Cooperative Perceptual Systems for Partner Robots Based on Sensor Network

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Summary
This paper proposes a method for cooperative perception of partner robots on a sensor network. While the perception of a robot is restricted locally, the observation from an environmental system is global. Therefore, the robot can easily perceive the environment by receiving and integrating the global information from the environment. Furthermore, the size of robot can be small because the robot does not equip with many sensors if the environmental information is easily available through a wireless network. In this paper, we focus on the localization of human and robots by the integration of camera image and infrared line sensor, and we apply steady-state genetic algorithms for extracting humans and target objects from camera images. Furthermore, we propose a sensor network based on the cooperation between partner robots and environmental system. The proposed method is applied for a navigation task of partner robots interacting with humans and environmental system. Finally, we show several experimental results based on our proposed method.
Key words:
Sensor Networks, Partner Robots, Computational Intelligence, Visual Perception, Intelligent Space.

1. Introduction

Various types of pet robots, amusement robots, and partner robots have been developed for the next generation society. A human-friendly partner robot requires the capabilities of perceiving, acting, communicating, learning, and surviving, while interacting with a human. Especially, the robot should perform human recognition, voice recognition, and gesture recognition in order to realize natural communication with a human, but it is very difficult for the robot to realize these functions successfully in real world conditions. Two different approaches have been discussed to improve these capabilities and functions. One approach is to use conventional intelligent technologies based on various sensors equipped with a robot. As a result, the size of a robot becomes large. The other is to use ambient intelligence technologies of environmental systems based on the structured information available for a robot. The robot directly receives the environmental information through a local area network without measurement by the robot itself.

The research on wireless sensor networks combines three components of sensing, processing, and communicating into a single tiny device [1]. The main roles of sensor networks are (1) environmental data gathering, (2) security monitoring, (3) and object tracking. In the environmental data gathering, the data measured at each node are periodically transmitted to a database server. While the synchronization of the measurement is very important to improve the accuracy of data in the environmental data gathering, an immediate and reliable emergency alert system is very important in the security monitoring. Furthermore, the security monitoring does not need to transmit data to the emergency alert system, but the information on features or situations should be transmitted fast. Therefore, the basic network architecture is different between data gathering and security monitoring. On the other hand, the object tracking is performed through a region monitored by a sensor network. Basically, objects can be tracked by tagging them with a small sensor node. Radio frequency identification (RFID) tags are often used for the tracking system owing to low cost and small size.

Sensor networks and ubiquitous computing have been incorporated into robotics. These researches are called network robotics and ubiquitous robotics, respectively [2]. The ubiquitous computing integrates computation into the environment [3]. The ubiquitous computing is conceptually different from sensor network, but both aim at the same research direction. If the robot can receive the environmental data through the network without the measurement by sensors, the size of the robot can be easily reduced and the received environmental data are more precise because the sensors equipped in the environment is designed suitable to the environmental conditions. On the other hand, network robots are divided into three types; visible robots, unconscious robots, and virtual robots [4]. The role of visible robots is to act on users with their physical body. The role of unconscious robots is mainly used to gather environmental data, and this kind of unconscious robot is invisible to users. A virtual robot indicates a software or agent in a cyber world. A visible robot can easily perceive objects by receiving object information from RFID tags, and this technology has been applied for the robot navigation and the localization of the self-position [5,6]. Furthermore, Hashimoto et.al proposed Intelligent Space (iSpace) in order to achieve human-centered services, and developed distributed intelligent network devices composed of color CCD camera including processing and networking units [7-9]. A robot can be used not only as a human-friendly life-support system, but also as an interface connecting the physical world with the cyber world [10-16]. Therefore, in this research, we focus on cooperative perceptual systems for human-friendly partner robots used as a communication interface. The cooperative perception can share environmental information among robots, and each robot send or receives environmental information according to the facing situation (Fig. 1). In this paper, we propose a cooperative perceptual system, and apply the proposed method to navigation method.

This paper is organized as follows. Section 2 explains the hardware architecture of partner robots, image processing methods, and the sensor network among robots and their environment. Section 3 shows several experimental results of the proposed system, and discusses the effectiveness.

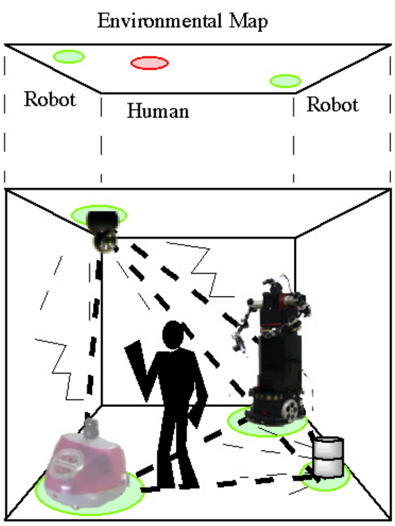


Fig. 1 The cooperative perception based on the sensor network among robots and their environment.

2. Sensor Network for Partner Robots

2.1 Partner Robots

We developed two different types of partner robots; a human-like robot called Hubot [18] and a mobile PC called MOBiMac [19] in order to realize the social communication with humans (Fig. 2). Hubot is composed of a mobile base, a body, two arms with grippers, and a head with pan-tilt structure. The robot has various sensors such as a color CCD camera, two infrared line sensors, microphone, ultrasonic sensors, and touch sensors (Fig.3(a)). The color CCD camera can capture an image with the range of -30° and 30° in front of the robot. Two CPUs are used for sensing, motion control, and wireless network communication. The robot can take various behaviors like a human. MOBiMac is also composed of two CPUs used for PC and robotic behaviors (Fig.3(b)). The robot has two servo motors, four ultrasonic sensors, four light sensors, a microphone, and CCD camera. The basic behaviors of these robots are visual tracking [20], map building [21], imitative learning [22,23], human classification [24], gesture recognition [25], and voice recognition. These robots are networked, and share environmental data each other. Furthermore, the environmental system based on a sensor network provides a robot its environmental data measured by the equipped sensors. Next, we explain the detail of human detection and object recognition for cooperative perceptual systems based on image processing.

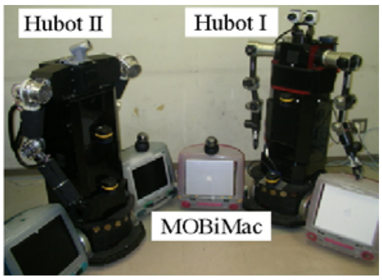
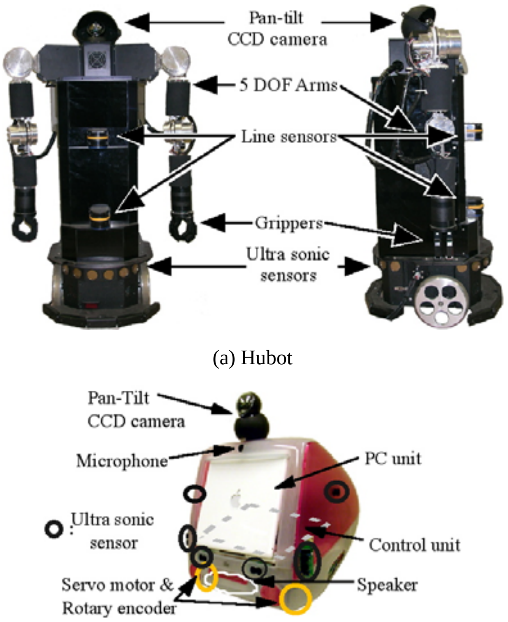


Fig. 2 Human-like partner robots; Hubot and PC type mobile robot; MOBiMac.



(a) Hubot

(b) MOBiMac

Fig. 3 Hardware architecture of partner robots.

2.2 Image Processing for Human Detection and Object Recognition

Pattern recognition has been performed by various methods such as template matching, associative memory, Hopfield neural networks, cellular neural networks, neocognitron, and dynamic programming (DP) matching [26-32]. In general, the pattern recognition is composed of two steps of target detection and classification. The aim of target detection is to extract a target from the image, and this includes the figure-ground problem [33]. The aim of the classification is to identify the target from candidates. Recently, evolutionary computation [34,35] has been used for image processing [36,37], and image processing is considered as a search in images.

An image is taken from the CCD camera attached on the top of the robot. The robot must detect a human face and objects from complex background speedily for the natural communication with the human. Since the image processing takes much time and computational cost, the robot detects a moving object for the fast human search. First, the robot selects pixels by the differential extraction, and *K*-means clustering is used for the clustering of pixels to reduce the search area on the image. The *K*-means clustering is one of the most popular iterative descent clustering methods [38]. The inputs to *K*-means clustering are the central position of templates candidates; $\mathbf{v}_j$ (=($p_{j,1}$, $p_{j,2}$)), j=1,2, ... , n). When the reference vector of the ith cluster is represented by $\mathbf{r}_i$, the Euclidian distance between the jth input vector and the ith reference vector is defined as

$$d_{j,i} = \left\| \mathbf{v}_j - \mathbf{r}_i \right\| \tag{1}$$

where $\mathbf{r}_i$=($r_{i,1}$,$r_{i,2}$) and the number of reference vectors (output units) is l. Next, the reference vector minimizing the distance $d_{j,i}$ is selected by

$$c_j = \arg\min_i \left\{ \left\| \mathbf{v}_j - \mathbf{r}_i \right\| \right\} \tag{2}$$

where c_j is the cluster number of the jth input. After selecting the nearest reference vector to each input, the ith reference vector is updated by the average of the inputs belonging to the ith cluster. This updating process is continued until all reference vectors are not changed at the clustering process. The reference vectors of *K*-means clustering are used for the search by a steady-state genetic algorithm (SSGA) for human detection and object detection. The colors for the search are extracted from an original image by using thresholds on HSV (Hue, Saturation, Value) color space. SSGA simulates the continuous model of the generation, which eliminates and generates a few individuals in a generation (iteration) [39]. In this paper, SSGA for human detection is called SSGA-H, while SSGA for object detection is called SSGA-O. SSGA can easily obtain feasible solutions through environmental changes with low computational costs. Additionally, although many face detection methods deal with one image, we use two continuous images to detect a moving object based on the differential extraction and a continuous search based on SSGA. It reduces computational costs and improves the accuracy of face detection in the image with complex background.

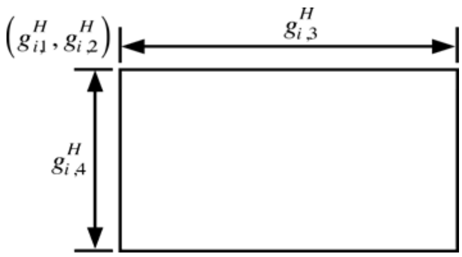
We explain the detail of human detection. A human skin and hair colors are detected by using SSGA-H based on template matching. Figure 4 (a) shows a candidate solution of a template used for detecting a target. A template is composed of numerical parameters of $g_{i,1}^H$, $g_{i,2}^H$, $g_{i,3}^H$, and $g_{i,4}^H$. The number of individuals is G. In SSGA-H, only a few existing solutions are replaced by new candidate solutions generated by genetic operators in each generation. In this paper, the worst candidate solution is eliminated ("delete least fitness" selection), and is replaced with the candidate solution generated by the crossover and the mutation. We use elitist crossover and adaptive mutation. The elitist crossover randomly selects one individual and generates an individual by combining genetic information from the randomly selected individual and the best individual. Next, the following adaptive mutation is performed to the generated individual,

$$g_{i,j}^H \leftarrow g_{i,j}^H + \left(\alpha_j^H \cdot \frac{f_{\max}^H - f_i^H}{f_{\max}^H - f_{\min}^H} + \beta_j^H \right) \cdot N(0,1) \tag{3}$$

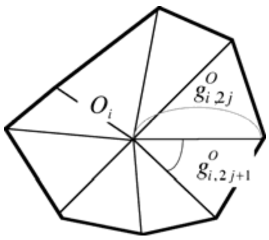
where f_i^H is the fitness value of the ith individual, $f_{\max}^H$ and $f_{\min}^H$ are the maximum and minimum of fitness values in the population; $N(0,1)$ indicates a normal random value; α_j^H and β_j^H are the coefficient and offset, respectively. In the adaptive mutation, the variance of the normal random number is relatively changed according to the fitness values of the population. Fitness value is calculated by the following equation,

$$f_i^H = C_{Skin}^H + C_{Hair}^H + \eta_1^H \cdot C_{Skin}^H \cdot C_{Hair}^H - \eta_2^H \cdot C_{Other}^H \quad (4)$$

where C_{Skin}^H, C_{Hair}^H and C_{Other}^H indicate the numbers of pixels of the colors corresponding to human skin, human hair, and other colors, respectively; η_1^H and η_2^H are coefficients. Therefore, this problem results in the maximization problem. By using SSGA-H, the robot detects a human face. Furthermore, the individuals with high fitness values are survived into the search of the next image, and this realizes a continuous search on multiple images.



(a)



(b)

Fig. 4 (a) A template used for human detection in SSGA-H, (b) A template used for object recognition in SSGA-O.

Next, we explain color-based object detection with SSGA-O based on template matching. The shape of a candidate template is generated by SSGA-O. We used an octagonal template of the angle fixed at 45° in order to improve the shape recognition capability. Figure 4(b) shows a candidate template used for detecting a target where the jth point $g_{i,j}^O$ of the ith template is represented by $(g_{i,1}^O+g_{i,j}^O\cos(g_{i,j+1}^O),\ g_{i,2}^O+g_{i,j}^O\sin(g_{i,j+1}^O))$, i=1, 2, ... , n, j=1, ... , 2×m+2; O_i (=($g_{i,1}^O$, $g_{i,2}^O$)) is the center of a candidate template on the image; n and m are the number of candidate templates and the searching points used in a template, respectively. Therefore, a candidate template is composed of numerical parameters of ($g_{i,1}^O$, $g_{i,2}^O$,... , $g_{i,2m+2}^O$). Its fitness value is calculated as follows.

$$f_i^O = C_{Target}^O + \eta^O \cdot C_{Other}^O \quad (5)$$

where η_1^O is a coefficient for penalty; C_{Target}^O and C_{Other}^O indicate the numbers of pixels of the colors corresponding to a target and other colors included in the template, respectively. This object recognition is used for detecting robots and landmarks in the environment.

2.3 Cooperative Perception

As the development of ubiquitous computing and sensor network, we should discuss the intelligence technologies in the whole system of robots and environmental systems. Here intelligence technologies related with measurement, transmission, modeling, and control of environmental information is called as ambient intelligence. From the viewpoint of sensing, a robot is considered as a movable sensing device, and an environmental system is considered as a fixed sensing device. If the environmental information is available from the environmental system, the size of robots can be reduced, and flexible and dynamic perception can be realized by integrating environmental information.

We explain how to share and exchange the information for cooperative perception among partner robots and environmental systems. Because it is very difficult to localize the self-location of the robot by the dead-reckoning using the internal sensors, the environmental system informs the robot of the position by detecting it in the environment. The robots send the information of the color and shape used for the detection by the environmental system, and also send its task to the environmental system. According to the task, the environmental system generates a plan and sends it back to the robot. In the following, we assume the navigation of a robot as one of important tasks.

The robot receives the information on the colors and shapes of landmarks for visual navigation to the target point from the environmental system. The robot can reach the target point by sequentially tracing the landmarks one by one. Furthermore, a robot can directly receive the data measured by other robots, and the environmental system integrates these data to improve the quality of the observation. Actually, the environmental system updates the environmental map according to the data gathered by sensor nodes.

3. Experimental Results

This section shows several experimental results of the cooperative perception in the navigation of a partner robot;

MOBiMac through the interaction with its environment and other partner robot; Hubot. A color CCD camera is equipped with the ceiling of a room (Fig.5), and an infrared line sensor of a partner robot is used for localizing the position of human and robot (see Fig.14, 15). The line sensor can measure the distance up to 5,000 [mm] in 180 directions.

The number of reference vectors in *K*-means clustering after the differential extraction is 10. The population sizes of SSGA-H and SSGA-O are 50 and 40, respectively. The iteration (evaluation) times of SSGA-H and SSGA-O are 500 and 300, respectively. The threshold of the fitness value for detecting a human is set at 800. These parameters are decided by preliminary experiments. In the following, we show preliminary experimental results of human detection and object recognition, and an experimental result of navigation of the partner robot interacting with other robot and the environmental system.

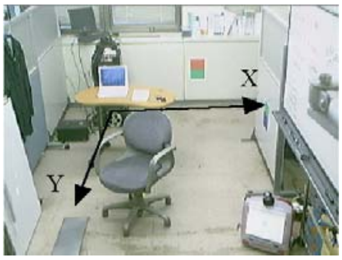


Fig. 5 The ceiling view from a color CCD camera.

3.1 Human Detection and Object Recognition by SSGA

We show experimental results of the image processing, first of all. The human detection is performed by the series of differential extraction, *K*-means clustering, and SSGA-H. Figure 6 shows human detection results from the robot view. In this figure, two people are detected from the time series of images. The fitness values of the best individuals in these results are 17296 and 13894, respectively. These values are larger than the predefined threshold for the human detection.

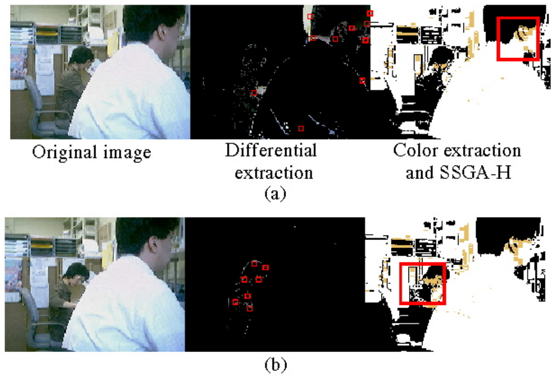


Fig. 6 Human detection results from the robot view by SSGA-H.

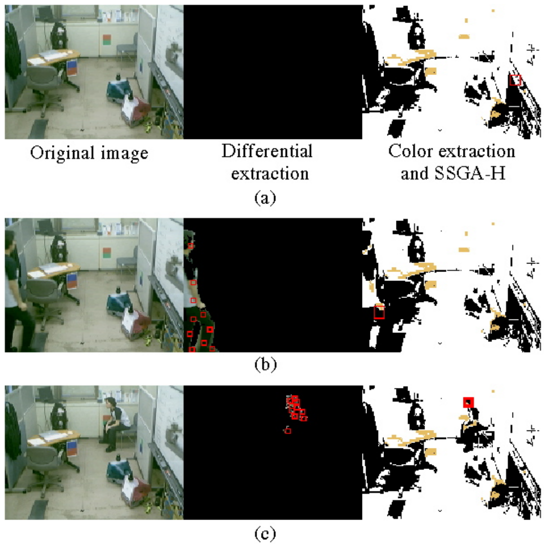


Fig. 7 Human detection results from the ceiling view by SSGA-H.

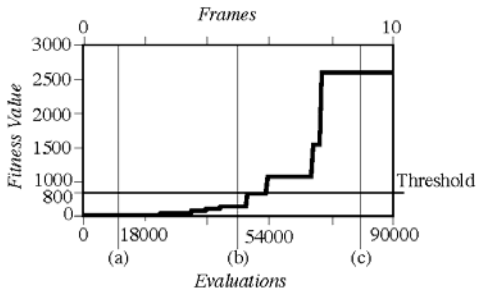


Fig. 8 The history of the fitness value of the best individual in SSGA-H.

Next, Figs.7 and 8 show human detection results form the ceiling view and the history of the fitness value of the best individual in SSGA-H, respectively. In Fig.7 (a), because nobody is in the room, the fitness value of the best individual is 0 (Fig. 8). Afterward, when a person appears on the image (Fig.7 (b)), the fitness value is gradually increasing, but the fitness value does not reach the threshold. As a result, a person is not yet recognized in this stage. Although the person is very small on the image (Fig.7 (c)), the person is successfully detected. By using the time series of images, a human is easily detected and the environmental map is sequentially updated.

Next, we show experimental results of landmark recognition and object recognition. Since the aim of the robot is to reach a target point, we use simple landmarks for the robot navigation. We prepare 6 different types of landmark patterns with different color sets. These landmarks are put on walls or the plain side of desks and partitions for the localization. Figures 9 and 10 show several landmark recognition results and the history of fitness value of the best individual in each frame, respectively. First, since the robot does not detect the target landmark on the image (Fig.9 (a)), the fitness value of the best individual is still 0. Figure 11 shows object recognition results of the robot from the ceiling view. The leftmost to the rightmost images are an original image, differential extraction, human detection, object recognition, and total results, respectively. The experimental result shows that the environmental system can successfully detect both of human and robot at the same time.

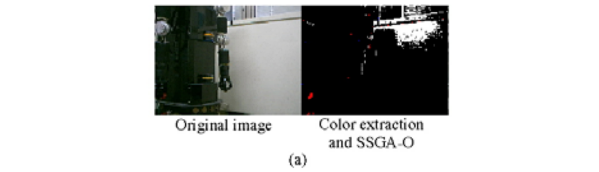


Fig. 9 Landmark recognition results by the robot using SSGA-O.

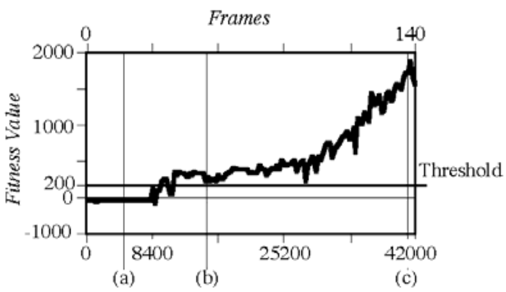


Fig. 10 History of fitness value of the best individual in each frame in Fig.9 in 140 frames.

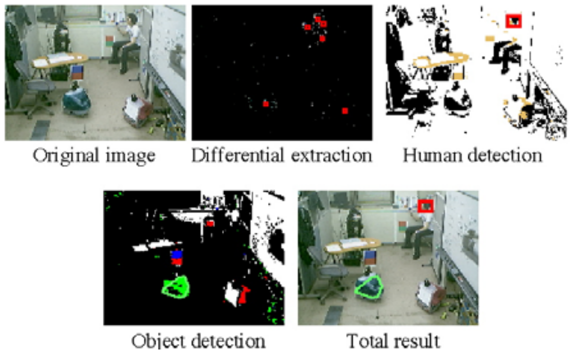


Fig. 11 Human detection and object recognition results of the robot from the ceiling view.

3.2 Navigation of The Partner Robot

MOBiMac moves toward its target point by integrating the sensed data and the received data from the environmental system (Fig. 12). The environment system updates the environmental map according to the gathered data. Figure 13 shows the update of the environmental map. The degree of color of squares corresponding to humans and robots is dark as the time step passes by. The map is updated according to human position and MOBiMac position detected by the CCD camera. The environmental system sends MOBiMac the landmark information based on the robot position by referring the environmental map. However, the position of a robot calculated by the CCD camera is not exact, because some occlusion may exist on the image. Therefore, we use the infrared line sensor of Hubot to improve the localization of MOBiMac. Figure 14 shows the measurement result of the infrared line sensor. Here a black circle indicates the average distance of five times of measurement used as a steady state when the differential extraction does not detect moving objects. A red circle is depicted if the different between the measured distance and the steady state is larger than the threshold, which is considered as moving objects. The rightmost figure of Fig.15 shows the recognition result of person where the red large square and red small square indicate the position detected by image processing and the infrared line sensor, respectively. While the recognition results in fail owing to the separate use of image processing and the infrared line sensor in Figs.15(a) and (b), the integrated recognition by both sensors is successful in Fig.15 (c). By using this position information, the environmental system updates the environmental map for the robot navigation.

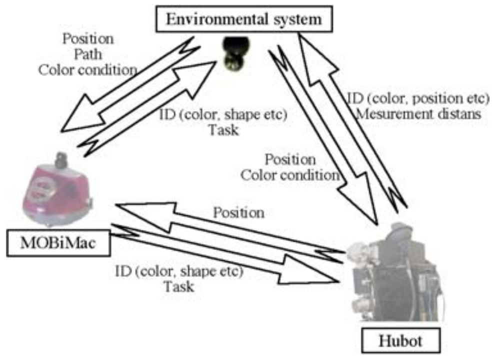


Fig. 12 Network between the environmental system and robots.

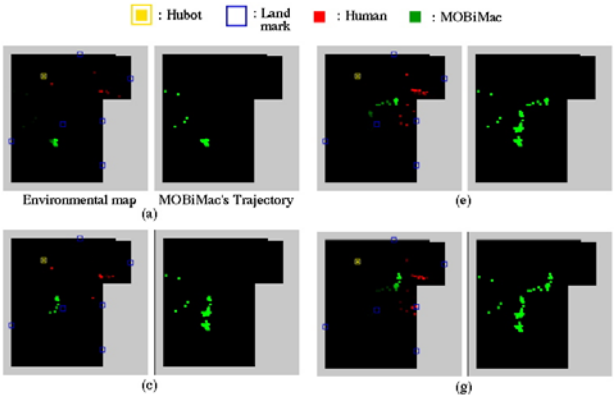


Fig. 13 Environmental map and trajectory of MOBiMac.

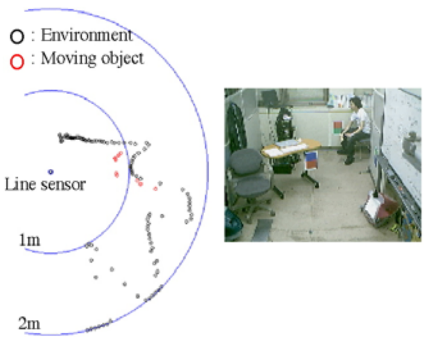


Fig. 14 Measurement result of the infrared line sensor.

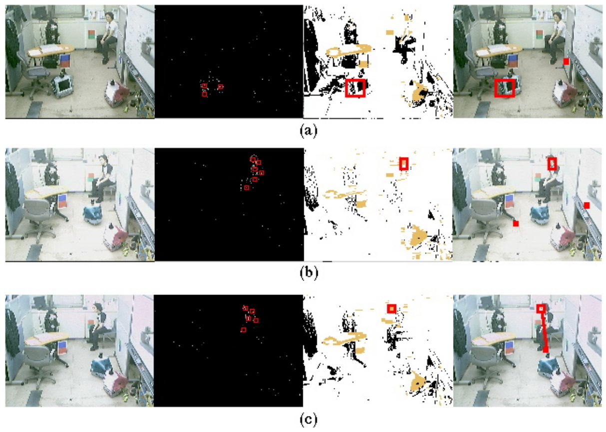


Fig. 15 Human detection and localization by image processing and the infrared line sensor.

Figure 16 shows experimental results of the robot navigation. The task given to MOBiMac is to deliver a letter to a target person. After sending the task information to the environmental system, MOBiMac receives a path to reach the target person (Fig.16 (a)). At first, MOBiMac searches for the first target landmark (Fig.16 (b)), and reaches it (Fig.16 (c)). And then, MOBiMac searches for the second target landmark, and approaches it (Figs.16 (d), (e)). After reaching the third target landmark (Figs.16 (f), (g)), MOBiMac finds the target person and delivers a letter to the person (Fig.16 (h), (i)). Figure 17 shows the trajectory of MOBiMac. On the other hand, the environmental system sequentially updates the environmental map (Fig.13). MOBiMac receives the self-position information by asking the environmental system about the self-position.

4. Concluding Remarks

In this paper, we proposed a method for cooperative perception in the sensor network based on the relationship between robots and environmental systems. First, we discussed the sensor network in distributed sensing of robots and environmental systems. Basically, a robot is considered as a movable sensing device, while an environmental system is considered as a fixed sensing device. By integrating these sensing data, the flexible and dynamic monitoring is realized. In the experimental result, we used the infrared line sensor of Hubot as a movable sensing device to make up for the accuracy of the localization by the color CCD camera equipped with the ceiling. These experimental results support the effectiveness of the proposed method. Finally, these results on the navigation task are not new in the field of robotics, and actually path planning and navigation can be performed

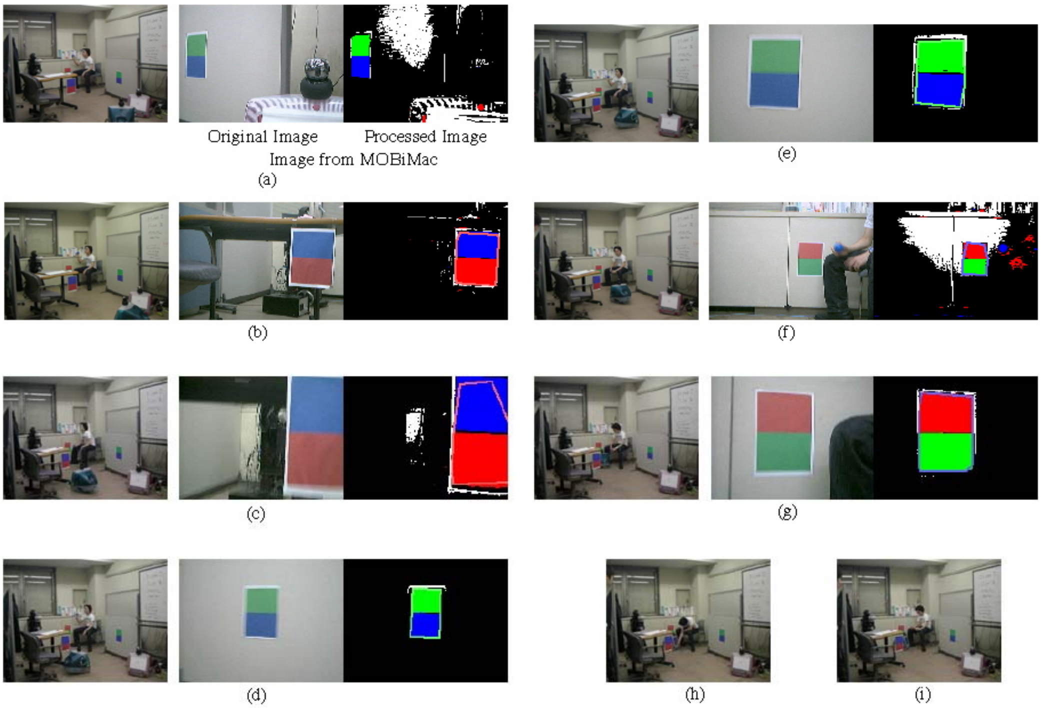


Fig. 16 Navigation task by MOBiMac.

Fig. 17 Trajectory of MOBiMac in this navigation task

by the robot itself without help of the environmental system [40-42]. In this paper, we discussed the importance of the cooperation between robots and environmental systems, the design of robot in ambient intelligence, and the flexible and dynamic search of environmental information.

As future works, we intend to develop the behavior coordination of multiple robots for the cooperative perception through interaction with the environmental system. Furthermore, we will discuss the communication method of a human with the environment in detail.

References

[1] I. Khemapech, I. Duncan and A. Miller, "A Survey of Wireless Sensor Networks Technology," Proc. of The 6th Annual PostGraduate Symposium on The Convergence of Telecommunications, Networking and Broadcasting, 2005.

[2] J-H. Kim, Y-D. Kim, and K-H. Lee, "The Third Generation of Robotics: Ubiquitous Robot," Proc. of 2nd International Conference on Autonomous Robots and Agents, 2004, pp.1-12.

[3] I. Satoh, "Location-based Services in Ubiquitous Computing Environments", International Journal of Digital Libraries, Springer, 2006.

[4] K. Kemmotsu, T. Tomonaka, S. Shiotani, Y. Koketsu, and M. Iehara, "Recognizing Human Behaviors with Vision Sensors in Network Robot Systems," Proc. of The 1st Japan-Korea Joint Symposium on Network Robot Systems (JK-NRS2005), 2005.

[5] D. Hafnel, W. Burgard, D. Fox, K. Fishkin, and M. Philipose, "Mapping and Localization with RFID Technology," Proc. of the IEEE International Conference on Robotics and Automation (ICRA), 2004.

[6] Kulyukin, et al., "RFID in Robot-Assisted Indoor Navigation for the Visually Impaired," Proc. 2004 IEEE/RSJ

International Conference on Intelligent Robots and Systems (IROS 2004), 2004, pp. 1979-1984.
[7] K. Morioka, H. Hashimoto, "Appearance Based Object Identification for Distributed Vision Sensors in Intelligent Space," Proc. of the 2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS'04), Vol.1, 2004, pp.199-204.
[8] P. T. Szemes, H. Hashimoto, "Fuzzy Neural Network based Mobile Agent Control for Intelligent Space ", Proc. of SICE Annual Conference 2004, 2004, pp.1372-1377.
[9] H. Hashimoto, P. T. Szemes, "Ubiquitous Haptic Interface in Intelligent Space", Proc. of SICE Annual Conference 2003, 2003, pp.3277-3282.
[10] H. Ishiguro, M,. Shiomi, T. Kanda, D. Eaton, and N. Hagita, Field experiment in a science museum with communication robots and a ubiquitous sensor network, Proceedings of Workshop on network robot system at ICRA2005, 2005.
[11] T. Mori, A. Takada, H. Noguchi, T. Harada, and T. Sato, "Behavior Prediction Based on Daily-Life Record Database in Distributed Sensing Space," Proc. of IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2005, pp. 1833-1839.
[12] S. Thrun et al. :Probabilistic algorithms and the interactive museum tour-guide robot minerva. International Journal of Robotics Research, 19(11), pp.972-999, 2000.
[13] M. Imai, T. Ono, H. Ishiguro: Physical Relation and Expression: Joint Attention for Human-Robot Interaction, IEEE Transactions on Industrial Electronics, Vol.50, No.4, pp.636-643, 2003.
[14] Y. Nakauchi, R. Simmons, A Social Robot that Stands in Line, Journal of Autonomous Robots, Vol. 12, No. 3, pp.313-324, 2002.
[15] N. Ando, T. Suehiro, K. Kitagaki, T. Kotoku, W.-K. Yoon, RT-Middleware: Distributed Component Middleware for RT (Robot Technology), 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2005), pp.3555-3560, 2005.
[16] N. Y. Chong, H. Hongu, K. Ohba, S. Hirai, and K. Tanie, "A Distributed Knowledge Network for Real World Robot Applications," Proc. IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS 2004), 2004, pp. 187-192.
[17] T.Fukuda, N.Kubota, An Intelligent Robotic System Based on a Fuzzy Approach, Proceedings of IEEE, 87(9): 1448-1470, 1999.
[18] N.Kubota, K.Tomoda, "Behavior Coordination of A Partner Robot based on Imitation", Proc. of 2nd International Conference on Autonomous Robots and Agents, 2004, pp.164-169.
[19] N.Kubota, D.Hisajima, F.Kojima, and T.Fukuda, "Fuzzy and Neural Computing for Communication of A Partner Robot," Journal of Multiple-Valued Logic and Soft-Computing 9(2), 2003, pp. 221-239.
[20] I.A. Sulistijono and N. Kubota, "Visual Perception for a Partner Robot Based on Computational Intelligence," Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol.9 No.6, 2005, pp. 654-660.
[21] N. Kubota, K. Nishida, "Development of Internal Models for Communication of A Partner Robot Based on Computational Intelligence," Proc. Of 6th International Symposium on Advanced Intelligent Systems, 2005, pp. 577-582.
[22] N.Kubota and K.Nishida, "Fuzzy Computing for Communication of A Partner Robot Based on Imitation," Proc. (CD-ROM) of 2005 IEEE International Conference on Robotics and Automation, 2005, pp.4391-4396.
[23] N.Kubota, "Computational Intelligence for structured Learning of A Partner Robot Based on Imitation," Information Sciences, No.171, 2005, pp. 403-429.
[24] N.Kubota, K.Nishida, "Human Recognition of A Partner Robot Based on Relevance Theory and Neuro-Fuzzy Computing," Proc. (DVD-ROM) of 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005, pp.2812-2817.
[25] N. Kubota and M. Abe, "Interactive Learning for A Partner Robot Based on Cyclic Gestures," Proc. (CD-ROM) of The 5th International Conference on Simulated Evolution And Learning, 2004, SWA-1.
[26] C.-H. Chen, L.-F. Pau, and P.-S-P. Wang, Handbook of Pattern Recognition & Computer Vision, World Scientific Publication Co. Pte. Ltd., 1993.
[27] K. Fukushima, "Neural network model restoring partly occluded patterns," Knowledge-Based Intelligent Information and Engineering Systems, (7th International Conference, KES 2003), Part II, eds: V. Palade, R. J. Howlett, L. Jain, Berlin - Heidelberg: Springer-Verlag, 2003, pp. 131-138.
[28] K. Fukushima, "Restoring partly occluded patterns: a neural network model with backward paths", Artificial Neural Networks and Neural Information Processing - ICANN/ICONIP 2003, eds. O. Kaynak, E. Alpaydin, E. Oja, L. Xu, Berlin - Heidelberg: Springer-Verlag, 2003, pp. 393-400.
[29] J.A.Anderson and E.Rosenfeld, Neurocomputing, The MIT Press, 1988. 9.
[30] S.V.Kartalopoulos, Understanding Neural Networks and Fuzzy Logic, The IEEE Press, 1996.
[31] W.T.Miller, R.S.Sutton, and P.J.Werbos, Neural Networks for Control, The MIT Press, 1990.
[32] T. Kohonen, *Self-organization and associative memory*, Springer, New York, 1984.
[33] A.M. Arsenio, "Figure/ground segregation from human cues", Proc. (CD-ROM) of 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2004, pp.3244-3250, 2004.
[34] D.B. Fogel and C.J. Robinson, Computational Intelligence, IEEE Press, 2003.
[35] D.B. Fogel, Evolutionary Computation, IEEE Press, 1995.
[36] Andy Song, "Texture Analysis by Genetic Programming," Proc. of the 2004 Congress on Evolutionary Computation (CEC2004), 2004, pp. 2092-2099.
[37] Mark E. Roberts, Ela Claridge, "An Artificially Evolved Vision System for Segmenting Skin Lesion Images," Proc. of 6th International Conference of Medical Image Computing and Computer-Assisted Intervention (MICCAI 2003) (1), 2003, pp. 655-662.
[38] T.Hastie, R.Tibshirani, and J.Friedman, The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer-Verlag, New York, 2001.
[39] G.Syswerda, A Study of Reproduction in Generational and Steady-State Genetic Algorithms, In Foundations of Genetic Algorithms, Morgan Kaufmann Publishers, Inc., 1991.

[40] J. Y. Donnart and J. A. Meyer, “Learning reactive and planning rules in a motivationally autonomous animat,” *IEEE Trans. Syst., Man, Cybern. B*, vol. 26, pp. 381–395, Mar. 1996.
[41] J. Tani, “Model-based learning for mobile robot navigation from the dynamical systems perspective,” *IEEE Trans. Syst., Man, Cybern. B* , vol. 26, pp. 421–436, Mar. 1996.
[42] J. R. Millan, “Rapid, safe, and incremental learning of navigation strategies,” *IEEE Trans. Syst., Man, Cybern. B*, vol. 26, pp. 408–420, Mar. 1996

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