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Flexible Navigation Strategies by Predicting Human Motion Tendency

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Abstract: When service robots present in environments coexist with people, human-aware navigation become an important problem to be addressed. For doing so, this study designed a human-aware motion planner by inference of human motion modes in a camera network. Given a grid map of an indoor environment, human motion mode can be defined as a probabilistic form and fused into a probabilistic grid map in order to adjust robot navigation strategies. First, a two-level learning algorithm is employed to learn motion modes of persons based on collections of trajectories which are recorded by a camera network. Subsequently, a chain of Gaussian distributions are applied to describe each motion mode. Based on these modes, human motion prediction can be computed. Experimental results show the effectiveness of fusing human motion tendency to adapt robot navigation behaviors.

Key words: Motion modes, navigation, multi-camera tracking, camera network, motion trajectories, fuzzy K-means algorithm

INTRODUCTION

Once service robots enter into our living space and help us in our daily life, it is necessary to take account of how to coexist harmoniously between robots and persons. For this problem, Nonaka *et al*. (2004) point out that two aspects of human's safety need be considered: physical safety and mental safety. For the former, there are too many successful researches in the field of service robotics. But, for the latter, there are no mature theories or schemes to design human-aware planning for service robots. To achieve more human friendly behaviours, this study solves the problem of how knowledge about representative motion patterns of people can be employed to improve the navigation behaviour of the robot.

Although, automatically modeling of motion modes is a novel research field, some pioneering investigations of this problem have already been began. For this problem, Bui *et al*. (2006) employed an AHMM method to compute human short-term motion tendency during robot navigation process. Schulz *et al*. (2003) and Kluge *et al*. (2007) also designed a HMM method to compute human motion tendency to direct the robot to choose appropriate plans in order to prevent interfering with persons in the robot's circumambience. The above approaches only can predict human short-term motions. However, these methods do not describe how to cluster different motions into motion patterns and how to make use of the learning results to improve the navigation behaviors of mobile robots. Bennewitz *et al*. (2005) propose an EM method for learning motion modes of people and derive a HMM method to predict human motion tendency. However, the disadvantage in their method is that the Gaussian distributions for all motion modes with a same standard deviation can not image of motion mode characteristics.

In this study, we present a system for learning people motion patterns which are then used to predict their behaviors for improving the robot's navigation performance. Present system is original in the following ways:

- We use a camera network to detect and track persons in the environment. Our system can simultaneously track many persons and acquire their trajectories
- Based on the fuzzy K-means algorithm, we propose a new hierarchical trajectory clustering method
- Based on the clustered trajectories, we learn the characteristics of each motion mode represented by a chain of Gaussian distributions with different standard deviations. Based on the learned probabilistic motion patterns, we can predict human motions into robot's navigation plans

LEARNING MOTION MODES OF PEOPLE

A series of trajectories $\Gamma = \{\Gamma_1,..., \Gamma_i..., \Gamma_M\}$ can be attained by tracking people using a camera network (Section 4), where M is the number of sample trajectories

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and Γ_l is the lth trajectory. These trajectories can be used to learn motion modes $\Phi = \{\phi_1,..., \phi_j,...\phi_c\}$, where C is the number of motion modes and ϕ_j is the jth motion mode.

Two-level clustering algorithm of trajectories: The aim of clustering trajectories is to divide similar trajectories into the same class (Hu *et al*., 2004). In order to learn a number of trajectories, trajectories were hierarchically classified based on different characteristics. The sample trajectories are classed with two levels: spatial-based clustering and temporal-based clustering.

For the spatial-based class, input trajectories given to our algorithm have the same number of observed positions, i.e., that $T_l = T$ for $\forall l \in M$. To realize this object, all trajectories are transformed in Γ into a normalized set D of M trajectories using a linear interpolation such that each $D_i = \{x_i^1, x_i^2, \cdots x_i^T\}$ has a constant length T.

In the fuzzy K-means-based algorithm (Rui and Wunsch, 2005; Ali *et al*., 2009; Dechang and Xiaolin, 2008) for classifying the trajectories, each clustering center corresponds to a cluster of normalized trajectories. Each clustering center is represented by a vector whose dimension is the same as the normalized trajectories. The clustering center vectors are initialized randomly. Suppose K denote the number of clustering centers and W_j (a T-dimensional vector) denote clustering center j (j = 1,..., K). For given sample vectors {D} ($1 \le l \le M$), the fuzzy weight $\omega_{l,j}$ of each sample l (l = 1,2,..M) to each clustering center j (j = 1,2,..K) can be computed as:

$$\omega_{lj} = \frac{|D_l - W_j|}{\sum_{m=1}^{K}(|D_l - W_m|)} \tag{1}$$

It is not difficult to see Eq. 1 that, the less the distance between a sample and a clustering center, the more the weight of the class. Based on the computed weights, each clustering center can be updated as:

$$W_j(t+1) \leftarrow W_j(t) + \sum_{l=1}^{M} \omega_{lj}(t) \cdot |D_l - W_j(t)| \tag{2}$$

Until the following stability condition is satisfied:

$$\max_{1 \le j \le K}\{|W_j(t+1) - W_j(t)|\} < \varepsilon \tag{3}$$

Corresponding to above classing algorithm, all normalized trajectories are classed into K subsets:

$$\Omega = \{\{D_{1,1}, \cdots, D_{1,M_1}\}, \cdots, \{D_{i,1}, \cdots, D_{i,M_i}\}, \cdots, \{D_{K,1}, \cdots, D_{K,M_K}\}\} \tag{4}$$

The scale of each subset Ω_J is much less than that of the whole sample trajectories, so temporal information is introduced to further class each subset of trajectories. By the first classing, the trajectories in each subset have the similar geometrical shape. But it does not consider the direction of each trajectory. To address this problem, we need to find out the initial positions of all trajectories in each subset. Then the fuzzy K-means algorithm is again applied to class each subset. The clustering procedures are the same as the spatial-based classing. Accordingly, the normalized trajectories in Ω_J are classed into K_i (K_i = 1 or 2) classes. After the temporal-based clustering, all normalized trajectories are classed into C classes:

$$\Omega = \{\{D_{1,1}, \cdots, D_{1,M_1}\}, \cdots, \{D_{j,1}, \cdots, D_{j,M_j}\}, \cdots, \{D_{C,1}, \cdots, D_{C,M_C}\}\} \tag{5}$$

Probabilistic motion modes of people: Each motion mode ϕ_j can be denoted by a series of N probability distributions $\{\phi_{j,1},..., \phi_{j,i},..., \phi_{j,N}\}$. In the motion mode ϕ_j, each probability distribution $\phi_{j,i}$ corresponds to β = [T/N] continuous point vectors in a sample trajectory. Suppose that each $\phi_{j,i}$ yields a Gaussian distribution and let $\mu_{j,i}$ and $\Sigma_{j,i}$ be the mean and the covariance matrix of Ω_i, respectively, the parameters of $\phi_{j,i}$: $\mu_{j,i}$ and $\Sigma_{j,i}$ can be estimated by the point feature vectors in the sample trajectories in Ω_j. Let k = iβ, the parameters of $\phi_{j,i}$ can be computed by point feature vectors $x^k, x^{k+1},... x^r$ in Ω_j:

$$\begin{cases} \mu_{j,i} = \sum_{n=1}^{M_j}\sum_{m=k}^{k+\beta} x_n^m \\ \Sigma_{j,i} = \sum_{n=1}^{M_j}\sum_{m=k}^{k+\beta}(x_n^m - \mu_{j,i})(x_n^m - \mu_{j,i})^T \end{cases} \tag{6}$$

Consequently, the probability of a point x^t falling into probability distribution $\phi_{j,i}$ is as:

$$P(x^t \mid \phi_{j,i}) = (2\pi)^{-\frac{1}{2}}|\Sigma|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}(x^t - \mu_{j,i})\Sigma_{j,i}^{-1}(x^t - \mu_{j,i})^T\right) \tag{7}$$

Predict human motion tendency: To be able to apply the learned motion modes to predict their future trajectories, we need to compute the probability that an observed sequence pertains to every motion modes. Given a sequence x = $\{x^1, x^2,..., x^R\}$ of a person's positions observed by a camera network, the probability $P(\phi_j|x)$ that the person belongs to motion mode ϕ^j given x can be computed as:

$$P(\phi_j \mid x) = \frac{P(x \mid \phi_j)P(\phi_j)}{\sum_j P(x \mid \phi_j)P(\phi_j)} \tag{8}$$

where, P (ϕ_j) is the prior probability for motion mode ϕ_j and P ($x|\phi_j$) is the probability of the data given motion mode ϕ_j. In Eq. 8, how to compute the term P ($x|\phi_j$) is the most important. However, x may not begin from the initial position of a motion mode. It is assumed that $\phi_{j,n}$ ($1 \le n \le N$) of ϕ_j is the position corresponding to the first observed position x^1 and $\phi_{j,n'}$ ($n \le n' \le N$) is the position corresponding to the last observation position x^R. Considering that both n and n′ are unknown, an alternative method described by Bennewitz *et al.* (2003) is designed to use all possible compounding of n and n′ to compute P ($x|\phi_j$). However, the method must know the prior probabilities of all compounding of n and n′ in advance but these probabilities are not easy to acquire. Instead, we propose a novel method to compute P ($x|\phi_j$) without the prior probabilities. In our method, a first way is to determine which probability distribution of a motion mode ϕ_j an observed position x^r belongs to by the following equation:

$$\hat{i}_j^r = \underset{i(1\le i\le N)}{\operatorname{argmax}} P\left(x^r \mid \phi_{j,i}\right) \tag{9}$$

Based on Eq. 9, we can realize a mapping of the individual observations x^1, x^2,..., x^R to components $\phi_{j,n}$,...$\phi_{j,n'}$ of ϕ_j. The following task is to compute P ($x|\phi_j$). Along with the monotonic increment of r, if the condition $\hat{i}_j^r \ge \hat{i}_j^{r-1} (\forall 0 < r \le R)$ is satisfied, P ($x|\phi_j$) can be computed as follows:

$$P\left(x \mid \phi_j\right) = \sum_{r=1}^{R} P\left(x^r \mid \phi_{j,\hat{i}_j^r}\right) \Big/ \sum_{j=1}^{C}\sum_{r=1}^{R} P\left(x^r \mid \phi_{j,\hat{i}_j^r}\right) \tag{10}$$

Otherwise, if $\hat{i}_j^r < \hat{i}_j^{r-1}$ ($\exists 0<r\le R$), P ($x|\phi_j$) = 0.

NAVIGATION MECHANISMS

How the robot can employ above information to adapt its navigation strategies will be described in this section. We employ the T^* algorithm for path planning and for finding out the minimum cost path in robot's three dimensional time-space configurations. Let P ($grid_{x,y}$) represent the occupied likelihood of every grid ⟨x, y⟩. To merge human motion tendency to robot path planning method, every grid ⟨x,y⟩ is additionally re-computed based on the probability which one of the persons moves to grid ⟨x,y⟩ at time t. Assuming that our camera network has observed L persons and P ($grid_{x,y,i}|x_l$) denotes the probability that a person l moves to grid ⟨x,y⟩ at time t, we can compute the cost $Cost_{grid}$ (x, y ,t) as:

$$Cost_{grid}(x,y,t) = \sum_{l=1}^{L} P\left(grid_{x,y,t} \mid x_l\right) = \sum_{l=1}^{L}\sum_{j=1}^{C}\left(P\left(grid_{x,y,t} \mid \phi_j, x_l\right)\cdot P\left(\phi_j \mid x_l\right)\right) \tag{11}$$

The latter term can be attained based on Eq. 11. The remaining work is to compute the term P ($grid_{x,y,i}|\phi_j$, x_l) that a person motion belongs to motion mode ϕ_j will arrive at grid ⟨x, y⟩ at time t based on the observed sequence x_i. The grid on ϕ_j has the displacement v (t-t′) from the latest observed position $x^{t'}$ at time t′. Here, v is the human motion velocity in the observations x_j. So, the person's motion tendency can be predicted from location $x^{t'}$ using the average velocity v and the trajectory given by ϕ_j.

Ultimately, the total cost of traversing a cell ⟨x, y⟩ at time t is determined by the occupancy probability P ($grid_{x,y}$) plus the probability that persons covers ⟨x, y⟩ at that time:

$$Cost\,(x, y, t) = P\,(grid_{x,y}) + Cost_{cov}\,(x, y, t) \tag{12}$$

After acquiring time-varying probability occupancy map of human existence, we can apply T* search to plan the motion of the robot. As a result, the robot can plan a collision-free path.

PEOPLE DETECTION AND TRACKING

To acquire the sample trajectories, non-overlapping multiple cameras are applied to detect and track people in the indoor environment. As viewed from whole, the system is divided into two parts: Single camera detecting on each camera node and multi-camera information fusion and tracking on a center server. The system architecture is shown in Fig. 1. Each camera node communicates with the center server over a communication protocol called IPC, developed by Simmons (2010) at Carnegie Mellon University.

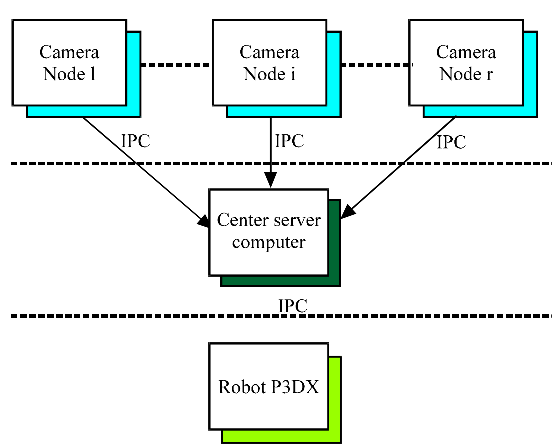

Fig. 1: System architecture

Single camera detecting: Our algorithm adopts fast adaptive background subtraction proposed by De-Gui *et al*. (2008). It uses only luminance components of sample image sequence pixels and models every pixel in a probabilistic model. The algorithm is robust in two aspects: one is to incorporate adaptively slow and sudden lighting changes into background to make background pixels update fast. The other is to combine block-based method with pixel-based model by dividing each frame into many small regular pixel-blocks and modeling each pixel value with a probabilistic model which makes it fast to track and accurate to extract moving objects. Besides, a method (Javed and Shah, 2002.) is employed to classify objects based upon detecting recurrent motion for each tracked object. A specific feature vector called a Recurrent Motion Image (RMI) is developed to calculate repeated motion of objects. Different types of objects (including people and robots) yield very different RMIs and therefore can easily be classified into different categories on the basis of their RMIs.

Multi-camera information fusion and tracking: To tracking objects across multi cameras, it is necessary to find out the invariable characteristics of the same moving object in visual fields of different cameras for fusing multi-camera information and then label it as a same marker. Our algorithm implements multi-camera tracking by combining the luminance-based change of the moving objects.

The main task of multi-camera tracking system is to determine whether the new appearing object in the Field of View (FOV) of one camera is a new one or the tracked one by another camera (Bouzenada *et al*., 2007; Liao and Chu, 2009; Liao and Lee, 2010). The environment luminance may change along with different spatial place and time, so a brightness transfer function (BTF) f_{ij} proposed by Javed *et al*. (2005) is computed for every pair of cameras C_i and C_j:

$$B_j = f_{ij}\,(B_i) \tag{13}$$

Additionally, when an object enters one camera's FOV from another camera's FOV, brightness histogram is applied to describe the object's characteristic. Given two m-bin histograms:

$$p=\{\hat{p}_u\}_{u=1..m},\sum_{u=1}^{m}\hat{p}_u=1 \text{ and } q=\{\hat{q}_u\}_{u=1..m},\sum_{u=1}^{m}\hat{q}_u=1$$

then the distance between the two histograms is computed as:

$$D(p,q)=\sqrt{1-\sum_{u=1}^{m}\sqrt{\hat{p}_u\hat{q}_u}} \tag{14}$$

D (p, q) is a Bhattacharyya coefficient (Comaniciu *et al*., 2000). Consequently, the matching degree of shape characteristics corresponding to two histograms can be analyzed according to the coefficient.

Let denote C_1, C_2,..., C_b calibrated cameras and Z denote the set of all moving objects, then the characteristics of all objects are denoted $Z = \{Z_i\,(P, A)|\, i = N\}$, where p is the planar coordinates of corresponding a moving object's centriod in the world coordinates, A is the brightness information of the corresponding object. If a camera C_1 detects m trajectories $P1 = \{P_{i1},..., P_{i2}...P_{im}\}$, where, P_{ij} denotes the jth trajectory in the ith camera, the whole process of multi-camera information fusion and tracking is described as follows:

- Learn all inter-camera brightness transfer functions f_{ij} ($\forall$I, j$\le$r and I $\neq$j) and let object set Z = ϕ
- Do detect new objects for all cameras and acquire the trajectories and brightness characteristics of objects. If the jth camera detects a new object, then record the trajectory and brightness histogram q of the object
- Compare the new object information with all recorded object information in Z. If Z = ϕ then go to Eq. 5, else continue to next step
- Take an object Z_k from Z, its corresponding brightness histogram is q_k. Let $q_{k,i}$ denote the brightness histogram when Z_k appears in the ith camera. So D $(q, q'_{k,j})$ is computed according to the BTF $q'_{k,j} = f_{ij}\,(q_{k,i})$. If D $(q, q'_{k,j})$<H (H) is a threshold constant), then label the new object as the same marker as object Z_k and go to Eq. 2, else continue to next step
- If all objects in Z are compared, then label the object as a new marker and add it to Z and go to Eq. 2, else go to Eq. 3.

Based on the algorithm above, the training set Γ can be attained.

EXPERIMENTAL RESULTS

All experiments were carried out using an ActivMedia P3-DX robot named Robocare in the environment of School of Automation at Southeast University. The environmental grid-based map (size: 30×23 m) is shown in Fig. 2. In the Fig. 2, the five red points (A-E) are specific locations people might be interested in approaching and seven green points denote the positions of CCD cameras (height: 2.5 m) which is distributed over the environment and are used in the experiments for people tracking. Each CCD camera is linked to one PIII 800Hz+256M RAM PC running Redhat Linux 9.0 by a BT848 card.

The first experiment is designed to demonstrate that our approach can reliably predict the possible trajectory of a person and appropriately incorporate this information into Robocare's motion plans. The task of Robocare was to travel along the hallway of our building from initial position 1 to C using localization algorithms (Liang *et al*., 2010; Maohai *et al*., 2011; Quan and Ming, 2011; Guo-quan and Zhan-ming, 2011). At the same time, a person who was walking in the opposite direction from initial position 2 was close to the robot (Fig. 3). From the first fifteen observed positions of the person moving from position 3 to position 4, we can compute probabilities that the trajectory belongs to each motion mode using our approach (Fig. 3a). As a result, it is the most probable that the trajectory leading to the locations A, B and E. Furthermore, all the corresponding motion modes lead through the hallway so that Robocare was likely to interfere with the person. Accordingly, the cost-optimal action for Robocare was to drive into position 2 and to wait (Fig. 3b). When the person arrived the position 5, the likelihood that the person's trajectory leads to the ocation E becomes 0.785 and is the most. According to the prediction, Robocare resumed moving towards its designated goal location C after the person had passed through the hallway (Fig. 3c).

The following experiment continues to illuminate how our robot Robocare plans a collision-free path which respects the human's safety and comfort. In this experiment, the task of Robocare was to travel along the hallway of our building from initial position 6 to A. When

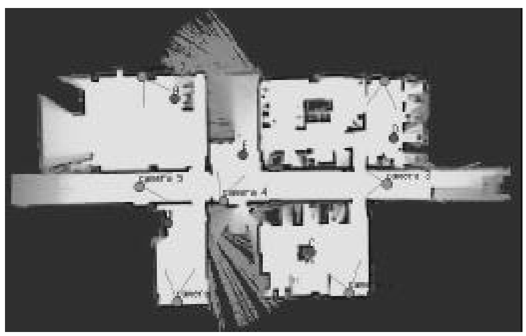

Fig. 2: Experimental map and system deployment

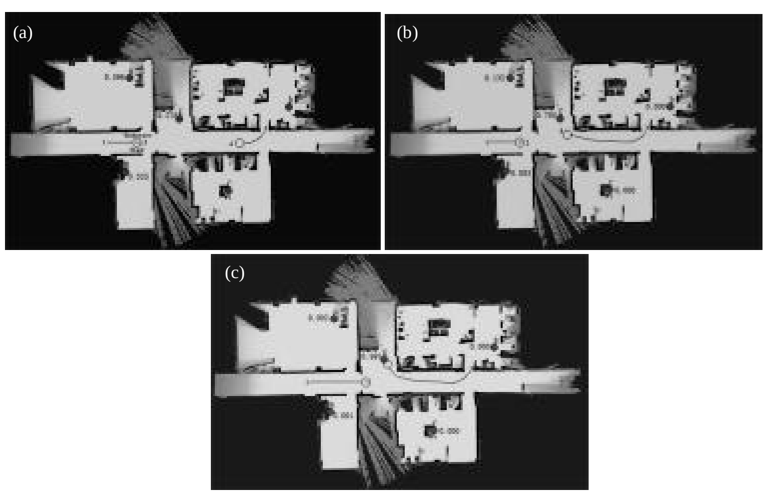

Fig. 3(a-c): Compliant navigation. The number beside each red point denotes the possibility that a trajectory leads to the location. (a) Robocare moved from position 1 to 2 to wait until the person passed through the hallway. (b) Robocare started to move towards its designated goal location C on the person passing through the hallway. (c) The position of Robocare when the person arrived at E

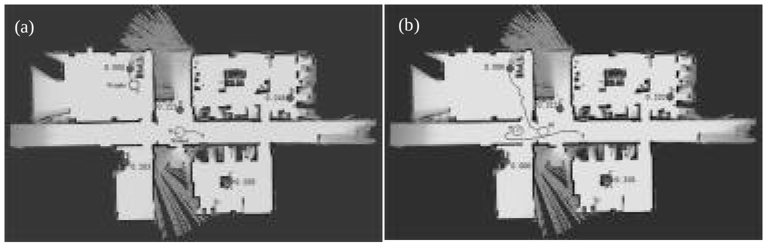

Fig. 4(a-b): Collision-free path planning which respects the human's safety and comfort. (a) Robocare traveled along the hallway from position 6 to position 8 when a person walked from location A to position 7 (b) In order to prevent interfering with the person, Robocare was to drive into positon 9 to wait the person passing through the doorway

robocare moved to position 8 as shown in Fig. 4a, the camera network had acquired nine observed positions of a person moving from A to position 7. According to our approach, the likelihoods that the trajectory belongs to each motion modes can be attained. Consequently, the possible trajectory leads to the locations B, C, D and E. Moreover, all corresponding motion modes lead through the doorway of the room on which location A locates. Thus, the cost-optimal action for Robocare was to drive into position 9 and to wait (Fig. 4b). When the person walked out of the room, the robot then resumed moving its designated goal A.

CONCLUSIONS

In this study, we present a method for learning and utilizing motion modes of persons and furthermore present experiments illustrating the effectiveness of our method. A future study is to furtherly extend the application of our method to more complex dynamic environments, such as many people coexisting in the same space (Sisbot *et al*., 2007).

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