Methods for Environment Recognition based on Active Behaviour Selection and Simple Sensor History

Takahiro Miyashita[1], Reo Matsumura[2], Kazuhiko Shinozawa[1], Hiroshi Ishiguro[2] and Norihiro Hagita[1]
[1]ATR Intelligent Robotics and Communication Laboratories, [2]Osaka University Japan

1. Introduction

The ability to operate in a variety of environments is an important topic in humanoid robotics research. One of the ultimate goals of this research is smooth operation in everyday environments. However, movement in a real-world environment such as a family's house is challenging because the viscous friction and elasticity of each floor, which directly influence the robot's motion and are difficult to immediately measure, differ from place to place. There has been a lot of previous research into ways for the robots to recognize the environment. For instance, Fennema et al. (Fennema et al., 1987) and Yamamoto et al. (Yamamoto et al., 1999) proposed environment recognition methods based on range and visual information for wheeled robot navigation. Regarding humanoid robots, Kagami et al. (Kagami et al., 2003) proposed a method to generate motions for obstacle avoidance based on visual information. They measured features of the environment precisely before moving or fed back sensor information to a robot's controller with a short sampling period. It is still difficult to measure the viscous friction or elasticity of the floor before moving or by using short term sampling data, and they did not deal with such features.

Thus, we propose a method for recognizing the features of environments and selecting appropriate behaviours based on the histories of simple sensor outputs, in order to achieve a humanoid robot able to move around a house. Figure 1 shows how our research differs from previous research according to length of the sensor history and number of types of sensors. The key idea of our method is to use a long sensor history to determine the features of the environment. To measure such features, almost all previous research (Shats et al., 1991; Holweg et al., 1996) proposed methods that used several kinds of sensors with a large amount of calculations to quickly process the sensor outputs. However, such approaches are unreasonable because the robot lacks sufficient space on its body for the attached sensors and processors. Hence we propose using sensor history to measure them because there are close relationships between sensor histories, motions, and environments.

When the robot performs specific motions in specific environments, we can see those features in the sensor history that describe the motion and the environment. Furthermore, such features as viscous friction or floor elasticity do not change quickly. Thus we can use a long history of sensor data to measure them.

Source: Humanoid Robots: Human-like Machines, Book edited by: Matthias Hackel
ISBN 978-3-902613-07-3, pp. 642, Itech, Vienna, Austria, June 2007

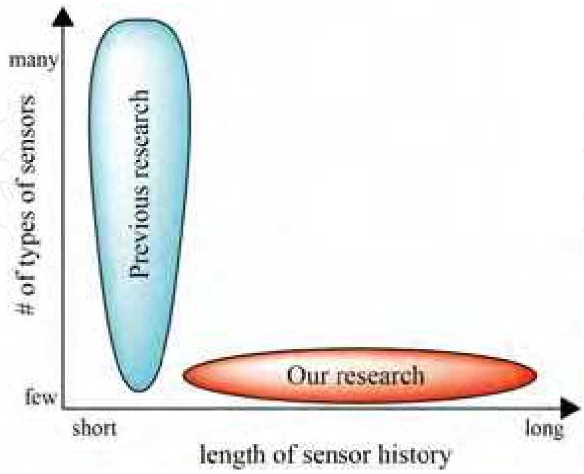


Figure 1. Difference between our research and previous research

In the next section, we describe our method for behaviour selection and environment recognition for humanoid robots. In section 3, we introduce the humanoid robot, named "Robovie-M," that was used for our experiments. We verify the validity of the method and discuss future works in section 4 and 5.

2. Behaviour selection and environment recognition method

2.1 Outline of proposed method

We propose a method for humanoid robots to select behaviours and recognize their environments based on sensor histories. An outline of the method is as follows:

A-1 [preparation 1] In advance, a user of the robot prepares basic motions appropriate to the environment.

A-2 [preparation 2] For each basic motion and environment, the robot records the features of the time series data of its sensors when it follows the motions.

A-3 [preparation 3] For each basic motion, the robot builds decision trees to recognize the environments based on recorded data by using a binary decision tree generating algorithm, named C4.5, proposed by Quinlan (Quinlan, 1993). It calculates recognition rates of decision trees by using cross-validation of the recorded data.

B-1 [recognition 1] The robot selects the motion that corresponds to the decision tree that has the highest recognition rate. It moves along the selected motion and records the features of the time series data of the sensors.

B-2 [recognition 2] The robot calculates reliabilities of the recognition results for each environment based on the decision tree and the recorded data. Then it selects the environments that have reliability greater than a threshold as candidates of the current environment. The threshold is decided by preliminary experiments.

B-3 [recognition 3] The robot again builds decision trees based on the data recorded during the process (**A-2**) that correspond to the selected candidates for the current environment. Go to (**B-1**).

By iterating over these steps, the robot can recognize the current environment and select appropriate motions.

2.2 Robot's motions and features of the environment

Figure 2 shows the motions that the robot has in advance. In our method, there are two kinds of motions: basic and environment-dependent. The basic motions are comprised of a set of motions that can be done in each environment without changing the loci of joints, such as standing up, lying down, etc. All environment-dependent motions are generated in advance by the user. By utilizing our method, once the environment is recognized, the robot can select the suitable motions for it from the environment-dependent motions.

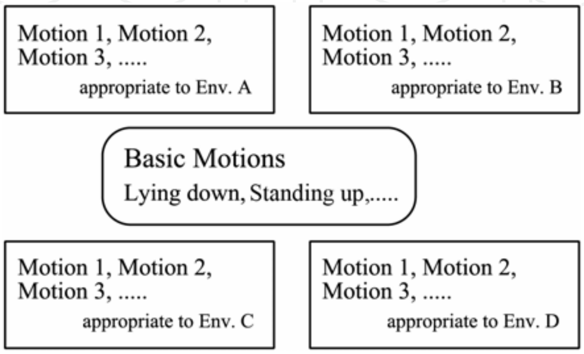


Figure 2. Robots have two kinds of motions: basic and environment-dependent. Both motions are generated by users in advance

In this paper, we use not only averages and standard deviations of the time series data of the sensor outputs, but also averages and standard deviations of the first and second derivatives of those outputs, as the features of the environment. Table 1 shows an example of features of sensor histories by taking different basic motions in a tiled floor environment. We use a set of the features of sensor history $s_n(t)$ as a feature of an environment.

Basic motions	Lying down	Standing up	......
Label of environment	Tiled floor	Tiled floor	......
Ave. of $s_n(t)$	136.19	149.15	......
Std. dev. of $s_n(t)$	21.429	25.64	......
Ave. of $\mathrm{d}s_n(t)/\mathrm{d}t$	131.13	128.84	......
Std. dev. of $\mathrm{d}s_n(t)/\mathrm{d}t$	6.1985	6.2903	......
Ave. of $\mathrm{d}^2s_n(t)/\mathrm{d}t^2$	157.83	132.89	......
Std. dev. of $\mathrm{d}^2s_n(t)/\mathrm{d}t^2$	11.292	13.554	......

Table 1. Example of features of sensor histories by taking different basic motions in a tiled floor environment. $s_n(t)$ denotes time series data of sensor s_n

2.3 Decision tree based on relationships between basic motions, sensor histories, and environments

A decision tree to recognize the environment is made by C4.5 (Quinlan, 1993), which is a program for inducing classification rules in the form of binary decision trees from a set of given examples. We use the relationships described in Table 1 as examples and make decision trees for each basic motion by using knowledge analysis software WEKA (Witten, 2000) that can deal with C4.5. Figure 3 shows an example of a decision tree for the lying down motion.

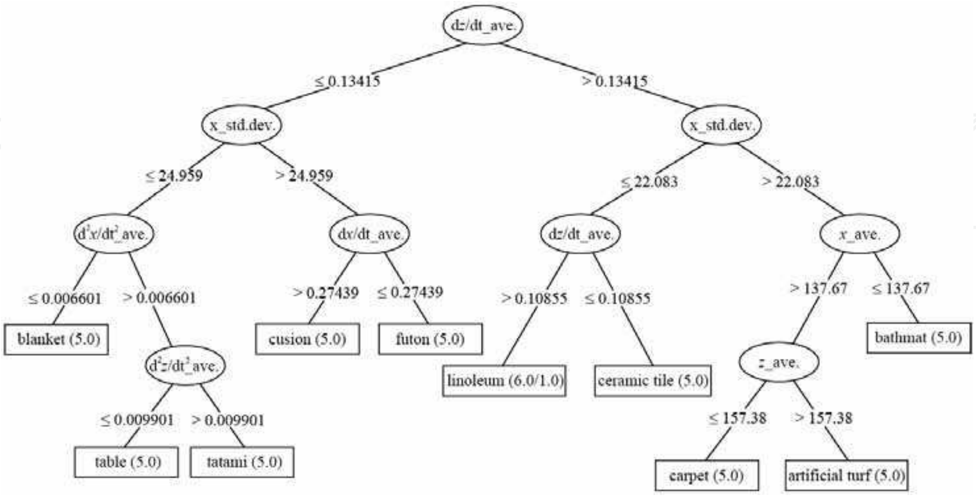


Figure 3. Decision trees recognize environments based on relationships between a motion (lying down), possible environments, and sensor histories. Circles denote features of sensor history. Rectangles denote environments

We can also determine the recognition rate of a decision tree for each basic motion and the reliabilities of the recognition results by cross-validation as follows. The recognition rate of a decision tree for the *k*-th basic motion, r_k, is calculated as follows:

$$r_k = \frac{S_k}{N} \quad , \tag{1}$$

where N and S_k denote the number of all data sets for candidates of the current environment that were obtained in the preparation processes and the number of correctly classified data sets by the decision tree, respectively. After selecting the decision tree that has the highest recognition rate and moving along the *l*-th basic motion that corresponds to the tree, the robot records the data set and obtains a recognition result by using the tree. We calculate following two types of reliabilities from the result. When the environment A is the result of the recognition, the reliability that the result is the environment A, rel_A, is calculated as follows:

$$rel_A = \frac{S_{lAA}}{N_A} \quad , \tag{2}$$

where N_A and S_{lAA} denote the number of all data sets for the environment A that were obtained in the preparation processes and the number of correctly classified data sets by the tree, respectively. The reliability that the result is one of the other environments, for example the environment B, is as follows:

$$rel_B = \frac{S_{lBA}}{N_B} \quad , \tag{3}$$

where N_B and S_{lBA} denote the number of all data sets for the environment B that were obtained in the preparation processes and the number of incorrectly classified data sets that are classified as the environment A by the tree, respectively. This is same as the misrecognition rate that the robot recognizes the environment B as the environment A by the tree.

3. Humanoid robot

In this section, we introduce a small-size humanoid robot, Robovie-M, developed by us. Figure 4 (a) and (b) show an overall view and hardware architecture of Robovie-M. The robot has a head, two arms, a body, a waist, and two legs. Degrees of freedom (DOFs) of the robot are as follows. The robot has 4 DOFs for each arm, 2 DOFs for waist, and 6 DOFs for each leg. The total number of DOFs is 22. As shown in Figure 4 (b), we attached two 2-axial acceleration sensors to the left shoulder of the robot to acquire acceleration values along three orthogonal axes as $s_n(t)$ in Table 1. Table 2 describes specifications of the sensor. Sampling rate of the sensor is 60 [Hz]. The robot can send data of the sensors and get commands of the behaviour from a host PC via a serial cable (RS-232C).

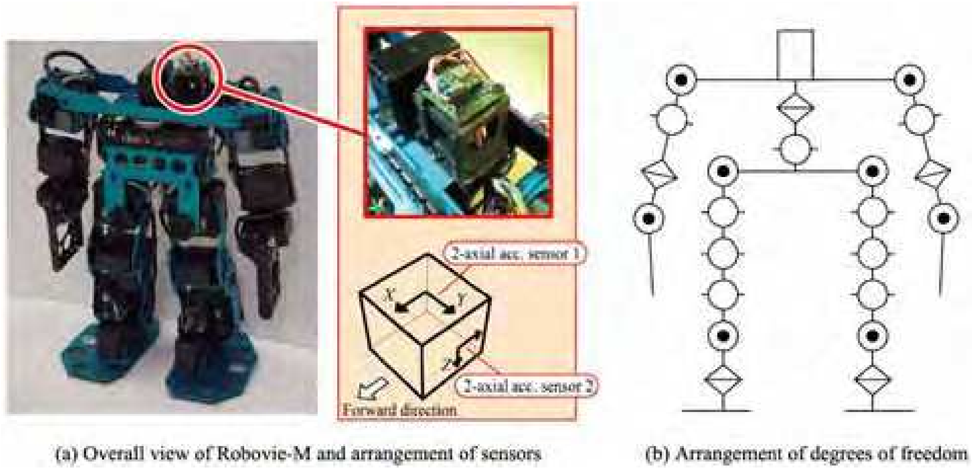


Figure 4. Left image shows humanoid robot Robovie-M, and center images indicate sensor arrangement. On the robot's left shoulder, two 2-axial acceleration sensors are attached orthogonally to acquire acceleration values along three axes that describe horizontal and vertical motions. The right image shows an arrangement of robot's degrees of freedom

Model	ADXL202E (ANALOG DEVICES)
# Axis	2
Range	-2 g ~ +2 g
Sensitivity	12.5 % / g
Nonlinearity	0.2 %
Size	5 x 5 x 2 mm

Table 2. Specifications of 2-axial acceleration sensor attached to the robot

4. Experiments

To verify the validity of the proposed method, we conducted a preliminary experiment with our small humanoid robot, Robovie-M. Table 3 and Figure 5 show environments for recognition, the basic motions and time lengths for each motion in the experiments. Figure 6 shows sequences of pictures for each basic motion. We recorded the time series data of the sensor outputs ten times in each environment and for each motion.

Environments		Basic motions	time [s]
Ceramic tiled floor	Linoleum floor	Lying down	4.5
Wooden table	Tatami mat	Standing up	3.0
Cushion	Futon	Tossing and turning	4.0
Carpet	Bathmat	Stepping with one leg	4.5
Blanket	Artificial turf	Stepping with both legs	4.5

Table 3. The left column describes environments used in the experiment. The right column describes the basic motions. Environments are selected from a typical Japanese house

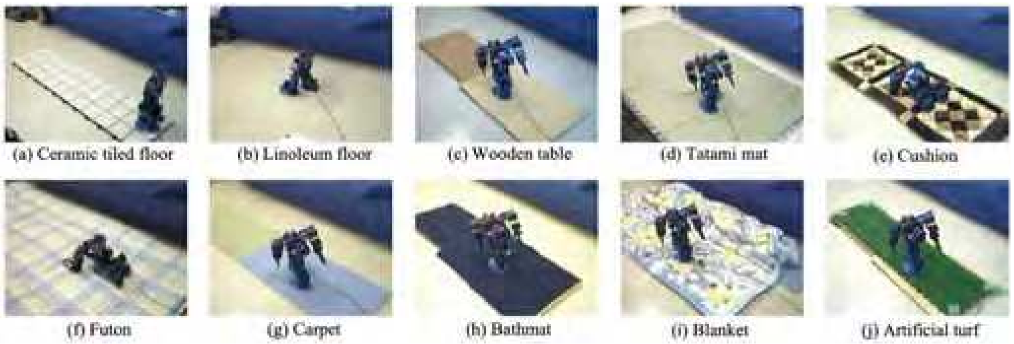


Figure 5. Pictures of environments in experiments

Figure 6. Sequences of pictures for each basic motion

For instance, let us consider the recognition process for the *futon* (a Japanese mattress) environment. First, the robot selected the *stepping with both legs* motion because the motion's decision tree has the highest recognition rate. All recognition rates calculated by equation (1) are described in Figure 7. Second, the robot obtained the sensor history while doing the *stepping with both legs* motion and classified it by using the motion's decision tree. The result of classification was the *blanket* environment. The reliabilities of the result for each environment were obtained, as shown in Table 4. The reliability for the *blanket* environment was calculated by equation (2) and the reliabilities for the others were calculated by equation (3). This time the reliability threshold was 0.2. Then the selected candidates of the current environment were *tatami*, *futon*, *artificial turf*, and *blanket*. Next, the robot made decision trees for each basic motion based on the data of the candidates. By calculating their recognition rates, as shown in Figure 8, the robot selected the *stepping with one leg* motion. As a result of performing the selected motion, the robot classified the data as the *futon* environment and obtained *artificial turf* and *futon* as candidates, as shown in Table 5. The robot selected the *lying down* motion from the recognition rates based on the candidate's data shown in Figure 9. Finally, the robot obtained the data while lying down and recognized the current environment as the *futon* environment shown in Table 6. We verified that the robot recognized all environments shown in Table 3 by using our method. The maximum times of the iteration of these processes for the environment recognition was three.

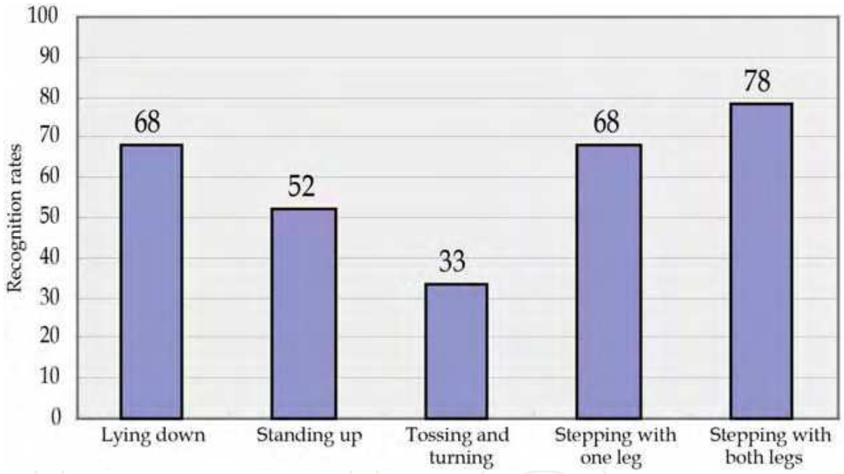


Figure 7. Recognition rates of decision trees for each motion based on all data. The highest rate is obtained by the Stepping on both legs motion

Environment	Reliability	Environment	Reliability
Ceramic tiled floor	0.0	Futon	0.2
Linoleum floor	0.0	Carpet	0.0
Wooden table	0.0	Bathmat	0.0
Tatami mat	0.2	Blanket	0.4
Cushion	0.0	Artificial turn	0.2

Table 4. Reliabilities for each environment when the decision tree of the stepping with both legs motion classifies data to the blanket environment

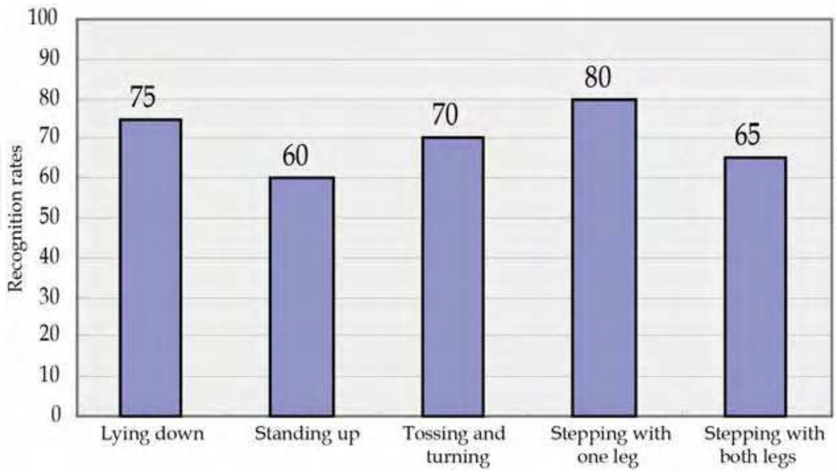


Figure 8. Recognition rates of decision trees for each motion based on data that correspond to tatami, futon, artificial turf, and blanket

Environment	Reliability	Environment	Reliability
Ceramic tiled floor	0.0	Futon	0.8
Linoleum floor	0.0	Carpet	0.0
Wooden table	0.0	Bathmat	0.0
Tatami mat	0.0	Blanket	0.0
Cushion	0.0	Artificial turn	0.2

Table 5. Reliabilities for each environment when the decision tree for the stepping with one leg motion classifies data to the futon environment

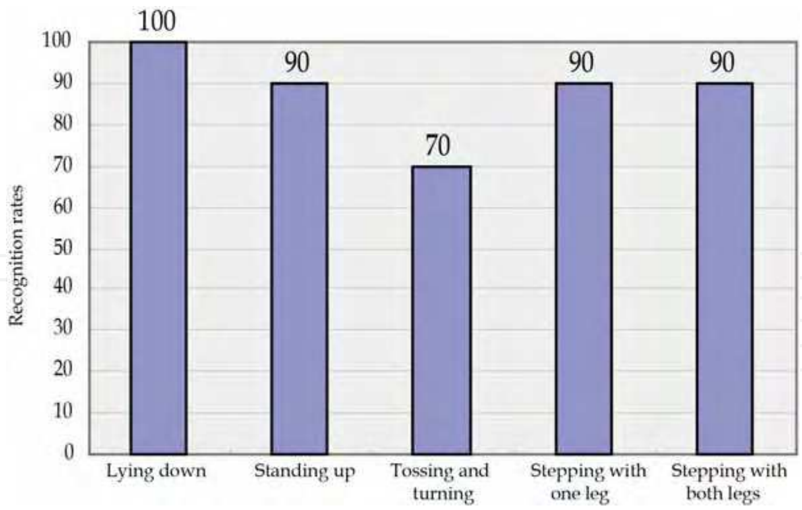


Figure 9. Recognition rates of decision trees for each motion based on data that correspond to futon and artificial turf

Environment	Reliability	Environment	Reliability
Ceramic tiled floor	0.0	Futon	1.0
Linoleum floor	0.0	Carpet	0.0
Wooden table	0.0	Bathmat	0.0
Tatami mat	0.0	Blanket	0.0
Cushion	0.0	Artificial turn	0.0

Table 6. Reliabilities for each environment when the decision tree for the lying down motion classifies data to the futon environment

5. Conclusion

In this paper, we proposed a method for recognizing environment and selecting appropriate behaviours for humanoid robots based on sensor histories. By using the method, the robot could select effective behaviours to recognize current environment.

For ten different environments that are typical in a Japanese family's house, the results of these experiments indicated that the robot successfully recognized them by five basic motions shown in Table 3. However, we should consider the case when number of candidates of current environment does not converge to one. In the case, the robot should acquire new sensor data and rebuild the decision trees, then recognize the environment, again. After these processes, when the number of candidates of the environment becomes one, the robot can decide that the environment is inexperienced. Otherwise, prepared basic motions are not enough for recognizing the environments and an additional basic motion is necessary. In future work, we will clarify dynamical relationships between basic motions and features of environments, and confirm proposed basic motions enough for recognizing the environments. Then, we will extend our method to deal with inexperienced environments.

6. Acknowledgment

This research was supported by the Ministry of Internal Affairs and Communications.

7.References

Fennema, C.; Hanson, A.; Riseman, E.; Beveridge, J.R. & Kumar, R. (1990). Model-Directed Mobile Robot Navigation, *IEEE Transaction on Systems, Man and Cybernetics*, Vol. 20, No. 6, pp. 1352-1369, ISSN: 0018-9472.

Yamamoto, T.; Maeyama, S.; Ohya, A. & Yuta, S. (1999). An implementation of landmark-based position estimation function as an autonomous and distributed system for a mobile robot, *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS '99)*, Vol. 2, pp. 1141-1148, ISBN: 0-7803-5184-3, Kyongju, South Korea, Oct. 1999.

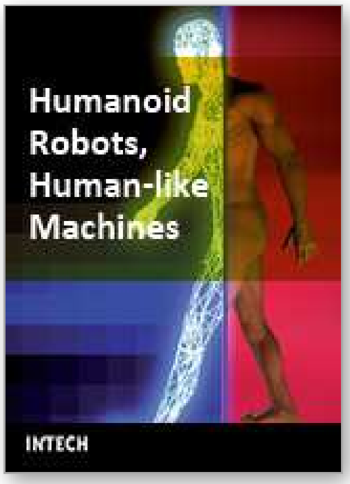
Kagami, S.; Nishiwaki, K.; Kuffner, J.J.; Okada, K.; Inaba, H. & Inoue, H. (2003). Vision-Based 2.5D Terrain Modelling for Humanoid Locomotion, *Proceedings of IEEE International Conference on Robotics and Automation (ICRA2003)*, Vol. 2, pp. 2141-2146, ISBN: 0-7803-7736-2, Taipei, Taiwan, Sept. 2003.

Shats, S.; Cohen, G. & Cohen, L. (1991). Identification of the linear and nonlinear parameters of an electro-mechanical system, *Proceedings of 17th convention of Electrical and Electronics Engineers in Israel*, pp. 95-97, ISBN: 0-87942-678-0, Tel Aviv, Israel, Mar. 1991.

Holweg, E.G.M.; Hoeve, H.; Jongkind, W.; Marconi, L.; Melchiorri, C. & Bonivento, C. (1996). Slip detection by tactile sensors: algorithms and experimental results, *Proceedings of IEEE International Conference on Robotics and Automation*, Vol. 4, pp. 3234-3239, ISBN: 0-7803-2988-0, Minneapolis, MN, USA, April 1996.

Quinlan, J. R. (1993). *C4.5: Programs for Machine Learning*, Morgan Kaufman, ISBN: 1-55860-238-0, CA, USA.

Witten, I.H. & Frank, E. (2000). *Data Mining - Practical Machine Learning Tools and Techniques with JAVA Implementations* -, Morgan Kaufman, ISBN: 1-55860-552-5, CA, USA.



Humanoid Robots, Human-like Machines

Edited by Matthias Hackel

ISBN 978-3-902613-07-3
Hard cover, 642 pages
Publisher I-Tech Education and Publishing
Published online 01, June, 2007
Published in print edition June, 2007

In this book the variety of humanoid robotic research can be obtained. This book is divided in four parts: Hardware Development: Components and Systems, Biped Motion: Walking, Running and Self-orientation, Sensing the Environment: Acquisition, Data Processing and Control and Mind Organisation: Learning and Interaction. The first part of the book deals with remarkable hardware developments, whereby complete humanoid robotic systems are as well described as partial solutions. In the second part diverse results around the biped motion of humanoid robots are presented. The autonomous, efficient and adaptive two-legged walking is one of the main challenge in humanoid robotics. The two-legged walking will enable humanoid robots to enter our environment without rearrangement. Developments in the field of visual sensors, data acquisition, processing and control are to be observed in third part of the book. In the fourth part some "mind building" and communication technologies are presented.

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821