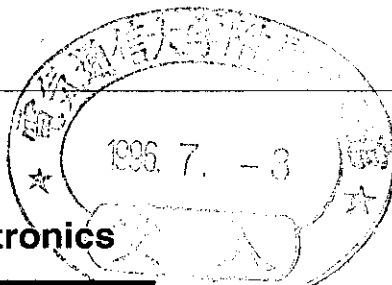
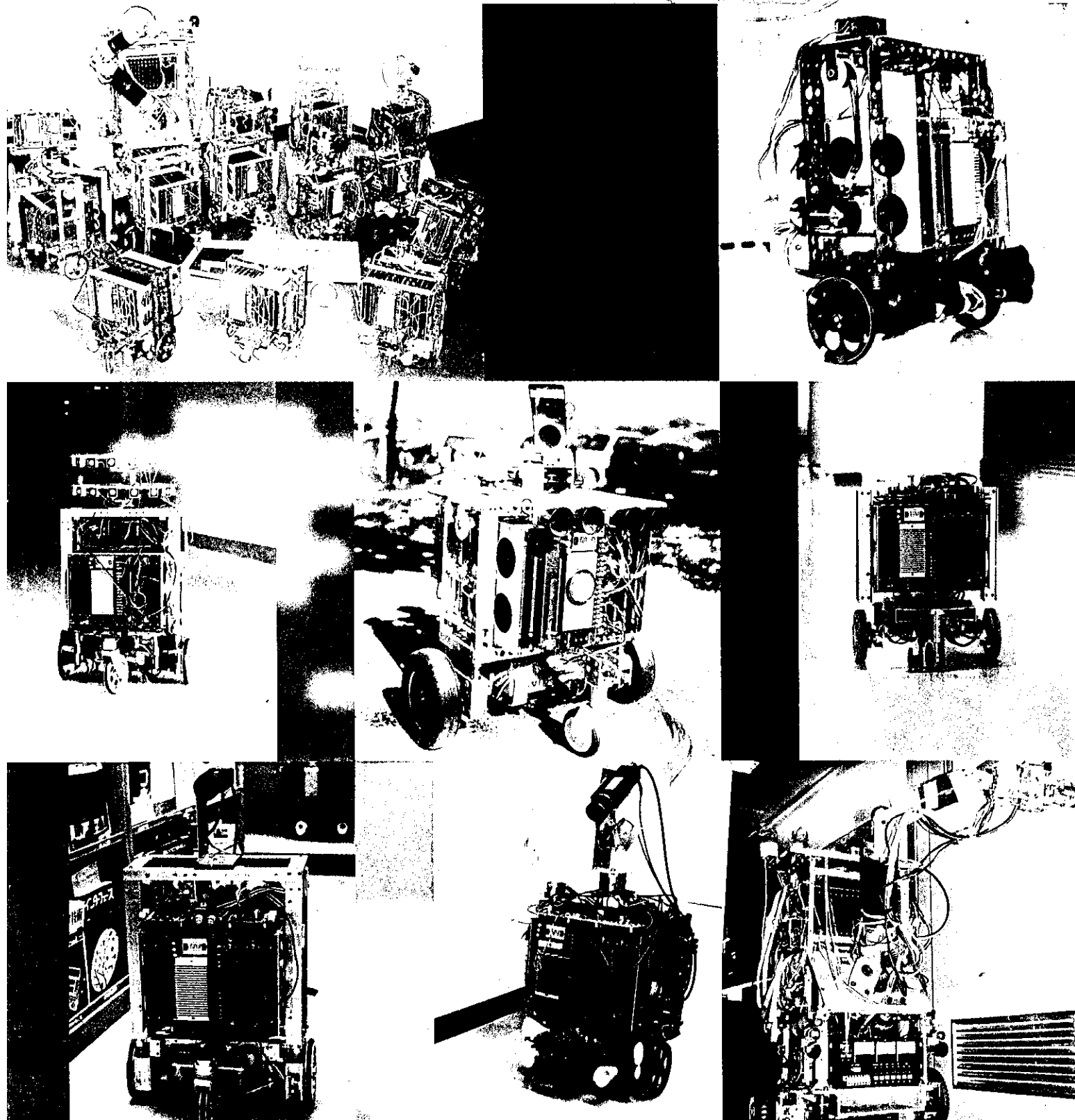


Journal of Robotics and Mechatronics

Vol.8 No.3 June 1996



■ Special Issue on Control Systems in Mechatronics



Paper:

GA in Continuous Space and Fuzzy Classifier System for Opening a Door with a Manipulator of Mobile Robot: New Benchmark of Evolutionary Intelligent Computing

J. Ohwi, S.V. Ulyanov and Kazuo Yamafuji

The University of Electro-Communications,
1-5-1 Chofugaoka, Chofu Tokyo, 182 Japan
[Received March 1, 1996; accepted April 15, 1996]

An intelligent mobile robot for service use which is mainly utilized in office buildings has been developed. It can locomote autonomously from one room to others in different floors and buildings using elevators. The robot equips a 5DOF manipulator and must often conduct opening and closing doors operation. For realizing door opening operation of a manipulator in cooperation with locomotive mechanisms, it is necessary to develop efficient and intelligent computing algorithms for next two requirements: (1) determination of initial position of the mobile robot in front of a door-knob like parking a car and (2) path planning of manipulator trajectory for opening a door. This paper provides these algorithms. We propose an algorithm on basis of Fuzzy Classifier System (FCS) for (1). The FCS is a kind of Genetic Algorithms (GA) in which a chromosome expresses each fuzzy rule. And we develop a method of making a trajectory of the flexible manipulator using Genetic Algorithms in Continuous Space (GACS) for (2).

Keywords: Mobile robot, Path planning, Genetic algorithms, Fuzzy classifier system, Open a door

1. Introduction

In our previous paper¹⁾, an intelligent mobile robot (MR) for service use mainly in office buildings was developed. For this MR, intelligent control systems based on GA, FNN, and fuzzy controllers were proposed in our recent paper.²⁾ The MR for service use installs a manipulator and moves in unstructured environments in the presence of many peoples and unexpected obstacles. It can navigate from one room to other environments including corridors, elevators and so on using a manipulator. In this case, it must often conduct door opening operation. The complex processes of opening a door seem to be a mechanical analogy of evolutionary computing (new mechanical benchmark proposed here) and requires a new intelligent strategic operation for the MR manipulator. The successful fulfillment of this evolutionary operation depends on the selection of the initial position of the MR and path planning of manipulator trajectory motion. For flexible realization of this evolutionary operation, it is necessary to develop efficient and intelligent computing algorithms for two requirements: (1) determination of the in-

itial position of the MR in front of a door-knob like parking a car and (2) path planning of manipulator trajectory motion of opening a door. We present new methods for making these algorithms. For the *first case*, we propose an algorithm on the basis of the Fuzzy Classifier System (FCS) applying the classifier system to fuzzy production rules. This FCS is a kind of GA in which a chromosome expresses a fuzzy rule like a classifier system. For the *second case*, we develop a method of making a trajectory for the MR manipulator by means of GA for opening a door, and using GACS (Genetic Algorithms in Continuous Space) instead of GA. By these algorithms, the MR has succeeded in opening a door. Comparisons of GA and GACS on the basis of simulation results are presented. Characteristics of genetic operators (crossover and mutation rates) and convergence of GACS are also discussed.

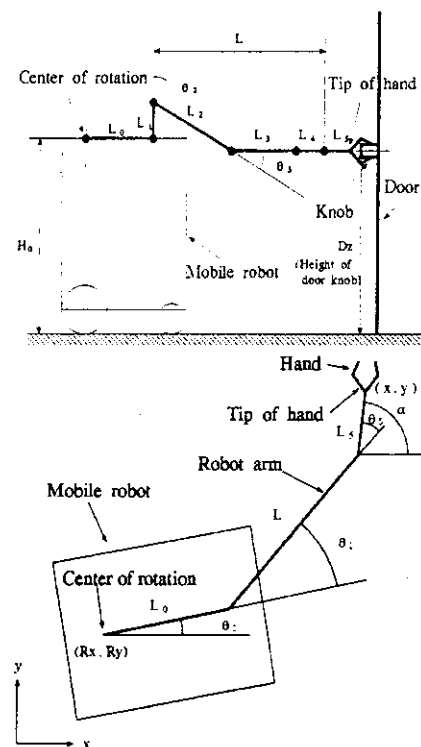


Fig. 1. Geometrical model of mobile robot.

2. Geometrical Model of the MR Manipulator

The developed MR (Fig.1) references 1) and 2) is a 2DOF (degree of freedom) autonomous vehicle and mounts a 5DOF manipulator on locomotive mechanisms. The MR constitutes totally seven DOF systems. However, six of the seven DOF are fixed at a position in front of a door knob in order to open the door. On the other hand, each angle of an arm and wheels are not fixed. Therefore we must decide that only one DOF (direction of the MR motion) which is controlled by GA. As depicted in Fig.1, the angles θ_2 and θ_3 are fixed by the height of the door knob. For the simplification of the computation, we assume that the robot arm is of three links.

3. Positioning of the MR with FCS

Before conducting some operation (for example, opening a door), the MR must move to approaching a position to execute it. If the position is inaccurate (the right or left side of the present position) for the robot, it must approach near the objectives while it is moving front or backwards just like parking a car. This operation can be described by using fuzzy production rules and the control system of the MR can correct the position using ultrasonic or image sensors. For solving very vague problems, fuzzy control can be successfully applied.³⁾ However, the number of fuzzy rules becomes very large as the number of inputs is large; thus, it is difficult even for the human expert to make the look-up table of fuzzy production rules. Therefore, we propose an algorithm (soft computing) as FCS (Fuzzy Classifier System) applying the classifier system to the production of fuzzy rules. The algorithm of FCS on basis of GA is shown in Fig.2(a).

3.1. Fuzzy Classifier System

In computer simulation, FCS is a kind of GA in which a chromosome expresses a fuzzy production rule as "if...then," like the classifier system. Fuzzy rules are expressed according to Fig.2(b). The algorithm of FCS for soft computing is described as follows: (1) evolution in parallel from individual that has a small number of inputs (low individual) to individual that has a large number of inputs (high individual); (2) high individuals are expressed as colonies of low individuals; (3) the chromosome expresses connection of each individual; (4) each individual is evaluated as a rule set; (5) if evaluation of a high individual is better than that of a low individual connected with it, the low one gets a new evaluation of the high one.

3.2. Results of Computer Simulation

A part of fuzzy rules in a look-up table obtained by FCS is shown in Table 1, and the MR motion simulation using these rules is shown in Fig.3. In Table 1, FCS was made of unbalanced rules for θ . An expert may make the same rules, but there is no guarantee that they set best. With soft computing on FCS, a flexible learning process without stereotype examples was presented. In Fig.3, the robot moves like switch back motion, and we obtained very good simulation

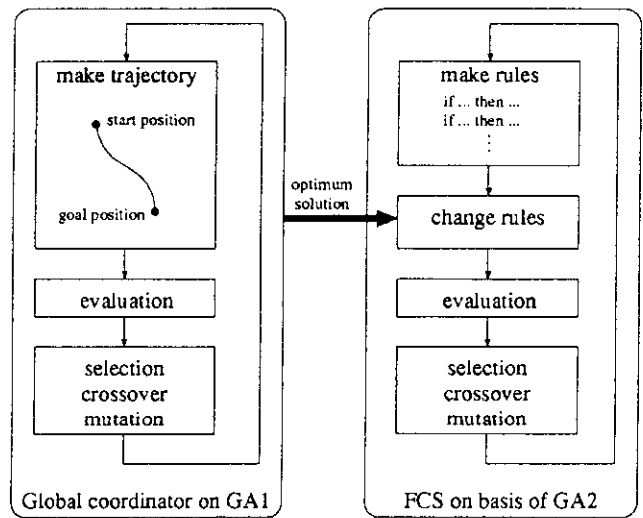


Fig. 2(a). Algorithm of FCS.

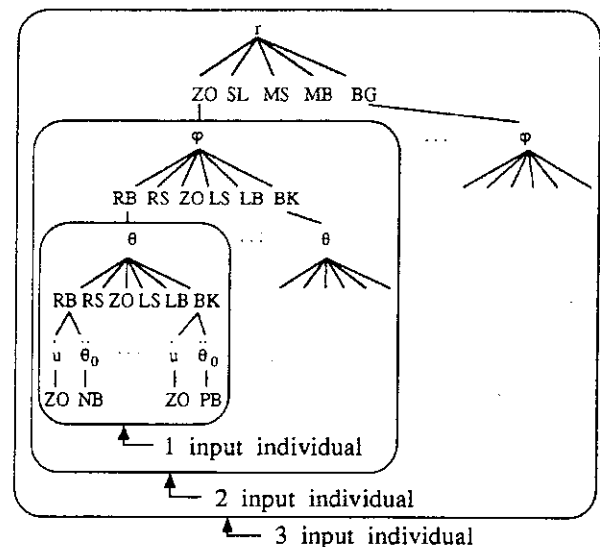


Fig. 2(b). Fuzzy classifier system (FCS).

Table 1. Part of look-up tables obtained by FCS.

input					output	
θ_0	u	r	ϕ	θ	\dot{u}	θ_0
ZO	ZO	ZO	ZO	RB	PS	PM
ZO	ZO	ZO	ZO	RS	PS	-
ZO	ZO	ZO	ZO	ZO	PS	PS
ZO	ZO	ZO	ZO	LS	-	PB
ZO	ZO	ZO	ZO	LB	NS	NB
ZO	ZO	ZO	ZO	BK	NB	PB

- r : distance up to final position
- ϕ : difference from final angle
- θ : direction of final position
- u : velocity of mobile robot
- θ_0 : direction angle of mobile robot
- ZO, RB etc. : fuzzy-set values

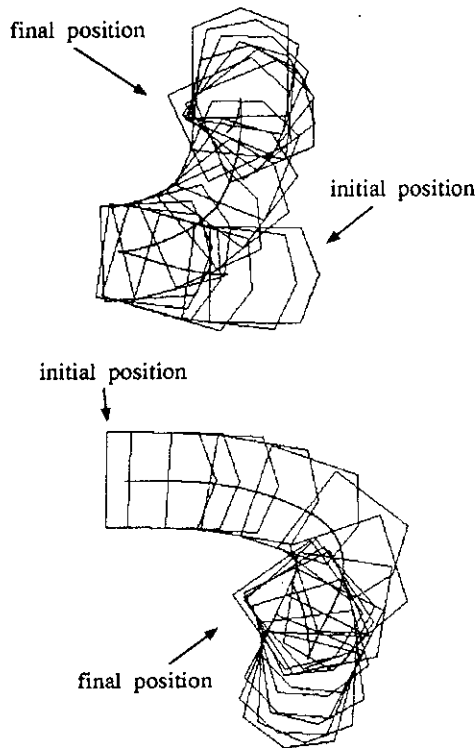


Fig. 3. Sample motion of the mobile robot.

results: (1) fuzzy production rules to let the MR move to the goal were made automatically by FCS; and (2) the robot behaves with intelligent motion just like switch back motion. However, the MR could not reach a goal exactly because FCS cannot adapt itself to slight differences of position. For the realization of an evolutionary process as opening a door with a small inaccurate position of the MR, we utilized a new approach for intelligent computation based on GACS.⁴⁾

4. Evolutionary Process of Opening a Door using GA

We develop an evolutionary intelligent computing method to make the trajectory of manipulator motion for opening a door by GA and discuss effects of GA's parameter change using GACS instead of GA.

4.1. Evolutionary Intelligent Computing Method

Because of the difficulty of describing the relation between an unknown quantity and evaluation function in explicit equations, we apply the GA scheme. Encoding methods based on GA and GACS are shown in Fig.4. A trajectory can be decoded by expressing a curve in order to pass two points (t_1, θ_{01}) and (t_2, θ_{02}) using a spline function (where, t – time, and θ_0 – angle direction of the MR motion). Each angle of an arm and velocity of the MR is fixed values at a position of a door knob. As illustrated in Fig.4, the chromosome of GACS is a real number. Genetic operations of GACS are the same as GA except for operator of mutation. Mutation of GACS is due to Gaussian additive muta-

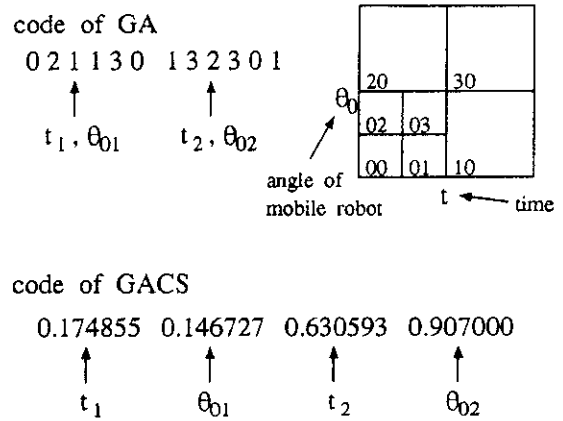


Fig. 4. Encoding process.

tion.⁴⁾ We define evaluation fitness function F as

$$F = A(D_y - D_w/2 - y_1 |_{x_1=D_x})^2 + B\theta_0 |_{x_1=D_x}^2 + C \alpha_{total} + D \theta_{over} \dots \dots \dots (1)$$

where, x_1, y_1 – coordinates of the first shaft; D_x, D_y – coordinates of a door's rotational center; D_w – width of a door; α_{total} – sum of absolute of wheel angle acceleration; θ_{over} – maximum angle of limit; A, B, C, D – coefficients.

This function means physically that the robot goes straight to the center of the door as advancing across the door, acceleration is assumed small, and angles of the arm will not overrun their limits. If F is small, fitness is large. In this case, we solve the following optimization problem:

$$\arg \min_x F(x) \dots \dots \dots (2)$$

and for GA it is needed⁵⁾ that F has only many finite global maxima, $0 < F(x) < \infty, \forall x \in \Gamma \subseteq R^m$, is a feasible region of a real parameter vector: $F(x)$ has many finite discontinuous points. For function F , this conditions are fulfilled from Eq.(1).

In our case, genetic operations are following: (1) operators – one point crossover and mutation: (2) parent selection techniques – roulette wheel selection: (3) fitness techniques – linear normalization⁶⁾; (4) reproduction method – generational replacement with elite strategy. In case of GACS, we use Gaussian additive mutation.^{3,4)}

4.2. Soft Computing with GACS

After a sufficiently long time, the probability density function (PDF) of the population will become narrow and concentrate around the global minimum of the fitness function. In this case, $x_{k+1}^i = x_k^i + w_k^i, i = 1, 2, \dots, N$, where $w_k^i, i = 1, 2, \dots, N$ are independent and identically distributed m -dimensional random vectors with zero mean and a common density $f_{w_i}(\cdot), N \rightarrow \infty; x_k^i$ – intermediate population after selection at time k (but before mutation with conditional PDF $f_{w_i}(\cdot)$ that characterizes the mutation operator a time k).

$$f_{x_{k+1}}(x) = \int_{\Gamma} f_{x_k}(y) F(y) f_{w_k}(x|y) dy$$

$$\int_{\Gamma} f_{x_k}(y) F(y) dy \dots \dots \dots (3)$$

or

$$f_{x_{k+1}}(x) = f'_k(x) * f_{w_k}(x), f_k(x)$$

$$= f_k(x) F(x) / E[F(x_k)] \dots \dots \dots (4)$$

Operator * - *m*-dimensional linear convolution. From Eqs.(3) and (4), it is shown how evolution process consists of an alternation of implication with the fitness function (selection) and convolution with the mutation density (mutation): the former tends to “squeeze” the density of *x* around global minimum of the fitness function, whereas the latter “spreads” the resulting distribution. This quality of GACS was marked in reference 4) and used in this paper. Then, the average radius of mutation is defined as

$$\bar{r}(k, x) = \int_{\Gamma} \|y - x\| f_{w_k}(y - x) dy \dots \dots \dots (5)$$

and

$$\int_{\Gamma} \bar{r}(k, x) f_k(x) dx \leq L^{-1} Var[F(x_k)] \dots \dots \dots (6)$$

where *L*-Lipschitz number. It is a sufficient condition for monotonous increase of average fitness. A large current average fitness requires small noise to guarantee a monotonous characteristic, then the population has already concentrated itself on regions with large fitness. A large fitness variance corresponds to a population which is still rather spread out and can tolerate large mutation effects. At convergence $Var[F(x_k)] \rightarrow 0$, the mutation can be reduced accordingly. From our simulation results of a benchmark problem such as opening a door, we have observed that conditions similar to the aforementioned lead to satisfactory solutions in many cases for common classes of radially symmetric mutation densities. In this case, it is reported that very effective integration of GA and fuzzy neural network computation were carried out.⁷⁾

4.3. Results of Computer Simulation

A typical opening door motion trajectory made by GA is shown in Fig.5. Thus, the MR succeeded to open a door.

Figure 6 shows differences of convergence between GA and GACS in accordance with the change of crossover rate and mutation rate as shown in Table 2. These data are obtained as the average of five data points in changing random seed. If the mutation rate was large, both GA and

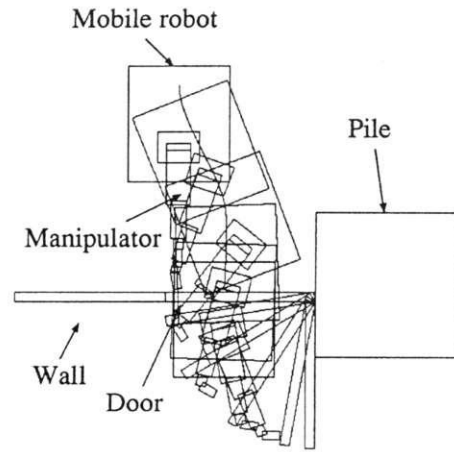
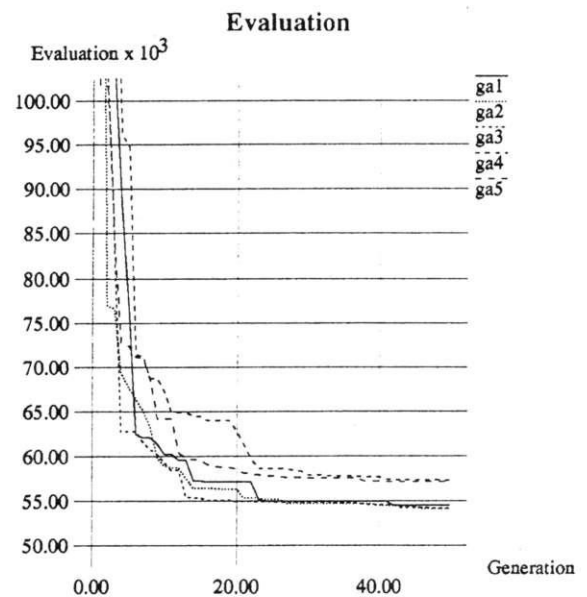
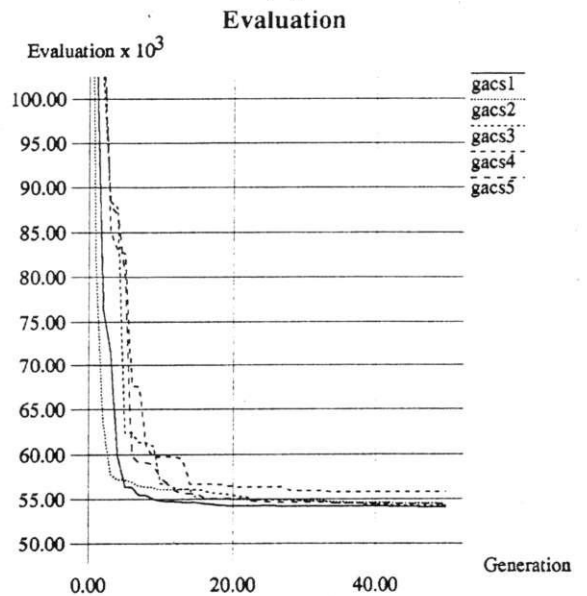


Fig. 5. Sample trajectory.



(a)



(b)

Fig. 6. Effect of parameter change.

(a) -GA, (b) - GACS

Table 2. Parameters of GA and GACS.

genetic operator	No. of GA and GACS				
	1	2	3	4	5
crossover rate	0.0	0.5	1.0	1.0	1.0
mutation rate	1.0	1.0	1.0	0.001	0.5

GACS converged quickly, because we used *elite* strategy, which simply always retained the best chromosome out of the population.³⁻⁵⁾ When the crossover rate as large, GA converged quickly, but GACS did not. It shows that mutation is more important than crossover on GACS. We have compared GA and GACS, and confirmed that each algorithm had the following merits as well as demerits:

GA: (1) strong in local optimum, (2) weak in local search, and (3) crossover is important to accelerate convergence.

GACS: (1) strong in local search, (2) mutation is more important than crossover in order to accelerate convergence, and (3) weaker in local optimum than GA.

5. Conclusion

- (1) The authors proposed a method in which human beings only input the size of a door and the MR such as changing size, and the MR automatically makes a trajectory for opening a door.
- (2) It succeeded in computer simulation and the MR's opening a door smoothly in experiment.
- (3) For making a 7DOF mobile manipulator trajectory motion we used GA and GACS. Both algorithms are flexible, but GACS converged more quickly than GA.

References:

- 1) A. Ishiwaka, K. Miyagawa, T. Tanaka and K. Yamafuji, "Development of Intelligent Mobile Robot for Service Use," Proc. of Japan Soc. Mech. Engineers Ann. Conf. Robotics and Mechatronics (ROBOMECH'94), A, 353-358 Kobe (1994).
- 2) S.V. Ulyanov, K. Yamafuji, K. Miyagawa, T. Tanaka and T. Fukuda, "Intelligent Fuzzy Motion Control of Mobile Robot for Service Use,"

Proc. of Intern. Conference on Human Robot Interaction and Cooperative Robots (IROS'95), 3, 486-491, Pittsburgh (1995).

- 3) V.N. Zhakarov and S.V. Ulyanov, "Fuzzy Models of Intelligent Industrial Controllers and Control Systems. Pt. 4. Simulation on GA and FNN," Techn. Cybernetics, 5, 168-210 (1994). (in Russian)
- 4) X. Qi and Palmieri Francesco, "Theoretical Analysis of Evolutionary Algorithms with an Infinite Population Size in Continuous Space. Pts.1,2," IEEE Transactions on Neural Networks, 5-1, 102-129 (1994).
- 5) D.B. Fogel, "Applying Evolutionary Programming to Selected Control Problems," Computers Math. Applic., 27-11, 89-104 (1994).
- 6) L. Davis, "Handbook of Genetic Algorithms," Academic Press (1991).
- 7) T. Fukuda and T. Shibata, "Integration and Synthesis of Neural Network Fuzzy Logic and Genetic Algorithms for Intelligent Systems," Transactions of Japan Soc. Mech. Eng., 59-563, 2282-2289 (1993). (in Japanese)



Name:
Junji Ohwi

Affiliation:

Graduate Course Student, Department of Mechanical and Control Engineering, Electro-Communications, Graduate School of Electro-Communications

Address:

1-5-1 Chofugaoka, Chofu, Tokyo, 182 Japan

Brief Biographical History:

1995 - Graduated University of Electro-Communications and entered Graduate School of University of Electro-Communications

Main Works:

- "Development of Intelligent Mobile Robot for Service Use (8th Report, Intelligent path planning for mobile robot)", JSME Annual Conference on Robotics and Mechatronics (ROBOMECH '95), A, 501-502 (1995).

Membership in Learned Societies:

- The Japan Society of Mechanical Engineers (JSME)



Name:
Ulyanov Sergei V.

Affiliation:

Professor, Department of Mechanical and Control Engineering, University of Electro-Communications

Address:

1-5-1 Chofugaoka, Chofu, Tokyo, 182 Japan

Brief Biographical History:

1975 - Central Institute of Building Constructions
1983 - Central Institute of Biomedical Engineering
1992 - Institute of Physicotechnical Problems
1994 - Institute for Problems in Mechanics
University of Electro-Communications

Main Works:

- "Fuzzy Models of Intelligent Industrial Controllers and Control Systems, Pts 1,2,3", Journal of Computer and Systems Sciences International, 33-1, pp.123-144 (1994), 33-2, 94-108; 117-136 (1995).
- "Expert Fuzzy-Neuro Controller Design for Wall Climbing Robot for Decontamination of Nuclear-Power Station," Journal of Robotics and Mechatronics, 7-1, 75-85 (1995).
- "Development of Intelligent Mobile Robots for Service Use and Mobile Automation Systems Including Wall Climbing Robots", International Journal of Intelligent Mechatronics, 1-3, 111-143 (1995).

Membership in Learned Societies:

- Russian Society of Fuzzy Systems (RSFS)



Name:
Kazuo Yamafuji

Affiliation:

Professor, Dr., Department of Mechanical and Control Engineering, University of Electro-Communications

Address:

1-5-1, Chofugaoka, Chofu, Tokyo, 182 Japan

Brief Biographical History:

1973 - Graduated from Graduate School of Engineering, University of Tokyo Dr. of Engineering
Lecturer, Faculty of Engineering, Yamanashi University
1974 - Associate Professor
1988 - Professor, University of Electro-Communications

Main Works:

- Chemical Engineering & Micrometrics
- Fluid Mechanics & Turbo-machinery
- Hydraulics & Pneumatics
- Manufacturing Automation
- Industrial Robot & Assembly Automation
- Robotics & Mechatronics
- Intelligent Robotics & Systems

Membership in Learned Societies:

- Japan Society of Mechanical Engineering
- Robotics Society of Japan et al.