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Behavior Prediction based on Obstacle Motion Patterns in Dynamically Changing Environments

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Abstract

This paper proposes a behavior prediction method for navigation application in dynamically changing environments, which predicts obstacle behaviors based on learned Obstacle Motion Patterns (OMP) from observed obstacle motion trajectories. A multi-level prediction model is then proposed that predicts long-term or short-term obstacle behaviors. Simulation results show that it works well in a complex environment and the prediction is consistent with actual behaviors.

1. Introduction

Mobile vehicles/robots that are able to navigate and perform autonomous tasks will become an integral accessory of our lives in the future. At present, most practical mobile vehicles are able to avoid collision in some unknown static environments based on motion planning [1]. In the real world, obstacles (humans or other vehicles) can move freely in space at varying speed and direction, which makes navigation methods designed for static environments unsuitable for dealing with the tougher collision avoidance requirement [2].

When Dynamically Changing Environment (DCE) is concerned, a potential approach is to actively predict obstacles' motions and use the overall prediction result to derive the agent's next action decision. Both current and historical motion data can be used in techniques such as neural network [2], Markov models [3], and Kalman filter [4] for this purpose. However, these methods only offer prediction of a single time-step (a short-term prediction), which is restrictive because they treat the collision avoidance problem locally and in a suboptimal manner [5].

Recently, some researchers have attempted long-term behavior prediction for global collision avoidance [6, 7]. It predicts over a number of future time-steps giving the agent a better chance of making the right action decision. In [6], it treats the final destination point of the obstacle's movement as a long-term prediction goal, though this does not guarantee collision-free motion because there are many possible routes and motion patterns between each origin-destination pair. In [7], long-term prediction is made based on a set of trajectories between a number of resting places where people stop and stay. It requires the locations of these resting places be known a priori for the formation of Obstacle's Motion Patterns (OMP). In more realistic DCE, prior knowledge of OMP is usually not available.

In this paper, we propose a new prediction method that predicts obstacle behaviors based on learned OMP from observed obstacle motion trajectories. The observed trajectories are clustered using the CGC algorithm [8] to form OMP. For each clustered OMP, it is evaluated for completeness against a criterion. Based on these OMP, a multi-level prediction model is proposed. It consists of three levels of prediction in which the high and middle levels are both long-term predictions that predict future trajectories over a number of time-steps. The low level uses an AR model [9] to predict future trajectories over the next time step. The results of a number of simulation experiments show that it works well in a multiple pedestrian environment and the prediction is consistent with actual behavior.

The rest of this paper is organized as follows. In Section 2, we present an overview of the proposed method. Section 3 depicts the experimental results and finally, the paper is concluded in Section 4.

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2. Proposed Method

Our proposed method consists of the following functions: (1) OMP Clustering; (2) OMP Classification; and (3) Obstacle Behavior prediction; as depicted in Figure 1.

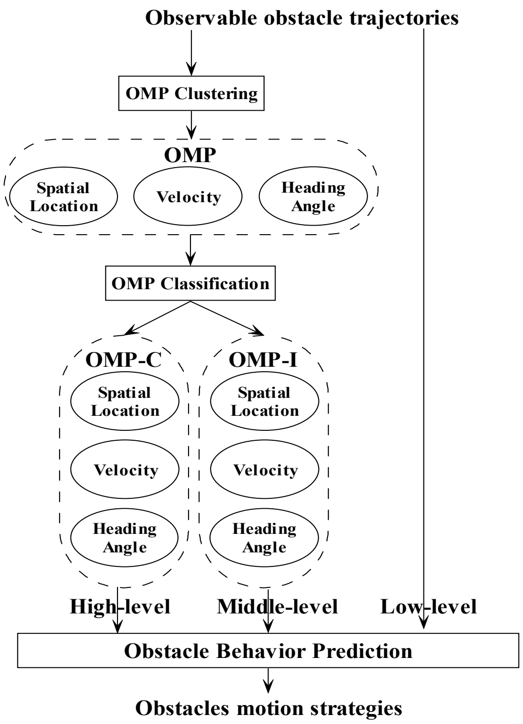

Figure 1. Proposed method

2.1 OMP Clustering

To cluster OMP from trajectories of one of the three feature dimensions (e.g. spatial location), we employ the constrained gravitational clustering (CGC) method as described in [8]. Analogy to gravitational force, trajectories separated by a short distance are more likely to form a cluster compared with those separated by a long distance. The 'gravitational force', $F_{T_mT_n}$ between trajectories T_m and T_n is given as:

$$F_{T_mT_n} = C\frac{g_m \times g_n}{\left|s_m - s_n\right|^3}\left(s_m - s_n\right), \qquad (1)$$

where C is the gravitational constant which is set 1 here, g_m and g_n are the mass represented by numbers of trajectories in the m^{th} and n^{th} clusters respectively, and s_m and s_n are the mean location vectors in the feature space. Similar clustering effect can be found in the velocity and heading angle trajectories. The OMP clustering step is repeated at each time step.

2.2 OMP Classification

OMP are then classified as *complete* OMP (OMP-C), which represents pattern that does not change much over time, or as *incomplete* OMP (OMP-I), which may be updated after subsequent prediction. To classify OMP, we propose a criterion based on the triangle algorithm [10]. Let N_i denotes the number of observable trajectories in the i^{th} OMP cluster. The criterion is presented by setting a threshold R_x for N_i. For the i^{th} OMP, if $N_i>R_x$, then the OMP is classified as an OMP-C, otherwise it is classified as an OMP-I. Initially, all OMP are ordered in a descending order in terms of N_i.

2.3 Obstacle Behavior Prediction

The purpose of the proposed method is to predict obstacle motion behavior in the most appropriate manner based on the OMP-C, OMP-I and current trajectories, through a multiple prediction hierarchy.

Let T_k denote the observable trajectory of the k^{th} obstacle, and P_j^i and P_l^c represent the j^{th} OMP-I and the l^{th} OMP-C respectively. For representing spatial location, velocity and heading angle features, T_k is given by $\{\boldsymbol{T_k^s}, \boldsymbol{T_k^v}, \boldsymbol{T_k^\varphi}\}$ and P_j^i and P_l^c are given by $\{\boldsymbol{P_j^{s,i}}, \boldsymbol{P_j^{v,i}}, \boldsymbol{P_j^{\varphi,i}}\}$ and $\{\boldsymbol{P_l^{s,c}}, \boldsymbol{P_l^{v,c}}, \boldsymbol{P_l^{\varphi,c}}\}$, respectively. Let T^*_k denotes the predicted behavior of k^{th} obstacle in any future motion. T^*_k is also given by $\{\boldsymbol{T^*_k}^s, \boldsymbol{T^*_k}^v, \boldsymbol{T^*_k}^\varphi\}$. If T_k is defined up to t, then T^*_k is defined from $t+1$ onward. For illustration convenience, we can simply choose the spatial location feature as an example for presenting the multi-level prediction process. Thus T_k, P_j^i, P_l^c and T^*_k in this case are all simplified into $\{\boldsymbol{T_k^s}, Ø, Ø\}$, $\{\boldsymbol{P_j^{s,i}}, Ø, Ø\}$, $\{\boldsymbol{P_l^{s,c}}, Ø, Ø\}$ and $\{\boldsymbol{T^*_k}^s, Ø, Ø\}$, respectively. Suppose there are a total of N observable trajectories and M OMP with m_1 OMP-I and m_2 OMP-C ($m_1+m_2=M$). The algorithmic steps are given below:

Step 1: If $P_l^c \notin Ø$, proceeds to *Step 2*. Otherwise mark all T_k as *first-unpredicted* and go to *Step 3*.

Step 2: For each T_k, where $1 \le k \le N$, match it with each P_l^c, where $1 \le n \le m_2$. If match is successful, then output corresponding prediction result T^*_k. Otherwise, mark T_k as *first-unpredicted*.

Step 3: For each *first-unpredicted* T_k, where $1 \le k \le n_1$ and $n_1 \le N$, match it with each P_j^i, where $1 \le m \le m_1$. If match is successful, then output corresponding prediction result T^*_k. Otherwise, mark T_k as *second-unpredicted*.

Step 4: For each *second-unpredicted* T_k, where $1 \leq k \leq n_2$ and $n_2 \leq n_1$, predict a single time step based on an AR model, and output the corresponding prediction result T^*_k.

3. Experiment

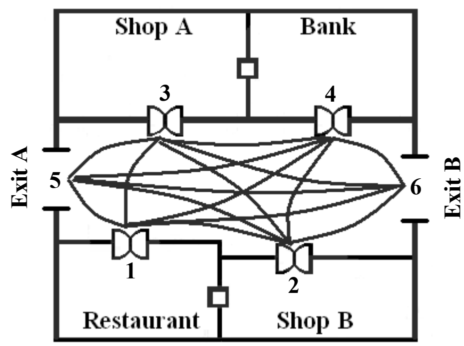

Figure 2. Experiment scenario

In this section, we present a navigation experiment in a DCE to demonstrate our proposed method. The simulation concerns people walking in a shopping mall which is shown in Figure 2. We also use spatial location feature as the example in this experiment. At some time step, all observable obstacle trajectories in the scenario and their corresponding clustered OMP are shown in Figure 3. Since there are bi-directional trajectories in the scenario, two OMP are accordingly clustered between each pair of entrances and we use real-curve and dot-curve to differentiate them.

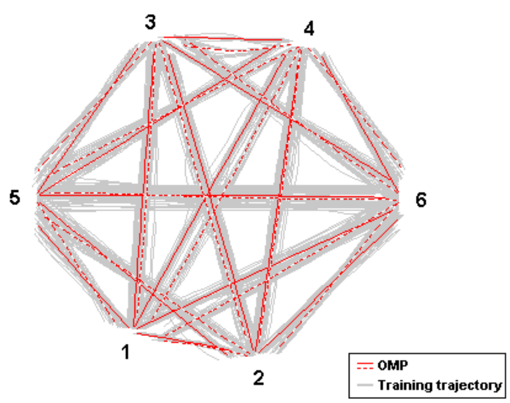

Figure 3. Observable obstacle trajectories and clustered OMP

Figure 4 depicts 10 new-born trajectories (black-curve) at some time step and all clustered OMP (red-curve). The multi-level prediction results are together depicted in Figure 5. 8 observable obstacle trajectories locate in high-level or middle-level prediction. For predicted behaviors (blue-curve) of the trajectories shown in Figure 5, it can be seen that (1) the matching allows slight variations in spatial locations; (2) the prediction is long-term; and (3) the essence of the OMP is reasonably captured in the predicted behaviors, not the actual spatial locations. For the other 2 observable obstacle trajectories that could not find a match in either high or middle levels, it can be seen that both trajectories are quite different from all existing OMP. In this case, a long-term behavior prediction would be inappropriate, and the proposed method makes a next step action prediction shown by a blue cross.

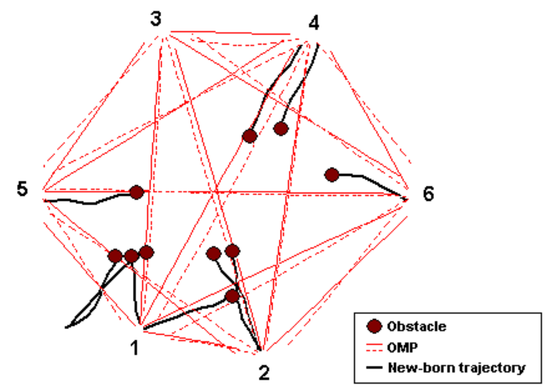

Figure 4. New-born trajectories for prediction

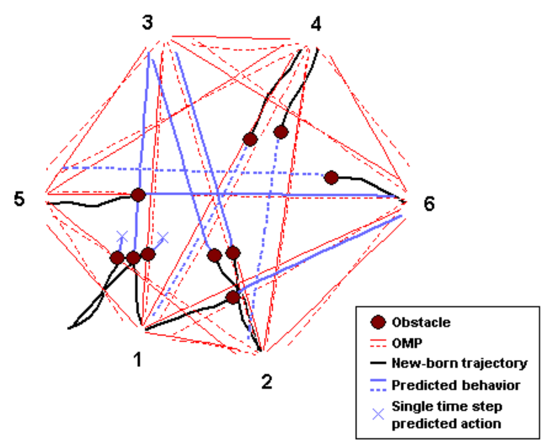

Figure 5. Multi-level prediction results

In order to evaluate the performance of the proposed method, we have conducted 5 separate simulation experiments and compare the predicted behavior with the actual behavior. For the predicted behavior B_k of each obstacle O_k, a prediction error ε_k is computed as the ratio between the distance deviation during the whole prediction process, and the actual total traversed distance. The calculation of ε_k is performed as:

$$\varepsilon_k = \frac{d_n{}^e}{\sum_{i=1}^{n} d_i}, \tag{2}$$

where $d_n{}^e$ is the accumulated deviated distance between the predicted location and the actual location at the last time step, and d_i is the actual traversed distance at each time step. Here, n is the total number of time steps in the prediction.

Table 1. Prediction errors

No.	Number of obstacles	Minimal error ε_{min}	Maximal error ε_{max}	Average error ε_{avg}
1	8	5.693%	10.127%	8.296%
2	12	5.372%	10.009%	8.192%
3	9	5.921%	10.426%	8.397%
4	7	4.925%	9.481%	7.975%
5	13	5.097%	9.659%	8.022%

The prediction errors of all 5 experiments are then calculated and given in Table 1. In each experiment, we list ε_{min} , ε_{max} and ε_{avg} for error analysis. ε_{min} and ε_{max} mean the minimal and the maximal ε_k respectively among all obstacles in the experiment, and ε_{avg} means the average prediction error for all obstacles in the experiment. It is found that the average prediction error is around 8% and the prediction can be considered as reasonable.

4. Conclusion

In this paper, we presented a multi-level prediction model based on OMP clustering and classification for long-term obstacle behavior prediction in DCE. From the simulation result, it can be concluded that the proposed method is effective and appropriate in deploying high-level, middle-level and low-level predictions for different trajectory behaviors. The main contribution of the proposed method is to offer a potential approach to predict long-term behavior rather than a next step action, which is more common in existing methods. Long-term behavior would be beneficial for analyzing and identifying behavior patterns that indicate some particular events or help avoid some particular scenarios. Thus, we believe behavior prediction would have substantial impact to navigation in DCE for intelligent vehicles on the road as well as mobile robots in general. Furthermore, for other related application areas, such as crowd control, behavior prediction could also make important contribution. Based on the general innovative idea and the proposed framework, our future work will mainly focus on three aspects: (1) to conduct simulation study based on velocity and heading angle; (2) to investigate other features to characterize obstacle behavior; (3) to research online management of OMP and to improve the accuracy of obstacle behavior prediction based on online updated OMP.

5. Acknowledgement

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