules are automatically selected by the genetic algorithm and the proposed fuzzy-sliding mode controller provides reliable tracking performance during the polishing process.

Keywords: self tuning inference method, genetic algorithm, fuzzy-sliding mode control, gradient descent method, Akaike's information criterion, polishing robot

I. Introduction

To solve tracking errors related to the unmodeled dynamics in the operation of industrial robots, many researchers have used the sliding mode control which is robust against parameter variations and payload changes [1]-[5]. Lee and Aoshima [4] proposed a sliding mode control algorithm where a nonlinear and unmodeled dynamic terms were considered as external disturbances to apply the algorithm to a robot. And, the sliding mode control algorithm with two dead zones was proposed to reduce the chattering [5]. However, these algorithms 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 using the fuzzy rules [6]. The trajectory tracking experiments showed that the chattering could be reduced prominently by the fuzzy-sliding mode controller and the controller was robust in spite of a change of payload [6]. However, the number of inference rules and the shape of membership functions of the fuzzy-sliding mode controller should be determined only through the trial and error method by an expert who had the expert knowledge of robot systems. And also, it could not be guaranteed whether the selected inference rules were the global optimal solution or not because the expert used the trial and error method to determine the inference rules.

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Seok-Jo Go: Department of Machine System, Dongeui Institute of Technology(sigo@dit.ac.kr)

Min-Cheol Lee: School of Mechanical Engineering, Pusan National University(mclee@hyowon.pusan.ac.kr)

Min-Kyu Park: Graduate school of Department of Mechanical and Intelligent Systems Engineering, Pusan National University (frwe@mkparkhyowon.pusan.ac.kr)

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This paper proposes 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 [7]. Using the genetic algorithm, in this study, the number of inference rules and the shape of membership functions of the fuzzy-sliding mode controller are optimized without the expert in robotics. And, the fuzzy outputs of the consequent part are updated 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 [8][9] expressing the quality of the inference rules. Therefore, although a designer is a non-expert who has not the expert knowledge of robot systems, the fuzzy-sliding mode controller can be designed by the proposed self tuning fuzzy inference method based on the genetic algorithm.

To automate the polishing process, this study developed the polishing robot [10][12]. The developed polishing robot has always a big contact force change by removing tool marks and a vibration of tool by rotating a polishing tool during polishing [10][12]. Unless disturbances of polishing robot are compensated for properly, satisfactory control performance cannot be expected. Therefore, in order to evaluate the learning and the trajectory tracking performances of the fuzzy-sliding mode controller using the genetic algorithm, the trajectory tracking simulation and experiment of the polishing robot are carried out. And, polishing experiments on the die of the shadow mask are performed to evaluate the trajectory tracking performances of the proposed fuzzy-sliding mode controller during polishing process.

II. Design of fuzzy-sliding mode controller with the trial and error

The simplified dynamic equation of a robot can be written as follow [4]-[6][12]-[14]:

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

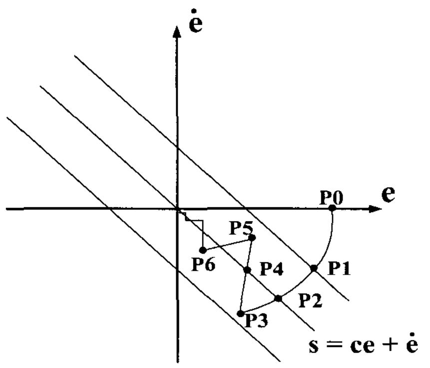


Fig. 1. Phase plane around the switching line.

where 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 viscosity friction of link i. The disturbance term F_i is the summation of the nonlinear terms: inertia moments, the Coriolis and centrifugal forces, the gravity force, and the Coulomb friction term. The k_i is a constant to be determined from the motor torque coefficient, the reduction rate of gears, and the armature resistance. ui is the control input voltage.

To reduce the inherent chattering of the sliding mode control, in the previous study, the fuzzy-sliding mode controller was proposed [6]. A control input of the fuzzy-sliding mode controller can be easily obtained from the simplified dynamic (1). In order to satisfy the existence condition of the sliding mode, when the unmodeled nonlinear terms are replaced by disturbances, a control input is proposed as follows [6]:

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

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 the desired angular velocity $\dot{\theta}_{di}$ and the desired angular acceleration $\ddot{\theta}_{di}$ on the trajectory tracking. ψ_{fuzzy} is the control input term for compensating disturbances. In (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 sliding mode. And, ψ_{fuzzy} is selected by fuzzy rules within a predetermined dead zone as shown in Fig. 1 [6].

Fuzzy input variables selected in the previous study were the state value 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 were established from a state value and a change rate of state value on phase plane [6]. In Fig. 1, the state space at the point P1 represents the state that s_i is positive big and $\dot{s}_i$ is negative medium. That is, s_{fi} is PB(positive big), $\dot{s}_{fi}$ is NM(negative medium). In order to quickly approach on the switching line without overshooting the line at this state, a fuzzy output u_{fi} is selected as NS(negative small). The state space at the point P2 represents the state that s_{fi} is ZO(zero), $\dot{s}_{fi}$ is NM(negative medium). Therefore, u_{fi} is selected as PM(positive medium) because this state is far away from the switching line. Also, at the same method, the fuzzy rule about other points P3, P4 and P5 can be established as follows:

P1 : If s_{fi} is PB and $\dot{s}_{fi}$ is NM, then u_{fi} is NS. (3)
P2 : If s_{fi} is ZO and $\dot{s}_{fi}$ is NB, then u_{fi} is PM.
P3 : If s_{fi} is NB and $\dot{s}_{fi}$ is NB, then u_{fi} is PB.
P4 : If s_{fi} is ZO and $\dot{s}_{fi}$ is PB, then u_{fi} is NM.
P5 : If s_{fi} is PM and $\dot{s}_{fi}$ is PB, then u_{fi} is NB.

And, the control input term ψ_{fuzzy} for compensating disturbances was determined by the selected fuzzy rules and defuzzification. Therefore, the fuzzy-sliding mode controller could reduce the inherent chattering because the controller changed the excessive switching input around the sliding surface into the small optimal control input [6].

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

III. Design of fuzzy-sliding mode controller with the genetic algorithm

1. Individuals and a fitness function

In order to optimize the number of inference rules and the shape of membership functions of the fuzzy-sliding mode controller, this study proposes a self tuning fuzzy inference method by the genetic algorithm. In the genetic algorithm, a solution candidate is expressed by binary coding. Thus, the number and shape of membership function are expressed in terms of string 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 bits of a string are set 1. The solution candidate expressed by a string is called an individual. A set of individuals is called a population. The individuals are determined by uniform random numbers. And, 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.

To evaluate fitness of each individual in the population, the Akaike's information criterion C [8][9] is employed and the fitness function E is defined as follows:

$$C(S_i) = N_i \log(ERROR) + 2 M_i \qquad (4)$$

$$\text{ERROR} = \sum_{i=0}^{n}(\theta_i(t) - \theta_{di})^2 \tag{5}$$

$$\text{E}(\text{S}_i) = \text{maxj}\ (\text{C}(\text{S}_i)) - \text{C}(\text{S}_i) \tag{6}$$

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 ith individual S_i and $E(S_i)$ is the fitness value of the S_i. $max_j(C(S_i))$ is the largest value among all information criteria from the initial generation to the jth generation.

The information criterion C shows the overall capability for learning: the number of inference rules and the trajectory tracking performance. The smaller the information criterion is, the better the inference rules and the trajectory tracking performance are. Therefore, the number and position of membership functions maximizing the fitness in a string can be obtained by using the proposed self tuning fuzzy inference method.

2. Updating of the fuzzy outputs

All the universes of discourse of the fuzzified variables have a specified universes which is performed by a fuzzifier [9]. 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. Therefore, in the previous study, the range of variables s_i, $\dot{s}_i$, 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 [6]. However, these scaling factors were determined only through the trial and error by an expert in robotics.

To solve this problem, this study uses the gradient descent method [9]. The fuzzy outputs of the consequent part are adjusted by a updating law derived from the gradient descent method. 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

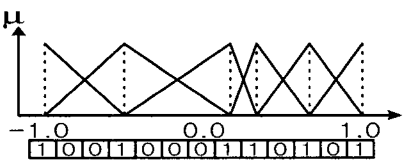


Fig. 2. String and membership function.

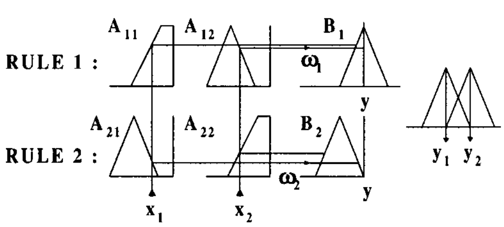


Fig. 3. Height method.

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 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 [9]. This process is necessary because in many practical applications crisp control action is required to actuate the control system. Therefore, this study uses the height method for defuzzification [13]-[15]. The defuzzification process is shown in Fig. 3. 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:

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

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

To update 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 industrial robot, the kth desired fuzzy output $y^{(rk)}$ against parameter variations and payload changes is an unknown value. Thus, the cost function H is redefined as follows:

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

where $\theta^{(rk)}$ is a desired trajectory, and $\theta^{(k)}$ is a measured trajectory. 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 part is adjusted by an amount Δy_i to be proportional to the negative gradient H at the current location:

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

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

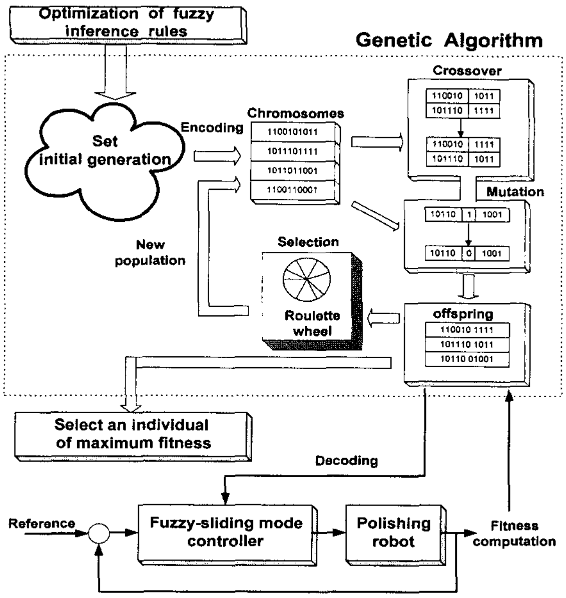


Fig. 4. Learning procedures of the genetic algorithm.

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

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. A learning procedure of the genetic algorithm

The learning procedures of the genetic algorithm consist of the several steps as shown in Fig. 4 [13][14]. First, a base population of individuals is established. The individual is expressed in terms of strings consisting of 0 and 1 by uniform random numbers as shown in Fig. 2. Second, to evaluate the fitness value of all individuals of a current population, the trajectory tracking simulation of a robot is carried out by the proposed fuzzy-sliding mode control. During the simulation, the real number y_i of the consequent part is updated by using (13). And, this step is continued until the following condition is achieved.

$$|\ \mathrm{ERROR}(n') - \mathrm{ERROR}(n'-1)\ | < \delta \qquad (14)$$

where δ is a threshold value to judge the convergence of the tracking error *ERROR* as shown in (5). Third, the selection probability of each individual is calculated by using the fitness values. Fourth, the new individuals are generated by three genetic operators: reproduction, crossover, and mutation. These operators are applied repeatedly until the new individuals take over the entire population. Finally, these steps are repeated until the number of generation exceeds the predetermined value. Therefore, as these steps are repeated, individuals of the new population have higher fitness than those of the previous generation.

IV. Simulation

This study developed the two-axis polishing robot to automate the polishing process as shown in Fig. 5 [10]-[12].

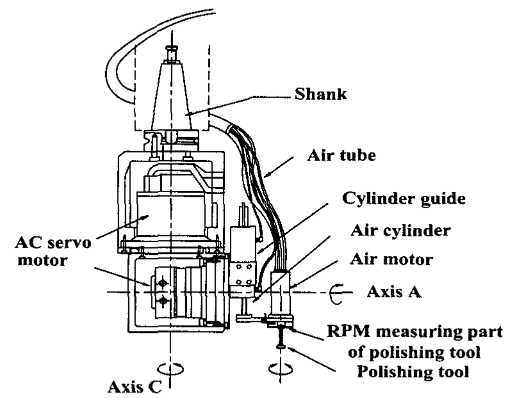


Fig. 5. Polishing robot with two degrees of freedom.

The polishing robot has always a big contact force change by removing tool marks and vibration by rotating a polishing tool during polishing. Unless disturbances of polishing robot are compensated for properly, satisfactory control performance cannot be expected. Therefore, in order to evaluate the learning and trajectory tracking performance of the proposed fuzzy-sliding mode controller using the genetic algorithm, a trajectory tracking simulation of a polishing robot is carried out. And also, the proposed controller is compared with the fuzzy-sliding mode controller using the trial and error method, which was proposed in the previous study.

First, the trajectory tracking simulation is carried out by the fuzzy-sliding mode controller 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 method by an expert in robotics. Using (3), the inference rules are established as listed in Table 1. The membership function determined by the expert is shown in Fig. 6. And, the determined 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. 7.

Table 1. Fuzzy rules determined by the expert.

$\dot{s}_{fi}$ / 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

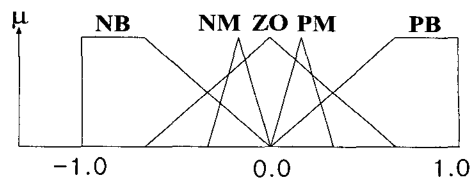


Fig. 6. Membership function determined by the expert.

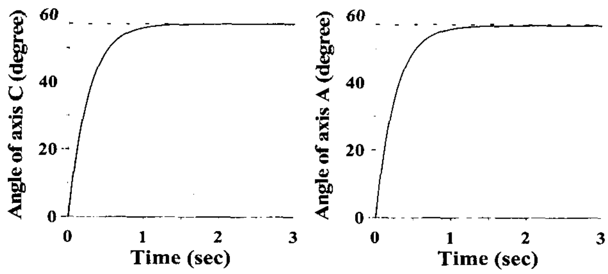


Fig. 7. Angle of axis C and A by the fuzzy-sliding mode control based on the trial and error.

Second, 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. In order to determine the number of inference rules and the shape of membership functions of the sliding-mode controller, the learning procedure mentioned in Fig. 4 is used. The shape of membership function determined by the learning procedure is shown in Fig. 8. And, this selected inference rules become the global optimal solution by optimizing the Akaike's information criterion. The simulation results of the proposed algorithm are shown in Fig. 9.

Comparing Fig. 7 with Fig. 9, trajectory tracking simulation shows that the optimal fuzzy inference rules are automatically selected by the genetic algorithm and the control result of the proposed fuzzy-sliding mode control is almost similar to the result of the fuzzy-sliding mode control which is selected through the trial and error method by an expert. Therefore, although a designer is a non-expert who has not the knowledge of robot systems, the fuzzy-sliding mode controller can be designed by the proposed self tuning fuzzy inference method based on the genetic algorithm.

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

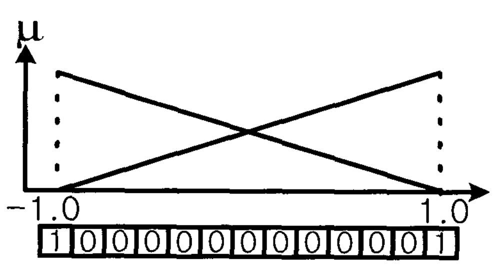


Fig. 8. Membership function determined by the genetic algorithm.

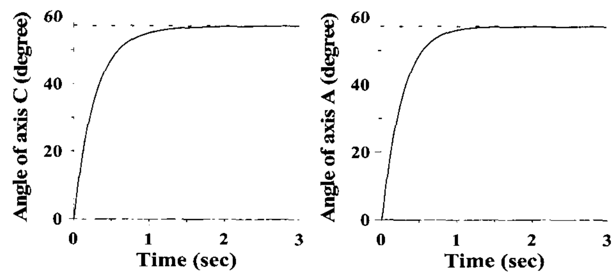


Fig. 9. Angle of axis C and A by the fuzzy-sliding mode control based on the genetic algorithm.

Fig. 10. The automatic polishing robot system.

V. Experiment

1. Learning and trajectory tracking performance

In order to evaluate results of simulation by experiment, the proposed algorithm is implemented to the automatic polishing robot system which was developed in the previous study. The automatic polishing robot system, named POLYEM, is composed of a host computer, a machining center, and a polishing robot, as shown in Fig. 10 [10]-[12]. A DSP(Digital Signal Processor) board for real-time calculations is used to control the two-axis polishing robot, and a FANUC controller is used to control the machining center. The proposed algorithm is stored in ROM(Read Only Memory) of the DSP board.

In order to determine the number of inference rules

Table 3. 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 4. Limit values of switching parameters.

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

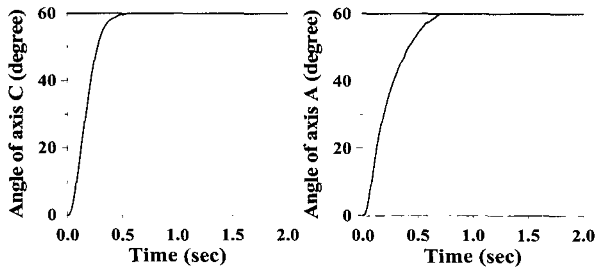


Fig. 11. Angle of axis C and A by the fuzzy-sliding mode control based on the genetic algorithm.

and the shape of membership functions of the fuzzy-sliding mode controller, learning experiments of the polishing robot is carried out. First, to determine the switching parameter $\psi_{\alpha i}$, $\psi_{\beta i}$, and $\psi_{\gamma i}$ in (2), the values of inertia J_i and damping coefficient B_i of a robot system are estimated by the signal compression method which identifies unknown parameters of system [11][12][16]. Using the signal compression method, the unknown parameters of the polishing robot are estimated as listed in Table 3. When slopes of switching line are c_1 = 4 and c_2 = 4, the limit values of the switching parameter which are satisfied the existence condition of sliding mode are derived as listed in Table 4. Second, the initial conditions for the genetic algorithm of experiment and simulation are the same. By using a learning procedure of the genetic algorithm in Fig. 4, the shape of membership functions is determined as shown in Fig. 8. And, the experiment results are shown in Fig. 11. Therefore, results of experiment and simulation are the same.

2. Polishing of the die of shadow mask

In the polishing process of the die, the polishing robot has always a big contact force change by removing tool marks and vibration by rotating a polishing tool during polishing. And, when the velocity of the polishing tool is 1200 [rpm] and polishing sheet is 100 [mesh], the efficiency of polishing is best at the 40 [N]-polishing force. However, when the velocity of the polishing tool is 1200 [rpm] and the number of polishing sheet is 800 [mesh], the polished surface is singed black at the 20 [N]-polishing force [11][12]. Therefore, the magnitude of polishing force must be restricted to 20 [N] at 800 [mesh] and 1200 [rpm] because heat is generated by friction between the polishing tool and the surface of die.

In order to evaluate the robust trajectory tracking performances of the proposed fuzzy-sliding mode controller during polishing process, polishing experiment on the die of the shadow mask is performed. The material of the die is STD, and its size is 570 [mm] × 340 [mm] as shown in Fig. 10 and Fig. 12. The desired polishing trajectory pattern for the die of a shadow mask is generated by PolyCAM, a dedicated CAM software for the system [11][12]. The generated polishing trajectory pattern is shown in Fig. 13.

First, polishing condition (I) is 1000 [mesh], 1300 [rpm] and 10 [N]. The control results along the zigzag pattern are shown in Fig. 14. Second, polishing condition (II) are 1000 [mesh], 1300 [rpm] and 20 [N]. The control results are shown in Fig. 15. In Fig. 14(b) and Fig. 15(b), the maximum error of axis A and axis C are 0.07 degrees. It is possible to correct this error because the structure of the polishing tool has some flexibility and the tool is always in contact with a polishing surface by a constant polishing force. Therefore, the results show that the proposed algorithm can provide reliable tracking performance during the polishing process.

Fig. 12. Die of shadow mask.

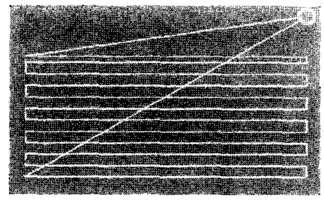
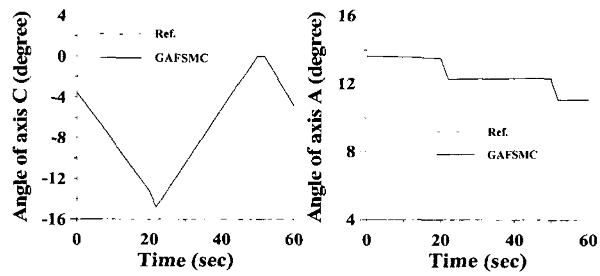
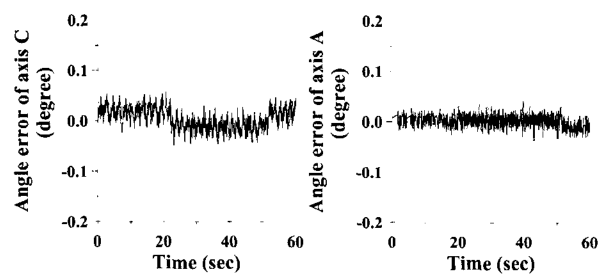


Fig. 13. Zigzag polishing pattern.



(a) Angle of axis C and A by the proposed fuzzy-sliding mode control

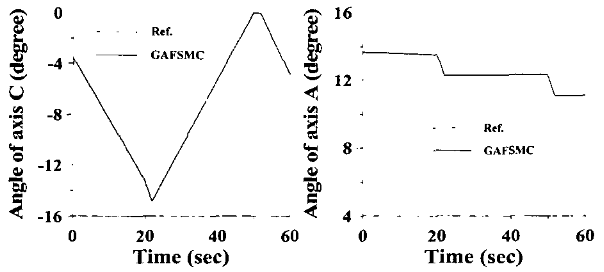


(b) Angle error of axis C and A by the proposed fuzzy-sliding mode control

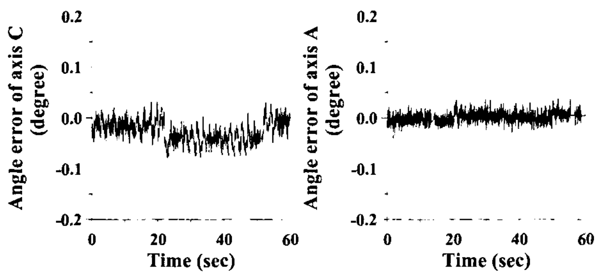
Fig. 14. The control results at polishing condition (I).

VI. Conclusion

This study proposed 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 were optimized without an expert in robotics. And, the fuzzy outputs of the consequent part were updated by the gradient



(a) Angle of axis C and A by the proposed fuzzy-sliding mode control



(b) Angle error of axis C and A by the proposed fuzzy-sliding mode control

Fig. 15. The control results at polishing condition (II).

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 investigate the learning and the trajectory tracking performances of the proposed fuzzy-sliding mode controller using the genetic algorithm, the trajectory tracking simulation of the polishing robot was carried out and the controller was compared with the fuzzy-sliding mode controller using the trial and error method, which was proposed in the previous study. Trajectory tracking simulation shows that the optimal fuzzy inference rules are automatically selected by the genetic algorithm and the control result of the proposed fuzzy-sliding mode control is almost similar to the result of the fuzzy-sliding mode control which is selected through the trial and error method by an expert. Therefore, although designer is a non-expert in robotics, the fuzzy-sliding mode controller can be designed by the proposed self tuning fuzzy inference method based on the genetic algorithm. To evaluate results of simulation by experiment, the proposed algorithm was implemented to the automatic polishing robot system. Results of experiment and simulation are the same. And, the proposed algorithm can provide reliable tracking performance during the polishing process. However, the proposed approach has some potential difficulties. Programming and debugging the proposed algorithm are a very time-consuming and tedious job because the program is very long and has a complex structure. And, a micro-process for real-time calculations is needed to control the robot because the learning procedure is long. Also, to evaluate the performance of the proposed algorithm, this study only applies the algorithm to the polishing robot. Thus, our future study will include the algorithm is applied to other general robots.

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Seok-Jo Go

He was born in Korea in 1969. He received the B.S. in Mechanical Engineering from Pusan National University in 1994 and M.S. in Mechanical Engineering from Pusan National University in 1996. He had been with DAEWOO Electronics Company as a research engineer from 1995 to 1997. He is now a Ph.D. candidate in the School of Department of Mechanical and Intelligent Systems Engineering, Pusan National University. And, he is a full-time lecturer in the Department of Machine System, Dongeui Institute of Technology. His research interests includes intelligent control, nonlinear control, robotics, and system identification.

Min-Kyu Park

He was born in Korea in 1972. He received his B.S. in Mechanical Engineering from Yeungnam University in 1996, and M.S. in Mechanical Engineering from Pusan National University in 1998, respectively. He is currently a Ph.D. candidate in the School of Department of Mechanical and Intelligent Systems Engineering, Pusan National University. Also, he has been with RIMT(Research Institute of Mechanical Technology) at Pusan National University since 2000. His research interests includes the identification and robust control for a nonlinear system, and the robust observer design.

Min-Cheol Lee

He was born in Korea in 1960. He received the B.S. in Mechanical Engineering from Pusan National University in 1983, and M.S. and Ph.D. in Engineering Sciences from the Tsukuba University, Japan, in 1988 and 1991, respectively. He is now an associate professor in the School of Mechanical Engineering, Pusan National University. His research interests includes mechatronics, control of digital servo system, robotics, sensor application, and system identification.