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Intelligent Space as a Platform for Human Observation

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1. Introduction

In the recent years, the needs for physical support such as release from household work, care for the elderly people and so on are rising. Therefore, researches on robots for daily life are being pursued actively. However, highly dynamic and complicated living environments make it difficult to operate mobile robots.

In order to solve this problem, it is important to design the environment for mobile robots as well as making mobile robots intelligent to adapt to it. But environmental design in the living space is limited because it should not have a big influence on human lives. We also have to consider how to deal with the dynamic environment. So, it is not enough just to apply a passive approach (e.g. elimination of difference in level on the floor, installation of markers on the wall and so on). Moreover, to provide appropriate service to the human according to the circumstances, mobile robots have to understand the request from human based on observation. The information extracted from observation of humans can also be used for the action of mobile robots because humans are expected to be producing intelligent reactions when confronted with various situations. However, it is not practical that a mobile robot keeps on observing humans while doing other tasks. In addition, owing to restrictions of the capability of mounted sensors and computers, it is difficult to observe humans using on-board sensors.

In order to realize this, we utilize "Intelligent Space (iSpace)" where many intelligent devices are distributed. (Lee & Hashimoto, 2002). Such an environment is referred as smart environment, smart space, intelligent environment and so on. The smart environments observe the space using distributed sensors, extract useful information from the obtained data and provide various services to users. This means their essential functions are "observation," "understanding" and "actuation."

The research field on smart environment has been expanding recently (Cook & Das, 2004) and, under the concept of ubiquitous computing, many researchers have developed smart environments for providing informative services to the users (e.g. support during meeting (Johanson, et al., 2002), health care (Nishida et al., 2000), support of the elderly (Mynatt et al., 2004), information display using a pan-tilt projector (Mori et al., 2004)). On the other hand, smart environments are also used for support of mobile robots. Kurabayashi et al. (Kurabayashi et al., 2002) evaluated an efficiency of multi-robot transportation task when the route to the goal is selected by individual mobile robots and by a smart environment (or

specific locations in the environment which can gather information). The formulation and simulation result showed that decision making by the intelligent environment achieved better performance. In (Mizoguchi et al., 1999), document delivery robot system was developed in an office room. When the user sends a request to the system, a delivery robot moves to receive the document either from the user or a handling robot which is located next to the printer. The mobile robot then takes it to the client. During the task, infrared sensors and cameras embedded in the space are used to localize and navigate mobile robots. Another intelligent environment was also developed to perform transportation of heavy items in a hospital (Sgorbissa & Zaccaria, 2004). In the research, distributed beacons are used for mobile robot localization. However, the authors of the paper consider that the environment design is a temporary solution to develop an intelligent robot. We think that the support of mobile robots' movement (e.g. localization or path planning) is just one application of intelligent environments. Smart environments and mobile robots have their own advantages, so it is desirable to realize services by their mutual cooperation.

As described above, although various smart spaces are proposed, few researches have focused on both support for mobile robots and human observation. Therefore, in this paper, we aim to develop a mobile robot navigation system which can support and navigate mobile robots based on the observation of human walking.

The rest of this paper is organized as follows. In section 2, we introduce the concept and present the configuration of iSpace. Section 3 describes a method for acquisition of human walking paths and extraction of information from obtained walking paths. In section 4, mobile robot navigation based on human observation is explained. Experimental results are shown in section 5. Finally, conclusion and future work are given in section 6.

2. Intelligent Space

2.1 Concept of Intelligent Space

Fig. 1 shows the concept of Intelligent Space (iSpace), which is a space with many distributed and networked sensors and actuators. In iSpace, not only sensor devices but sensor nodes are distributed in the space because it is necessary to reduce the network load in the large-scale network and it can be realized by processing the raw data in each sensor node before collecting information. We call the sensor node devices distributed in the space DINDs (Distributed Intelligent Network Device). A DIND consists of three basic components: sensors, processors and communication devices. The processors deal with the sensed data and extract useful information about objects (type of object, three dimensional position, etc.), users (identification, posture, activity, etc.) and the environment (geometrical shape, temperature, emergency, etc.). The network of DINDs can realize the observation and understanding of the events in the whole space. Based on the extracted and fused information, actuators such as displays or projectors embedded in the space provide informative services to users.

In iSpace, mobile robots are also used as actuators to provide physical services to the users and for them we use the name mobile agents. The mobile agent can utilize the intelligence of iSpace. By using distributed sensors and computers, the mobile agent can operate without restrictions due to the capability of on-board sensors and computers. Moreover, it can understand the request from people and offer appropriate service to them.

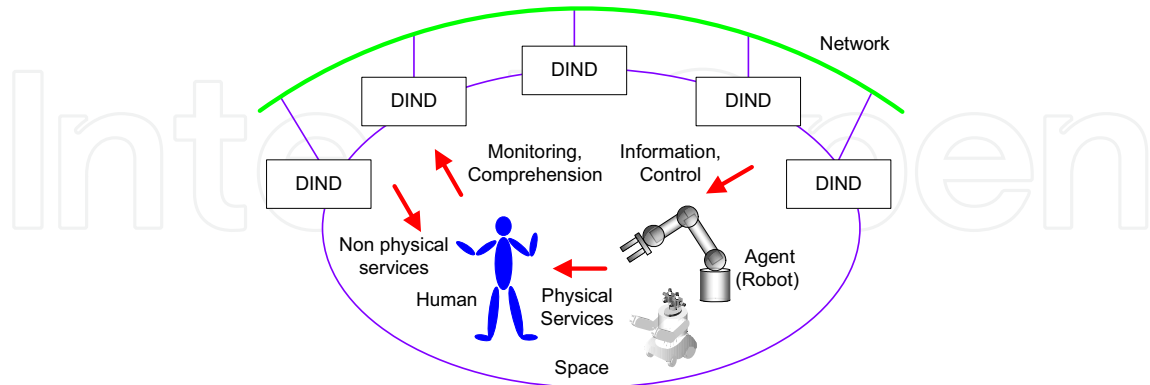


Figure 1. Concept of Intelligent Space

2.2 Configuration of Intelligent Space

Fig. 2 and 3 show a picture and configuration of the implemented iSpace. ISpace is currently implemented in a laboratory environment which has an area of about 5 meters \times 5 meters. In this research, six CCD cameras and a 3D ultrasonic positioning system are used as sensors of DIND. The cameras are connected in pairs to computers with two video capture boards. As a result, each camera DIND can get the three dimensional position of objects by stereo vision. The 3D ultrasonic positioning system involves 96 ultrasonic receivers installed on the ceiling. This system can measure the three dimensional position of an ultrasonic transmitter to an accuracy of 20-80 millimeters using triangulation method. Moreover, a differential wheeled robot is used as mobile agent. For estimating the position and orientation of the robot, two ultrasonic transmitters are installed on the top of the mobile robot. The mobile robot is also equipped with a wireless network device to communicate with iSpace.

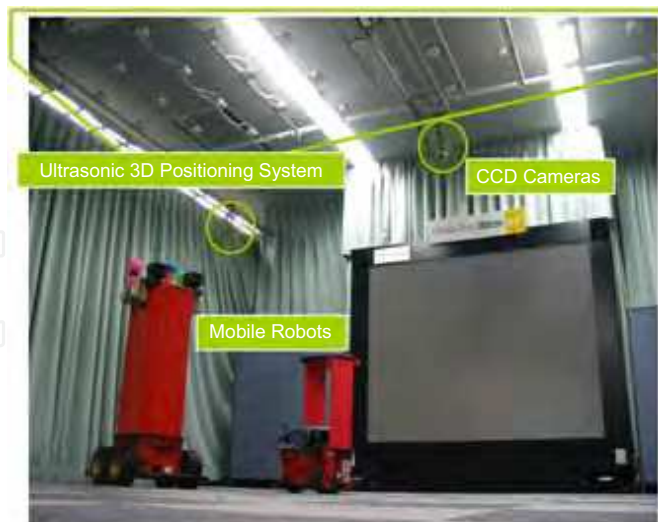


Figure 2. Sensors and mobile agents

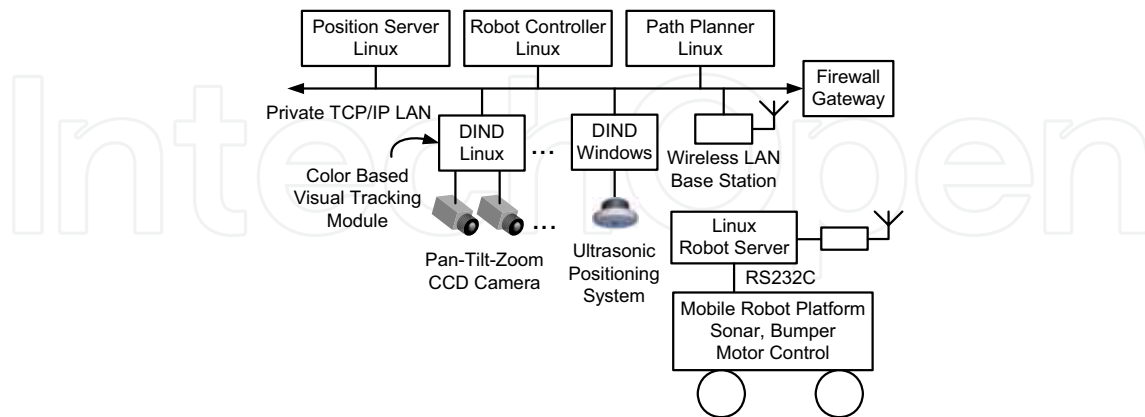


Figure 3. Implemented configuration

3. Observation of Human Walking for Mobile Robot Navigation

3.1 Proposed Method and Related Work

In this research, we focus on human observation for mobile robot navigation since moving through the space is one of the most basic functions for mobile robots. Related to this, some researchers have utilized human walking for mobile robot navigation and control.

In (Appenzeller, 1997), it was proposed that the area where human walks is also traversable for mobile robots and described a system that can generate topological maps for mobile robots by measuring the positions of people in iSpace. The same idea is found in (Tanaka et al., 2003) where mobile robot on-board sensors were used for observation. However, these maps are built based only on the positions of humans. This means that mobile robots can move along a safe path, but since the generated path doesn't reflect the human motion, robot's movement may interfere with humans'.

To the contrary, by avoiding the regions which have a high probability of the presence of people, a path which minimizes the expected travel time (sum of the travel time and the time needed for passing a person on the way) or probability of encountering people was generated in (Kruse & Wahl, 1998). However the authors utilized the observation result of the past and didn't take into account the current positions of people. As a result, mobile robots generate an inefficient path in case that no person exists between the start and the goal point. Furthermore, their motion may be unnatural for humans since the mobile robots move in the area where human doesn't walk. So, some researchers aim to navigate a mobile robot by predicting a future motion of currently tracked human from the history of the observed paths in the environment and changing the motion of the mobile robot only when it is needed (Bennewitz et al., 2005; Foka & Trahanias, 2002; Rennekamp et al., 2006; Vasquez et al., 2004). This approach is efficient because with the obtained path the mobile robots avoid unnecessary contact with people. However, these researches mainly focus on the prediction method and the initial path planning of the mobile robots in human-robot shared space isn't taken into account.

Therefore, in this paper, we consider the method for planning an efficient and natural path which is suitable for mobile robot navigation in a living environment based on observation of human walking.

When a person moves with purpose, the start and the goal point have meaning for the desired action and can be regarded as important points in the space. We also consider that paths frequently used by human are efficient and contain the “rules of the environment.” So, we extract important points from the observation and average the human walking paths between two important points to get frequently used paths. The averaged paths are utilized as paths of the mobile robots. By using the important point based paths, mobile robots can choose to explore the parts of space that are meaningful to humans. Furthermore, since such a path is similar to the human chosen path, it is especially useful for robotic guidance applications. By comparing currently observed paths and the frequently used paths, we can combine a motion generation method based on the prediction of the human walking.

3.2 Acquisition of Human Walking Paths

We use vision sensors for tracking so that humans don't have to carry any special devices, e.g. tags for ultrasound system. In the tracking process, the position and field of view of all cameras are fixed. The intrinsic and extrinsic camera parameters are calculated beforehand using a camera calibration method (e.g. (Tsai, 1987; Zhang, 2000)).

In each DIND, human tracking based on background subtraction and color histogram is performed, and the three dimensional position is reconstructed by stereo vision. Then the position information of humans is sent to the position server. The position server also synchronizes the actions of DINDs.

In the position server, fusion of information is done in order to acquire global information about the whole space. Each position sent from DINDs $(x_{\text{send}}, y_{\text{send}}, z_{\text{send}})$ is compared with positions stored on the server (x_i, y_i, z_i) , $(i=1, 2, \dots, n)$. Let $\sigma_x, \sigma_y, \sigma_z, a_x, a_y$ and a_z be positive constants. If the sent information satisfies

$$|x_{\text{send}} - x_i| < \sigma_x \text{ and } |y_{\text{send}} - y_i| < \sigma_y \text{ and } |z_{\text{send}} - z_i| < \sigma_z \quad (1)$$

the position information is set to the sent information which has the minimum value of

$$a_x (x_{\text{send}} - x_i)^2 + a_y (y_{\text{send}} - y_i)^2 + a_z (z_{\text{send}} - z_i)^2. \quad (2)$$

In case no stored information satisfies (1), it is recognized as a new object's information. Then the position server creates a new ID and stores the information. The ID assigned to the new tracked human is sent back to the DIND. After that, if the DIND can continue to track the human, the DIND sends the ID as well as position information to the position server. In this case, the position server identifies the object based on ID and (1), and doesn't search all information. If more than one DIND can observe the same human, the mean value is used to determine the position of the human.

To avoid increasing the number of objects stored on the server as time passes, the information of a human who is not detected for a certain period of time (5 seconds in this research) is erased.

A human walking path is generated by projecting the time-series data of a human to the x - y (ground) plane. However human often stays in the same place. Therefore, the tracking system has to determine if the human is walking or not because human never completely stops in such a situation.

In order to do this, we define the absolute value of the velocity in the x - y plane v_{xy} , and x and y components of the mean position $x_{\text{mean}}, y_{\text{mean}}$ in the past k steps:

$$v_{xy} = \frac{\sqrt{(x_{t_{\text{now}}} - x_{t_{\text{now}}-1})^2 + (y_{t_{\text{now}}} - y_{t_{\text{now}}-1})^2}}{\Delta t}, \quad (3)$$

$$\begin{aligned} x_{\text{mean}} &= \frac{1}{k} \sum_{t=t_{\text{now}}-k\Delta t}^{t_{\text{now}}} x_t, \\ y_{\text{mean}} &= \frac{1}{k} \sum_{t=t_{\text{now}}-k\Delta t}^{t_{\text{now}}} y_t \end{aligned}, \quad (4)$$

where Δt is the sampling rate, x_t and y_t is the position of human at time t in x and y components, respectively, and t_{now} is the current time. If v_{xy} is lower than a given threshold σ_v for k consecutive time steps, the system judges that the human is stationary at $(x_{\text{mean}}, y_{\text{mean}})$. Once the static condition is satisfied, the human is considered to stay there until he/she gets more than a certain distance σ_d away from $(x_{\text{mean}}, y_{\text{mean}})$.

3.3 Extraction of Frequently Used Paths

The extraction of frequently used paths from the obtained walking paths is done by three steps: 1) extraction of important points, 2) path clustering and 3) path averaging. The reason not to do path clustering directly but to extract important points at the beginning is that path clustering needs appropriate parameters to be set for every situation, which is more difficult than extraction of important points.

First, we explain the extraction of important points. In this research, we define important points as entry/exit points which are useful for mobile robots to move from one area to another, and stop points which are helpful when mobile robots approach humans to provide services. The entry/exit points are extracted based on the points where the tracking system finds new objects or loses objects. On the other hand, the stop points are extracted based on the points where the static condition (section 3.2) is satisfied. These candidates for entry/exit and stop points are grouped by hierarchical clustering and considered as important points if a cluster which consists of many points is formed. We use Euclidean distance in the x - y plane as measure of distance between the points. The clustering process is continued until the distance between clusters exceeds a certain value σ_c because it is hard to determine how many important points are in the environment.

In the next step, for all combinations of two important points, we consider paths which have these points for start and goal points. If there is more than one path that connects the two points path clustering is performed.

We use a hierarchical clustering method based on the LCSS (Longest Common Subsequence) similarity measure (S1 similarity function presented in (Vlachos et al., 2002)). There are several advantages in using this method. First, it can cope with trajectories which have different length, different sampling rates or different speeds. Second, it is robust to noise compared to Euclidean distance or DTW (Dynamic Time Warping) distance. Third, it can be calculated efficiently by using a dynamic programming algorithm.

Let A and B be two trajectories with n and m data points respectively, that is $A = ((a_{x,1}, a_{y,1}), \dots, (a_{x,n}, a_{y,n}))$, $B = ((b_{x,1}, b_{y,1}), \dots, (b_{x,m}, b_{y,m}))$. The LCSS models measure the similarity between A and B based on how many corresponding points are found in A and B . Similar to DTW method this model allows time stretching so the points which has close spatial position and the order in the path can be matched. The best match obtained under the

condition that the rearranging of the order of the points is prohibited is used for calculation of the similarity. This is formulated as follows. Let $Head(A)$ and $Head(B)$ be trajectories with $n-1$ and $m-1$ data points expressed as $Head(A) = ((a_{x,1}, a_{y,1}), \dots, (a_{x,n-1}, a_{y,n-1}))$, $Head(B) = ((b_{x,1}, b_{y,1}), \dots, (b_{x,m-1}, b_{y,m-1}))$. Given an integer δ (parameter of time stretching) and a real number ε (threshold for matching two values), $LCSS_{\delta,\varepsilon}(A, B)$ is defined as:

$$LCSS_{\delta,\varepsilon}(A, B) = \begin{cases} 0 & (A \text{ or } B \text{ is empty}) \\ 1 + LCSS_{\delta,\varepsilon}(Head(A), Head(B)) & (|a_{x,n} - b_{x,m}| < \varepsilon \text{ and } |a_{y,n} - b_{y,m}| < \varepsilon \text{ and } |n - m| \leq \delta) \\ \max(LCSS_{\delta,\varepsilon}(Head(A), B), LCSS_{\delta,\varepsilon}(A, Head(B))) & (\text{otherwise}) \end{cases} \quad (5)$$

The ratio of the number of corresponding point to the number of points in the shorter path is defined as the similarity. As the similarity has a value of 0 (dissimilar) to 1 (similar), the distance between A and B is defined as $1 - (\text{similarity})$. So a distance function $D(\delta, \varepsilon, A, B)$ is expressed as follows:

$$D(\delta, \varepsilon, A, B) = 1 - \frac{LCSS_{\delta,\varepsilon}(A, B)}{\min(n, m)}. \quad (6)$$

Using the distance function (6), clustering of paths can be performed.

Finally, clustered paths are averaged to extract frequently used paths in the environment. An averaged trajectory is derived from corresponding points between two trajectories, which can be obtained from the LCSS similarity measure. The middle point of corresponding points is used to acquire averaged paths.

4. Mobile Robot Navigation Based on Observation of Humans

4.1 Model of the Mobile Robot

We consider a two-wheeled mobile robot model shown in Fig. 4. Let $O-w_xw_y$ be the coordinate system fixed to iSpace (world coordinate system) and $C-R_xR_y$ be the coordinate system fixed to the mobile robot (robot coordinate system). The position and orientation of the mobile robot are denoted by (x, y, θ) in world coordinate system. The control inputs for the mobile robot are the translational velocity v and rotational velocity ω . Here, the kinematic model for the mobile robot is expressed as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix}. \quad (7)$$

In addition, two ultrasonic transmitters used with the ultrasonic positioning system are installed on the mobile robot. Their coordinates in the robot coordinate system are $(L_1, 0)$, $(-L_2, 0)$.

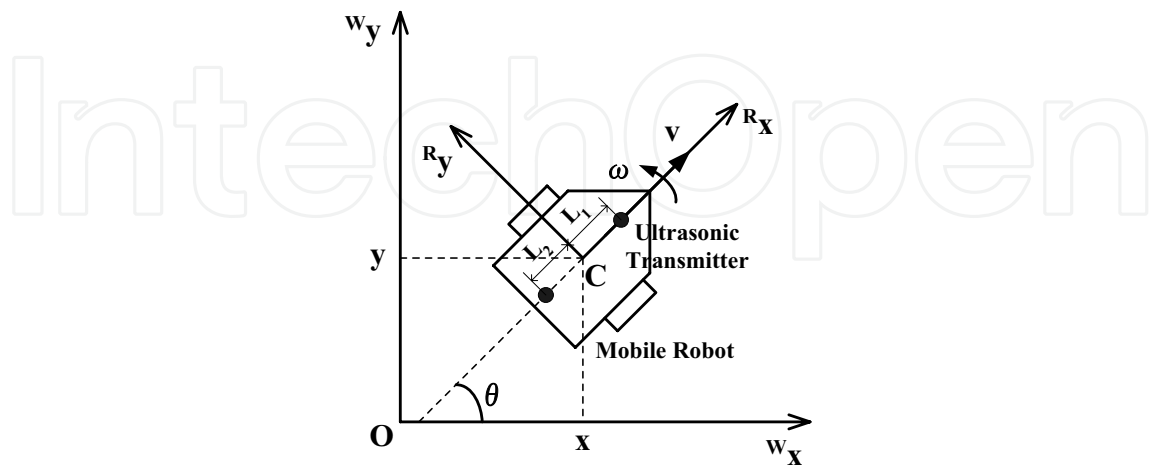


Figure 4. Model of a mobile robot

4.2 Navigation System

Fig. 5 shows the mobile robot navigation system. This system consists of the position server, the robot controller and the path planner. As shown in Fig. 3, each module is connected through the TCP/IP communication network. These modules are described below.

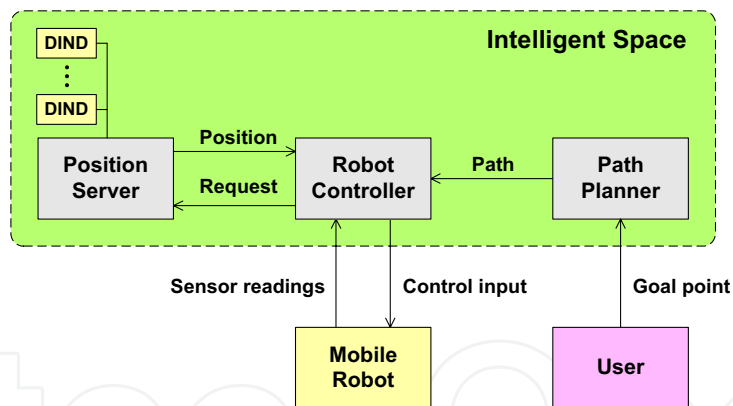


Figure 5. Navigation system

1. **Position Server:** The position server stores the position information of the mobile robot obtained by DINDs. Unlike in the case of human, ultrasonic transmitters can be installed on the mobile robot in advance. Therefore, the position of the mobile robot is measured by the 3D ultrasonic positioning system.
2. **Robot Controller:** The robot controller estimates the position and orientation of the mobile robot based on data from iSpace (3D ultrasonic positioning system) and mobile robot (wheel encoder). The dead reckoning method is frequently used to determine the position of the mobile robot. However, it has cumulative error because of slipping motion of wheels. On the other hand, localization using the 3D ultrasonic positioning

system shows high accuracy, but it suffers from errors, such as failure to receive the ultrasonic wave from the transmitter. So, those two measurement data are fused using EKF (Extended Kalman Filter) to minimize the position error.

In order to implement the EKF, the model of the system has to be developed. Discretizing (7), we obtain the following state equation:

$$\begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + v\Delta t \cos\theta_{k-1} \\ y_{k-1} + v\Delta t \sin\theta_{k-1} \\ \theta_{k-1} + \omega\Delta t \end{bmatrix} + \mathbf{W}_k w_k, \quad (8)$$

where x_k , y_k and θ_k denote position and orientation of the mobile robot at time k , Δt is the sampling rate, v and ω are the translational velocity and the rotational velocity obtained from encoders, respectively. See (Welch & Bishop, 1995) for other symbols.

The observation equation is expressed as follows:

$$\begin{bmatrix} x_{zps} \\ y_{zps} \end{bmatrix} = \begin{bmatrix} x_k + L\cos\theta_k \\ y_k + L\sin\theta_k \end{bmatrix} + \mathbf{V}_k v_k, \quad (9)$$

where (x_{zps}, y_{zps}) is the position of the ultrasonic transmitter in world coordinate system, and L equals L_1 or $-L_2$ depending whether the signal is from the front or rear transmitter.

Linearizing the state equation, Jacobian matrix \mathbf{A}_k is obtained:

$$\mathbf{A}_k = \begin{bmatrix} 1 & 0 & -v\Delta t \sin\theta_{k-1} \\ 0 & 1 & v\Delta t \cos\theta_{k-1} \\ 0 & 0 & 1 \end{bmatrix}. \quad (10)$$

We consider that the noise on the encoder is white noise with a normal distribution. Here, Jacobian matrix \mathbf{W}_k is expressed as follows:

$$\mathbf{W}_k = \begin{bmatrix} -\Delta t \cos\theta_{k-1} & 0 \\ -\Delta t \sin\theta_{k-1} & 0 \\ 0 & -\Delta t \end{bmatrix}. \quad (11)$$

From the observation equation, Jacobian matrix \mathbf{H}_k is

$$\mathbf{H}_k = \begin{bmatrix} 1 & 0 & -L\sin\theta_k \\ 0 & 1 & L\cos\theta_k \end{bmatrix}. \quad (12)$$

Jacobian matrix \mathbf{V}_k is determined as follows:

$$\mathbf{V}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}. \quad (13)$$

In this research, we assume the process noise covariance \mathbf{Q} and measurement noise covariance \mathbf{R} are constant and use diagonal matrices. The values are tuned experimentally.

In the beginning of the experiment, using the ultrasonic positioning system measurement data the initialization process is done:

$$\begin{bmatrix} x_1 \\ y_1 \\ \theta_1 \end{bmatrix} = \begin{bmatrix} \frac{L_2 x_{zps1} + L_1 x_{zps2}}{L_1 + L_2} \\ \frac{L_2 y_{zps1} + L_1 y_{zps2}}{L_1 + L_2} \\ \text{atan2}(y_{zps1} - y_{zps2}, x_{zps1} - x_{zps2}) \end{bmatrix}, \quad (14)$$

where (x_{zps1}, y_{zps1}) and (x_{zps2}, y_{zps2}) are the positions of the front and rear transmitters, and $\text{atan2}(\cdot)$ denotes the four-quadrant inverse tangent function. After that, estimation is done using the EKF equations.

In addition, the robot controller controls the mobile robot along the paths generated by the path planner. In this research, we use the control law based on the dynamic feedback linearization. The dynamic compensator is given by (See (Oriolo et al., 2002) in detail):

$$\begin{aligned} \dot{\xi} &= u_1 \cos \theta + u_2 \sin \theta \\ v &= \xi \\ \omega &= \frac{u_2 \cos \theta - u_1 \sin \theta}{\xi} \end{aligned} \quad (15)$$

Given a desired smooth trajectory $(x_d(t), y_d(t))$, u_1 and u_2 are given as follows:

$$\begin{aligned} u_1 &= \ddot{x}_d + k_{p1}(x_d - x) + k_{d1}(\dot{x}_d - \dot{x}) \\ u_2 &= \ddot{y}_d + k_{p2}(y_d - y) + k_{d2}(\dot{y}_d - \dot{y}) \end{aligned} \quad (16)$$

where k_{p1} , k_{p2} , k_{d1} and k_{d2} are positive constants.

3. Path Planner: The path planner generates the path which connects two important points. But the averaged path is not always suitable for mobile robots because it may consist of points aligned at irregular intervals or windingly. Therefore, the path planner extracts the significant points on the averaged path using the method shown in (Hwang et al., 2003) and interpolates them by cubic B-spline function.

5. Experiment

5.1 Experiment of Acquisition of Human Walking Paths

In the environment shown in Fig. 6, human walking paths are obtained. The observable area of each DIND on the ground plane is also shown in this figure. The arrangement of DIND is determined in order to make the observable region as large as possible.

Human walking paths obtained by the tracking system are shown in Fig. 7. We set the parameters in (1) and (2) to $\sigma_x = \sigma_y = 0.3\text{m}$, $\sigma_z = 0.5\text{m}$, $a_x = a_y = 1$ and $a_z = 0.25$. The objects that were observed outside of the experimental environment or vanished within 1 second since their appearance were ignored as noises. The parameters to determine the stop state are defined

by $\sigma_v=0.3\text{m/s}$, $k=20$ and $\sigma_d=0.5\text{m}$. This figure also shows some broken paths at the edges of the environment. These results were influenced by the observable region of DIND.

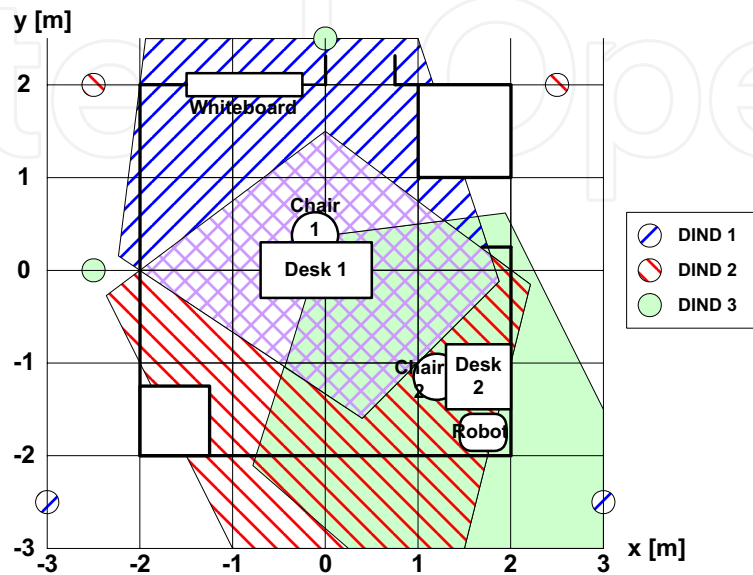


Figure 6. Experimental environment



Figure 7. Obtained human walking paths

5.2 Experiment of Extraction of Frequently Used Paths

First of all, important points are extracted to obtain frequently used paths. Important points are defined by clusters including the points over 15% of the total at $\sigma_c=0.5\text{m}$ in both cases of

entry/exit points and stop points. In addition, the distance between clusters is updated by using the centroid method. Fig. 8 and Fig. 9 show the results of clustering. In these figures, the clusters extracted as important points are indicated with ellipses.

In either case, the clusters that consisted of more than 30% of the total number of points were formed and important points were extracted. However, there were some points around Desk 1 that appeared as candidates for entry/exit points because of tracking interrupts. The results were caused by unobservable occlusions because the flow of people behind the Desk 1 was very intense. In order to solve the problem, in our future work entry/exit points will not be determined by extraction based on clustering but preset based on configuration of the space.

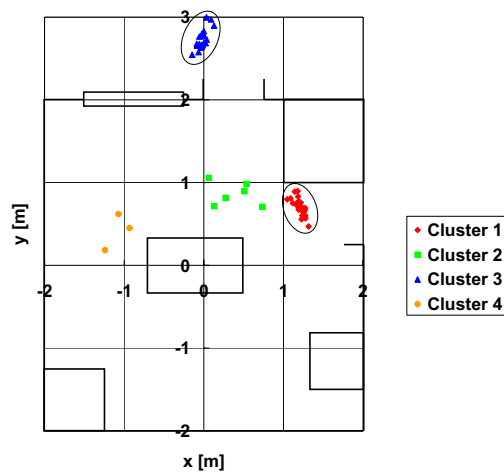


Figure 8. Extraction of entry/exit points

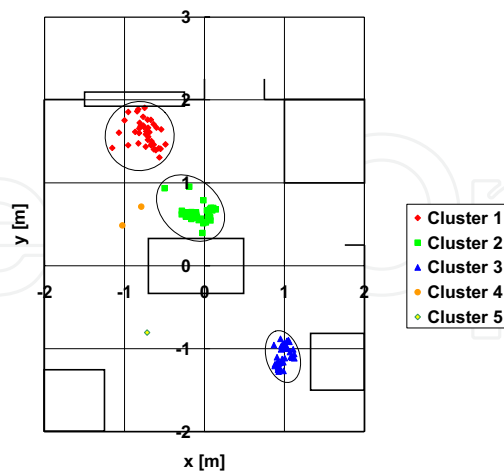


Figure 9. Extraction of stop points

After the extraction of important points, the walking paths between important points are clustered and averaged. Clustering parameters are defined by $\delta=10$, $\epsilon=0.3$ in every case and the process is continued until the minimum distance between clusters is over 0.4. Moreover, the distance between clusters is recalculated using the furthest neighbor method.

Fig. 10 (left) shows the result of averaging for the path from the important point around Desk 2, as shown in Cluster 3 of Fig. 9, to the entry/exit as shown in Cluster 3 in the upper part of Fig. 8. Five walking paths are obtained and the averaged path is positioned approximately in the center of them. On the other hand, Fig. 10 (right) shows the result of averaging for the path from the important point around the whiteboard as shown in Cluster 1 of Fig. 9 to the important point around Desk 2 as shown in Cluster 3 of Fig. 9, respectively. Nine walking paths are acquired and two paths are obtained by averaging. If the paths were calculated using the mean value, the obtained path would be located in the center of them, which means it would collide with Desk 1. The proposed method distinguishes the whole paths by using path clustering so that it is able to average clustered paths independently.

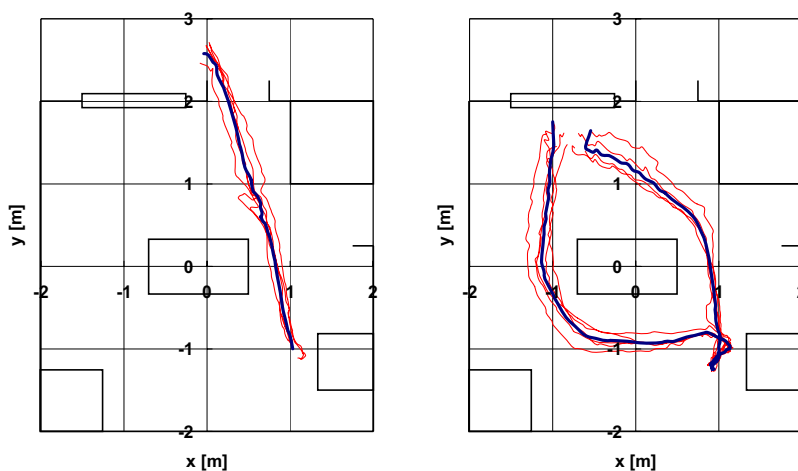


Figure 10. Examples of averaging

Fig. 11 shows all the averaged paths. We can observe that paths between important points were obtained. Moreover, between almost every pair of important points two similar paths were obtained. Pairs of paths were obtained because the direction in which the humans walked was taken into account. By including the direction information, some important details about the environment can be extracted, e.g. the robot should keep to the right side here, this street is one-way, etc.

5.3 Experiment of Mobile Robot Navigation

In this experiment, the mobile robot moves from the entry/exit as shown in Cluster 1 in the right part of Fig. 8 to the entry/exit as shown in Cluster 3 in the upper part of Fig. 8 through important point around whiteboard (Cluster 1 in Fig. 9) and important point around Desk 2 (Cluster 3 in Fig. 9). The experimental result is shown in Fig. 12. The mobile robot followed the paths generated by the path planner and reached the goal point successfully.

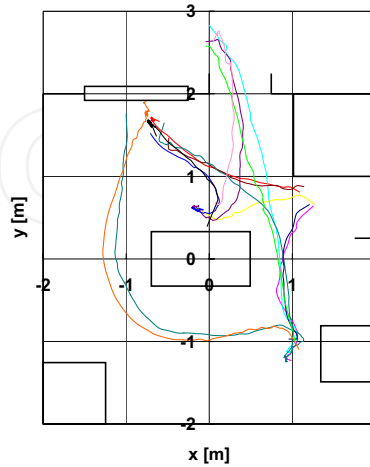


Figure 11. Averaged walking paths

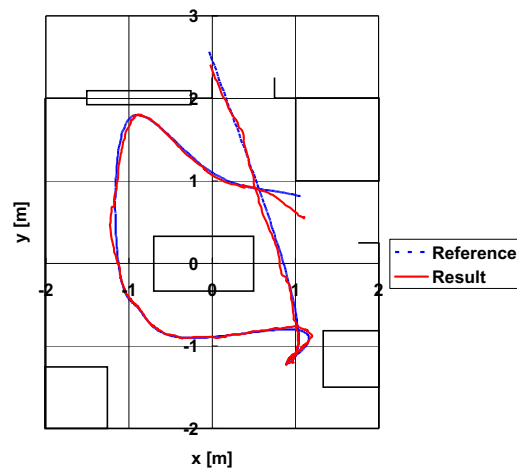


Figure 12. Result of the mobile robot navigation

6. Conclusion

In this paper, we propose that environmental design for mobile robots and human observation are important tasks to develop robots for daily life, and that utilization of many intelligent devices embedded in the environment can realize both of these tasks. As an illustration, we investigate a mobile robot navigation system which can localize the mobile robot correctly and navigate based on observation of human walking in order to operate in the human shared space with minimal disturbance to humans. The human walking paths are obtained from a distributed vision system and frequently used paths in the environment are extracted. The mobile robot navigation based on observation of human is also performed with the support of the system. The position and orientation of the mobile robot are estimated from wheel encoder and 3D ultrasonic positioning system measurement data

using extended Kalman filter. The system navigates the mobile robot along the frequently used paths by tracking control.

For future work, we will develop a path replanning and speed adjustment method based on the current positions of the people. Furthermore, we will apply iSpace to a larger area. Another research direction is to expand this framework into other applications such as human-robot communication, object manipulation and so on. In this paper, the mobile robot doesn't have any external sensors and it is fully controlled by the space. But an intelligent mobile robot can carry out observation and provide iSpace with additional information. This means it behaves as a mobile sensor as well as an actuator. Cooperation between mobile robots and iSpace should also be considered to get more detailed information about human and environment.

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Human-robot interaction research is diverse and covers a wide range of topics. All aspects of human factors and robotics are within the purview of HRI research so far as they provide insight into how to improve our understanding in developing effective tools, protocols, and systems to enhance HRI. For example, a significant research effort is being devoted to designing human-robot interface that makes it easier for the people to interact with robots. HRI is an extremely active research field where new and important work is being published at a fast pace. It is neither possible nor is it our intention to cover every important work in this important research field in one volume. However, we believe that HRI as a research field has matured enough to merit a compilation of the outstanding work in the field in the form of a book. This book, which presents outstanding work from the leading HRI researchers covering a wide spectrum of topics, is an effort to capture and present some of the important contributions in HRI in one volume. We hope that this book will benefit both experts and novice and provide a thorough understanding of the exciting field of HRI.

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