International Journal of Fuzzy Logic and Intelligent Systems, vol. 4, no. 1, June 2004 pp. 101-110

On Motion Planning for Human-Following of Mobile Robot in a Predictable Intelligent Space

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Abstract

The robots that will be needed in the near future are human-friendly robots that are able to coexist with humans and support humans effectively. To realize this, humans and robots need to be in close proximity to each other as much as possible. Moreover, it is necessary for their interactions to occur naturally. It is desirable for a robot to carry out human following, as one of the human-affinitive movements. The human-following robot requires several techniques: the recognition of the moving objects, the feature extraction and visual tracking, and the trajectory generation for following a human stably.

In this research, a predictable intelligent space is used in order to achieve these goals. An intelligent space is a 3-D environment in which many sensors and intelligent devices are distributed. Mobile robots exist in this space as physical agents providing humans with services. A mobile robot is controlled to follow a walking human using distributed intelligent sensors as stably and precisely as possible. The moving objects is assumed to be a point-object and projected onto an image plane to form a geometrical constraint equation that provides position data of the object based on the kinematics of the intelligent space. Uncertainties in the position estimation caused by the point-object assumption are compensated using the Kalman filter. To generate the shortest time trajectory to follow the walking human, the linear and angular velocities are estimated and utilized. The computer simulation and experimental results of estimating and following of the walking human with the mobile robot are presented.

Key Words : Mobile robot, distributed sensors, intelligent space, CCD camera, estimating & following

I. Introduction

IN RECENT years, the research field on the intelligent environment has been expanding [1, 2]. An intelligent Environment is the space where many intelligent devices, such as computers and sensors, are distributed. According to the cooperation of many intelligent devices, the environment comes to have intelligence. The environment supports human, who exists in the intelligent environment, physically and informationally, so that he can use advanced computers and complicated mechanical system without feeling the stress. In order for humans and robots to coexist and to perform a certain amount of cooperative work, robots and humans have to interact closely. The human-following robot in this research is a method of maintaining a certain relative positional relationship between the human and the robot. The following are examples of the sorts of services that human-following mobile robots are able to provide. The robot can carry loads that are required by people working in hospitals, airports, etc. The robot can work as an assistant for humans in various situations. Moreover, since such a robot always accompanies a human, the robot is able to easily acquire detailed information associated with target people. It has been reported that the approach of a human and a mobile robot leads to mutual interactions [1, 2]. Reference [3] describes a mobile robot which always faces and follows human acts as an assistant robot.

This robot is aimed at guiding a wheelchair in a hospital or a station and has the ability to estimate the position and velocity of humans and to avoid obstacles. In [4], four-legged mobile robots for following humans were considered. However, these studies only addressed the problem of how to follow humans, not how to detect the presence of humans. They developed their studies on the premise that human detection is possible. Some technology which includes the recognition of humans, a position estimation technique for a mobile robot and humans, and a control strategy for following humans who are walking in a stable way, is required in order to realize robot"human-following behavior. In order to recognize humans, most human-following robots are mounted with many sensors, such as charge-coupled device (CCD) cameras, ultrasonic sensors, etc. These sensors detect the relative position from the mobile robot to the target human. The mobile robot in [1] recognizes a human's skin color using a CCD camera, and traces the target human by combining pan-tilt control of a CCD camera. In addition to the vision sensor, a voice recognition sensor and LED sensors are mounted in the mobile robot [5, 6], and is able to follow humans in an outdoor environment. Most of the proposed human-following robots burden the target human with special equipment. It is very difficult for a mobile robot to continue following a human in the shortest path and time while avoiding other obstacles, without missing the target while walking at a natural speed, since the stand-alone robot has limitations in terms of recognition performance.

Manuscrip received Apr. 27, 2004 revised Jun. 3, 2004

This work was supported by the Post-doctoral Fellowship Program of Korea Science & Engineering Foundation (KOSEF).

In this research, an intelligent environment is used in order to solve these problems. A mobile robot cooperates with multiple intelligent sensors, which are distributed in the environment. The distributed sensors recognize the walking human and the mobile robot, and give control commands to the robot in order to follow walking human in the shortest time path. The mobile robot receives the necessary support for human-following control from the environmental sensors. We aim to achieve a human-following robot without applying any burden to the human with a mobile robot that is simple in structure. We propose predictable intelligent space (ISpace) as an intelligent environment with many intelligent sensors to estimate the shortest path and time, and are building an environment where humans and mobile robots can now coexist. The human-following robot of this research is one of the physical agents for human support in ISpace.

2. Human-Following Robot in ISpace

2.1 Structure of ISpace

ISpace [7] is a space where many intelligent devices are distributed throughout the whole of the space, as shown in Fig. 1.

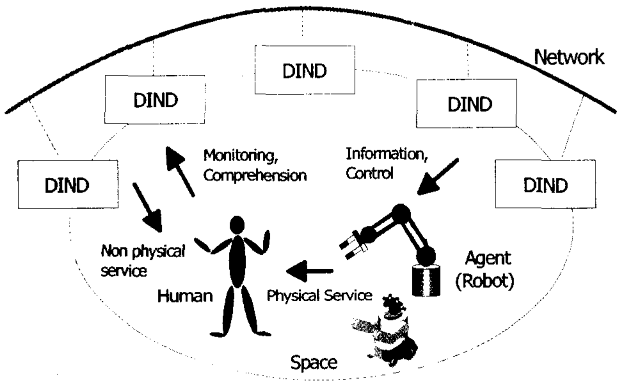


Fig. 1. Structure of Intelligent space.

These intelligent devices have sensing, processing and networking functions, and are named distributed intelligent networked devices (DINDs). These devices observe the positions and behavior of both humans and robots coexisting in the ISpace. The information acquired by each DIND is shared among the DINDs through the network communication system. Based on the accumulated information, the environment as a system is able to understand the intention of humans. For supporting humans, the environment/system utilizes machines including computers and robots.

Up until now, the position estimation of human and mobile robots [8], human behavior recognition [9], and mobile robot control under ISpace [10, 11] have been studied. These are the basic functions of space information understanding and human support by robots. One DIND consists of a CCD camera for acquiring space information, and a processing computer which has the functions of data processing and network interfacing. It becomes easy to install new technology as a new module to the ISpace if the protocol and data structure between the DINDs and modules are decided in advance. In an intelligent space, this enable the achievement of a flexible system based on this feature. The human-following robot introduced in this paper is a new module for ISpace, as it is one of the applications located in a level higher than the mobile robot position estimation module.

2.2 Human-FollowingBasic Concept in ISpace

In this section, the basic concepts for the human-following robot in ISpace are described. A new scheme for a mobile robot to estimate and follow walking human using images of cameras in ISpace is proposed. The position of a walking human and a mobile robot was estimated respectively using the kinematics of camera adopted as the sensor in ISpace and images of the objects, walking human and mobile robot, assuming that it is flat and small on the floor.

The linear and angular velocities of the walking human were estimated for the human-following robot to predict the future trajectory of the human, which plans the shortest time path to estimate and follow the walking human. A state estimator was designed to overcome the uncertainties from the image data caused by the point-object assumption and physical noises, using a Kalman filter. Based on the estimated velocities of the human, the pose of the human-following robot was controlled to follow a walking human on the center of the image frame.

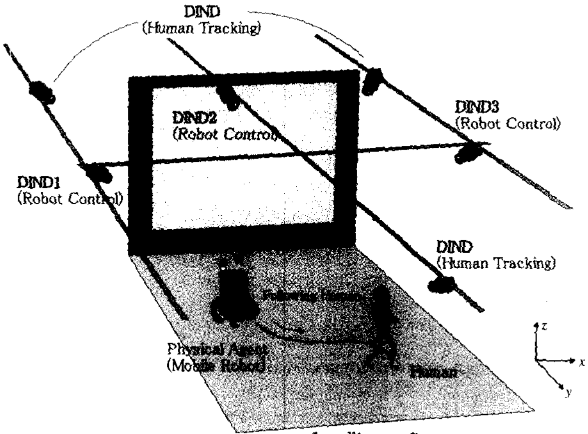
3. Configuration of the ISpace

In ISpace, the CCD camera is adopted as the sensor for DINDs, and the tracking of target objects, walking human and mobile robot, is performed. There are two advantages in using CCD cameras. One is that the position measurement of the targets is a noncontact method. The other is that the human doesn't have to carry any special devices for the DINDs to be able to measure his position. This section describes the configuration of the tracking system and a mobile robot in ISpace.

3.1 Tracking System

Currently, our laboratory room, which is about 7 m in both width and depth, is used for the ISpace. The ISpace has a mobile robot as a human-following agent, six DINDs which can obtain the situation in the environment, and a projector and a screen which present suitable information to the human. Each module is connected through the network communication.

Three DINDs are used in order to recognize the mobile robot and to generate the control commands. The other three DINDs are used to recognize the position of the human. DINDs are placed as shown in Fig. 2(a). Fig. 2(b) is a picture of the actual ISpace. The placement of the three DINDs for human recognition is optimized to expand the viewable area of the cameras [12] so that the head and hands of the human can be recognized over a wide area. On the other hand, the placement of DINDs for the mobile robot has to be decided by trial and error. It is desirable that the DINDs for the mobile robot recognize the whole of the area covered by three DINDs for human recognition in order to achieve the human-following system and reliable mobile robot control. Thus, three DINDs are placed so that the area for human recognition is completely covered. Human walking information is extracted by background subtraction and by detecting the skin color of a face and hands on captured images. A threedimensional (3-D) position is reconstructed by stereo vision using two cameras.



(a)

(b)

Fig. 2. Experimental environment.

In the coordinate system of the ISpace, the axis is parallel to the screen, the axis is perpendicular to it, and the axis follows the right-hand system. Each DIND measures 3-D positions, which are based on this coordinate system.

3.2 Mobile Robot in the ISpace

In this research, a differential wheel velocity-type mobile robot is used for the human-following robot. Since the DINDs take charge of the sensing and processing in ISpace, the mobile robots do not need any special functions nor devices, except for an ability to move and a wireless network device to allow for communication with the DINDs. Moreover, since this type of robot has a simple and compact structure, it is suitable for a physical agent that has to interact with humans in complicated environments. Our mobile robot is based on the Pioneer2-DX by ActivMedia Robotics [13].

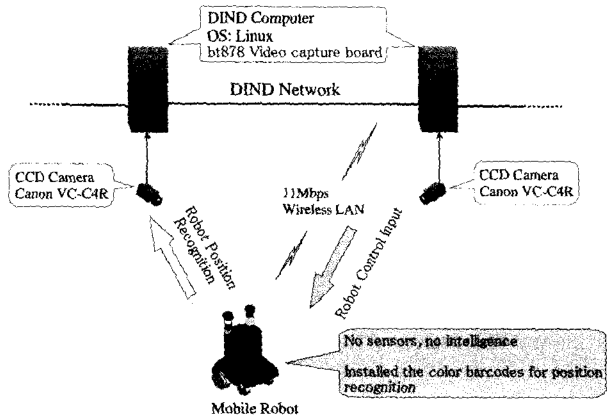


Fig. 3. Mobile robot in ISpace.

This mobile robot is connected to the DIND network via wireless LAN, as shown in Fig. 3, and shares the resources of the DIND's. For recognizing the position of the robot, one color panels are installed around the mobile robot. The pattern of the color panel is recognized by the DIND and it estimates the posture and position of the robot by kinematics of robot projected onto an image plane. Since the height of the mobile robot is already known, the position of a mobile robot is reconstructed from one camera image.

4. Mobile Robot Control for Trajectory Generation

4.1 Tracking Control

In order to follow a human, tracking control is performed. Many studies have been performed in the field of the tracking control. However, the trajectory which a mobile robot tracks is limited in most cases to continuous and smooth ones. A human following robot should be able to track actual human walking trajectories, including abrupt changes in velocity and direction. Therefore, stable tracking may not be achieved when conventional tracking control is used. A special control method for the mobile robot to follow humans is required.

In the control of a nonholonomic mobile robot, Brockett's theorem proved that a smooth state feedback law for an asymptotically stable to one point of the state space does not exist [15]. However, it is necessary to construct a closed-loop control system in which the error between the reference point and the state vector of a mobile robot should become zero for the tracking control of a mobile robot. In recent years, various closed-loop control systems which can overcome the feedback stabilization impossibility of Brockett's theorem, have been proposed. Reference [16] proposed piecewise-continuous controllers which neglect the "smoothness" and [17] proposed tracking control in which a mobile robot follows the trajectory planned as a function of time. These techniques are very effective in tracking control.

In ISpace, since a human walking trajectory is newly generated in every step, it can be considered that it is a function of time. Therefore, the application of tracking control is effective. However, although the target trajectory of a mobile robot is continuous and smooth in the usual tracking control, a human-following robot tracks the actual human walking trajectory that is generally unstable. Stable human following may not be achieved when the usual tracking control is used. In the following subsection, a tracking control method in ISpace for following humans is proposed.

4.2 Design of Human-Following Control

Fig. 4. shows a human's walking velocity actually measured by ISpace. The estimated human position data by DIND is not the proper control input required for a mobile robot to follow a human since estimated position data contains errors in the form of calibration error and image processing error. When the heads of humans are measured by vision sensors in a short sampling period, their velocity and direction also change drastically.

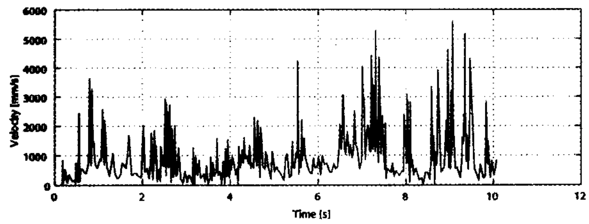


Fig. 4. Human walking as measured by ISpace.

Both the estimated position of humans and human walking action are unstable. The direction and velocity of human walking sometimes changes suddenly and unpredictably. In this case, the mobile robot may fail to follow the human and lose the stable movement by a sudden change in the velocity input. When conventional control law is used, which is derived only from the distance between the human and the mobile robot, it is considered that a mobile robot cannot follow the human. In order to solve such problems, a special control method for human following is required.

4.3 Kinematics of the camera system and Coordinates

The camera system in ISpace has the ability of panning and tilting, as shown in Fig. 5. The position and posture of the camera are defined with respect to the base frame. According to the Denavit- Hartenberg convention, the homogeneous matrix can be obtained after establishing the coordinate system and representing parameters and an attitude vector of the homogeneous matrix represents Roll(θ_R), Pitch (θ_P) and Yaw(θ_Y) angles by tilting and panning angles of the camera as [18].

To measure the distance from a camera to objects using the camera images, at least two image frames that are captured for the same object at different locations, are necessary. Usually a stereo-camera system has been used to obtain the distance information [19]. However there exist uncertainties in feature point matching and it takes too much time to be implemented in real-time. This approach requires only a frame to measure the distance to the object from the CCD camera. Since the approach becomes possible by assuming that a point-object is located on the floor, there also exist uncertainties in the position estimation. To minimize the uncertainty in the position estimation and to estimate the velocities of the moving object together, a state estimator is designed based on the Kalman filter. The image coordinates for the point object, (j, k), is transformed to the image center coordinates which is orientation invariant in terms of the Roll angle, θ_R in [18], and the size of the image frame, P_x and P_y, (j', k'):

$$\begin{bmatrix} j' \\ y' \end{bmatrix} = \begin{bmatrix} \cos(\theta_R) & -\sin(\theta_R) \\ \sin(\theta_R) & \cos(\theta_R) \end{bmatrix} \begin{bmatrix} j-\dfrac{P_x}{2} \\ k-\dfrac{P_y}{2} \end{bmatrix} \tag{1}$$

where P_x and P_y represent x and y directional size of the image frame in pixels, respectively.

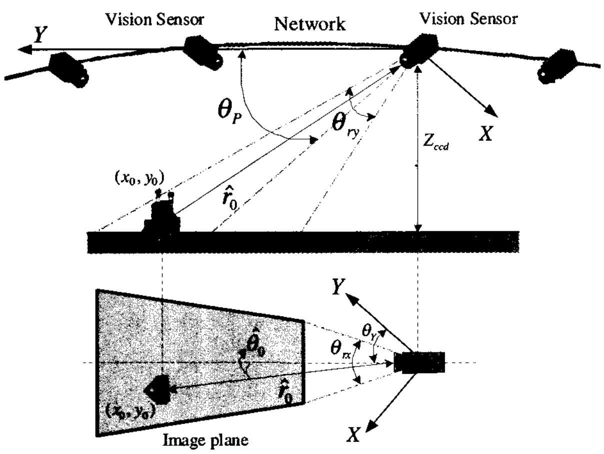


Fig. 5. Estimation of position information, $\hat{r}_0$(upper figure), $\hat{\theta}_0$(lower one).

To estimate the real location, (x_0, y_0), $\hat{\theta}_0$ and $\hat{r}_0$ are estimated using the linear relationship between the real object range within the view angle and the image frame. That is, for a given set of ($\hat{\theta}_0$, $\hat{r}_0$), there is one-to-one correspondence between the real object point and the image point. When a point image is captured at (j', k') on the image center frame, the real object position, $\hat{\theta}_0$ and $\hat{r}_0$, can be estimated as follows, as it is illustrated in Fig. 5:

$$\hat{r}_0 = \frac{z_{ccd}}{\cos\left(\frac{\pi}{2} - \theta_P + \frac{k'}{P_y}\theta_{ry}\right)} \tag{2}$$

$$\hat{\theta}_0 = \frac{j'}{P_x}\theta_{rx} \tag{3}$$

where θ_{rx} and θ_{ry} represent the x and y directional view angles of the CCD camera, respectively. When (j, k) is a image coordinate for the point object, (j', k') is a image coordinate transformed to the image center coordinate. The position of the object with respect to the robot coordinates, (x, y) can be estimated using the $\hat{\theta}_0$ and $\hat{r}_0$ [20] as follows:

$$\hat{x}_0 = r_{ccd}\cos(\theta_Y) + \hat{r}_0\cos(\theta_Y + \hat{\theta}_0) \tag{4}$$

$$\hat{y}_0 = r_{ccd}\sin(\theta_Y) + \hat{r}_0\sin(\theta_Y + \hat{\theta}_0) \tag{5}$$

where θ_Y represents the angle between the mobile robot and the camera of DINDs.

5. Trajectory Estimation of a Walking Human

5.1 Modeling of a walking human

When the velocity and acceleration of the walking human and mobile robot can be estimated respectively, the next human position $\hat{T}_x, \hat{T}_y$ can be predicted as follows [21]:

$$T_{x+\delta t} = \hat{T}_x + \hat{V}_x\delta t + \frac{1}{2}\hat{A}_x\delta t^2 \tag{6}$$

$$T_{y+\delta t} = \hat{T}_y + \hat{V}_y\delta t + \frac{1}{2}\hat{A}_y\delta t^2 \tag{7}$$

where δt is the sampling time, and $(\hat{T}_x, \hat{T}_y)$, $(\hat{V}_x, \hat{V}_y)$ and $(\hat{A}_x, \hat{A}_y)$ are the current Cartesian coordinate estimates of the human position, velocity and acceleration respectively.

In the X-Y coordinates, movement of the object can be decomposed into the linear velocity element and the angular velocity element, as follows [22]:

$$\begin{aligned}\delta x_{k+\delta t,k} &= v_k\delta t\cos(\theta_k + 1/2\,\omega_k\delta t)\\ &\approx v_k\cos(\theta_k)\delta t - 1/2\omega_k v_k\sin(\theta_k)\delta t^2\end{aligned} \tag{8}$$

$$\begin{aligned}\delta y_{k+\delta t,k} &= v_k\delta t\sin(\theta_k + 1/2\,\omega_k\delta t)\\ &\approx v_k\sin(\theta_k)\delta t + 1/2\omega_k v_k\cos(\theta_k)\delta t^2\end{aligned} \tag{9}$$

$$\delta\theta_{k+\delta t,k} = \omega_k\delta t \tag{10}$$

$$\delta v_{k+\delta t,k} = \zeta_v \tag{11}$$

$$\delta\omega_{k+\delta t,k} = \zeta_\omega \tag{12}$$

where v_k and w_k are linear velocity and angular velocities of the objects, and w_k and ξ_w are the variations of linear velocity and angular velocity, respectively.

From (8)-(12), we can obtain the state transition matrix, as follows:

$$\begin{aligned}\mathrm{x}_k &= \Phi_{k,k-1}\,\mathrm{x}_{k-1} + \mathrm{w}_{k-1}\\ Z_k &= H_k\,\mathrm{x}_k + \mathrm{v}_k\end{aligned} \tag{13}$$

where

$$\mathrm{x}_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \\ v_k \\ \omega_k \end{bmatrix},\ \Phi_{k,k-1} = \begin{bmatrix} 1 & 0 & 0 & \delta t\cos(\theta_{k-1}) & -\frac{1}{2}v_{k-1}\delta t^2\sin(\theta_{k-1}) \\ 0 & 1 & 0 & \delta t\sin(\theta_{k-1}) & \frac{1}{2}v_{k-1}\delta t^2\cos(\theta_{k-1}) \\ 0 & 0 & 1 & 0 & \delta t \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$Z_k = \begin{bmatrix} x_k \\ y_k \end{bmatrix},\ H_k = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix},\ \mathrm{v}_k = \begin{bmatrix} \gamma_x \\ \gamma_y \end{bmatrix},$$ and

$$\mathrm{w}_{k-1} = [0\ 0\ 0\ \xi_v\ \xi_\omega]^T$$

Notice that Φ_k is the state transition matrix, w_k is the vector representing process noise, Z_k is the measurement vector, H_k represents the relationship between the measurement and the state vector, and γ_x and γ_y are x and y directional measurement errors, respectively.

5.2 State estimation of a walking human based on a Kalman filter

Input data such as image information include uncertainties and noises generated during the data capturing and processing steps. And the state transition of a moving object also includes irregular components. Therefore as a robust state estimator against these irregularities, a Kalman filter was adopted to form a state observer [18, 23-25]. The Kalman filter minimizes the estimation error by modifying the state transition model based on the error between the estimated vectors and the measured vectors, with an appropriate filer gain. The state vector which consists of position on the x-y plane, linear/angular velocities, and linear/angular accelerations can be estimated using the measured vectors representing the position of a moving object on the image plane.

The covariance matrix of estimated error must be calculated to determine the filter gain. The projected estimate of the covariance matrix of estimated error is represented as

$$P'_k = \Phi_{k,k-1}P_{k-1}\Phi_k^T + Q_{k-1} \tag{14}$$

where P'_k is a zero-mean covariance matrix representing the prediction error, Φ_k represents system noise, P_{k-1} is an error covariance matrix for the previous step, and Q_{k-1} represents other measurement and computational errors.

The optimal filter gain K_k that minimizes the errors associated with the updated estimate is

$$K_k = P'_k H_k^T[H_k P'_k H_k^T + R_k]^{-1} \tag{15}$$

where H_k is the observation matrix and R_k is the zero-mean covariance matrix of the measurement noise.

The estimate of the state vector $\hat{x}_k$ from the measurement Z_k is expressed as

$$\hat{x}_k = \Phi_{k,k-1}\hat{x}_{k-1} + K_k[Z_k - H_k\Phi_{k,k-1}\hat{x}_{k-1}]. \tag{16}$$

Therefore, $\hat{x}_k$ is updated based on the new values provided by Z_k. The error covariance matrix that will be used for the prediction, P_k, can be updated as follows [26, 27];

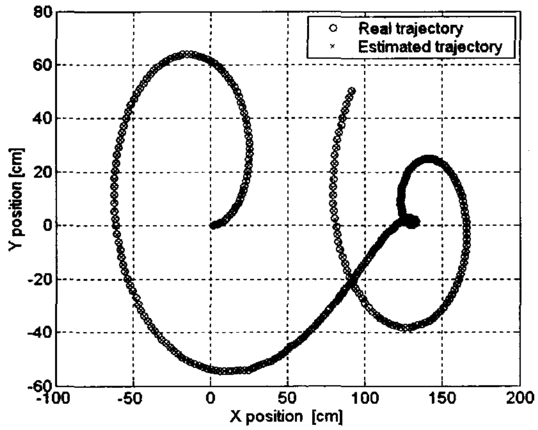
$$P_k = P'_k - K_k H_k P'_k \tag{17}$$

After the current time is updated to $k+1$, a new estimation can be provided using Eqs. (14) to (17). Fig. 6(a) represents a real and an estimated trajectory of a moving object, while Fig. 6(b) represents the estimation |error| when the trajectory was estimated by the Kalman filter.

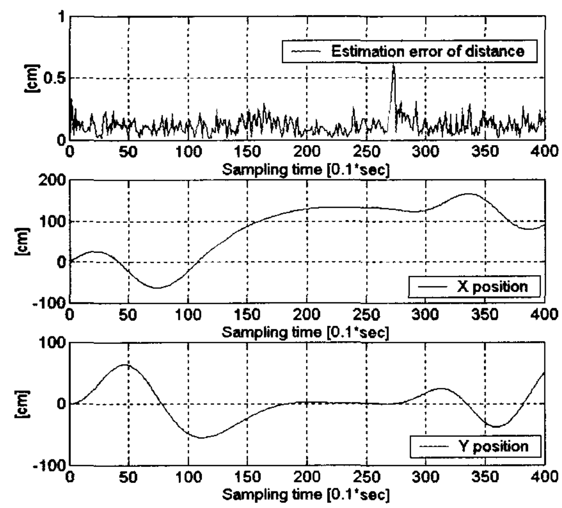
To incorporate the measurement noise which is empirically assumed to be zero-mean, Gaussian random noise with the variance of 2, the linear and angular velocities of the object were set as follows:

$$\begin{aligned} v_k &= 15(\sin(0.02\times k)+1)+\xi_v \\ w_k &= 0.7\cos(0.01\times k)+\xi_w \end{aligned} \tag{18}$$

where the linear and angular velocities (ξ_v, ξ_w) were assumed to include the Gaussian random noise with the variance of 3 and 0.1, respectively. Fig. 7 shows that the Kalman filter estimation of the states under a noisy environment.



(a) Trajectory of walking human.



(b) Estimation error along the trajectory.
Fig. 6. State estimations using a Kalman filter.

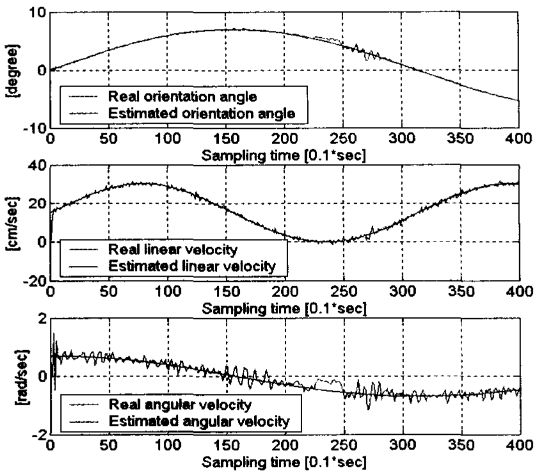


Fig. 7. State estimations, θ_k, v_k, and ω_k, using a Kalman filter.

5.3 Trajectory estimation of a Walking Human

The states of a moving object can be estimated if the initial state and input are given for the state transition model. Therefore, the states can be estimated for the next inputs by estimating the linear velocity and angular velocity of the moving object using the Kalman filter as a state estimator. From the linear velocity/acceleration and rotational angular velocity/acceleration data, the next states can be approximated, as in the following first order equations:

$$v_{k+n} = \widehat{v}_k + \widehat{a}_{lk} nT \tag{19}$$

$$\omega_{k+n} = \hat{a}_{\omega k} nT \tag{20}$$

In Fig. 7, the result includes possible noise since it is a dynamically varying system, although it is surpressed by the Kalman filter. Therefore the least square estimation method is utilized, which has robust anti-noise characteristics [28].

$$\widehat{E} = (A^T A)^{-1} A^T y \tag{21}$$

where $E = \begin{bmatrix} \widehat{v}_k & \widehat{\omega}_k \\ \widehat{a}_{lk} & \widehat{a}_{\omega k} \end{bmatrix} A = \begin{bmatrix} 1 & -T \\ 1 & -2T \\ \vdots & \vdots \\ 1 & -mT \end{bmatrix}$, and $y = \begin{bmatrix} v_{k-1} & \omega_{k-1} \\ v_{k-2} & \omega_{k-2} \\ \vdots & \vdots \\ v_{k-m} & \omega_{k-m} \end{bmatrix}$.

From the estimated inputs and using the state transition model, the trajectory of a moving object can be estimated as follows:

$$\hat{x}_{k+m} = x_k + \sum_{h=0}^{m} v(h)\cos[\theta(h)]T \tag{22}$$

$$\hat{y}_{k+m} = y_k + \sum_{h=0}^{m} v(h)\cos[\theta(h)]T \tag{23}$$

$$v(h) = \widehat{a}_k + \hat{a}_{lk} hT \tag{24}$$

$$\theta(h) = \widehat{\theta}_k + \widehat{\omega}_k hT + \frac{1}{2}\hat{a}_{\omega k} hT^2. \tag{25}$$

6. Motion Planning for Human-Following

To follow a walking human, the mobile robot needs to be controlled by considering the relation between the position of the mobile robot and the position of the walking human. Fig. 8shows the motion planning process of a mobile robot for following a walking human.

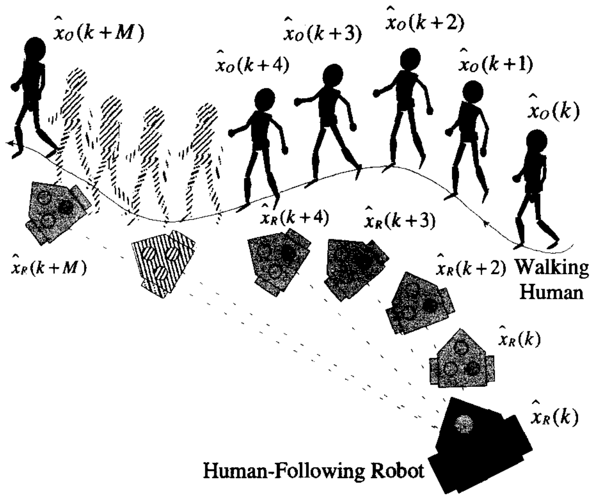


Fig. 8. Estimation of the trajectory for Human- following.

Each DIND computer system estimates the position of the moving object within m sampling time and selects the shortest distance from its current position to the walking human, assuming the its location is known a priori. The localization scheme of the mobile robot using the information on the walking human, which improves the accuracy in capturing, is developed in [18]. The target point of the mobile robot at k-th sampling time is denoted as $\hat{x}_R(k+m)$ which is one of the estimated points of the mobile robot after m sampling time.

$$\hat{x}_R(k+m_{opt}) = \min_{m=1-m} \|\hat{x}_O(k+m) + \hat{x}_R(k+m)\| \quad (26)$$

where $\hat{x}_R(k+m)$ is the position of the mobile robot after m sampling time, and the mobile robot moves along the shortest path towards the target point $\hat{x}_0(k+m)$.

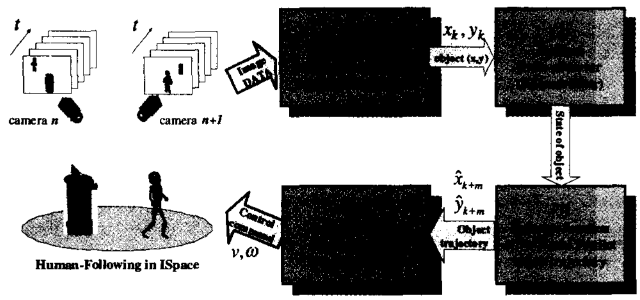


Fig. 9. Mobile robot control for estimating and following.

The position of the moving objects in the cartesian coordinate system is acquired using the relation between image frames. The linear and angular velocities of the moving objects are estimated by the state estimator, Kalman filter. After estimating the trajectory of the moving objects, the optimal trajectory and motion planning of the mobile robot are decided in order to follow the walking human in the shortest time. The following figure shows the overall structure of mobile robot control for human following.

7. Robot Control by DIND

7.1 Robot Control in the Environment with DINDs

The network of six DINDs, which consist of three DINDs for the mobile robot and three DINDs for the human, is used in the experimental environment. Since the area that each DIND is able to cover is limited, the DINDs must share information acquired by themselves, in order to realize human following in the whole of the experimental environment.

In this environment, the DINDs are required to cooperate with each other. Effective communication and role assignment are required for the cooperation of the DINDs. We define a DIND that has the control authority of a robot as the dominant DIND for the robot. Each DIND compares the reliability rank based on measurement error and so on. When a robot moves from one area to a different area, the dominant DIND for a robot needs to be changed automatically to the DIND that has the higher reliability rank. This is called handing over of the control authority. The dominant DIND has the control authority of the robots, and only one dominant DIND exists for a given robot at any one time. Details about the handing over are described in [11]. In order to achieve a definite hand over, the monitoring areas need to overlap. Moreover, in the proposed control law, the past velocity input is required in order to calculate the new velocity input. When the control authority moves to another DIND, information about the input velocity also has to be transmitted from the last dominant DIND to the new dominant DIND. Therefore, it is possible to input a continuous velocity into the mobile robot. The information which the DINDs share is defined as [7, 11]

The human-following module of a DIND is realized with the software configuration as shown in Fig. 10. A DIND basically makes connections to other DINDs with the client/server method of UDP protocol. A server program of each DIND is always running in order to receive requests for passing the control authority from other DIND's. The client programs are executed according to the situation, such as DIND requests to other DIND's, and so on. When the DIND transmits the velocity input to the mobile robot, the client program for making a connection to the mobile robot will become active if the DIND has the control authority.

7.2 Robot Position Estimation

Due to the processing time and the network communication time, there is a position gap between the robot at the time of performing the control and the robot at the time of capturing the image with the CCD camera, since the robot moves. The processing time includes clustering, 3-D reconstruction, etc. Therefore, it is necessary to estimate the robot's position and posture at the real time at which the control is performed. A mobile robot controller exists in the DIND side, and the modified velocity input signal to the mobile robot is determined before the network communication.

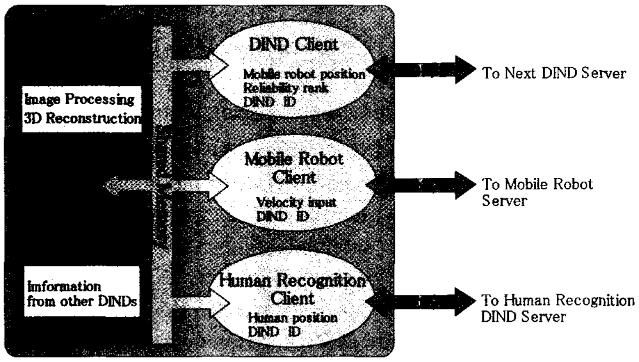


Fig. 10. Network software configuration of the DIND.

8. Experiments

To demonstrate and illustrate the proposed method, we present an example. It is assumed that the velocity limit of a mobile robot is 30 cm/sec and the initial locations of the mobile robot and the moving object are (-50, -50) and (-250, 300) in cm with respect to the reference frame, respectively. The velocity and angular velocity of moving object are as follows:

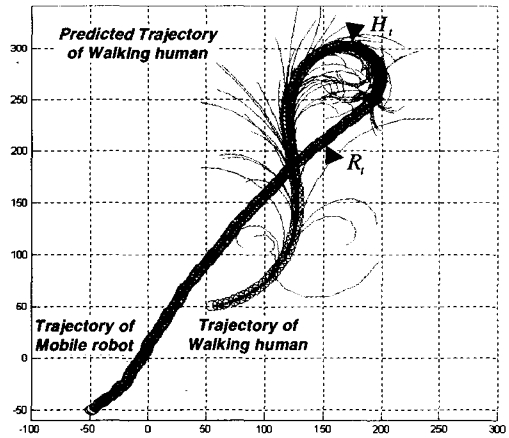
$$v_k = 30(\cos(0.01\times k)+1)+\xi_v[cm/\sec] \quad (27)$$

$$w_k = 0.7\sin(0.03k+\frac{\pi}{1.5})+\xi_w[rad/\sec] \quad (28)$$

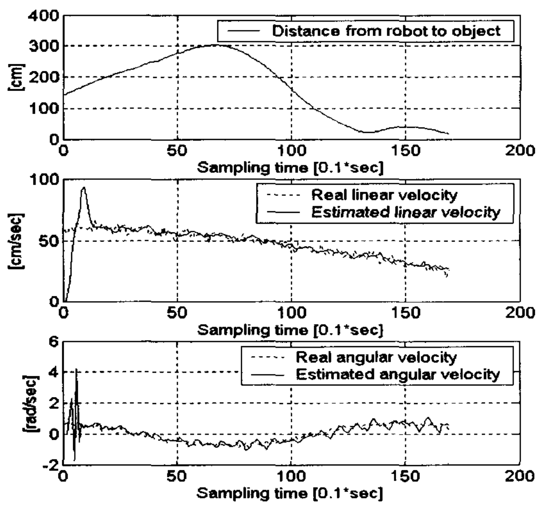
The forward direction and rotational angular velocity of the moving object are Gaussian random variable with variances of 2 and 0.1, respectively, which are obtained experimentally.

Fig. 11(a) presents the trajectory of a walking human and the mobile robot trying to follow the humanby estimating the trajectory. Fig. 11(b) represents the distance between the mobile robot and the walking human, the error between the estimated velocity and the real velocity, and the error between the estimated angular velocity and the real angular velocity, respectively. Although the error of the estimated velocities is high at first, they converge to zero immediately.

Experiments that include the proposed algorithm were applied to a mobile robot that was developed in ISpace, as shown in Fig. 2. To control the wheels in real time, a distributed control system is implemented using a DIND based network. Six DIND-based controllers are connected to the network, among which a controller gathers the vision data and sends them to the wheel controllers. The DIND network was connected to a higher-level ISA bus which connects the 2 d.o.f pan/tilt camera controllers to a main controller (a Pentium PC board). Every 100msec, the position of an object in 3D space was calculated using the posture of the camera and the object position on the image frame to plan the trajectory of the mobile robot. The planned trajectory commands were sent to the wheel controllers that uses PID algorithm to control the angle every 10 msec.



(a) Trajectory



(b) Estimated state.

Fig. 11. Results of experiment.

Experiment was performed to show the estimating and following a waling human. Fig. 12 shows the experimental results for estimating and following a walking human. Mobile robot is attached with 70x20[cm] red-colored panels. Human walks random velocities in the range of 45-50[cm/sec]. First, mobile robot detects the moving human using cameras in ISpace. When a walking human is detected within view, mobile robot tracks it following the proposed method. And Fig. 12 illustrates that the mobile robot following a human in the shortest time path as temporary position of Fig. 11(a). The minimum path was estimated using the trajectories of the mobile robot and the human, while the mobile was tracking the walking human.

(a)

(b)

Fig. 12. Experimental results for Human-following at human position, H_t and robot position, R_t.

9. Conclusion

This paper proposes a method of human-following for mobile robot to track and follow a walking human in ISpace environment. First, a control algorithm using a position estimation of moving objects, walking human and mobile robot, based on the kinematic relationship of consecutive image frames was proposed for a mobile robot in order to follow a walking human whose position is estimated incompletely. The proposed model is able to absorb the gap between the motion of the human and the mobile robot. It was shown that movement estimation of the objects using a Kalman filter based DINDs for tracking and motion planning of a mobile robot to follow the walking human, based on its estimated trajectory, within the shortest time.

Next, cooperation between the multiple DINDs was described. The position of the human and the mobile robot in ISpace was measured with DINDs. To control a mobile robot in a wide area, cooperation of the DINDs, effective communication and role assignment are required. The handing-over protocol[18] for a mobile robot control and the communication method with DIND for human recognition were explained. Finally, an experiment into the human-following control of a mobile robot was performed using the proposed method. It was shown that human following is easily achieved in ISpace. As a result, this research shows that the proposed method is effective in assisting a mobile robot to follow a human. Moreover, the fundamental human-following system is achieved in ISpace where many DINDs are arranged in the space.

Future studies will involve applying this system to complex environments where many people, mobile robots and obstacles coexist. Since the proposed algorithm absorbs the kinematic differences between humans and robots, any kind of mobile robot, including legged robots, can be used as human-following robots, as long as the robot is able to move at the speed of human walking.

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