International Journal of Fuzzy Logic and Intelligent Systems, vol. 6, no. 4, December 2006, pp. 293-298

Fuzzy Neural Network Based Sensor Fusion and It's Application to Mobile Robot in Intelligent Robotic Space

TaeSeok Jin[1], MinJung Lee[2], and Hideki Hashimoto[3]

[1] Dept. of Mechatronics Eng., DongSeo University, Busan, 617-716, Korea
[2] RIC for Ubiquitous Appliance, DongSeo University, Busan, 617-716, Korea
[3] IIS, University of Tokyo, 4-6-1 Komaba Meguro-ku Tokyo 153-8505, Japan

Abstract

In this paper, a sensor fusion based robot navigation method for the autonomous control of a miniature human interaction robot is presented. The method of navigation blends the optimality of the Fuzzy Neural Network(FNN) based control algorithm with the capabilities in expressing knowledge and learning of the networked Intelligent Robotic Space(IRS). States of robot and IR space, for examples, the distance between the mobile robot and obstacles and the velocity of mobile robot, are used as the inputs of fuzzy logic controller. The navigation strategy is based on the combination of fuzzy rules tuned for both goal-approach and obstacle-avoidance. To identify the environments, a sensor fusion technique is introduced, where the sensory data of ultrasonic sensors and a vision sensor are fused into the identification process. Preliminary experiment and results are shown to demonstrate the merit of the introduced navigation control algorithm.

Key Words : Fuzzy Neural Network, CCD cameras, Mobile robot, Recognition, Obstacle avoidance.

I. Introduction

The Intelligent Robotic Space(IRS) propagates mobile robots in the space, which act in the space in order to change the state of the space. These mobile robots are called mobile agents. Mobile Agents cooperating with each other and with the core of the IRS to realize intelligent services to inhabitants. Mobile robots become more intelligent through interaction with the IRS. Moreover, robots can understand the requests (e.g. gestures) from people, so that the robots and the space can support people effectively. The Intelligent Robotic Space can physically and mentally support people using robot and VR technologies; thereby providing satisfaction for people. These functions will be an indispensable technology in the coming intelligence consumption society (Fig. 1). An autonomous mobile robot is intelligent robot that performs a given work with sensors by identifying the surrounded environment and reacts on the state of condition by itself instead of human. Unlike general manipulator in a fixed working environment [1],[2] it is required intelligent processing in a flexible and variable working environment. Recently studies on a fuzzy-neural-network control are attractive in the field of autonomous mobile robot. The fuzzy-neural-network control is suitable for adopting sensor fusion techniques in order to increasing the ability of the mobile robot to react to dynamic environment as well as ensuring collision avoidance with both moving and non-moving obstacles [3],[4]. Generally, fuzzy inference approaches tend to de-emphasize the goal-directed navigation and focus more upon handling reactive and reflexive situations. The results of the fuzzy inference controller generally do not tend towards the optimal path [5]. However, unexpected and rapidly moving obstacles are avoided safely than other methods [6],[7].

This paper is organized as follows. This section introduces the concept of Intelligent Robotic Space. Section 2 introduces the mobile agent and human behavior model, which is used to understand human behavior directly from observation. Section 3 shows experiment for observation of human behavior using the distributed sensory intelligence of the Intelligent Robotic Space and control the mobile agent using the acquired behavior.

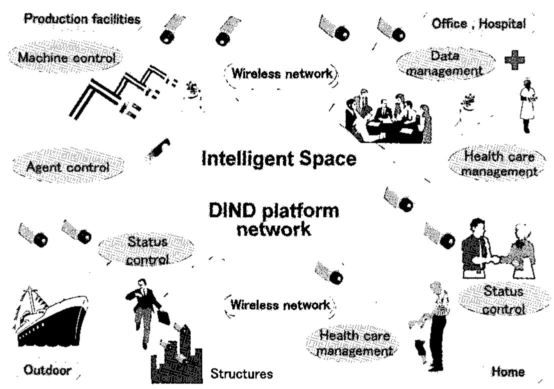


Fig. 1. Vision of IRS, as a Human Support System for More Comfortable Life

Manuscript received Nov. 29, 2006; revised Dec. 15, 2006.

2. Fuzzy Neural Network Controller Design

2.1 Structure of Navigation Algorithm

The proposed fuzzy neural network controller is shown as Fig. 1. We define three major navigation goals, i.e., target orientation, obstacle avoidance and rotation movement; represent each goal as a cost function. Note that the fusion process has a structure of forming a cost function by combining several cost functions using weights.

In this fusion process, we infer each weight of command by the fuzzy algorithm that is a typical artificial intelligent scheme. With the proposed method, the mobile robot navigates intelligently by varying the weights depending on the environment, and selects a final command to keep the minimum variation of orientation and velocity according to the cost function. In the type of fuzzy neural networks based on BP, neurons are organized into a number of layers and the signals flow in one direction. There are no interactions and feedback loops among the neurons of same layer,

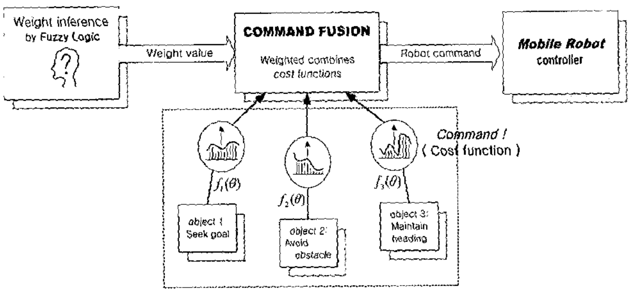


Fig. 2. Overall Structure of Navigation Algorithm

2.2 Command for Moving toward Target Orientation and Avoiding Obstacle

The orientation command of mobile robot is generated as the nearest direction to the target point. The command is defined as the distance to the target point when the robot moves present with the orientation, θ and the velocity, v. Therefore, a cost function is defined as Eq. (1).

$$E_d(\theta) = \{x_d - x_c + v \cdot \Delta t \cdot \cos\theta)\}^2 + \{y_d - (y_c + v \cdot \Delta t \cdot \sin\theta)\}^2 \quad (1)$$

where, v is $v_{\max} - k \cdot |\theta_c - \theta|$ and k represents the reduction ratio of rotational movement. Also the cost function is represented as the values in the most surface when the robot moves with velocity, and orientation, θ, as shown in Fig. 3.

We use the method of representing the cost function for obstacle-avoidance as the shortest distance to an obstacle based upon the sensor data in the form of histogram. The distance information is represented as a form of second order energy, and represented as a cost function by inspecting it about all θ as shown in Eq. (2).

$$E_0(\theta) = d^2_{sensor}(\theta) \quad (2)$$

To navigate in a dynamic environment to the goal, the mobile robot should recognize the dynamic variation and react to it. For this, the mobile robot extracts the variation of the surrounded environment by comparing the past and the present. For continuous movements of the robot, the transformation matrix of a past frame *w.r.t* the present frame should be defined clearly.

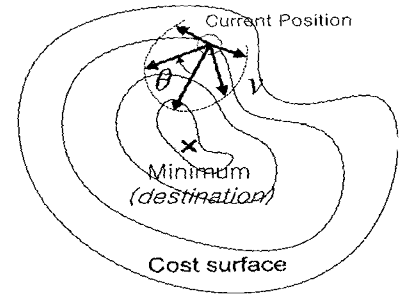


Fig. 3. Function of θ, v in Cost Surface

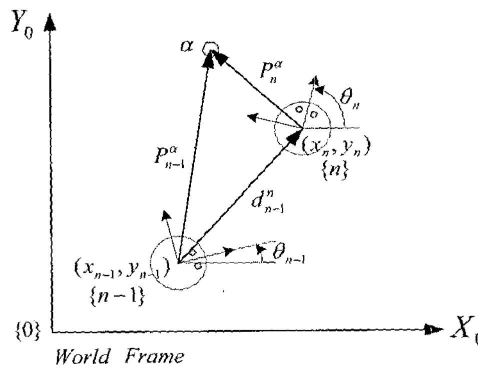


Fig. 4. Transformation of Frame

In Fig. 4, a vector, P^{α}_{n-1} is defined as a position vector of the mobile robot *w.r.t* the {n-1} frame and P^{α}_{n} is defined as a vector *w.r.t* the {n} frame. Then, we obtain the relation between P^{α}_{n-1} and P^{α}_{n} as follow.

$$P^{\alpha}_{n} = R^{n}_{n-1}(P^{\alpha}_{n-1} - d^{n}_{n-1}) \quad (3)$$

Here, R^{n}_{n-1} is a rotation matrix from {n-1} to {n} frame defined as Eq. (4), and d^{n}_{n-1} is a translation matrix from {n-1} frame to {n} frame as shown in Eq. (5).

$$R^{n}_{n-1} = \begin{bmatrix} \cos(\Delta\theta) & \sin(\Delta\theta) \\ -\sin(\Delta\theta) & \cos(\Delta\theta) \end{bmatrix} \quad (4)$$

$$where\ \Delta\theta = \theta_n - \theta_{n-1}$$

$$d^{n}_{n-1} = \begin{bmatrix} \cos\theta_{n-1} & \sin\theta_{n-1} \\ -\sin\theta_{n-1} & \cos\theta_{n-1} \end{bmatrix} \begin{bmatrix} x_n - x_{n-1} \\ y_n - y_{n-1} \end{bmatrix} \quad (5)$$

According to the Eq. (3), the environment information measured in the {n-1} frame can be represented *w.r.t* the {n} frame. Thus, if W_{n-1} , and W_n are the environment information in the polar coordinates measured in {n-1} and {n} frames, respectively, we can represent W_{n-1} *w.r.t* the {n} frame, and extract the moving object by the Eq. (6) in the {n} frame.

$$movement = {}^{n}W_{n-1} \cdot ({}^{n}W_{n-1} - W_n) \quad (6)$$

where ${}^{n}W_{n-1}$ represents W_{n-1} transformed into the {n} frame.

2.3 Command for Minimizing Rotational Movements

Minimizing rotational movement aims to rotate wheels smoothly by restraining the rapid motion. The cost function is defined as minimum at the present orientation and is defined as a second order function in terms of the rotation angle, θ as Eq. (7).

$$E_r(\theta) = (\theta_c - \theta)^2 \quad \theta_c : present\ angle \quad (7)$$

The command represented as the cost function has three different goals to be satisfied at the same time. Each goal differently contributes to the command by a different weight, as shown in Eq. (8).

$$E(\theta) = w_1 \cdot E_d(\theta) + w_2 \cdot E_o(\theta) + w_3 \cdot E_r(\theta) \quad (8)$$

3. Inference of Cost Function by Fuzzy Neural Network

3.1 Structure of Control System

An interesting architecture for a fuzzy neural controller has been proposed by Jang [10] and our controller is based on this idea. Fuzzy neural controllers can be regarded as fuzzy controllers implemented using a neural network, often in the form of a modified radial basis function network. By this means the learning algorithms developed for neural networks become available for the training of the fuzzy controller.

We infer the weights of Eq. (8) by means of fuzzy algorithm. The main reason of using fuzzy neural network algorithm is that it is easy to reflect the human's intelligence into the robot control. Fuzzy inference system is developed through the process of setting each situation, developing fuzzy-neural with proper weights, and calculating weights for the commands. Fig. 5 shows the structure of a fuzzy-neural inference system. We define the circumstance and state of a mobile robot as the inputs of fuzzy-neural inference system, and infer the weights of cost functions. The inferred weights determine a cost function to direct the robot and decide the velocity of rotation. For the control of the mobile robot, the results are transformed into the joint angular velocities by the inverse kinematics of the robot.

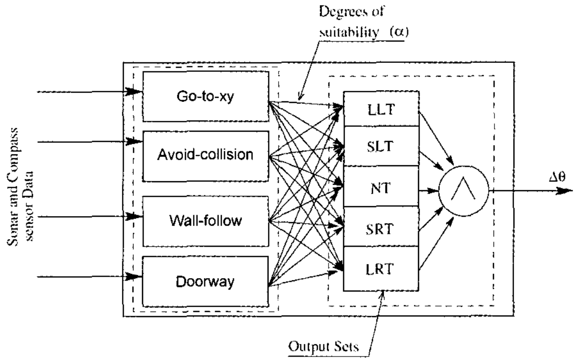


Fig. 5. Structure of Fuzzy Neural Network Control System

3.2 Behavior Approximation with Fuzzy Neural Network

Fuzzy-Neural Netwok(FNN) is applied in the behavior approximation framework in order to handle the non-linear mapping of target tracking, obstacle avoidance. The FNN is class of adaptive network that is functionally equivalent to fuzzy inference systems. Takagi-Sugeno fuzzy inference system (TS-FIS) is an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set [7]. A typical fuzzy rule of the TS-FIS model:

$$\begin{aligned} R = &IF(x_1\ is\ A_{i1})AND\ldots AND(x_j\ is\ A_{ij})AND\ldots AND(x_n\ is\ A_{in}) \\ &THEN(y_i = w_{i0} + w_{i1}x_1 + \cdots + w_{ij}x_j + \cdots + w_{in}x_n) \end{aligned} \quad (9)$$

where R_i denotes the i^{th} fuzzy rule, $(i = 1\ldots r)$, r is the number of fuzzy rules, $\vec{x}$ is the input vector, $\vec{x} = [x_1 \ldots, x_j \ldots, x_n]^T$, $A_{i,j}$ denotes the antecedent fuzzy sets, $(j = 1\ldots n)$, y_i is the output of the i^{th} linear subsystem, and w_{ij} are its parameters, $(l = 0\ldots n)$. The nonlinear system of FNN forms a collection of loosely coupled multiple linear models. The degree of firing of each rule is proportional to the level of contribution of the corresponding linear model to the overall output of the TS-FIS model. For Gaussian-like antecedent fuzzy set, the degree of membership is

$$\vec{\mu}_{ij} = \vec{e}^{-\| x_j - x_{ij}^{*} \|^2} , \quad (10)$$

where x_j is the j^{th} input, x_{ij}^{*} denotes the center of A_{ij} membership function, $\alpha = 4/r^2$ and r is positive constant, which defines the spread of the antecedent and the zone of the influence of the i^{th} model (radius of the neighborhood of a data point); too large value of r leads to averaging. The firing level of rules are defined as Cartesian product or conjunction of respective fuzzy sets for this rule, The output of the TS-FIS model is calculated by the weighted averaging of individual rules' contributions,

$$y = \sum_{i=1}^{r} \lambda_i y_i = \sum_{i=1}^{r} \lambda_i x_e^T \pi_i , \quad (11)$$

where $\lambda_i = (\tau_i / \sum_{j=1}^{r} \tau_j)$ is the normalized firing level of the i^{th} value, y_i represents the output of the i_{th} linear model, $\pi_i = [w_{i0}, w_{i1}, \ldots, w_{ij}, \ldots, w_{in}]^T$ is the vector of parameters of the i^{th} linear model, and $x_e = [1 \;\; x^T]^T$ is the expanded data vector.

4. Experimentation

4.1 Mobile Agent

This proposed navigation method is applied for a mobile robot named as Pioneer-DX that has been developed in Laboratory for Intelligent Robot, DSU as shown in Fig. 6. We use a DC motor for each wheel, and use a ball-caster for an assistant wheel. Two encoders, a gyro-sensor (ENV-05D), an ultrasonic sensor and a vision sensor are used for the navigation control. The gyro sensor is used for recognizing the orientation of robot by measuring the rotational velocity; the ultrasonic sensor (Polaroid 6500) is used for recognizing environment, which is rotated by a step motor within 180 degrees; the CCD camera (Samsung SFA-410ED) is used for detecting obstacles. A Pentium 4, 2.45Ghz processor is used as a main controller and an 80C196KC microprocessor is used as a joint controller.

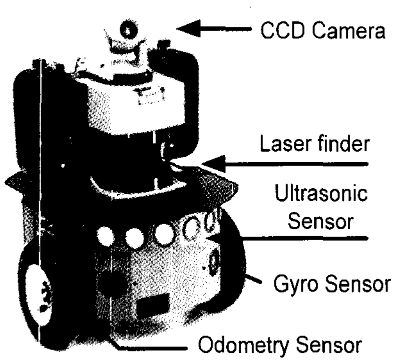


Fig. 6. Mobile Agent, Pioneer-DX

4.2 Experiment Results

Ultrasonic sensor is good in distance measurement of the obstacles, but it also suffers from specular reflection and insufficient directional resolution due to its wide beam–opening-angle. So, we use a sensor fusion method to decide the distance and width of obstacles and avoid them during the navigation. Mobile agent examines whether measured value is data of distance to real obstacle or distance to its shadow. If difference of measured data by vision and ultrasonic sensor is within the error tolerance, mobile agent uses measured data by vision sensor as distance to obstacle. Otherwise, mobile agent uses measured data by vision sensor as distance to obstacle.

Fig. 7(a) depicts sensing coverage of vision and ultrasonic sensor used this experiment. Ultrasonic sensor can detect obstacles within 7m and Vision system can detect obstacles within the range of between 130cm and 870cm. Fig. 7(b) shows the mapped relation between CCD image and real obstacle. Eq. 9 and 10 are relation equations between distance to obstacle from mobile robot on real environment and pixel coordination about each direction x and y on CCD image.

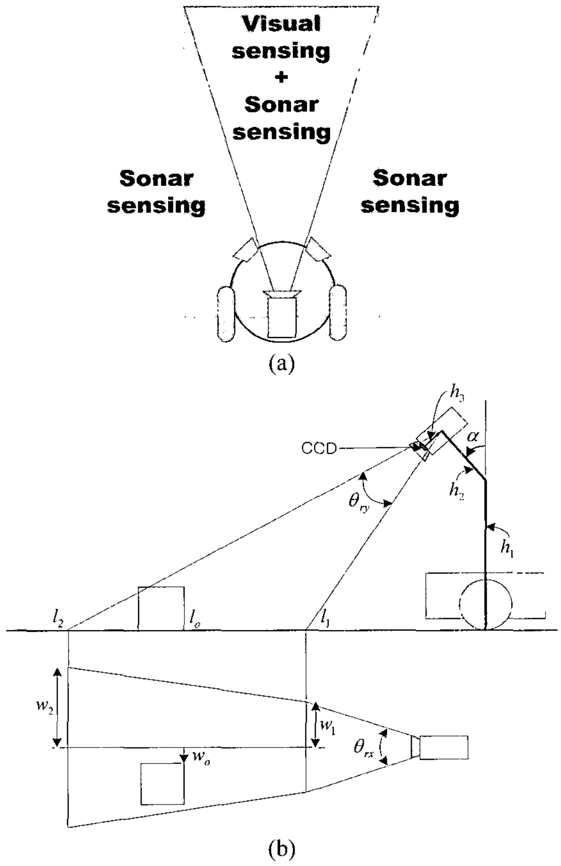


Fig. 7. Sensing Coverage and Mapping between CCD Image and Real Obstacle

where, p_x, p_y are maximum values of each x and y coordination on CCD image frame. Parameter values used for experiment are shown in Table 1.

Table 1. Parameter Values Used for Experiment

h_1	39cm	h_2	7.5cm
h_3	4cm	α	15°
θ_{rx}	27°	θ_{ry}	20°
p_x	320 pixel	p_y	240 pixel

We experiment the recognition of obstacle using above equations and parameter values as shown in Fig. 8. Fig. 9(a) is the image used on the experiment; Fig. 9(b) is the values resulted from matching after image processing. Fig. 9. shows that maximum matching error is within 4%. Therefore, it can be seen that above vision system is proper to apply to navigation. The mobile robot navigates along a corridor with 2m width and with some obstacles as shown in Fig. 10(a). The real trace of the mobile robot is shown in Fig. 10(b). It demonstrates that the mobile robot avoids the obstacles intelligently and follows the corridor to the goal.

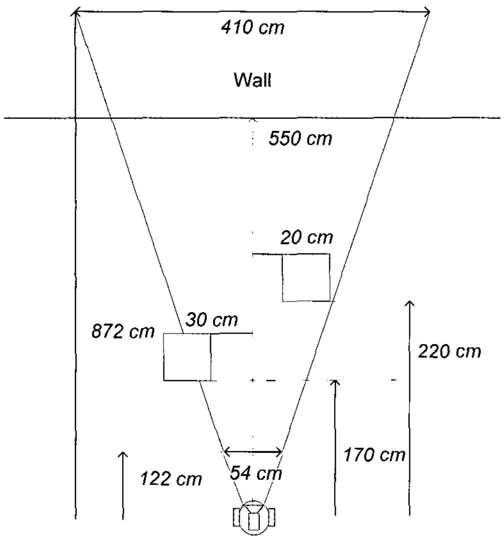
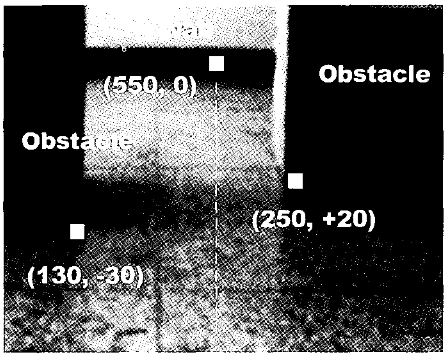
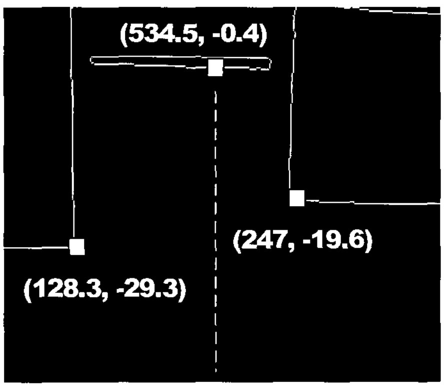


Fig. 8. Vision Area for Detecting and Tracking

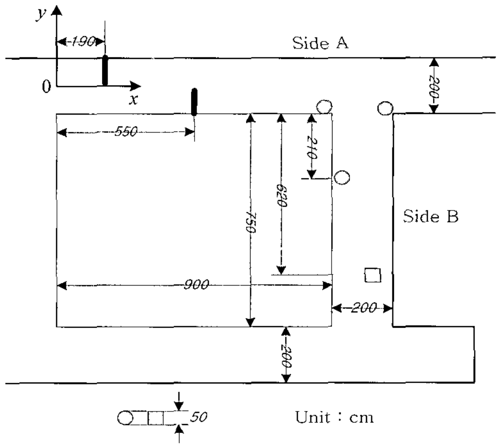


(a) Input image

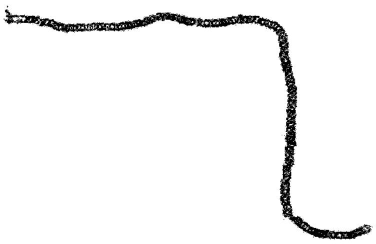


(b) Result of matching

Fig. 9. Experimental Result of the Vision System



(a)Diagram of Robot in a Corridor



(b) Composed World Map

Fig. 10. Navigation of the Mobile Robot in a Corridor

5. Conclusions

A fuzzy-neural-network control algorithm for both obstacle avoidance and path planning is proposed so that it enables the mobile robot to reach to target point in the Intelligent Robotic Space safely and autonomously. To show the efficiency of proposed method, real experiments are performed. The experimental results show that the mobile agent, Pioneer-DX can navigate to the target point safely under unknown environments and also can avoid moving obstacles autonomously. Obstacle avoidance and target tracing is approximated with Fuzzy-Neural Networks. Note that mobile agent is not able to detect moving obstacles that are faster than the mobile agent. Also, it is difficult to estimate motion-vectors of obstacles that are navigating fast and irregularly.

Further researches on the prediction algorithm of the obstacles and on the robustness of performance are required. Also, we involve improving the detecting accuracy for the mobile robot and applying this system to complex environments where many people, mobile robots and obstacles coexist. Moreover, it is necessary to survey the influence of the mobile agent which maintains a flexible distance between the robot and the human, and introduces the knowledge of cognitive science and social science

References

[1] Morioka, K., Lee, J.H., Hashimoto, H.: Human-Following Mobile Robot in a Distributed Intelligent Sensor Network. *IEEE Trans. on Industrial Electronics*, Vol.51, No.1, 2004, pp. 229-237.

[2] Appenzeller, G., Lee, J.H., Hashimoto, H.: Building Topological Maps by Looking at People: An Example of Cooperation between Intelligent Spaces and Robots. *IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 1997, pp. 1326-1333.

[3] Home Page of Inter Process Communication Package at: http://www.ri.cmu.edu/ projects/ project_394. html.

[4] Home Page of Player/Stage Project at: http:// playerstage.sourceforge.net/

[5] McFarland, D.: What it means for a robot behavior to be adaptive. In. J.-A. Meyer and S.W. Wilson (Eds.), From animals to animates: *Proc. of the First Int. Conf. on Simulation of Adaptive Behavior*, Cambridge, MA, MIT Press, 1990, pp. 22-28.

[6] Kanayama, Y.: Two Dimensional Wheeled Vehicle Kinematics. Proc. of IEEE Conf. on Robotics and Automation, San-Diego, California, 1994, pp. 3079-3084.

[7] Takagi, T., Sugeno, M.: Fuzzy Identification System and its Application to Modeling and Control. *IEEE Trans. on Systems, Man and Cybernetics*, 15, 1985, pp. 116-132.

[8] Jang, J.-S. R.: ANFIS: Adaptive-Network-based Fuzzy Interference Systems. *IEEE Trans. on Systems, Man, and Cybernetics*, 23(03): 1993, pp. 665-685.

Tae-Seok Jin

He received the Ph.D. degrees from Pusan National University, Busan, Korea, in 2003, in electronics engineering.

He is currently a full-time lecturer at Dongseo University. From 2004 to 2005, he was a Postdoctoral Researcher at the Institute of Industrial Science, The University of Tokyo, Japan. His research interests include Network sensors fusion, mobile robots, computer vision, and intelligent control. Dr. Jin is a Member of the KFIS, IEEK, ICASE, and JSME.

Phone : +82-51-320-1541
Fax : +82-51-320-1751
E-mail : jints@dongseo.ac.kr

Min-Jung Lee

He received the B.S. degree from Pukyong National University, Busan, Korea, in 1996, and the M.S. and Ph. D. degrees from Pusan National University, Busan, Korea, in 1998 and 2001, respectively, all in electrical engineering.

He was a Lecturer at Kyungnam College of Information and Technology, Busan, Korea, from 2003 to 2004, and a Principal Researcher at Kyungnam Technopark, Changwon, Korea, from 2005 to 2006. He is currently a Research Professor in the Dongseo University. His research interests are intelligent control, nonlinear control, robotics, power electronics, and home network.

Phone : +82-51-320-1936
Fax : +82-51-320-1940
E-mail : mnjlee@gdsu.dongseo.ac.kr

Hideki Hashimoto (S'83-M'84)

He received the B.E., M.E., and Dr. Eng. degrees in electrical engineering from The University of Tokyo, Tokyo, Japan, in 1981, 1984, and 1987, respectively.

He is currently an Associate Professor at the Institute of Industrial Science, The University of Tokyo. From 1989 to 1990, he was a Visiting Researcher at Massachusetts Institute of Technology, Cambridge. His research interests are control and robotics, in particular, advanced motion control and intelligent control. Dr. Hashimoto is a Member of the Society of Instrument and Control Engineers of Japan, Institute of Electrical Engineers of Japan, and Robotics Society of Japan

Phone : +81-3-5452-6258
Fax : +81-3-5452-6259
E-mail : hashimoto@iis.u-tokyo.ac.jp