Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Environment Recognition System Based on Multiple Classification Analyses for Mobile Robots

Atsushi Kanda, Kazuo Ishii
Kyushu Institute of Technology
KIT
Fukuoka, Japan
kanda-atushi@edu.brain.kyutech.ac.jp

Masanori Sato
Fukuoka IST
Fukuoka, Japan
m-sato@brain.kyutech.ac.jp

***Abstract*—Various mobile mechanisms have been developed combining linkage mechanisms and wheels, and the combination of passive linkage mechanisms and small wheels is one of research trends to enhance the mobility on irregular terrain. We have been working on a 6-wheeled mobile robot employing a passive linkage mechanism, which achieved climbing capability over a 0.20[m] height of bump and stairs, and developed velocity controllers using PID and neural network. In this paper, we propose an environment recognition system for the wheeled mobile robot, where multiple classification analyses such as Self-Organizing Map, k-means method and Principle Component Analyses are introduced and used for clustering robot's environments based on state variables such as joint angles and velocities of links, and attitude angles of the robot body. We evaluate the recognition performance through experiments.**

***Keywords*—wheeled mobile robot. neural network. self-organizing map. environment recognition**

I. INTRODUCTION

Mobile mechanism using wheels is one of the most popular mechanisms for mobile robots because the wheeled mobile mechanism's energy efficiency is high, the mechanism and the control system are well investigated. However, wheeled mobile robots like a car have difficulties in rough terrain movements. As a solution for maneuverability improvement, the mobile mechanism combined passive or active linkage and small wheels have been proposed and developed. For example, NASA/JPL developed Rocker-Bogie mechanism and installed it into Sojourner [1]; Kuroda, et al. developed PEGASUS mechanism and installed it into Micro5 [2]; EPFL developed linkage mechanisms and installed it into Shrimp and CRAB [3][4]; Hirose, et al. developed Tri-Star [16] which has three links with wheels. From the point of software, Riken developed control systems for omni-directional vehicle with step-climbing ability [5] which needs to use sensors for actual environment recognition, laser-range finder, stereo camera, etc [6].

In our previous research, we developed a 6-wheeled mobile robot employing a passive linkage mechanism, "Zaurus", to evaluate the maneuverability. Figures 1 and 2 show the overview of Zaurus and its degrees of freedom. The performances of controllers for rough terrain are compared using neural network and PID in [7]. The neural network controller showed better performance than a well-tuned PID controller. However, these controllers have difficulties to adapt environments, because environmental situation is not so simple and the robots need the adaptation function in each environment.

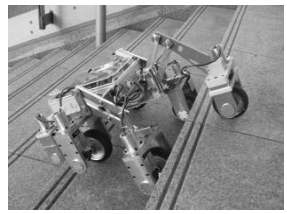

Figure 1 Overview of Zaurus.

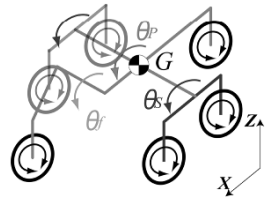

Figure 2 Degrees of freedom for Zaurus.

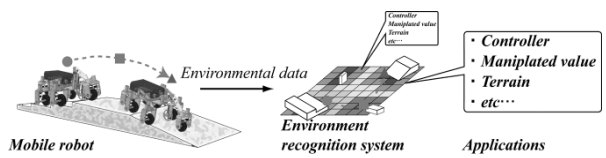

Figure 3 Concept of the environment recognition system.

In this paper, we proposed an environment recognition system selecting the adjusted controller in each environment. The input data are the linkage angles and fed to Self-Organizing Map (SOM), which is the basic information processing element of the environment recognition system and compared with other clustering methods; PCA and k-means.

II. ENVIRONMENT RECOGNITION SYSTEM

The proposed system classifies and estimates the current environment of the robot using linkage angle and attitude data. Figure 3 shows the concept of the environment recognition system. The system involves four steps. First, a time series of linkage and attitude data is obtained using the target mobile robot. Second, we classify the sampled data using multiple classification analyses and also design adaptive controllers for each environment concurrently. Finally, the system identifies the position, and selects an optimized controller for each environment.

A. Basic Environment Data

The joint angles of the passive linkage and the attitude of the robot can express the current environment; that is, the robot itself can be an "environment recognition sensor".

A time series data of joint angles in Fig. 2 and attitude angles becomes high dimension, so that some dimensional compression methods should be introduced for better

978-1-4244-2794-9/09/$25.00 ©2009 IEEE

understanding and feature extraction. In order to prepare the environmental data sets, experiments were conducted to sample state variables: front angle (θ_f), side link angle (θ_s), and attitude angle of pitch (θ_p) in the typical environments such as flat floor, bumps, stairs and slopes. The heights of bumps are 0.06, 0.12 and 0.18m respectively, and a simple PID-controller was employed for data sampling. The process of obtaining environmental data for multiple classification analysis is described as follows.

Basic state variables consist of the three angles mentioned above and their angular velocities. The sampling step, ΔT is 0.25 s for the state variables during 1.0 s, that is, the 4 sets of state variables in eq. (1), which compose a $\boldsymbol{X}(t)$ in eq. (2). (The period of the sampling cycle Δt is 0.05s.)

$$\boldsymbol{\theta}_*(t) = [\theta_*(t), \cdots \theta_*(t - n\Delta T)], (n = 1 \cdots) \tag{1}$$

where the * means that f is the front angle, s is the side angle and p is the pitch angle. The basic environment dataset (a single input) $\boldsymbol{X(t)}$ is expressed as

$$\boldsymbol{X} = \left[\boldsymbol{\theta}_f(t), \boldsymbol{\theta}_s(t), \boldsymbol{\theta}_p(t), \dot{\boldsymbol{\theta}}_f(t), \dot{\boldsymbol{\theta}}_s(t), \dot{\boldsymbol{\theta}}_p(t)\right] \tag{2}$$

Figure 4 shows an experimental data when the robot climbs up and down on a 0.12 m height bump. The index numbers in Fig. 4 mean the typical situations, 1: the robot is driving on a surface, 2 to 5: the robot is climbing upward, and 6 to 9: the robot is climbing downward.

We define environmental recognition as "Classifying environments by bump height using link angle data, obtaining basic environmental data, and identifying the environment". Typical multiple classification analysis, PCA, k-means method and SOM are compared against this definition and finally SOM is selected as the environment recognition system.

B. Principle Component Analysis

Principal Component Analysis (PCA) is a feature extraction algorithm for reducing multidimensional data sets to lower dimensions. The advantage of PCA is its data contraction and the feature extraction, and the principle components contain the important aspects of data. The method is used to detect characteristic points statistically. For example, Fujii et al. have employed PCA to find landmarks [10].

The algorithm for PCA is described as follows.

$$\boldsymbol{P} = \boldsymbol{W}^T \boldsymbol{X} \tag{3}$$

$$\boldsymbol{AW} = \lambda \boldsymbol{W} (\lambda \geq 0) \tag{4}$$

Where $\boldsymbol{P}$ is the principle component, $\boldsymbol{W}$ is an eigenvector and $\boldsymbol{X}$ is sampling data. PCA finds the maximum variance in $\boldsymbol{P}$. Here, $\boldsymbol{A}$ is the variance-covariance matrix of $\boldsymbol{X}$. The eigenvalue λ is obtained from (4) and the vector that takes the maximum λ is the first principle component. Here, $\boldsymbol{X} = \boldsymbol{X(t)}$.

Figures 5 and 6 show the principle component score of first principle component and second principle components. In Fig.5, the first principle component has the effect of first four elements, which correspond to front fork and side link angle

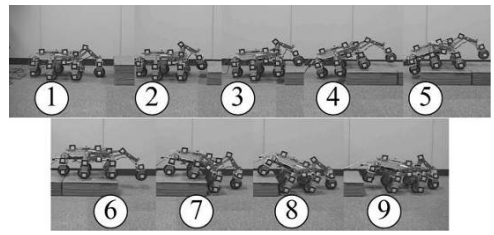

Figure. 4 Labeling of the attitude of the robot

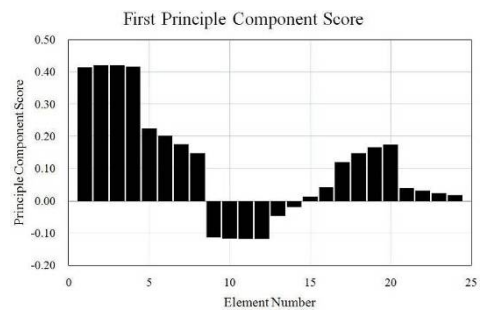

Figure. 5 First principle component score

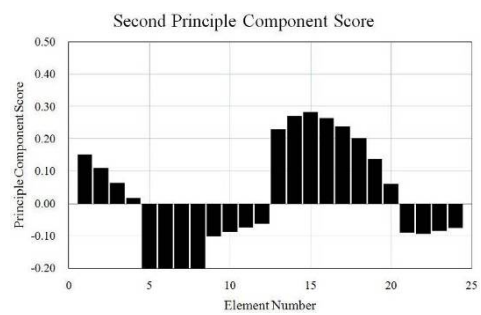

Figure. 6 Second principle component score

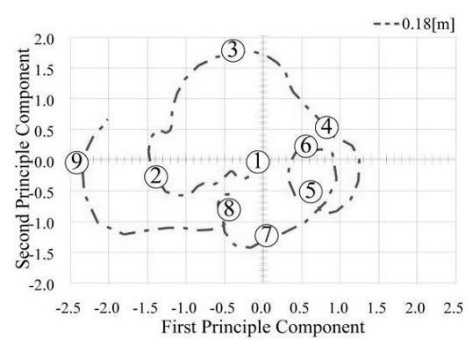

Figure. 7 Results of PCA: bump height of 0.18m

First-Second principle component

and side link angular velocity. In Fig. 6, the second principle component means the vector impressing on side link angle and front fork and side link angular velocity. The front fork and the side linkage data are dominant to recognize the environment.

Figures 7 and 8 show the trajectories using the first principle component and the second principle component when the robot moves on bumps of height 0.06, 0.12, and 0.18m. Figures 9 and 10 show the trajectories in the second-third principle component plane. The horizontal axis shows the first principle component and the vertical axis shows the second principle component. The trajectories show the feature that trajectories take round shapes and spread outward in proportional to the bump height. However, there exists many cross points between trajectories and it is difficult to decide which points belong to which trajectories in the first-second or second-third principle component plane

C. k-means Method

With regard to multiple classification analysis, the k-means method is one of the most popular non-hierarchical cluster analysis methods. The number of clusters, k, is assumed at first, and each input is classified into a cluster on similarity. Then, a new center of the cluster u_c (c = 1–k) is calculated using eqs. (5) and (6) and all data are re-classified into new clusters. Finally, the procedure described above is repeated until the error between all points and the centers of clustered data becomes sufficiently small.

$$k^* = \arg\min_k \left\| x - u_k \right\|^2 \tag{5}$$

$$u_c = \sum_N x_n / N(n \subseteq c) \tag{6}$$

In this analysis, we set the cluster number, k, as 9 and 27. The number of clusters is set to nine as it is assumed that Zaurus has nine phases when climbing a bump: it travels on a flat surface, the front wheel climbs over the bump, the side front wheels climb over the bump, the side rear wheels climb over the bump and the rear wheel climbs over the bump. Twenty seven clusters are assumed as the above nine situations can occur for each bump height. The number of clusters, k, is 9 on the top and 27 on the bottom. The horizontal axis shows the sampling step (0.25 s) and the vertical axis shows the index of classification.

As shown in Fig. 11, the data sets are clustered for the attitude where Zaurus is climbing over/down the bump. However, the height of the bumps is not clustered because the results for 9 and 27 clusters are almost the same.

D. SOM

The self-organizing map proposed by Kohonen is a well known method for classifying data while preserving topological features on a map [11]. The SOM is trained using unsupervised learning to produce a low dimensional representation of training data.

The algorithm for the SOM is described in (7) – (11). k^* is a number for indicating the winning unit as in (7). $\boldsymbol{w}^k$ is a reference vector of the k-th unit on a competitive layer and $\boldsymbol{x}_i$

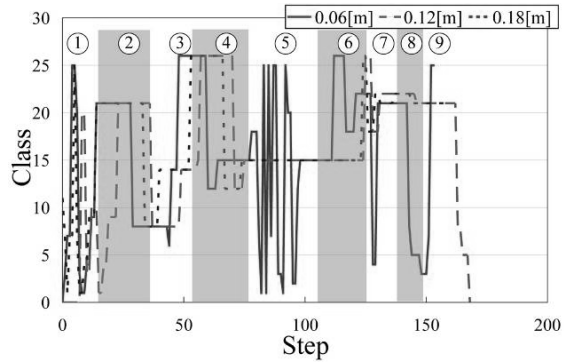

Figure 12 Results using k-means: cluster number is 27

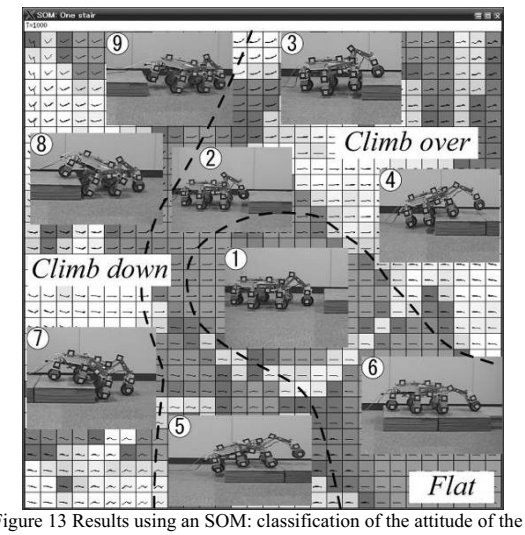

Figure 13 Results using an SOM: classification of the attitude of the robot

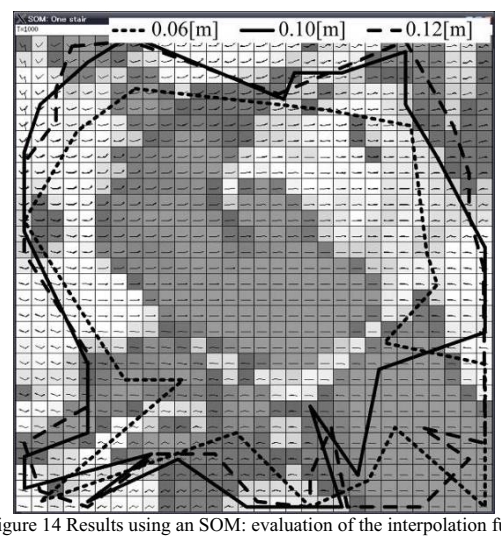

Figure 14 Results using an SOM: evaluation of the interpolation function

is the i-th input datum. The neighborhood function (ϕ) of the k-th unit to the i-th input datum is calculated by employing a neighborhood radius (σ) as in (8). The leaning coefficient (Ψ) is normalized using (9) and (10). The reference vector $\boldsymbol{w}^k$ is adapted using (11).

Figures 13 and 14 show the obtained feature map, with the color of each unit denoting the magnitude of the distance vector between the reference neighborhood units. White is used to indicate large separation and black to indicate that similar units are closely located.

The specifications of the map are a map size of 30 × 30, a learning time (t) of 1000 steps, neighbor radii of $\sigma_{\max} = 45$, $\sigma_{\min} = 1$, and a time constant (τ) of 50 steps. The learning is complete in about 500 steps.

$$k^* = \arg\min_k \left\| \boldsymbol{w}^k - \boldsymbol{x}_i \right\|^2 \tag{7}$$

$$\sigma = \sigma_{\min} + (\sigma_{\max} - \sigma_{\min}) \exp(-t/\tau) \tag{8}$$

$$\phi_i^k = \exp\left[\left(-d(k, k^*) \right) / 2\sigma^2 \right] \tag{9}$$

$$\psi_i^k = \phi_i^k / \sum_i \phi_i^k \tag{10}$$

$$\boldsymbol{w}^k = \sum_i \psi_i^k \boldsymbol{x}_i \tag{11}$$

As shown in Fig. 13, the map is classified based on the attitude of the robot. The movements of climbing up and down are arranged on opposite sides. Travelling on the flat floor is assigned to the center of the map. The SOM also includes the dynamics of the robot.

As shown in Fig. 14, we evaluate the interpolation function using unlearned experimental results for a 0.10m bump height. The path for a 0.10m bump height is similar to those for 0.06m and 0.12m bump heights, and the unlearned data are assigned as being between their two paths. The path for the 0.10m bump is shown by a black line. We can see that the map can estimate the attitude of the robot and height of the bump. The areas where the paths overlap correspond to where differences in the conditions are not clear.

III. DIMENTIONAL REDUCTION

In general, environment recognition methods using a template need many types of environment data for use in a variety of actual environments. However, the computation memory has limitations, so we need to compress the basic environment data. PCA is one of the basic compression methods that use image recognition [12]. In this research, we combine PCA and SOM.

We determine the number of required dimensions from the contribution ratio of basic environment data. Table 1 gives the sum of contribution ratios from the first component to the target number of dimensions. We assumed that the contribution ratio more than 85% is sufficient, so we choose the first five principle components.

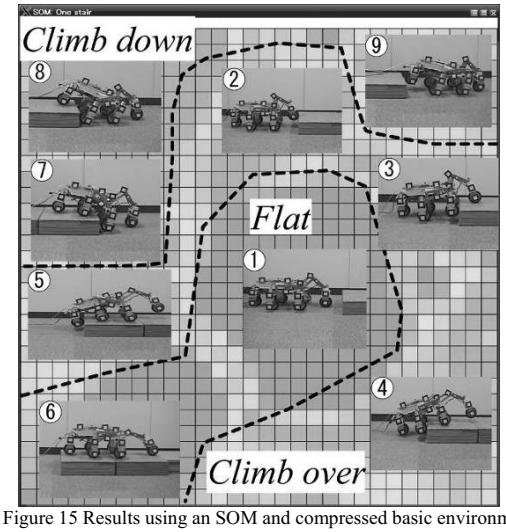

Figure 15 Results using an SOM and compressed basic environmental data: classification of the attitude of the robot

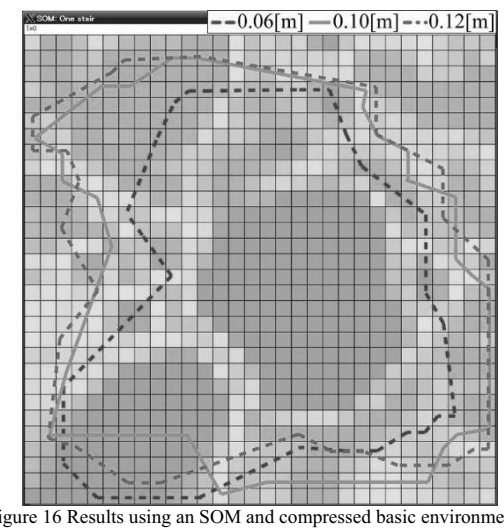

Figure 16 Results using an SOM and compressed basic environment data: evaluation of the interpolation function

As shown in Figs. 15 and 16, the map using compressed basic environment data can classify the attitude of the robot and evaluation of the arrangement of unlearned data (for the 0.10m bump height). The movements of climbing up and down are arranged on opposite sides. Travelling on the flat floor is assigned to the center of the map. The path for a bump height of 0.10m is similar to those for bump heights of 0.06m and 0.12m, and the unlearned data are assigned as being between those paths. These features are the same as those of Fig. 13. For this reason, an SOM using compressed basic environment data is expected to have the same performance as the map using original basic environment data.

IV. ONLINE RECOGNITION

The developed environment recognition system is introduced into Zaurus to evaluate the feature map classification online. The experimental environment is a bump with a height of 0.18m. In this experiment, our proposed environmental recognition system's database has three states: climbing up, climbing down and traveling on flat. We designed adjusted controllers for these three states using a neural network [13] [14]. The target velocity is 0.05m/s.

In Fig. 17, the velocity of the robot and the environment are used to categorize the current condition. The conditions are classified as being one of the three states. The velocity of the robot is controlled and the environment recognition is performed online. In the state of climbing down, the proposed system did not always recognize the correct situation. This is due to machine oscillation. The attitude sensor is a liquid type and has a weak oscillation.

V. CONCLUSION

We proposed an environment recognition system that classifies angle data. The proposed system comprises an environment recognition system using an SOM and an adjusted controller using a neural network. The basic environment map can classify the robot attitude and height of bumps. The system is able to recognize simple terrain while travelling. The environment recognition system using compressed basic environment data has the same performance as the proposed system using original high dimensional environment recognition data.

In future works, we will redesign the adjusted controllers for rugged environments and combine these with the proposed environment recognition system. We expect to be able to use the proposed environment recognition system in a real environment. Real environments have much rough terrain; for example, slopes and stairs. The proposed environment recognition system has difficulty in the classification of these terrains. The data for a slope are almost the same as data for a flat space. One solution would be to use an SOM of SOMs (SOM^2) in which the mapped objects are SOMs [15]. Fig. 18 shows the architecture of SOM^2. In SOM^2, each nodal unit of a conventional SOM is replaced by a function module of an SOM. We will classify basic environment data for rugged environments using SOM^2.

In addition, we will verify nonlinear dimensional reduction methods because the environmental dataset has nonlinearities. We will then verify the dimensional reduction using Isomap [16], which is an extension of multidimensional scaling that assumes that only the distance between two local points can be approximated by Euclidean distance, and that the distance between two points far away from each other should be inferred from the local distance.

ACKNOWLEDGMENT

This work was partly supported by the 21st Century COE program, and a grant from the Knowledge Cluster Initiative implemented by the Ministry of Education, Culture, Sports, Science and Technology.

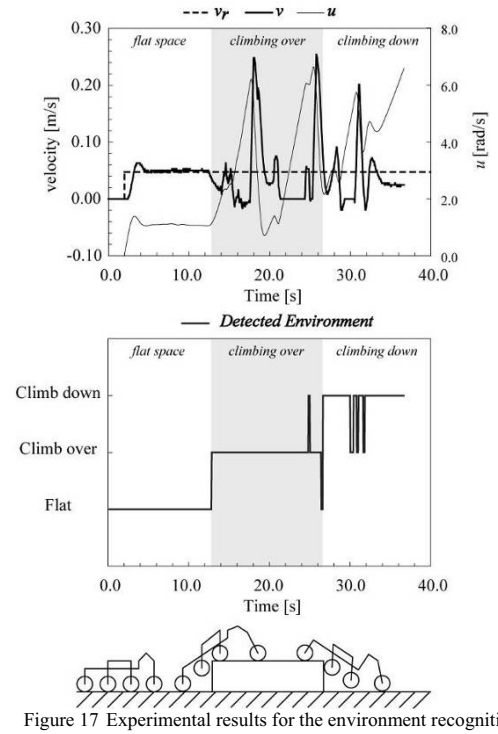

Figure 17 Experimental results for the environment recognition system

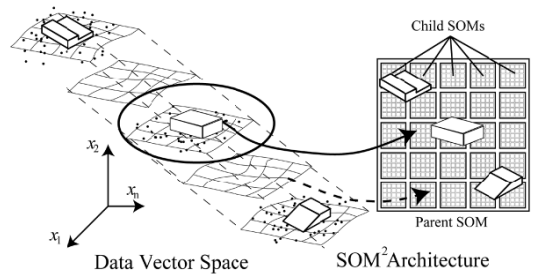

Figure 18 The architecture of an SOM of SOMs

TABLE I. CONTRIBUTION RATIO FOR DATA DIMENSIONALITY

Number of dimensions	1	2	3	4	5	6
Contribution ratio (%)	37.77	58.84	71.61	80.70	85.28	88.77

REFERENCESS

[1] Richard Volpe, Timothy Ohm, Richard Petras, Richard Welch, J. "The Rocky 7 Mars Rover Prototype", Proc. of IROS, 1996

[2] Yoji Kuroda, Teppei Teshima, Yoshinori Sato, Takashi Kubota, "Mobility Performance Evaluation of Planetary rover with Similarity Model Experiment", Proc. of ICRA, 2004

[3] T. Estier, Y. Crausaz, B. Merminod, M. Lauria, R. Piguet, and R. Siegwart "An Innovative Space Rover with Extended Climbing Abilities", Proc. of Space a Robotics 2000, 2000

[4] Thomas Thueer, Pierre Lamon, Ambroise Krebs, Roland Siegwart "CRAB-Exploration Rover with Advanced Obstacle Negotiation Capabilities " Proc. Of the 9th ESA Workshop on Advanced Space Technologies for Robotics, 2006

[5] Daisuke Chugo, Kuniaki Kawabata, Hayato Kaetsu, Hajime Asama **an**d Taketoshi Mishima, "Development of a control system for an omni-directional vehicle with step-climbing ability", Advanced Robotics, Vol19, No.1, pp.55-71, 2005

[6] Yoshiro Negishi, Jun Miura, Yoshiaki Shirai, "Map Generation of a Mobile Robot by Integrating Omni-directional Stereo and Laser Range Finder", JRSJ Vol21, No.6, pp.110-116, 2003(in Japanese)

[7] Masanori Sato, Kazuo Ishii, "A neural network based controller for a wheel type mobile robot", Brain-Inspired IT 3, 2006, pp. 261-264.

[8] Richard O. Duda, Pater E. Hart, Davit G. Stork,, "Pattern Classification Second Edition", John Wiley and Sons(2007)

[9] Jefferson Provost, Benjamin J. Kuipers, and Risto Miikkulainen, "Self-Organizing Perceptual and Temporal Abstraction for Robot Reinforcement Learning", In AAAI Workshop on Learning and Planning in Markov Processes, 2004.

[10] Takehiro Fujii, Akira Hayashi, Hidefumi Hida, "Using principle component analysis and non-hierarchical clustering to find landmarks", the 48th Annual Conference of the IPSJ, No.2, pp. 53-54, 1994 (in Japanese)

[11] T. Kohonen, "Self-Organizing Maps", Springer-Verlag(2001).

[12] Masanori Sato, Atushi Kanda, Kazuo Ishii, "A Neural Network Controller Designed for a Rough Terrain Mobile Robot 2nd Report : Effects on the controller property caused by the process of teaching data generation", Proceeding of the 2007 JSME Conference on Robotics and Mechatronics, Akita, Japan, May, 2A1-D10, 2007 (in Japanese)

[13] Masanori Sato, Atushi Kanda, Kazuo Ishii, "A Switching Controller System for a Wheeled Mobile Robot", Journal of Bionic Engineering, Vol.4, No.4, pp.281-289, 2007

[14] Takeshi Yamaguchi, Shun Yamamoto, Kazunori Komatani, Tesuya Ogata, Hiroshi Okuno, "Speech recognition of using lip images from various directions", The 18th Annual Conference of the Japanese Society for Artificial Intelligence, 1E2-02, 2004 (in Japanese)

[15] Tetsuo Furukawa, "SOM of SOMs: Self-organizing Map Which Maps a Group of Self-organizing Maps", Lecture Notes in Computer Science, Vol.3696,pp.391-396

[16] Shigeo Hirose, Naritoshi Ootsukasa, Takaya Shirasu, Hiroyuki Kuwahara, and Kan Yoneda : Fundamental Considerations for the Design of a Planetary Rover, Proc. ICRA, Nagoya, pp.1939-1944 (1995)