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Prediction of Human's Movement for Collision Avoidance of Mobile Robot

Shunsuke Hamasaki, Yusuke Tamura, Atsushi Yamashita and Hajime Asama

***Abstract*— In order to operate mobile robot that can coexist with human, it is necessary to strike a balance between safety and efficiency. It is effective to make a prediction about when and where human exist from data of pedestrian movement and environment. Then, we need to know how the configuration of environment effects pedestrian. This paper presents a measuring system of pedestrian movement tendency, and prediction system of pedestrian movement. We conducted the prediction experiment with real observed data, and proved that system can contribute to the balancing safety and efficiency of operating mobile robot.**

I. INTRODUCTION

A. Background of Research

Recent years, many kinds of robots are developed and utilized in human society, and they have become indispensable for us. There are two main types of robots, industrial robots utilized in manufacturing, and non-industrial robots utilized in other areas. Once industrial robots occupied most of the robot, however, due to development of robot technology, the research of non-industrial robots has become a thriving filed. Service robots which are used in environments coexisting with humans occupy an area of non-industrial robots, various forms of robots which are utilized in office work [1] or everyday life[2] have been developed. However, currently robots which can coexist with human in everyday life have not yet reached the stage of practical.

In order to operate mobile robots in an environment coexisting with human, collision avoidance is a huge problem. It is not so easy for mobile robots to avoid collision in a situation that humans can avoid each other easily, there has been considerable research on this problem. However, we should not give up the high-speed operation of mobile robots with the firm commitment to safety. Because there is a task to be accomplished to use the mobile robots, there is no point in using mobile robots if the task did not get accomplished efficiently. There are always a trade-off between safety and efficiency, the efficiency is reduced when the robot move slowly for the sake of safety, and the safety is reduced when the robot move quickly for the sake of efficiency. It is important to keep safeness, however the need to use mobile robots is decrease when the robot moves slowly as discussed previously. Hence, we can say that the system which enables to move efficiently while keeping safeness is necessary for mobile robot utilized in environments coexisting with humans.

S.Hamasaki, Y.Tamura, A.Yamashita and H.Asama are with Dept. of Precision Engineering, The University of Tokyo , Tokyo , Japan { hamasaki, tamura, yamashita, asama} @robot.t.u-tokyo.ac.jp

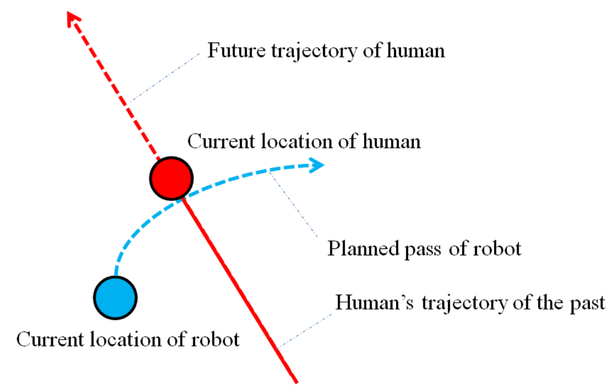

Fig. 1. Crossing Paths of Human and Robot

B. Related Works and Policy of Research

According to the preceding section, development of a system which enables to move efficiently while keeping safeness is important. There has been considerable research about collision avoidance. For example, collision avoidance methods with the sensor mounted on the mobile robots are one of the most common method [3], [4]. There are also researches aimed at improving the quality and quantity of information by adding new twist to the sensor mounted on the mobile robots. However, it is difficult to prevent the occurrence of occlusion exclusively by sensor mounted on the robot, thus the robot has to give priority to safety in the area where the occlusion may occur.

To reduce the effect of occlusion, there are a lot of methods to gain information, that the sensor on the robot cannot detect, from the sensors in the environment[5] [6] [7]. However, only the current state of human is not enough. For example. we simulate the situation as shown in Fig 1. The environmental sensor detects a human on the blue route that the robot is going to move, the robot will take avoidance movement such as stop or slowdown. However, human is going to move along red dashed line, this avoidance movement is unnecessary. If the robot could predict the future trajectory of human, the robot can escape an unnecessary avoidance movement.

We thought that we can realize more efficiently and more strategic collision avoidance, by predicting the absence of future collision between human and robot Without any information about future collision, the mobile robot always has to move at the speed focusing on safety enough to respond to the dangers if there is a possibility of collision. Knowing in advance the possibility of a collision, the robot

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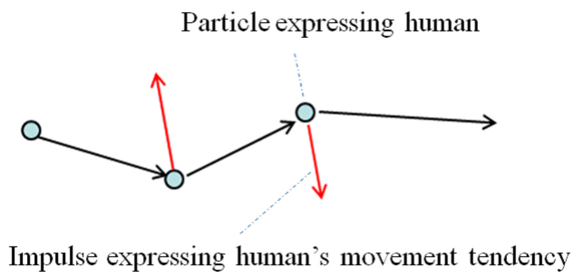

Fig. 2. Schematic view of Human's Movement Tendency

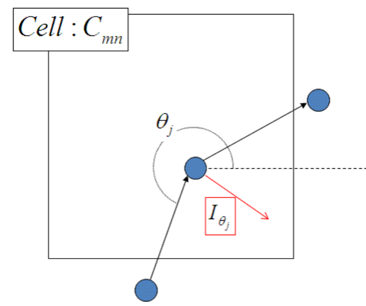

Fig. 3. Data in the Database

can make decisions, to move for efficiency when it have low possibility for collision, or to move for safety when it have high possibility for collision. Even when high possibility for collision is predicted, the mobile robots can keep safeness by acceleration or deceleration, without a lot of effects on efficiency.

There are some researches to predict the future trajectory of the human [8] [9] [10]. However, these researches require some data about environment which are determined by human manually. It is difficult to reconstruct the effect of environment on human's movement properly in the subjective experience. Thus, the system which derives the effects of environment on human's movement from observation is necessary.

From the above, we can say that making a prediction of future human's trajectory will allow the robot to be operated efficiently while maintaining safety. Thus, the purpose of this research is to develop system to predict future trajectory of the human. It is important in trajectory prediction of human that the environment always have some influenced on the movement of human. "environmental effect" has to be built in trajectory prediction, and it must not be determined manually. Therefore the environmental effect in this research should be derived automatically from observation.

The rest of this paper is organized as follows. Environmental effects are discussed in section II. In section III, details of the proposed algorithm are discussed. Experiments are described in section IV, and conclusions are given in section V.

II. Generation of Human's Movement Tendency Database

A. Human's Movement Tendency

To reflect the environmental effects on human's movement in the prediction, we analyzed the tendency of human's movement, and created a database. The transition of human's movement can be represented by a change of the velocity. By considering the movement of human as a particle which has mass M[kg], we can derive a virtual impulse from the change of the velocity as represented in Fig 2. In this work, we treat this impulse as human's movement tendency.

There are many kinds of sensor which can detect human's movement, such as optical sensor or ultrasonic sensor. In this research, we suppose we use laser range finder (LRF).

B. Generation of Database

In this section, we generate a database with the tendency of human's movement which derived in preceding section. The environmental sensor observed the movements of human for many hours at intervals of t_I. Observed environment is partitioned into cells (D[m] on a side), and the tendencies of movement in each cell are stored in the database. We input two kinds of data to a database of arbitrary cell, derived impulses expressing the tendency and angular component of the velocity in previous observation step. Data which stored in the database are described in (1).

$$C_{mn} = \{I_j, \theta_j | 0 < j \leq J \leq J_{max}, j \in \mathbf{Z}\} \quad (1)$$

C_{mn} is a set of data which are recorded in the database of the cell in the mth row and nth column. I is the impulse, and θ is the angular component of the velocity in previous observation step. j is the data number, J is the number of data in the cell, and J_{max} is the maximum number of data which are recorded in a cell. A data in database is shown in Fig 3 .

III. Trajectory Prediction Algorithm

A. Assumptions of Proposed Method

The proposed algorithm based on following assumptions.

Assumption 1

> The movement of human is affected by environment. For example, human would sometimes walk along the wall, or toward the door or book shelf. Thus human's movement is sensitive to characteristics of the environment.

Assumption 2

> The walking speed and direction of human, don't change significantly in a short time. It does not mean that the movement is constant. Moving of human at long times would well be change significantly with accumulation of small changes.

B. Information extraction from observed data

On making the trajectory prediction, the observed data forms the basis of prediction. The data which form the basis of prediction is generated from the observed data at present

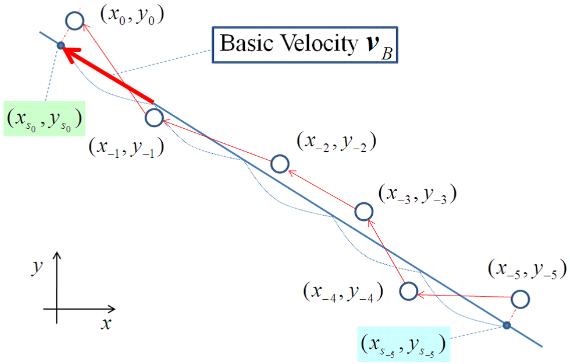

Fig. 4. Basic Velocity

time. We can get the barycentric position and velocity of the human from observation, however we have to consider the error of measurement. Especially the error of velocity will greatly effect prediction result.

First, N particles are generated in accordance with 2-dimensional normal distribution based on the barycentric position which is observed at present time. These particles are express the position distribution of the human. In order to reduce the margin of error in velocity, we generated the velocity $\boldsymbol{v}_B$ which form the basis of prediction from the observed data of human movement. If we calculate the velocity with the simple subtraction between the last two observed data, the calculated velocity is very sensitive to errors in observation. Thus, $\boldsymbol{v}_B$ is generated from the observed data of 0.5 second, with the method of least squares. Figure 4 show the derivation of $\boldsymbol{v}_B$. (x_0, y_0) -(x_{-5}, y_{-5}) are the data which is observed 0.5 second.

The line in Fig 4 is derived by (2). (x_{s_0}, y_{s_0}) ,$(x_{s_{-5}}, y_{s_{-5}})$ are the foot of a perpendicular to the line from (x_0, y_0) and (x_{-5}, y_{-5}).

$$ax + by + c = 0 \tag{2}$$

$$a = \sum_{k=0}^{n} x_{-k} y_{-k} - \sum_{k=0}^{n} x_{-k} \sum_{k=0}^{n} y_{-k} \tag{3}$$

$$b = \left(\sum_{k=0}^{n} x_{-k} \right)^2 - n \sum_{k=0}^{n} x_{-k}^2 \tag{4}$$

$$c = \sum_{k=0}^{n} x_{-k} \sum_{k=0}^{n} y_{-k} - \sum_{k=0}^{n} x_{-k} y_{-k} \sum_{k=0}^{n} y_{-k} \tag{5}$$

The line express the angular component of $\boldsymbol{v}_B$. In Fig 4 , $n = 5$. $\boldsymbol{v}_B$ is obtained from (6) and (7). $\boldsymbol{v}_{B_x}$ is X component of $\boldsymbol{v}_B$., $\boldsymbol{v}_{B_y}$ is Y component. t_0, t_{-5} are the observed time.

$$\boldsymbol{v}_{B_x} = \frac{x_{s_0} - x_{s_n}}{t_0 - t_{-n}} \tag{6}$$

$$\boldsymbol{v}_{B_y} = \frac{y_{s_0} - y_{s_n}}{t_0 - t_{-n}} \tag{7}$$

$\boldsymbol{v}_B$ is the velocity of the particles when the system starts the prediction.

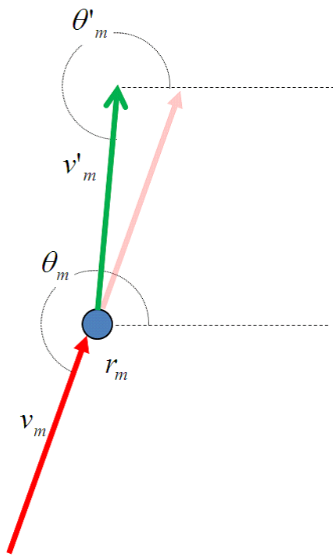

Fig. 5. Generation of $\boldsymbol{v}'_m$

C. Movement of the Particles

In preceding section, the probability distribution of the particles expressing the human's movements is generated. The proposed system makes a prediction sequentially at the same interval of time t_P. We discuss a particle at a certain point t_m. $\boldsymbol{r}_m$ is the coordinate of the particle, and $\boldsymbol{v}_m$ is the velocity. This particle is transferred from $\boldsymbol{r}_{m-1}$ at a velocity of $\boldsymbol{v}_m$. We have to predict the coordinate and velocity of the particle at $t_{m+1} = t_m + t_P$. According to assumptions, $\boldsymbol{v}_{m+1}$ is not so different from $\boldsymbol{v}_m$. Thus, $\boldsymbol{v}'_m$ is generated at random based on $\boldsymbol{v}_m$ for a probabilistic prediction. $\boldsymbol{v}'_m$ is generated by normal distribution.

Figure 5 show the generation of $\boldsymbol{v}'_m$. θ_m and θ'_m is the angular component of $\boldsymbol{v}'_m$ and $\boldsymbol{v}_m$.

To discuss environmental influence, we add a correction for $\boldsymbol{v}'_m$. It changes under the influence of one of the impulse stored in the database which generated in II-B . The probability is determined by (8) and (9) that an impulse is selected.

$$P_j = \frac{K_j}{\sum_{l=1}^{J} K_l} \tag{8}$$

$$K_j = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(\theta_j - \theta'_m)^2}{2\sigma^2} \right) \tag{9}$$

An impulse is selected according to probability 8 from the database that the particle exists. According to 10, $\boldsymbol{v}_{m+1}$ is generated.

$$Mv_{m+1} = Mv'_m + I \tag{10}$$

M is the mass of particle, I is selected impulse. Figure 6 show the generation of $\boldsymbol{v}'_m$.

$\boldsymbol{v}_{m+1}$ in Fig 6 is the velocity predicted from $\boldsymbol{v}_m$ and the database. The particles moved according to (11).

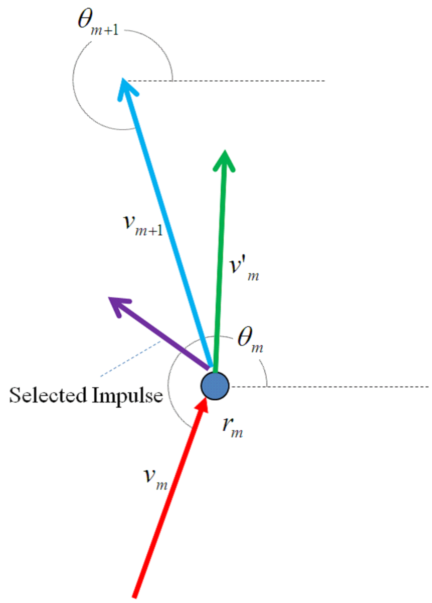

Fig. 6. Generation of $\boldsymbol{v}_{m+1}$

$$\boldsymbol{r}_{m+1} = \boldsymbol{r}_m + \boldsymbol{v}_{m+1} t_P \tag{11}$$

Prediction system makes a prediction for all N particles, and moves them at intervals of t_P. Figure 7 shows the overall flow of the proposed algorithm. Prediction system makes a prediction of the position distribution of the human in real time.

Even if pedestrian's movement change suddenly, prediction system makes a different prediction t_P seconds later from data after the change.

IV. Experiment

A. Overview of Experiment

In order to evaluate the proposed system, we made a simulation experiment with real observed data. First, we create database from 6 hours of observation at 8th-floor corridor of Faculty of Engineering Building 14 in University of Tokyo. We use UTM-30LX, the laser range finder manufactured by HOKUYO AUTOMATIC CO., LTD. Figure 8 shows the experimental environment.

We set the variables as 12 .

$$\begin{cases} D = 1.0[\text{m}] \\ t_I = 0.1[\text{s}] \\ N = 100 \\ t_P = 0.1[\text{s}] \end{cases} \tag{12}$$

1) Specification of virtual robot: In the simulation experiments, we assumed the mobile robot specification, as represented in Table.I . This virtual robot moves linearly for Goal Pint from Start Point in Fig 8 , with varying speed to avoid collisions. The robot can choose from three movement, to move on normal speed , reduced speed, and stop.

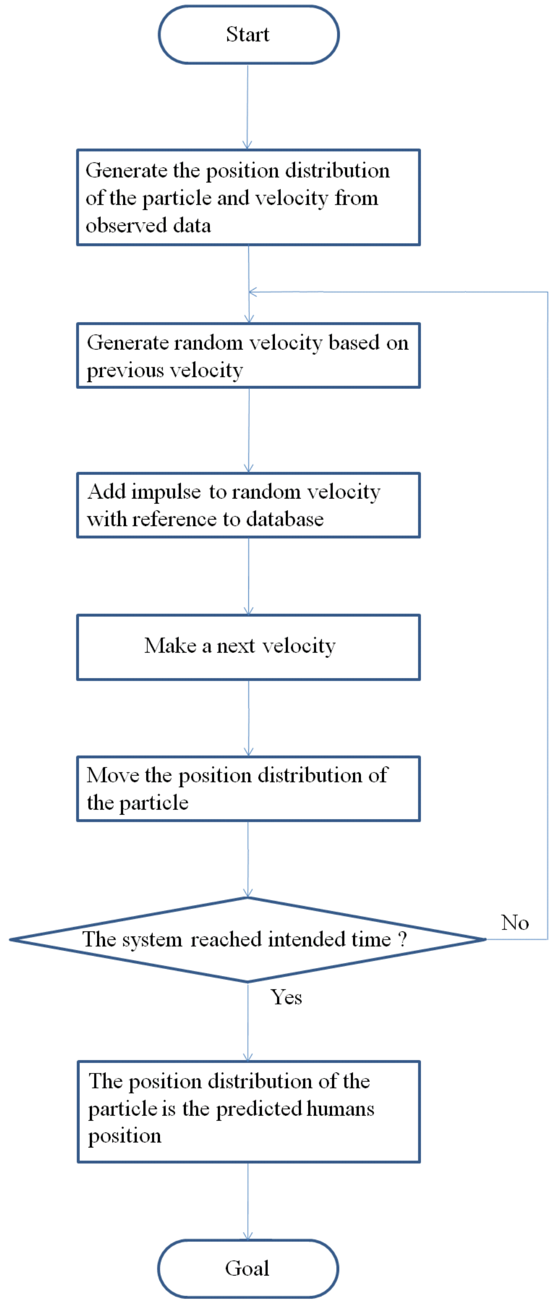

Fig. 7. Flowchart of Proposed Algorithm

2) Route of virtual human: The Robot begins to move at $t = 0$. On the other hand, virtual human begins to move at random timing between $-3 < t < 3$. The virtual human move along one of the routes which represented in Fig 9 .

The virtual human cannot take avoidance movement because its routes are actual data which was observed in environment without mobile robots. In this experiment, we considered the virtual robot crashed against virtual human when the robot and human contact while robot does not stop.

3) Motion planning of virtual robot: We conducted the simulation experiments in accordance with the following

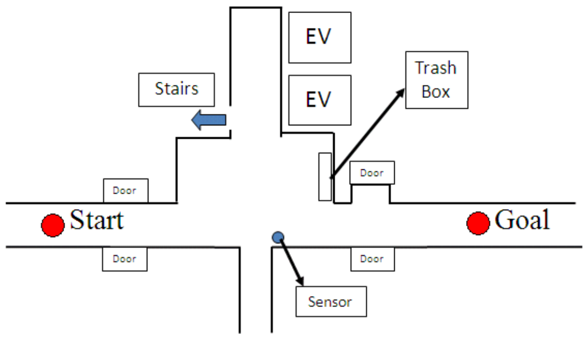

Fig. 8. Experimental environment

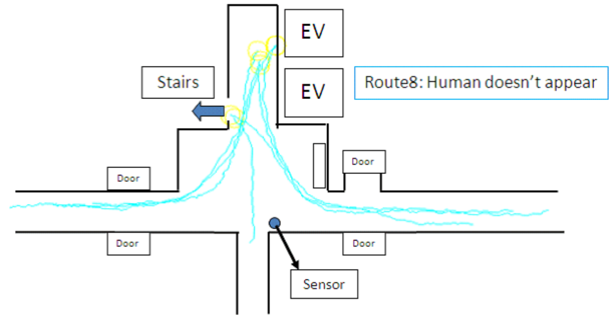

Fig. 9. Route of virtual human

TABLE I
SPECIFICATION OF VIRTUAL ROBOT

Normal Speed	3[m/s]
Reduced Speed	1[m/s]
Acceleration	2[m/s^2]
Measuring Range of Sensor	4[m]

TABLE II
NUMBER OF COLLISIONS

	Pattern A	Pattern B	Pattern C
Number of collisions	172	0	0

three motion patterns.

Pattern A
This pattern gives first priority to efficiency. Virtual robot always moves on normal speed, and tries to stop when the sensor mounted on the virtual robot detects human.

Pattern B
This pattern gives first priority to safety. Virtual robot moves on reduced speed in the area where the occlusion occurs, and moves on normal speed other areas. Also, the robot tries to stop when the sensor mounted on the virtual robot detects human.

Pattern C
This pattern uses proposed method. During environmental sensor detects human, prediction system makes prediction about possibility of collision. When a collision is not predicted, the virtual robot moves on normal speed. If the system predicts a collision in future between human and robot which moves on normal speed, the system begins to make a prediction about collision in future between human and robot which moves on reduced speed. When a collision is not predicted in the second prediction, the virtual robot moves on reduced speed. If a collision is predicted in both predictions, robot stops. Also, the robot tries to stop when the sensor mounted on the virtual robot detects human.

B. Experimental Result and Discussion

1) Experimental result: We conducted the simulation experiment 1000 times for each of three patterns, The results are shown in Table II and Fig 10 . Table II shows the number of collisions, and Fig 10 shows the required time when the robot can move without collision.

2) Discussion:

- Safety

First, according to Table II , in the case of employing Pattern C ,the pattern which is using proposed method, collision did not happen as with the case of pattern B. By contrast, in the case of Pattern A, the robot crashed against human at 17.2% of the simulation. This result is too dangerous to apply to real environment. In the case of Pattern A, the robot could not stopped before contact when the human came close from the blind area of the sensor mounted on the virtual robot. Even when the human came from the blind area, robot could stop because robot's speed was slow in Pattern B. In the case of Pattern C, the robot could move as safe as Pattern B.

- Efficiency

Secondly, we discussed about required time in the case of Pattern B and Pattern C. The reason we eliminate Pattern A is that Pattern A is inferior to other in safeness. According to Fig 10 , in the case of Pattern C, the robot could move more efficient than Pattern B. The required time of Pattern B and Pattern C compared by usuing a t-test, there are significantly different($p < 0.05$). The move of robot in Pattern B was safe, but not efficient. As against Pattern B that the robot slowed where there does not need to stop, the robot in Pattern C changed the speed strategic. As a result, in the case of employing Pattern C, the robot could move as efficient as Pattern A.

V. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

We proposed an algorithm to make a predict the future position of the human based on the data which is observed

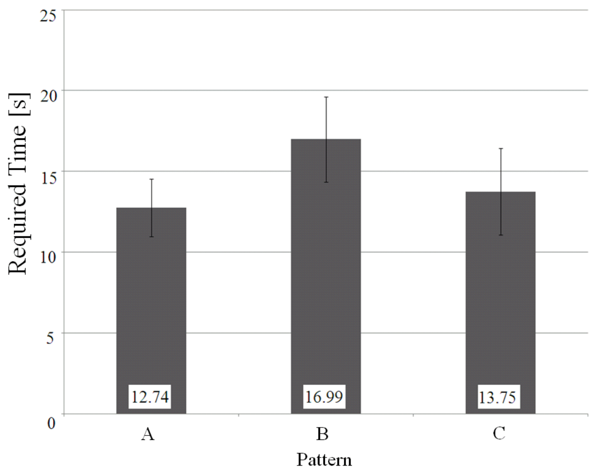

Fig. 10. Required time

by environmental sensor. Prediction which was taken into account the effect of the environment was realized by reflecting the tendency of human's movement on algorithm. Human's movement tendency was derived from the data of fixed-point observation, there is no need for the data which is determined by human manually. Furthermore, we made a simulation experiment with real observed data. As a result, we showed that the proposed method contributes to the operation of the mobile robot which combines the safety and efficiency.

B. Future Works

In future research, it is necessary to collect data from many types of environments to validation, and we have to discuss deeply about the variables. At present, the proposed method presupposes a long time observation for generating database, it is necessary to upgrade the system to be able to apply more general environments. Most importantly, the proposed system has to be applied to a mobile robot in the real environment. Also, the verification result has to be compared with existing methods.

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REFERENCES

[1] Asoh, H, Motomura, Y, Asano, F, Hara, I., Hayamizu, S, Itou, K, Kurita, T, Matsui, T, Vlassis, N, Bunschoten, R., Krose, B*Jijo-2: an office robot that communicates and learns.*. Intelligent Systems, IEEE. Volume 16,Issue 5,pp.46-55,2001

[2] T.Kanda, H.Ishiguro, T.Ono, M.Imai, T.Maeda, R.Nakatsu.*Development of "Robovie" as Platform of Everyday-Robot Research.*, The transactions of the Institute of Electronics, Information and Communication Engineers. D-I J85-D-I(4) pp.380-389, 2002.

[3] A.Dubrawski, P.Reignier.*Learning to Categoraize Perceptual Space of a Mobile Robot Using Fuzzy-ART Neural Netwark.*, Proceeding of the IEEE/RSJ/GI International Conference on Intelligent Robots and Systems, Vol.2, pp.1272-1277, 1994.

[4] B.Kurose, J.Dam.*Adaptive state space quantisation for reinforcement learning of collision-free navigation.*, Proceedings of the 1992 IEEE/RSJ International Conference on Intelligent Robots and Systems, Vol.2, pp.1327-1331, 1992.

[5] A.Hoover, B.Olsen. *Sensor Network Perception for Mobile Robotics.*, Proc. 2000 IEEE Int. Conf. on Robotics and Automation, pp.611-614, 2000.

[6] T.Sogo, H.Ishiguro, T.Ishida. *Mobile robot navigation by a distributed vision system.*, New Generation Computing, Vol.19, No.2, pp121-137, 2001.

[7] Lee.J, H.Hashimoto. *Intelligent Space - consept and contents.*, Advanced Robotics, Vol.16, No.3, pp.265-280, 2002.

[8] Tadokoro, S, Ishikawa, Y, Takebe, T, Takamori, T, *Stochastic prediction of human motion and control of robots in the service of human*, Systems, Man and Cybernetics, 1993. 'Systems Engineering in the Service of Humans', Conference Proceedings, Vol.1, pp.503-508, 1993

[9] Ka K. Lee, Yangsheng Xu *Boundary modeling in human walking trajectory analysis for surveillance* Robotics and Automation, 2004. Proceedings. ICRA '04. 2004 IEEE ,Vol.5, pp.5201-5205, 2004

[10] Thompson, S. Horiuchi, T. Kagami, S. *A probabilistic model of human motion and navigation intent for mobile robot path planning* Autonomous Robots and Agents, 2009. ICARA 2009. 4th ,pp. 663-668 . 2009