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Improved Multi-Level Pedestrian Behavior Prediction Based on Matching with Classified Motion Patterns

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***Abstract*—This paper proposes an improved multi-level pedestrian behavior prediction method based on our previous research work on learning pedestrian motion patterns and predicting pedestrian long-term behaviors as their motion instances are being observed. The improvement mainly focuses on the similarity matching criteria between the trajectory and the clustered MP whose main advantages are that (1) a reasonable similarity range of MP is automatically calculated instead of manually set; (2) the distance feature and the changing angle feature are considered together for similarity matching while only the distance feature is considered before. The improved method has been implemented and a study of how the new prediction method performs in real world scenario is conducted. The results show that it works well in real DCE and the prediction is consistent with the actual behavior.**

Keywords-motion patterns; similarity matching; multi-level behavior prediction; dynamically changing environment

I. INTRODUCTION

Traffic accident has been described as one of the major causes of death and injuries around the world in a World Health Organization report [1]. Compared with vehicle occupants, the vulnerable road users, such as pedestrians, suffer higher risk of death in traffic accidents [2]. Obviously, if pedestrian behavior can be captured, analyzed and predicted, then many potential traffic accidents may be avoided or the severity of the impact heavily reduced, which could eventually lower pedestrian fatalities as a result.

In a Dynamically Changing Environment (DCE) such as a busy street in a build-up area involving both vehicles and pedestrians, Collision Avoidance (CA) is no longer just a matter between vehicles, but also between vehicles and pedestrians. Assuming that most pedestrians have a certain ability of CA and would behave in a rational manner on the road, it would then be up to the vehicle or agent to navigate with a reasonably fast CA response. In order to do that, reactive response has to be replaced by the ability to look ahead into the future, i.e., prediction of pedestrian as well as vehicle movements or behaviors in the proximity of the agent.

Conventionally, object behavior prediction is performed in a short-term manner which focuses on pedestrian motion in the next time-step [3-8]. This has the advantage that short-term prediction is certainly more accurate than long-term prediction, although with only the next time-step predicted, navigation planning can only be short-term as well, without being able to consider a longer term path optimization. As such, some researchers have recently attempted long-term behavior prediction for global and optimal CA [9, 10]. Our previous research work also concentrated on long-term behavior prediction which first learned Motion Patterns (MP) from a series of observed pedestrian motion instances and then predicted long-term pedestrian behaviors over a number of future time steps [11]. Compared with the other long-term behavior prediction methods [9, 10], the main advantages of our previous method are that (1) no priori knowledge of pedestrian is needed for the construction of MP; (2) it predicts the entire path to be travelled by the pedestrian instead of just the destination.

In this paper, we propose an improved multi-level pedestrian behavior prediction method which succeeds the general idea of our previous research work. The improvement mainly focuses on the similarity matching criteria between the trajectory and the clustered MP. The new criteria are superior in two ways: (1) a reasonable similarity range of MP is automatically calculated instead of manually set; (2) the distance feature and the changing angle feature are considered together for similarity matching while only the distance feature is considered before. In the improved method, the observed pedestrian trajectories (in terms of spatial location, velocity or heading angle) are clustered using the clustering algorithm as described in [12]. For each clustered MP, it is either classified as a *complete* MP (MP_C), which represents pattern that is more-or-less consistent over time, or as an *incomplete* MP (MP_I), which represents an inconsistent pattern that may be updated in the future [11]. Based on these MP, multi-level prediction is employed. It consists of three levels of prediction, in which the high and middle levels are both long-term predictions based on the MP_C and MP_I that predict future trajectories over a number of time steps. On the other hand, the low level prediction predicts only the next time-step, equivalent to a short-term prediction. The improved method has been implemented and a study of how the new prediction method performs in real world scenario is conducted. The results show that it works well in real DCE and the prediction is consistent with the actual behavior.

The rest of this paper is organized as follows. In Section II, gives a brief introduction on the generalized multi-level prediction framework. In Section III, presents the improved matching-based pedestrian behavior prediction model. Section IV depicts the experimental results produced by the improved method, and Section V concludes the paper with a brief discussion of future research direction.

II. Generalized Multi-Level Prediction Framework

The generalized multi-level framework consists of four main functions: (1) Trajectory Formation; (2) MP Clustering; (3) MP Classification and Maintenance; and (4) Pedestrian Behavior Prediction; as depicted in Figure 1. When applied in a specific scenario, at some time step *t*, the observed new pedestrian instances are first associated with existing trajectories that have been assembled through the previous *t*-1 time steps. The association aims at optimizing a global shortest distance for all instances. Based on the newly formed trajectories with spatial location feature, the trajectories with velocity and heading angle features can be accordingly derived. When trajectories are obtained, MP clustering is performed for learning MP by using an instance-based clustering algorithm [12]. Each clustered MP represents a sub-group of trajectories that have similar characteristics with spatial location, velocity or heading angle feature. In MP classification and maintenance module, by evaluating the number of observable motion instances in each MP cluster, the MP is further classified into MP_C or MP_I [11].

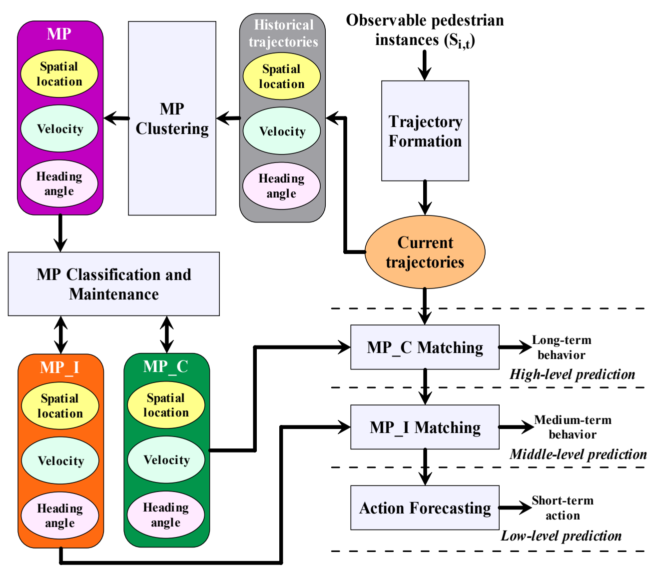


Figure 1. Overview of the generalized multi-level prediction framework.

Finally, pedestrian behavior prediction is performed which will be described in detail in the following Section. Pedestrian behavior prediction consists of three levels prediction. High-level prediction is first performed in MP_C matching module if there is some available MP_C. If a qualified match can be found between a trajectory and a MP_C, a long-term behavior of the trajectory is predicted to be similar to the MP_C. If there is no available MP_C or no qualified match, middle-level prediction is then performed in MP_I matching module for the remaining unmatched trajectories. If there is a qualified match when matching a trajectory with a MP_I, a medium-term behavior of the trajectory is predicted to be similar to the MP_I. If no qualified matching exists, low-level prediction is accordingly performed in action forecasting module, in which one single time-step action is predicted.

III. Matching-Based Pedestrian Behavior Prediction Model

A. General Algorithmic Flow

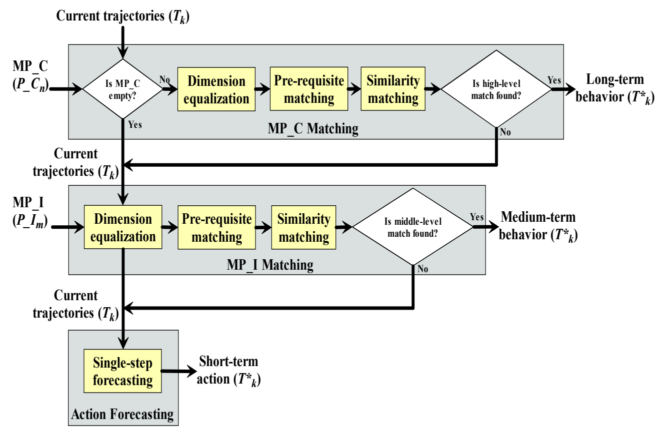


Figure 2. Block diagram of matching-based pedestrian behavior prediction model.

The focus of this multi-level prediction method is the matching-based pedestrian behavior prediction model, which aims to predict pedestrian behavior in the most appropriate manner based on the MP_C, MP_I and current trajectories, through a multiple prediction hierarchy as depicted in Figure 2. If there are available MP_C, the multi-level prediction starts from the high level, otherwise it starts from the middle level. In high-level prediction, when a current trajectory is matched with a MP_C, dimension of the current trajectory and the MP_C are equalized first. The matching process in the improved method consists of two stages: pre-requisite matching and similarity matching. In pre-requisite matching, a criterion based on distance between the current trajectory and the MP_C is proposed for deciding whether the current trajectory falls into a reasonable similarity range of the MP_C. In our previous method, this criterion depends on a manually setting parameter that defines a similarity range of the MP_C. It is improved that the similarity range of the MP_C can be automatically generated based on the left boundary and the right boundary of the MP_C. On the other hand, our previous method only considers the distance between the current trajectory and the MP_C when measuring their similarity. However, there are cases that the current trajectory may not be very similar to the MP_C although they are close to each other. In the improved method, we proposed a new similarity matching stage which is performed based on a criterion that considers changing angle calculation and comparison. Current trajectories are performed prerequisite matching first, and those that have matched MP_C can be performed similarity matching. If the current trajectory can further find a matched MP_C, then it has a long-term predicted behavior based on the matched MP_C, otherwise it is passed to middle-level prediction for predicting a medium-term behavior. Middle-level prediction follows a similar algorithmic flow as high-level prediction, while the difference is that MP_I are used for matching in middle-level prediction instead of MP_C. If the prediction for a current trajectory fails in both high level and middle level, low-level prediction is performed in which single-step forecasting will be done by using an Auto-Regressive (AR) model [13].

Let T_k denotes the observable trajectory of the pedestrian PD_k, and P_I_m and P_C_n represent the m^{th} MP_I and the n^{th} MP_C respectively. T_k is given by $\{T_k^s, T_k^v, T_k^{\varphi}\}$ in which T_k^s, T_k^v and T_k^{φ} represent the pedestrian trajectory in spatial location, velocity and heading angle feature spaces, respectively. P_I_m and P_C_n are given by $\{P\_I_m^s, P\_I_m^v, P\_I_m^{\varphi}\}$ and $\{P\_C_n^s, P\_C_n^v, P\_C_n^{\varphi}\}$ which similarly represent the MP_I and MP_C in three feature spaces. Let T^*_k denotes the predicted behavior of PD_k in any future motion. T^*_k is also given by $\{T^{*s}_k, T^{*v}_k, T^{*\varphi}_k\}$ for representing the predicted behavior in three feature spaces. If T_k is defined up to t, then T^*_k is defined from t+1 onward. For illustration convenience, we choose the spatial location feature as an example for presenting the multi-level prediction process. Thus T_k, P_I_m, P_C_n and T^*_k in this case are all simplified into $\{T_k^s, Ø, Ø\}$, $\{P\_I_m^s, Ø, Ø\}$, $\{P\_C_n^s, Ø, Ø\}$ and $\{T^{*s}_k, Ø, Ø\}$, respectively, in which $T_k^s = t_k^s(n_1,n_2) = \{r_k^s[n]\}$ and $T^{*s}_k = t^{*s}_k(n_3,n_4) = \{r^{*s}_k[n]\}$.

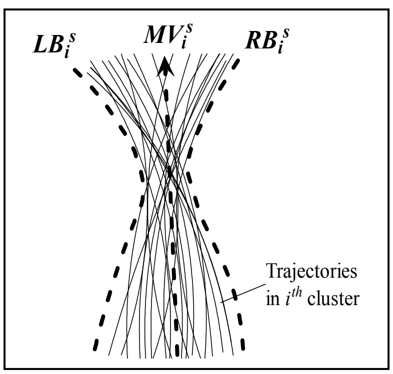


Figure 3. Description of MP.

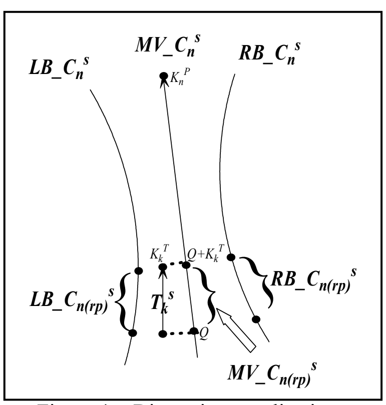


Figure 4. Dimension equalization.

In our previous method, $P\_I_m^s$ and $P\_C_n^s$ are only represented by the mean vector of m^{th} MP_I and n^{th} MP_C clusters, respectively. When MP_C and MP_I are used for matching with trajectories, a global parameter is manually set through extensive experimentation to define a similarity range for all MP_C and MP_I [11]. It is more reasonable that the similarity range of MP_C/MP_I can be automatically obtained based on the group of trajectories that generates the MP_C/MP_I. In the improved method, $P\_I_m^s$ and $P\_C_n^s$ are described by $\{LB\_I_m^s, MV\_I_m^s, RB\_I_m^s\}$ and $\{LB\_C_n^s, MV\_C_n^s, RB\_C_n^s\}$, respectively, as depicted in Figure 3. Let $P\_C_n^s$ be an example, besides using the mean vector $MV\_C_n^s = mv\_c_n^s(n_1,n_2) = \{r_{(mv\_c)n}^s[n]\}$ in our previous method, we further consider the deviation between the trajectories in the cluster and the mean vector. In terms of the moving direction of $MV\_C_n^s$, the left boundary $LB\_C_n^s = lb\_c_n^s(n_1,n_2) = \{r_{(lb\_c)n}^s[n]\}$ and the right boundary $RB\_C_n^s = rb\_c_n^s(n_1,n_2) = \{r_{(rb\_c)n}^s[n]\}$ represent maximal deviated distance in the left and the right sides of $MV\_C_n^s$, respectively. The following sub-sections will describe the focus of our improved method in detail.

B. Dimension Equalization

Since the current trajectories and MP_C/MP_I consist of spatial locations of different number of time steps, before matching is performed, their dimensions need to be equalized. To do that, we first segment $P\_C_n^s$ or $P\_I_m^s$ into portions which have the same data dimension with T_k^s. For example, if T_k^s has K_k^T time steps, and $P\_C_n^s$ has K_n^P time steps ($K_n^P > K_k^T$). We select the portion on $P\_C_n^s$ which has the smallest Euclidean distance to T_k^s as the representative of the whole $P\_C_n^s$ as depicted in Figure 4. The representative portion of $P\_C_n^s$ is denoted by $P\_C_{n(rp)}^s$. $P\_C_{n(rp)}^s$ is similarly described by $\{LB\_C_{n(rp)}^s, MV\_C_{n(rp)}^s, RB\_C_{n(rp)}^s\}$, which is given as:

$$\begin{aligned} MV\_C_{n(rp)}^s &= mv\_c_n^s(Q+1, Q+K_k^T), \\ LB\_C_{n(rp)}^s &= lb\_c_n^s(Q+1, Q+K_k^T) \quad 1 \le Q \le K_n^P - K_k^T. \\ RB\_C_{n(rp)}^s &= rb\_c_n^s(Q+1, Q+K_k^T), \end{aligned} \tag{1}$$

C. Pre-requisite Matching

In prerequisite matching, our concern is that whether a current trajectory falls into a reasonable similarity range of a MP_C/MP_I. So a criterion is proposed based on the distance between a current trajectory and a MP_C/MP_I. The distance function $D(T_k^s, P\_C_{n(rp)}^s)$ between T_k^s and $P\_C_{n(rp)}^s$ is defined as:

$$D(T_k^s, P\_C_{n(rp)}^s) = \sum_{i=1}^{K_k^T} \left(\frac{i}{H} \times d(r_k^s[i], r_{(mv\_c)_n}^s[Q+i]) \right), \tag{2}$$

where $d(\boldsymbol{r}_k^s[i], \boldsymbol{r}_{(mv\_c)n}^s[Q+i])$ refers to the Euclidean distance between the corresponding coordinate pair $\boldsymbol{r}_k^s[i]$ and $\boldsymbol{r}_{(mv\_c)n}^s[Q+i]$, and $\frac{i}{H}$ ($H = \sum_{i=1}^{K_k^T} i$) is a weight factor for each time step, which means an "older" time step has less impact when matching. We regard $P\_C_{n(rp)}^s$ as a Gaussian distribution model where the *Mean* locates at $MV\_C_{n(rp)}^s$. From $MV\_C_{n(rp)}^s$ to $LB\_C_{n(rp)}^s$ or $RB\_C_{n(rp)}^s$, a larger distance of T_k^s away from $MV\_C_{n(rp)}^s$ means a less likely matching. If T_k^s goes outside of $LB\_C_{n(rp)}^s$ or $RB\_C_{n(rp)}^s$, the matching fails as depicted in Figure 5. So the criterion for a successful matching between T_k^s and $P\_C_{n(rp)}^s$ is given as:

$$D(T_k^s, P\_C_{n(rp)}^s) \leq \sum_{i=1}^{K_k^T} \left(\frac{i}{H} \times DstMax(i) \right). \quad (3)$$

In (3), $DstMax(i)$ defines the largest acceptable distance at each time step by choosing the larger from the distance between $LB\_C_{n(rp)}^s$ and $MV\_C_{n(rp)}^s$, and the distance between $RB\_C_{n(rp)}^s$ and $MV\_C_{n(rp)}^s$, which is given as:

$$DstMax(i) = Max\{d(r_{(lb\_c)n}^s[Q+i], r_{(mv\_c)n}^s[Q+i]), d(r_{(rb\_c)n}^s[Q+i], r_{(mv\_c)n}^s[Q+i])\}. \quad (4)$$

If T_k^s satisfies (3), it is passed to similarity matching for further matching with $P\_C_n^s$, which is called a *candidate* MP_C after prerequisite matching. Otherwise, it is passed to middle-level prediction for predicting a medium-term behavior.

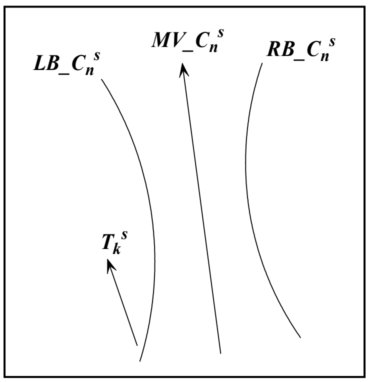


Figure 5. Failed pre-requisite matching.

D. Similarity Matching

In similarity matching, we consider the changing angle of the current trajectory at the time step which the prediction is performed for further measuring the similarity between the current trajectory and the *candidate* MP_C/MP_I. It is believed that a smaller changing angle means higher similarity between the current trajectory and the *candidate* MP_C/MP_I since there is less change in moving direction. The criterion for a qualified similarity matching between T_k^s and $P\_C_{n(rp)}^s$ is given as:

$$\left| \delta_{K_k^T} - \overline{\delta} \right| \leq \delta_d, \quad (5)$$

where $\delta_{K_k^T}$ is the changing angle of T_k^s at the time step K_k^T which the prediction is performed, $\overline{\delta}$ is the average of all changing angle of T_k^s at historical time steps and δ_d is the largest deviated angle when comparing all changing angles at historical time steps with $\overline{\delta}$, which is given as:

$$\delta_d = \arg_{\max}\left(\left| \delta_i - \overline{\delta} \right| \right), \quad 3 \leq i \leq K_k^T - 1. \quad (6)$$

For the current trajectory T_k^s, if more than one *candidate* MP_C/MP_I satisfies (5), the *candidate* MP_C/MP_I which has the smallest $\delta_{K_k^T}$ is chosen for generating the predicted behavior for T_k^s since it has the least change in direction.

For a current trajectory which could find a matched MP_C/MP_I in high-level/middle-level prediction, a long-term/medium-term predicted behavior is obtained based on the corresponding matched MP_C/MP_I. For example, if T_k^s has a matched MP_C $P\_C_n^s$, its long-term predicted behavior can be represented as follows when only considering spatial location feature:

$$T^{*s}_k = \{T^{*s}_k, \varnothing, \varnothing\} = \{r^{*s}_k[n]\}, \quad K_k^T+1 \leq n \leq K_k^T + K_n^P - S, \quad (7)$$

where S represents the time step of $P\_C_n^s$ which is closest to the time step K_k^T of T_k^s for performing prediction, and $r^{*s}_k[n]$ represents the predicted spatial location of T^{*s}_k at each time step after K_k^T, which is defined as:

$$r^{*s}_k[n] = r_{(mv\_c)n}^s[S+n-K_k^T] + (r_k^s[K_k^T] - r_{(mv\_c)n}^s[S]). \quad (8)$$

The medium-term predicted behavior of a current trajectory could be generated in the similar way based on the matched MP_I.

E. Single-step Forecasting

In low-level prediction, a single time step action is predicted as the motion strategy. The next position at time step $t+1$ can be predicted by the following equation:

$$w(t+1) = w(t) + v(t)T + Ba(t)T^2, \quad (9)$$

where $w(t)$ means the position at time step t, and $v(t)$ and $a(t)$ are corresponding velocity value and acceleration value. T is the durative time which a single time step represents. B is time-dependent and is updated by the adaptive algorithm in [13].

IV. EXPERIMENT

Figure 6. The scenario of the real experiment.

In this section, we demonstrate how the improved method works in a dynamically changing real-world environment. The scenario of the experiment is based on people walking in a shopping mall as shown in Figure 6. A fixed-background video for this scenario was taken over 10 minutes. From the video recording, a total of 326 observable pedestrian trajectories were accordingly derived. We also use spatial location feature as an illustration in this experiment. In this case, a continuous pedestrian trajectory is generally represented by a series of discrete positions which are recorded at the sampling time of T=1s, which is a flexible parameter that can be changed depending on how trajectories are extracted from the raw video data.

Figure 7. Observable pedestrian trajectories.

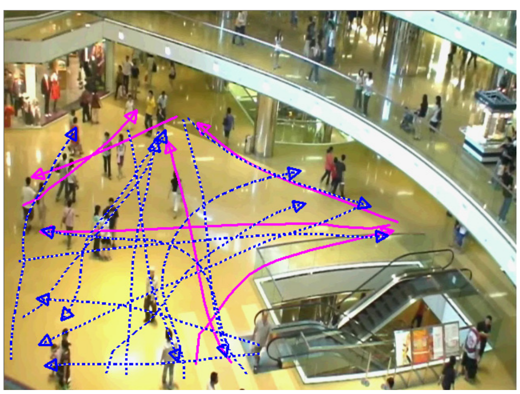


Figure 8. Clustered MP.

Out of all the observable pedestrian trajectories, we randomly select 300 trajectories for MP clustering and leave the remaining 26 trajectories for behavior prediction. Figure 7 depicts the selected 300 observable pedestrian trajectories in which red-lines and green-lines represent double-directional trajectories between each pair of entrances, respectively. There are altogether 20 MP which are clustered and the results are shown in Figure 8, in which the arrows are used for differentiating moving directions. By passing all 20 clustered MP to the MP classification, 5 of them are classified as MP_C as depicted by red solid-lines, and the other 15 MP are classified as MP_I which are represented by blue broken-lines. Figure 9 depicts the multi-level prediction results among the remaining 26 trajectories. In Figure 9(a) and (b), red solid-lines and blue broken-lines are used for representing MP_C and MP_I, respectively, and corresponding predicted long-term and medium-term behavior are shown by green-lines. Black-lines represent the actual behavior of the pedestrian for comparison and black-circles label the time step that the prediction was performed. Figure 9(c) depicts a single time step action predicted at the low level by green-lines, and black-circles also label the time step that the prediction was made.

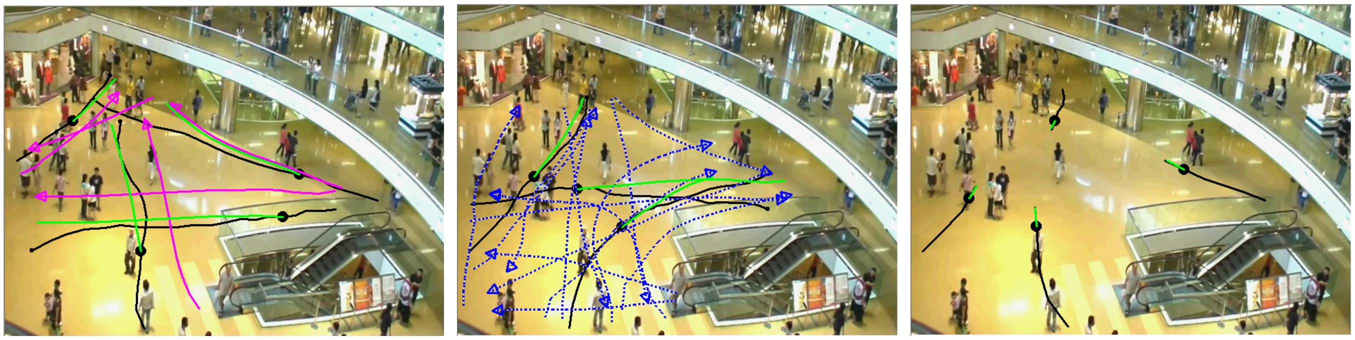
In order to evaluate the performance of the improved method, we compare the predicted behavior of each trajectory with the corresponding actual behavior for analyzing the error of the improved prediction method. For the predicted behavior T^{*s}_k of each pedestrian PD_k at the time step t, prediction error $e_{k(t)}$ is computed as:

$$e_{k(t)} = \frac{D^e_{k(t)}}{L_k}. \tag{10}$$

where $D^e_{k(t)}$ is the deviated distance between the predicted behavior and the actual behavior after time step t, and L_k is the actual total traversed distance between the origin-destination pair of the pedestrian PD_k. In order to work out a more accurate prediction error for each pedestrian, we calculate a series of $e_{k(t)}$, to generate a global prediction error ε_k of the pedestrian PD_k at all possible time steps t when a prediction can be performed. The calculation of ε_k is performed as:

$$\varepsilon_k = \frac{\sum_{t=3}^{n-1} e_{k(t)}}{N-3}. \tag{11}$$

where N is the total number of time steps of the pedestrian's trajectory from the origin to the destination. For all the 26 trajectories for prediction, we compare the improved multi-level prediction (IMP) method with our previous multi-level prediction (PMP) method and the recursive low-level prediction (RLP) method. For long-term or medium-term behavior predicted at high level or middle level from the IMP method, the RLP method also generates the behavior with the same number of future time steps by recursively predicting a single action in the next time step. Figure 10 depicts the calculated prediction error of all 26 trajectories generated by the IMP method, the PMP method and the RLP method, respectively. It can be seen that (1) the IMP method improved the prediction accuracy compared with PMP method; (2) the IMP method has an obviously better performance than the RLP method in most testing cases. In a minority of testing cases which have very well-defined trajectories, the IMP method is slightly worse than the RLP method. This is to be expected as RLP method works well with well-defined trajectories, and could fail disastrously when the trajectory changes direction frequently. Furthermore, we also compared the processing time of IMP method and PMP method, and it is concluded based on a very minor difference that the improved prediction accuracy of IMP method is not at the price of lower computational efficiency compared with PMP method.



(a) (b) (c)

Figure 9. Multi-level prediction results.

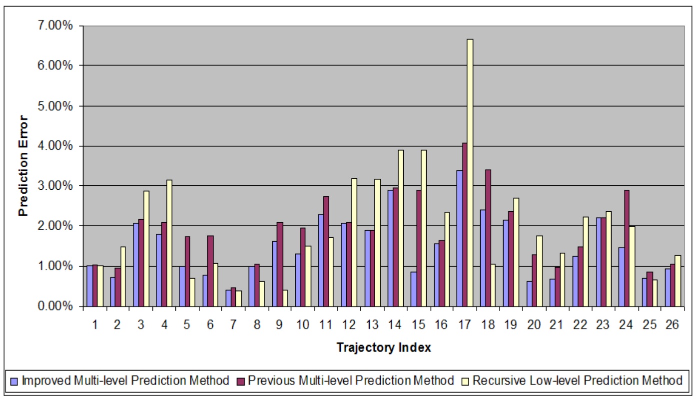


Figure 10. Prediction error comparison between the IMP method, PMP method and the RLP method.

V. CONCLUSION

In this paper, we presented an improved multi-level behavior prediction method based on a new matching algorithm with classified motion patterns. Based on our previous multi-level behavior prediction framework, the improved method proposed in this paper concentrated on improving the similarity matching criteria between the trajectory and the clustered MP for pedestrian behavior prediction. The new criteria are superior in two areas: (1) a reasonable similarity range of MP is automatically calculated instead of manually set; (2) the distance feature and the changing angle feature are considered together for similarity matching while only the distance feature is considered before. From the real-world experimental result, it can be concluded that the improved method generates more accurate predicted trajectories than our previous method, and it also has a better performance in most testing cases compared with the recursive low-level prediction method. From the improved multi-level behavior prediction method, our future research will focus on three aspects: (1) to integrate the prediction on spatial location, velocity and heading angle; (2) to investigate online learning of MP and to improve the accuracy of behavior prediction based on updated MP; (3) to define behavior patterns based on learned MP and to analyze pedestrians' motion intention based on their predicted behavior.

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