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Mobile Robot Navigation based on Human Walking Trajectory in Intelligent Space

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Abstract

This paper presents a mobile robot navigation method based on human walking trajectory in intelligent space. Unlike the traditional navigation methods, the proposed method enables the robot to walk a meaningful path, which reflects human activity patterns in daily life. Human walking trajectories are extracted using multiple distributed vision cameras in intelligent space. To group trajectories with the same direction, trajectory similarity measurement is implemented. Key points on human walking trajectories and typical transfer points are utilized to build a topological map. To navigate a mobile robot to walk along the trajectory of human walking, global path planning based on the topological map and local path planning based on gird map are carried out with the spared information in intelligent space. Experimental results illustrate the performance of the proposed navigation method.

Keywords: *mobile robot navigation; human walking trajectory; intelligent space; topological map; path planning*

1. Introduction

Researches on mobile robots for daily life are rising in the last decades. Some robots have successfully run into homes and offices to provide services. All of these existing applications have one problem in common: navigation. Steady progress in mobile robot navigation has been made in the past [1]. However, since environments of the real world are highly unpredictable, it is still an open problem to achieve efficient and robust navigation.

Whenever a robot is designed to provide service in the human populated environment, the ideal navigation pattern of the mobile robot is walking just like a human being [2]. In general, the motion of human is considered to be accustomed and optimal. Learning typical motion patterns of human is a good way to improve the behavior of the mobile robot. For example, human walking trajectory is regarded as a meaningful feature, which reflects the patterns of human activities in daily life. Indeed, using human walking trajectory to guide a robot sounds promising. The research on human tracking has been studied [3-6]. Most of human tracking results are used to monitor daily behaviors of elder people [4] or to realize human activity recognition [7]. Estimation of human behaviors for mobile robot control and navigation has been applied to many systems, for instance, path planning for obstacle avoidance and future motion prediction. Noguchi [8] introduced a global path planning method for mobile robot. Human presence probabilities are employed to realize flexible and safety mobile robot avoidance. In addition, Hamasaki [9] developed a human movement prediction system for mobile robot obstacle avoidance. Moreover, Motonaka [10] contributed at proposing a mobile robot path planning scheme, the Human Frequency Map (HFM) is achieved based on the observed human position. In

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[11], a mobile robot path planning method based on human motion and navigation intent is presented. The likely navigation intent of humans is considered to predict human motion. Most of existed approaches concentrated on predicting human motion for mobile robot obstacle avoidance. However, in this paper, we focus on to extract a natural and practical path of human walking. The mobile robot is required to walk along the trajectory of humans just walking like a human being.

Due to human behaviors are unpredictable and sensors on aboard powerless, human walking trajectory extraction in the dynamic environment is still a very challenging task. However, as the research on smart environments has been expanded in recent years [12], many applications have been developed, and the most distinctive one is the intelligent space. Intelligent space is an intelligent environment which provides both information and physical supports to humans and robots in order to enhance their performances [13]. Ubiquitous sensors are distributed in space to offer the spared support for human daily life. One of the important application fields of the intelligent space is its combination with mobile robot. It opened a new direction to the research and application for the robot. In this paper, vision sensors distributed in intelligent space are used to extract the trajectories of humans.

Figure 1 shows the overview of our intelligent space system. The key components of the intelligent space include: many kinds of distributed sensors (*e.g.*, vision cameras, laser scanners and temperature sensors) that are employed to collect information of the environment; a server computer system which is used for information processing and database management; network communication system (*e.g.*, WiFi and Zigbee system) and actuators (*e.g.*, mobile robot and smart TV). Compared to sensors on board, intelligent space as an information sharing platform enhanced the ability of information collection. There is no need to configure a wide variety of sensors for mobile robot. The service robot can obtain more comprehensive environmental information. The distributed pattern of sensors in intelligent space will not only reduce the cost of the whole system greatly, but also make the robot focusing on individual service performance under mission requirements. The robots serving in intelligent space will work more efficient, stable and accurately. Additionally, it ensures the robots adapt to the change of dynamic environment, which will accelerate promotion and application of the mobile robot assistant application.

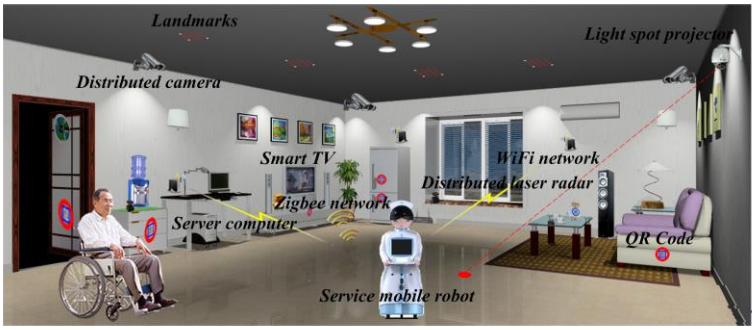

Figure 1. Overview of Our Intelligent Space System

The aim of this paper is to navigate the mobile robot to walk along a meaningful path that used frequently by humans. Distributed cameras in intelligent space are employed to extract human walking trajectories. Key points on trajectories and typical transfer points are utilized to build a topological map. Global path planning based on the topological map and local path planning based on gird map are carried out with the spared information of intelligent space to navigate a mobile robot to walk along the trajectory as much as possible. Mobile robot navigation results are conducted to illustrate the performance of the proposed method.

The remainder of this paper is organized as follows. Section 2 introduces human walking trajectory extraction, gives details of trajectory similarity measurement, as well as topological map building. Section 3 presents the components of our navigation system. Mobile robot localization and path planning are discussed. Experiment results are given in Section 4. Finally, we conclude this paper in Section 5.

2. Extraction of Human Walking Trajectory

2.1. Trajectory Generation

To capture the trajectory of human walking, distributed vision cameras are employed. In the process of human tracking, the field of view and position of cameras are fixed. All cameras are calibrated beforehand. The parameters of the intrinsic and extrinsic are obtained using the calibration method mentioned in [14]. To achieve the localization of human, the scheme of motion history image (MHI) is employed [7]. Human detection in the previous frame is predicted based on Kalman filter model. Measurement results in the current frame are merged with the prediction. The human walking trajectory is generated by projecting the processed position and velocity of the human to the environmental map. In this paper, human walking velocity is considered as an important stamp to distinguish the direction of the trajectory, as well as human positions.

2.2. Trajectory Similarity Measurement

Although human walking trajectory is acquired, it is still difficult to determine which trajectory to walk along. Due to the diversity of the trajectories, we have to separate the similar ones. In general, there are usually two kinds of trajectory on the passable path with different directions. To extract some meaningful paths from the human walking frequently used paths for mobile robot navigation, trajectory similarity measurement is put on the agenda.

A trajectory is made of a sequence of data points. Define $T_p = \{\vec{p}_i\}$ is a trajectory of human walking, where $\vec{p}_i = [x_i^p, y_i^p, \theta_i^p, v_i^p]$, (x_i^p, y_i^p) is the spatial coordinate of the ith points, θ_i^p is its direction, and v_i^p is the velocity of human walking. Considering two trajectories $T_m = \{\vec{m}_i\}$ and $T_n = \{\vec{n}_i\}$, for a point $\vec{m}_i$ on T_m, the nearest point on T_n is

$$\lambda(i) = \arg\min_{j \in T_n} \left\| (x_i^m - x_j^n, y_i^m - y_j^n) \right\| \tag{1}$$

The dissimilarity of the direction between two points can be calculated by Equation (2) [15].

$$d_s(\theta_i^m, \theta_{\lambda(i)}^n) = 1 - \frac{\vec{v}_i^m \cdot \vec{v}_{\lambda(i)}^n}{\left\|\vec{v}_i^m\right\| \cdot \left\|\vec{v}_{\lambda(i)}^n\right\|} \tag{2}$$

The spatial distance between the two trajectories can be calculated:

$$D(T_m, T_n) = \frac{1}{N_m} \sum_{\vec{m}_i} \left(\left\| (x_i^m - x_{\lambda(i)}^n, y_i^m - y_{\lambda(i)}^n) \right\| + \eta \cdot d_s(\theta_i^m, \theta_{\lambda(i)}^n) \right) \tag{3}$$

where η is a weighting parameter, and N_m is the number of the trajectory points on T_m. The similarity between the two trajectories can be measured by the following equation:

$$S_t(T_m, T_m) = \exp(-\min\{D(T_m, T_n), D(T_n, T_m)\} / \sigma) \tag{4}$$

where σ is constant. In this way, the similarity among all human walking trajectories is examined. All similar trajectories of human walking with the same direction are grouped together.

2.3. Map Building based on Human Trajectories

As mentioned above, trajectories contain some key points that describe the inner relationship of human walking. To navigate the mobile robot, a topological environment map is built. Key points and transfer points are used to denote the nodes, and the paths between them are employed to represent the edges of topological map. In this paper, key points are made of stop points where people stay for a long time, and transfer points indicate the necessary point for the mobile robot to move one area to another. Stop points reflect the details of human's activity such as the time spent in this position, which is useful to guide a mobile robot approaching human to provide services. In contrast, transfer points are some relatively unchanged point that can be defined in advance.

In general, a person is hardly to stay at one location completely, the vision based human tracking system has to determine whether he is walking or not. To extract the stop points, association gate based on the position and speed of human walking is employed. Equation (5) is an expression of association gate.

$$\frac{(x_t - x_{t-m})^2}{k^2\sigma_x^2} + \frac{(y_t - y_{t-m})^2}{k^2\sigma_y^2} + \frac{(v_t^x - v_{t-m}^x)^2}{k^2\sigma_{v^x}^2} + \frac{(v_t^y - v_{t-m}^y)^2}{k^2\sigma_{v^y}^2} \le 1 \tag{5}$$

where (x_t, y_t) is the position of human at time t, v_t^x, v_t^y denotes the speed of human walking at x and y direction at time t respectively, $\sigma_x^2, \sigma_y^2, \sigma_{v^x}^2, \sigma_{v^y}^2$ represent the covariance of the position and speed at x and y direction respectively, k is a constant, and m is a time sliding window.

Once the position and speed of human walking satisfied the constraint of association gate in a period of time, the current position of human is regarded as a stop point. Due to it is hardly to determine how many stop points at one location, Mean Shift cluster [16] is applied. The clustering process grouped the neighboring stop points. The centre of cluster is extracted as a key point that is used to build the topological map of the environment. As aforementioned above, each of the trajectories has its direction. Therefore, there will be two adjacent but different paths between topological points because human walking path follows some customs such as walking on the right. To use the human walking trajectory for mobile robot navigation, we have to average these similar trajectories. The corresponding points on similar trajectories are regrouped and smoothed based on the method of least square.

3. Navigation based on Topological Map and Human Trajectory

3.1. Kinetic Model of the Mobile Robot

The kinetic model of the robot is shown in Figure 2. Two differential driving wheels are mechanically distributed in the front and a universal wheel in the behind. The encoders return two distinct speeds of the wheels. Let the vector $\mathbf{x}_k=[x_k, y_k, \theta_k]^T$ describes the pose of the robot at time k, where (x_k, y_k) is the center point of the robot and θ_k is the heading orientation of the robot. The pose of robot can be calculated from the last sampling time x_{k-1} by Equation (6).

$$\begin{cases} x_k = x_{k-1} - v_{ave} \cdot \Delta t \cdot \sin\theta_k \\ y_k = y_{k-1} + v_{ave} \cdot \Delta t \cdot \cos\theta_k \\ \theta_k = \theta_{k-1} + \omega \cdot \Delta t \end{cases} \tag{6}$$

where $v_{ave} = \frac{v_R + v_L}{2}$ is average speed of the two driving wheels, $\omega = \frac{v_R - v_L}{l}$ is the angular velocity of the robot, v_R and v_L are the speeds of the two driving wheels, respectively. l is the distance between two driving wheels, and Δt is sampling time of the mobile robot.

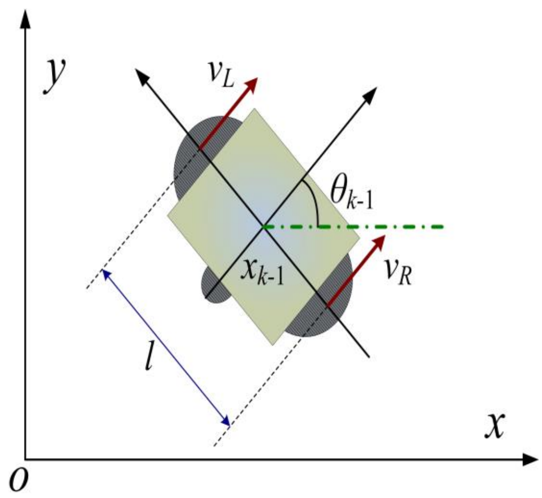

Figure 2. Kinetic Model of the Mobile Robot

3.2. Robot Localization based on Landmarks distributed in Intelligent Space

To navigate a robot autonomously, the first step is to obtain the pose of the robot globally. Dead reckoning is a common and basic method for mobile robot localization, which enables the robot to achieve its current pose by projecting its past position and speeds [17]. However, the displacement and orientation errors are inevitable in dead reckoning. Localization errors will accumulate and grow rapidly over time. In [3], a localization system utilizing color information of the mark attached on the mobile robot is introduced. Due to the dynamic of environment, it can hardly deal with illumination and occlusion problems. In this paper, to localize the mobile robot, landmarks distributed on the ceiling in intelligent space are employed to revise its pose periodically. Figure 3 illustrates the landmark detection sensor: StarGazer [18] and a numbered passive landmark. The detection sensor analyzes infrared ray image which is reflected from the passive landmark with an independent ID. The output of position and heading angle of the sensor is given with a precise resolution and high speed. Data from the observation of landmark is fused into the dead reckoning system based on Kalman filter. The accuracy of mobile robot localization can reach to 5cm.

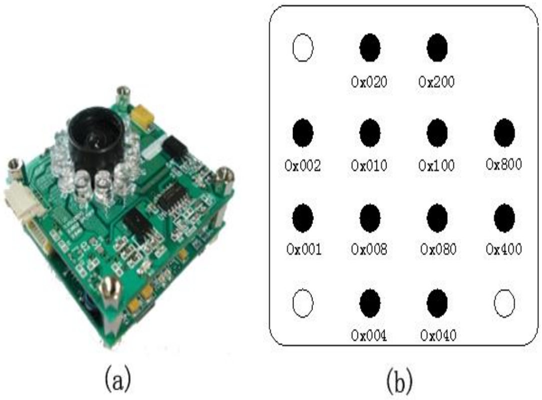

Figure 3. StarGazer Localization System (a) StarGazer; (b) Passive Landmark

3.3. Path Planning based Human Walking Trajectory

The path planning process in the proposed system includes two aspects: one is global path planning based on the topological map, and the other is local path planning based on gird map. Global path planning between two topological points is achieved using Dijkstra algorithm [19]. Due to lack of detail information in scale between two key points on the topological map, the robot is hardly walking along the trajectory of human. Hence, local path planning based on gird map is carried out. To make the robot running along the trajectory of human walking as much as possible, the grid that occupied by trajectory points is marked. The cost of the grid around the marked grid is reduced according to its occupancy rate. Therefore, the marked gird is more inclined to be programmed in the process of path searching.

4. Experiment Results

The mobile robot navigation system proposed in this paper has been implemented on a real robot and tested extensively in our intelligent space. Figure 4 illustrates our mobile robot system, which only equips a laser range finder that is used to obstacle avoidance and the localization sensor: StarGazer.

Figure 4. Mobile Robot System used to Verify the Proposed Method

Experimental environment is shown in Figure 5. Four distributed CCD cameras are employed to capture human walking trajectory. Four transfer points are set artificially in advance. Circular regions are used to represent transfer points. The transfer points on the environmental map from the left to the right are marked with symbols (tr_1, tr_2, tr_3, tr_4), respectively.

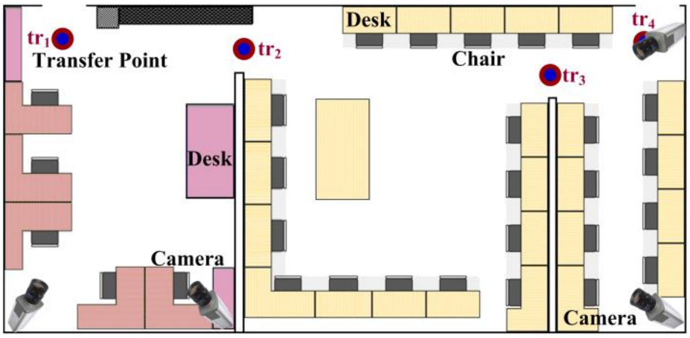

Figure 5. Experimental Environment and Distributed Cameras

4.1. Map Building

Figure 6 illustrates the obtained human walking trajectories using the vision-based tracking system. About 140 walking trajectories are collected in the experiment. To smooth the walking trajectories, Kalman filter is applied in the process of trajectory extraction. To determine the stop points described in Section 2. 3, the time sliding window is set as 5 second. The cluster centers of stop points are regarded as key points. In the environment above, six key points are extracted, but two of them are coincidence with transfer points.

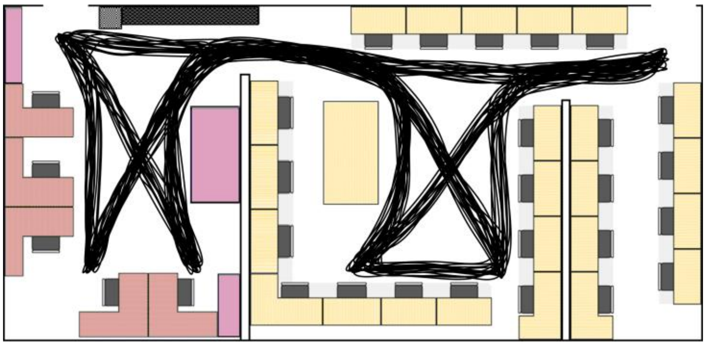

Figure 6. Obtained Human Walking Trajectories

Figure 7 shows the topological map, which generated based on the transfer points and key points. The extracted key points from the left to the right are represented by k_1 to k_4, respectively. Human frequently used paths described the incidence relationship among these topological points.

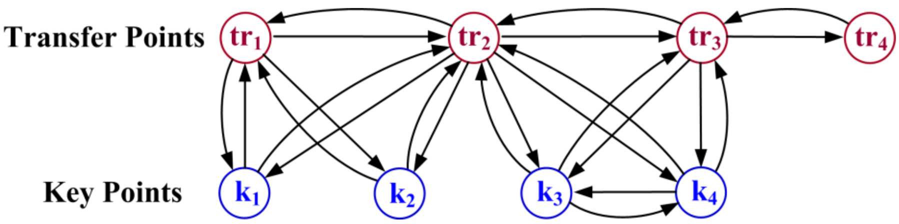

Figure 7. Topological Map Generated based on Human Walking Trajectories

4.2. Navigation based on Human Walking Trajectory

To illustrate the performance of the proposed navigation system, experiment is conducted. The robot was ordered to move from the key point k_2 to key point k_3. Figure 8 shows the compared results of planned paths based on the proposed method and A* algorithm [20]. *Path A* is generated based the famous *A** algorithm, and *path B* is created based the proposed method. Although *path A* seems to be more optimal in terms of length, *path B* is inclined to obey human's daily behavior. Humans tend to choose a broad path rather than the narrow one. In generally, this kind of path is more suitable for robot navigation because safety and friendly relationship between human and robot are more important in the human-robot coexistence environment. In this experiment, three persons (P_A, P_B, P_C) were walking on the planned path against the direction of the mobile robot as shown in Figure 8. The mobile robot can hardly across the gap when it encounters with person *A*. In contrast, path B is more suitable for mobile robot navigation.

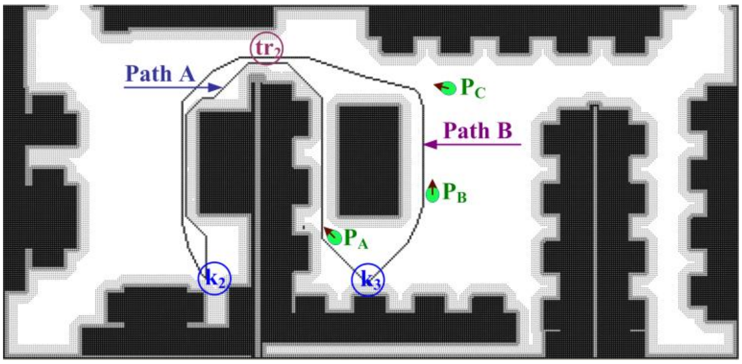

Figure 8. Comparison of Planned Paths based on the Proposed Method and A* Algorithm

Figure 9 illustrates the navigation result, and the trajectory of mobile robot is recorded. The maximum speed of the robot was set to 300 mm/s. On the way from transfer point tr_2 to key point k_3, the robot detected and encountered two unmodeled persons as shown in Figure 9. Due to the reference planned path is occupied by a walking person, the mobile robot walked off the path and glided on the right side of the obstacle just like a person walking on the right. However, once the robot can hardly walk on the right, the mobile robot will determine the more appropriate direction.

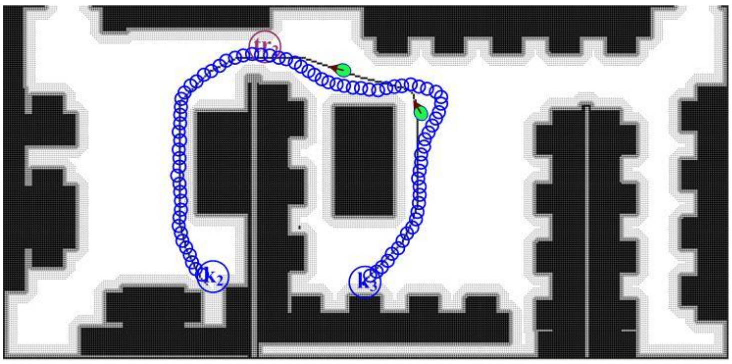

Figure 9. Mobile Robot Navigation Result based on Human Walking Trajectory

5. Conclusion and Future Work

In this paper, a mobile robot navigation system based on human walking trajectories is proposed. Human walking trajectories are regarded as meaningful features, which reflect the patterns of human activities. Using human walking trajectory to navigate a mobile robot sounds inspiring. Distributed cameras in intelligent space are employed to capture human walking trajectories. Transfer points and key points on the trajectories are extracted to build the topological map. In the path planning process, global path planning based on the topological map and local path planning based on gird map are carried out. Mobile robot navigation experiment result illustrates the effectiveness of the proposed method.

For future work, we would like to expand the proposed method to how to provide more suitable services for humans. Moreover, human trajectory is an advanced expression of human activity. Human activity recognition in daily living is also an interesting research direction based on human walking trajectory.

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