Human Interaction Analysis
Based on Walking Pattern Transitions

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Abstract—We propose a method that analyzes interaction between pedestrians based on their trajectories obtained using sensors such as cameras. Our objective is to understand the mutual relationship between pedestrians and to detect anomalous events in a video sequence. Under such situations, we can observe the interaction between a pair of pedestrians. This paper proposes a set of features that measures the interaction between pedestrians. We assume that a person is likely to change his/her walking patterns when he/she has been influenced by another person. Based on this assumption, the proposed method first extracts the transition points of a walking pattern from trajectories of two pedestrians and then measures the strength of the influence using the temporal and spatial closeness between them. Finally, experimental results obtained from actual videos demonstrate the method’s effectiveness in understating mutual relationships and detecting anomalous events.

I. INTRODUCTION

Human monitoring is an essential task of surveillance. It can be applied to not only criminal detection but also human navigation and urban planning. Nowadays, compact cameras and sophisticated processing technologies can be used to obtain detailed information about human activities [1]–[5]. Hence, we can easily utilize data such as a person’s position, movement speed, and body structure.

However, in practical visual surveillance applications, such “physical” data are often insufficient. For example, in order to detect crimes from observed videos and then try to prevent them, we must analyze the positions and velocities of walk-

Fig. 1. Visual Surveillance System

Fig. 2. Understanding Higher Information from Sensing Data

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trajectories. While some researchers have studied how to classify a single person into several categories such as visitors and residents [6] and how to detect unusual actions carried out by such a person [5], we focus on the mutual interaction between two or more persons using their motion trajectories. This study could potentially enhance our understanding of human group or community behavior.

II. HUMAN INTERACTION ANALYSIS

A. Related Works

Many studies have analyzed the interactions between walking persons [2]–[4], [7]–[9]. Most of these works are based on scenarios, and they seek a best-matched scenario for particular trajectories. For example, Oliver et al. first generated synthetic samples of interactions to train an HMM-based classifier. Then, they analyzed the samples for specific motion trajectories [3].

Although these top-down strategies seem to give good performance, it is clear that they cannot treat anomalous events that are not included in the scenarios. In addition, most of the existing studies mainly employ the distance between persons as a key feature that characterizes the interaction between them. Hence, sufficiently long trajectories are required to capture the interaction.

Those kinds of limitations first have to be overcome, because various types of interactions can be observed in videos obtained from distributed cameras.

B. Human Interaction Analysis based on Mutual Influence

In this paper, we propose a method that computes a set of features that characterize the interaction occurring between two pedestrians. We assume that the strength of interaction can be measured by the extent to which a certain person is influenced by another person, and we introduce features that quantify the mutual influence between persons.

For example, while friends and colleagues often interact with each other when walking, unrelated persons have less influence on each other. This implies that it is possible to estimate the mutual relationship between them from the computed mutual influence. In addition, a strong influence may imply a state of emergency such as a crime. This bottom-up approach is effective when prior scenarios are not available. Moreover, because both the scenario-based top-down methodology and the proposed bottom-up method complement each other, their integration would allow flexible understanding.

As will be discussed in the subsequent sections, we extract the transitions of a walking pattern in a trajectory. When persons change their walking pattern, such as when they stop, turn, and start walking again, they would have some reason for doing so, and the interaction with another person is one of them. We compute the influence of other persons at each transition point by taking into account the spatial and temporal distance between each person and the variation of the walking pattern after the transition. These factors characterize the other person’s strength of influence, as discussed below. This method enables us to capture the interaction between persons even when only short trajectories are available, while previously mentioned distance-based methods cannot do so.

This idea is inspired by Nishiyama et al. [10]. In order to analyze facial expressions, they divided facial expressions into several segments and exploited their timing structures for analyzing them. Their idea is that the transition from one segment to other abstract motion characteristics and their timing structures reveal underlying meaningful information.

We believe that the transitions within walking patterns also contain useful information. To the best of our knowledge, no existing works exploit similar cues for analyzing motion trajectory. Although we focus on interactions between two pedestrians, this concept could have a bearing on other applications related to the understanding of human behavior.

C. Walking Pattern Transition – An example

Before describing the proposed method, we show a typical example of interaction between pedestrians to illustrate our basic idea. Figure 3 shows an example: (1) two persons meet each other on the street, (2) one catches up to the other, and (3) they walk together.

In this interaction, there are three segments in the trajectory of the person who waited for the other on the street: walking upward, waiting for the other, and walking rightward. All transitions between these segments are caused by the influence from the other.

Our proposed method first extracts these transition points from each motion trajectory and quantifies the strength of the influence from the other person at each transition point. If there exists a certain relationship between the two walking persons, the two persons are likely to interact with each other repeatedly, and we observe a relatively strong influence from the other at transition points in each motion trajectory.

Additionally, when a person is assaulted by a thug, we would observe an extreme influence from the thug on the assaulted person. This situation can be detected using the influence measured from motion trajectories.
III. MEASURING MUTUAL INFLUENCE FROM WALKING PATTERN TRANSITIONS

This section describes the details of the proposed method. As mentioned in the previous sections, we quantify the strength of influence at the transition points of the walking pattern and analyze the mutual interaction between the pedestrians. Hereafter, the term transition denotes the transition points observed in motion trajectories.

A motion trajectory comprises a sequence of positions. Our method consists of the following two steps:

1) Extract transitions \( T_{p1}^{(A)}, T_{p2}^{(A)}, \ldots, T_{pN_A}^{(A)} \) in the motion trajectory of Person A. These transitions divide the trajectory into several segments where the trajectory is uniform in both direction and speed.

2) Compute the strength of the influence from other Persons B, C, ... at each transition \( I_{Tp1}^{(B \rightarrow A)}, I_{Tp2}^{(B \rightarrow A)}, \ldots, I_{TpN_A}^{(C \rightarrow A)}, I_{Tp1}^{(C \rightarrow A)}, \ldots, I_{Tp1}^{(D \rightarrow A)}, \ldots \).

Here, \( I_{Tp1}^{(B \rightarrow A)} \) denotes the influence from Person B to Person A at transition \( T_{p1} \). Note that the strength of influence would change when a sender and a receiver exchange places.

A. Extracting Walking Pattern Transitions

First, we compute velocities after and before a certain point. Let \( x_t^{(i)} \) denote the position of person \( i \) at time \( t \). For the trajectory at time \( t \) we compute the velocities for both \([t, t+T]\) and \([t-T, t]\) as follows:

\[
v_{(i)}^{(t+T)} = \frac{x_{(i)}^{(t+T)} - x_{(i)}^{(t)}}{T}, \quad v_{(i)}^{(t-T)} = \frac{x_{(i)}^{(t)} - x_{(i)}^{(t-T)}}{T}. \tag{1}
\]

Then, we examine whether \( v_{(i)}^{(t+T)} \) and \( v_{(i)}^{(t-T)} \) are different. If

\[
\text{Acc}^{(i)}(t) = \|v_{(i)}^{(t+T)} - v_{(i)}^{(t-T)}\| \geq T_{hv}, \tag{2}
\]

\( x_t^{(i)} \) is regarded as the transition point of two segments.

1If \( x_t^{(i)} \) contains much noise, we use its average within a certain time period instead of \( x_t^{(i)} \) itself.

According to Equation 2, before and after the transition point, the person changes walking speed and/or walking direction. Although this is quite simple to process, it provides sufficient results as shown in Section IV-A1. For the example shown in Figure 3, transitions are marked with inverted triangles.

It should be noted that when we apply the extraction process to actual trajectories, successive points are extracted as transitions, as shown in Figure 4. For this case, we combine them and treat them as one single transition point, and let the times \( t_s \) and \( t_e \) denote the start and end of successive transition points.

B. Influence from Another Person at Transition Point

Then, we measure the influence on a person \( i \) from another person \( j \) at transition \( T_{pi}^{(j)} \). Intuitively speaking, it would be possible to measure it using both (A) the strength of the influence the person \( i \) received and (B) the spatial closeness between persons \( i \) and \( j \). However, when a person notices another person at a distant position, the distance increases and it is difficult to capture the interaction between the two. For such cases, we make use of temporal closeness between transition points in the trajectories of persons \( i \) and \( j \). A set of features that measures the influence is defined as follows:

\[
I_{Tp1}^{(j \rightarrow i)} = \text{Acc}_{Tp1}^{(i)}, \text{Acc}_{Tp1}^{(i)}, T_{p1}, \text{Acc}_{Tp1}^{(i)}, p_{ij}, \tag{3}
\]

where \( \text{Acc}_{Tp1}^{(i)} \), which corresponds to (A), is defined for time duration \([t_s, t_e]\) as:

\[
\text{Acc}_{Tp1}^{(i)} = \|v_{(i)}^{(t+T)} - v_{(i)}^{(t-T)}\|. \tag{4}
\]

\( A_{ij} \) in Equation 3 corresponds to the above (B) and shows the spatial closeness between persons \( i \) and \( j \). It is quite natural.
that two persons are close to each other, such as A and B in Figure 5, when they have interactions. \(A_{ij}^{\beta}\) is defined as:

\[
D_{Tp_{ij}}^{ij} = \min_{t \in [t_a, t_b]} \|x_i^{(j)}(t) - x_j^{(j)}(t)\|,
\]

\[
A_{ij}^{\beta} = \alpha^{-D_{Tp_{ij}}^{ij}} (\alpha > 1),
\]

where we find the minimum distance while the transition of person \(i\) occurs and Equation 6 is introduced for normalizing the distance so that its maximum, which means that the two are quite close, becomes 1.

The other parameter \(B_{ij}^{\beta}\) in Equation 3 is used for measuring the temporal closeness between the two persons, as mentioned above. Figure 6 illustrates an example of its effectiveness. In the figure, person B notices his/her friend A at a distant position and B goes back to A. In this case, because \(A_{ij}^{\beta}\) is small, it is not possible to extract the interaction using spatial closeness. Instead, we introduce another feature:

\[
B_{ij}^{\beta} = \beta^{-D_{ij}^{\beta} \cdot \Delta t} (\beta > 1, \gamma > 1),
\]

where \(\Delta t\) denotes the minimum time difference between the extracted transition points of persons \(i\) and \(j\) that are nearest to time \(t\). When \(\Delta t\) is small, the two transitions have occurred simultaneously and there will be an interaction between the two persons. In Equation 7, we consider not only the temporal closeness but also the spatial closeness by multiplying \(D_{ij}^{\beta}\). This is because it is unlikely for one to receive an influence from another person at a great distance.

### C. Human Interaction Analysis using Computed Mutual Influence

\(I_{Tp_{ij}}^{(j \rightarrow i)}\) shows the strength of influence from a certain person \(j\) on another person \(i\) at time \(t\). If person \(i\) has \(N\) walking pattern transitions in his/her trajectory, we have a set of \(I_{Tp_{ij}}^{(j \rightarrow i)}\) as follows:

\[
I_{Tp_{ij}}^{(j \rightarrow i)} = \{I_{Tp_{ij1}}, I_{Tp_{ij2}}, \ldots, I_{Tp_{ijN}}\}.
\]

In the subsequent sections of this paper, we show its applicability to mutual relationship estimation and anomalous event detection.

1) Estimating Mutual Relationship between Pedestrians:

When two persons affect each other while walking, they are likely to be friends or acquaintances, as shown in the example in Figure 3. Therefore, the influence values introduced in the previous section, \(I_{Tp_{ij}}^{(j \rightarrow i)}\) and \(I_{Tp_{ij}}^{(i \rightarrow j)}\), are larger than those between unrelated persons. In order to estimate a mutual relationship, we define the mutual influence \(I_{Tp_{ij}}^{(i \rightarrow j)}\) as follows:

\[
I_{Tp_{ij}}^{(i \rightarrow j)} = \{I_{Tp_{ij1}}, I_{Tp_{ij2}}\}.
\]

As is clear from the definition, \(I_{Tp_{ij}}^{(i \rightarrow j)}\) is computed for each pair of persons, and it will be a cue for estimating the mutual relationship. However, the number of elements in \(I_{Tp_{ij}}^{(i \rightarrow j)}\) varies according to the number of transition points within person \(j\) 's trajectory. Hence, we compute the average and variance of the influences as:

\[
F_{Tp_{ij}}^{(i \rightarrow j)} = \left\{ \frac{I_{Tp_{ij1}}^{(i \rightarrow j)}}{N_t^{(i \rightarrow j)}}, \frac{1}{N_t^{(i \rightarrow j)}} \sum_{m=1}^{N_t^{(i \rightarrow j)}} \left( I_{Tp_{ij}}^{(i \rightarrow j)} - I_{Tp_{ijm}}^{(i \rightarrow j)} \right)^2 \right\},
\]

where \(N_t^{(i \rightarrow j)}\) denotes the number of transition points of person \(i\).

These parameters characterize the computed mutual influence and enable us to estimate the class of relationship, for example, acquaintances or unrelated persons, by learning through previously collected sample videos.

2) Detecting Anomalous Events: When anomalous events such as criminal acts occur, the mutual influence \(I_{Tp_{ij}}^{(i \rightarrow j)}\) changes as well. For example, the acceleration Acc\(_{ij}^{(i \rightarrow j)}\) included in \(I_{Tp_{ij}}^{(i \rightarrow j)}\) takes a higher value than in the normal interaction between persons; a person suddenly starts running or changes walking direction. In addition, while the mutual influence between friends is probably symmetric, the influence between a perpetrator and a victim would be asymmetric; the victim gets a large influence from the other. Therefore, it is possible to distinguish an anomalous interaction using the proposed feature \(I_{Tp_{ij}}^{(i \rightarrow j)}\) using a training data set.

### IV. Experiments

We applied the proposed method to the actual motion trajectories of persons observed in the scene shown in Figure 7. Pedestrians were manually detected in outdoor video sequences beforehand and their positions in an accompanying image were transformed to a 3D coordinate system to obtain \(\{x_i^{(j)}\}\) for each person. Figure 8 shows examples of the obtained trajectories. For \(\{x_i^{(j)}\}\) of various pedestrians, we compute the mutual influence \(I_{Tp_{ij}}^{(i \rightarrow j)}\) and conduct both mutual relationship estimation and anomalous events detection.
As discussed in Section III-A, actual motion trajectories contain a lot of noise. Before the computation of the mutual influence, we apply a smoothing operation for the obtained \( \{ x_t(i) \} \) as:

\[
(x_t, y_t) = \left( \frac{1}{N} \sum_{i=t-N/2}^{t+N/2} x_i, \frac{1}{N} \sum_{i=t-N/2}^{t+N/2} y_i \right).
\] (11)

In the following experiments, we set \( N = 5 \).

### A. Estimating Mutual Relationship between Pedestrians

First, we carry out mutual relationship estimation using the feature values defined by Equation 10. In this experiment, we use the trajectories of 198 persons. In these trajectories, there are 131 pairs of acquaintances and 775 pairs of unrelated persons. The categorization is carried out manually.

1) Extraction of Walking Pattern Transition: As shown in Section III-A, we first extract the walking pattern transitions from the trajectories. Here, we use parameters \( T = 30 \) [frame], \( Th_v = 0.02 \) in Equation 4. Figure 9 shows examples of the extracted transition points. Each color in the figure corresponds to each segment in a trajectory. The points where the colors change are extracted transition points.

Figures 9(a) and 9(b) show that the method successfully captures changes in direction at a corner. Figures 9(c) and 9(d) show the trajectories of a pair of friends. Both trajectories have transitions not only at a corner but also at other points on the trajectories. The other transitions reflect the interaction between them. For example, when person D starts running at a point where the color changes from yellow to green, person C notices it and slows down at a point where the color changes from red to yellow. Of course, although there are some incorrectly detected transitions, the proposed method successfully captures the overall interaction.

2) Computed Mutual Influence from Transition Points: Before showing the results of mutual relationship estimation, we show computed values of the mutual influence from the transition points. Figure 10 illustrates the distribution of the influence defined by Equation 3. In the figure, red and blue points correspond to the computed \( f_{T_{Pr}}^{(i-j)} \) for acquaintances and unrelated persons, respectively. There are 382 red points and 1324 blue points in the figure. In addition, the vertical and horizontal axes respectively denote \( Acc_{T_{Pr}}^{(i)}, A_{T_{Pr}}^{ij} \) and \( Acc_{T_{Pr}}^{(i)} B_{T_{Pr}}^{ij} \). These respectively characterize the spatial closeness and temporal closeness between the two pedestrians.

The distribution shown in the figure indicates that both values of acquaintances are larger than those of unrelated persons. Through this preliminary experiment, we confirm that the mutual relationship between persons has a significant correlation with the computed influence between them.
3) **Mutual Relationship Estimation:** This section shows the results of mutual relationship estimation using the computed mutual influence values. In order to confirm the advantage of our method, we carry out an estimation using the following three methods.

**Mutual Influence Computed at Transition Points**

Equation 10, introduced in Section IV-A, gives the mutual influence between two persons. Here, we make use of a four-dimensional feature vector for estimating the mutual relationship between two persons. We train an SVM classifier using a given training data set and examine its performance.

**Spatial Closeness between TwoPersons**

It is quite simple and natural to compute the spatial distance between the two for estimating their relationship; that is, if they are close to each other while walking, they are likely to be friends or acquaintances. Many existing works such as [3], [4] utilize spatial closeness. Hence, we compute the average distance between two persons as follows:

\[
D_{ij}^{(t)} = \| x_i^{(t)} - x_j^{(t)} \| 
\]

\[
F_{pos}^{i\rightarrow j} = \frac{1}{T^{(ij)}} \sum_{t'=t}^{t'+T^{(ij)}} \delta^{D_{ij}^{(t)}} (\delta > 1),
\]

where \( T^{(ij)} \) denotes the time duration in which both persons \( i \) and \( j \) are observed in a video. Note that \( F_{pos}^{i\rightarrow j} \) takes values between 0 and 1; 1 means that the two always stay in the same position.

**Integration of Spatial Closeness and Mutual Influence**

It should be noted that this paper does not claim that the proposed mutual influence is effective for all cases. As discussed in Section II, our idea is that walking pattern transitions are one of the cues for analyzing the interaction between pedestrians and it is possible to capture the difference or characteristics of interaction by considering the mutual influence derived from the walking pattern transitions. Therefore, we believe that spatial closeness and the mutual influence will compliment each other. We integrate both the features, i.e., a nine-dimensional vector, for estimating the mutual relationship. This is the method proposed in this paper.

As a preliminary experiment, we compute a histogram of the distance between all possible pairs of pedestrians. Figure 11 shows the histogram, and a partially enlarged histogram is shown in Figure 12. In both figures, red and blue lines correspond to acquaintances and unrelated persons, respectively. We can see from the histogram that it is possible to divide the data into two classes using simple thresholding. However, in Figure 12, there are some samples that cannot be classified correctly, that is, we have to incorporate other features.

We apply an SVM classifier for the three features. As mentioned above, we use videos containing 198 persons. Table I shows the accuracy of the estimation based on cross-validation.

![Figure 11. Histogram of Average Distance between Pedestrians](image1)

![Figure 12. Enlarged Histogram of Average Distance between Pedestrians](image2)

**TABLE I**

<table>
<thead>
<tr>
<th>Method</th>
<th>Accuracy(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mutual Influence</td>
<td>93.93</td>
</tr>
<tr>
<td>Spatial Closeness</td>
<td>97.02</td>
</tr>
<tr>
<td>Integrated — Proposed</td>
<td>98.79</td>
</tr>
</tbody>
</table>

The result shows that in all cases, the accuracy exceeded 90%. However, the proposed method, which integrates both the spatial closeness and the mutual influence derived from walking pattern transitions, has the best performance among the three methods. The followings discusses the differences between these methods using typical examples.

The first example is shown in Figure 9. Persons C and D, who are acquaintances, are successfully distinguished using mutual influence since it takes a high value when they change their walking directions. However, because they walk together in a short timespan, it is impossible estimate correctly using the spatial closeness.

Figure 13 shows the second example. In this case, two acquaintances are quite close to each other while walking.
Their trajectories are fairly similar. Although spatial closeness easily distinguishes them into the correct class, the mutual influence fails. This is because there are no transition points in their trajectories.

These examples suggest that either the spatial closeness or the mutual influence is not sufficient for estimation. We have to integrate them in order to analyze the actual interaction between persons. In fact, the integrated estimation correctly distinguishes the above two examples.

B. Detecting Anomalous Events

As discussed in Section III-C, the mutual influence can be used for detecting anomalous events such as crimes. Because it is difficult to collect data on actual crimes, we perform imitated actions and apply the proposed features. Therefore, we only show the results obtained from preliminary experiments in this section.

We collect the imitated actions including molestation, bag snatching and aberrant behaviors. The total number of actions is 33, that is, there are 66 trajectories in the test data. Figures 14 and 15 show examples of transition points in the trajectories. Figure 16 shows the distribution of the computed mutual influence between two persons, where pink squares correspond to the imitated actions.

In the figure, we can see that the mutual influences of anomalous actions take higher values than those of normal actions. This confirms our intuition: when anomalous events occur, a person changes his/her motion quickly and the higher values result from these large walking pattern transitions.

Using these data sets, we discriminate anomalous actions and normal actions. Normal actions are interactions between persons observed in the videos used for the experiments described in Section IV-A. There are 906 normal actions and 33 anomalous actions, which are imitated actions. As a result, we obtain an accuracy of 100% using an SVM classifier with the feature vector consisting spatial closeness and mutual influence.

Again, in this experiment, because we use the imitated actions, it is necessary to conduct further investigations in order to prove the effectiveness of the proposed method for anomalous event detection. However, this result demonstrates that the proposed method is promising.

V. Conclusion

In this paper, we have proposed a novel method for analyzing the interaction between pedestrians. It is based on the extraction of transition points between segments in motion trajectories. Based on the assumption that it reflects the influence from/on persons, the proposed method quantifies the mutual influence between two persons.
As an example of the application of the proposed method, we applied it to mutual relationship estimation. Experimental results showed that the values of mutual influence computed at each transition point play an important role in the estimation. By integrating this value and the spatial closeness factor, we could successfully distinguish between acquaintances and unrelated persons.

Then, we applied the proposed feature to anomalous event detection. For example, when criminal events occur, a person is likely to change his/her motion quickly. The experimental results demonstrated that it is possible to capture quick motions. Although more detailed examinations are required, we can consider that the proposed method is promising for anomalous event detections.

An important future work would be to make it possible to distinguish the cause of transition points. As discussed in Section II, there would be several reasons that give rise to walking pattern transitions. Interaction between persons is one. In order to analyze the interaction more accurately, we first have to estimate the cause of the transition. For example, the structure of a road is one of the causes; pedestrians will change walking direction at a corner. If we know the structure of the road in advance, it would be possible to distinguish the transitions caused by interaction and those caused by the structure.

ACKNOWLEDGMENT

This work was partially supported by JSPS, Grant-in-Aid for Young Scientists (B) 19700166. The authors would like to thank anonymous reviewers for their helpful comments on improving this paper.

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