Automated Analysis of Pedestrian Group Behavior in Urban Settings

Mohamed H. Zaki, *Member, IEEE*, and Tarek Sayed

***Abstract*— Movement trajectory of pedestrians, when tracked from video data, enables the automated analysis of individual's walking behavior. For example, speed preferences and walking strategies are typical behavior characteristics that benefit from this analysis. When pedestrians are walking in a group, they tend to adjust their speed and direction accordingly, while maintaining interpersonal distances. The adopted walking strategy leads to a coupling in their movement behavior. Such commonality, if considered, permits the discrimination between pedestrian groups and the distinction of pedestrians in different groups. Those are important factors when tracking a group of pedestrians or counting pedestrians in the crowd. The objective of this paper is localizing pedestrians in small groups using automated computer vision tracking. This paper describes the following tasks. First, to identify possible commonality in walking behavior between nearby pedestrians. This step is realized by proposing a new structural similarity measure of pedestrians' movement. Second, to provide a method for counting pedestrians in groups. A classification procedure accomplishes this task based on spatio-temporal criteria and the introduced movement similarity measure. Third, to show the feasibility of the method on a pedestrian group study from video data collected at a moderately dense pedestrian crosswalk in Vancouver, British Columbia. A validation of the group size classification demonstrated an accuracy of up to 77%. This paper enables a faster stream for comprehensive pedestrian data collection. Also, the new measure for group behavior can be useful when studying the mechanism of group formation and collision avoidance.**

***Index Terms*— Pedestrian behavior, pedestrian count, video analysis, sustainable transportation.**

I. Introduction

DRIVEN by the desire to create walkable and safe urban neighborhoods, steady progress is being made in developing tools to study pedestrian behavior. Innovations have been noted in addressing a broad range of pedestrians related research areas from data collection to simulation [1], [2] and safety assessment of walking facilities [3], [4]. Characterizing pedestrian walking behavior in the crowd is an important research objective in many of those applications [5]. Notable questions that are investigated include, for example; how a pedestrian group interacts with the surroundings? and What is the maneuvering behavior among its individuals? The walking behavior analysis is also related to speed selection, spatial configuration, group formation, and obstacle negotiation [6]. The majority of pedestrians walk in a small group of two or more as observed in [7]. Given the prevalence of small groups in the crowd, a proper microscopic scale understanding of crowd dynamic behavior [8], [9] begins with studying small pedestrian group behavior.

Manuscript received April 26, 2016; revised November 22, 2016 and May 4, 2017; accepted August 20, 2017. Date of publication September 26, 2017; date of current version May 29, 2018. The Associate Editor for this paper was S. Sun. *(Corresponding author: Mohamed H. Zaki.)*

The authors are with the Department of Civil Engineering, The University of British Columbia, Vancouver, BC V6T 1Z4, Canada (e-mail: mzaki@mail.ubc.ca; tsayed@civil.ubc.ca).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITS.2017.2747516

Data collection significantly affects the quality of research in pedestrian behavior analysis. As manual data collection of pedestrians is usually expensive, time-consuming and error-prone, there is an incentive to adopt computer-based methods to automate the data collection process. Camera sensors have several advantages. Besides being non-intrusive, cameras are low maintenance alternative for traffic video data collection. The video data are supported with a vast array of computer vision applications (CV) to enable automated the analysis of traffic scenes. CV systems are developed to detect and track moving objects in videos automatically. They proved practical in traffic scene interpretation through conflicts and collisions detection [10], [11]. Recent advances in computer vision enabled the analysis of pedestrian behavior through the automatic extraction of individuals' motion trajectories.

When pedestrians are walking in a group, they tend to adjust their speed and direction accordingly, while maintaining interpersonal distances [12]. The adopted walking strategy leads to a coupling in their movement behavior. Such commonality, if considered, permits the discrimination between pedestrian groups and the distinction of pedestrians in different groups [13]. Those are important factors when tracking a group of pedestrians or counting pedestrians in the crowd.

Movement trajectory of pedestrians, when tracked from video data, enables the automated analysis of individual's walking behavior. This information offers important cues on the walking mechanism as well as the interaction behavior among pedestrians in the crowd. For example, motion trajectory can explain much information on groups of pedestrians by unraveling shared attributes such as proximity, directional movements, speed selection and obstacle management [14]. Given the motion trajectory of pedestrians, it might be possible to implement the commonality rules and identify any potential coupling that can exist between nearby pedestrians. The objective of this paper is localizing pedestrians in small groups using automated computer vision tracking. The paper describes the following tasks:

- To identify possible commonality in walking behavior between nearby pedestrians. This step is realized by proposing a new structural similarity measure of

1524-9050 © 2017 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See http://www.ieee.org/publications_standards/publications/rights/index.html for more information.

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

pedestrians' movement. This measure is developed based on ordinal analysis, which is a computational approach for revealing nonlinear dynamical characteristics underlying a time-series similar to a pedestrian walking profile.

- To provide a method for counting pedestrians in groups. This task is accomplished by a graph based classification procedure based on spatio-temporal criteria and the introduced movement similarity measure.
- To show the feasibility of the method on a pedestrian group study from video data collected at a moderaly dense crosswalk in Vancouver, British Columbia.

The presented research enables a faster stream for comprehensive pedestrian data collection. Also, the new measure for group behavior can be useful when studying the mechanism of group formation and collision avoidance.

II. Literature Review

This section surveys the most significant work on automated pedestrian detection and behavior analysis. Identifying pedestrians in traffic scenes and capturing their behavior is one of the primary challenges facing wider deployment of vision-based technology. Many advances have been reported in several publications such as the surveys in [15] and [16]. The challenges in analyzing pedestrians using vision analysis can be attributed to the complex deforming shape of pedestrians, their somehow frantic movement pattern and their high susceptibility to frequent occlusions. Among the most common applications of vision analysis are pedestrians counting [5], safety analysis [17], [18] and violation detection [11].

A. Studies in Automatic Groups Analysis

Understanding group activities is an important task when studying crowd behavior. Examples of complex behavior include group formation, dispersal, as well as individual actions such as joining and leaving a group. Group behavior was studied based on the concept of individual personal space [19] as well as group configuration in [7]. Automated pedestrian group behavior can be traced to the research performed in [20]. In this work, McPhail and Wohlstein defined a set of rules to decide how to identify pedestrians that are traveling together. The rules are derived from spatial, directional constraints, and relative speed. Based on those rules, a clustering based group identification was demonstrated by Ge *et al.* [21] and Sandikci *et al.* [22]. The study in [23] presented a set of rules for the automatic identification of joint motion patterns of individuals moving together. The rules were based on the velocity and displacement vectors. Pellegrini *et al.* [24] considered the detection of pedestrian groups as a procedure to improve the detection of individuals where occlusion problems limit the individual pedestrian tracking. The approach considered individuals nearby each other and who are walking at a similar speed as part of a larger group regardless of their social affiliation to that group. Overlooking social interactions is a common shortcoming of the spatio-temporal measures. To address this limitation, semantically derived rules were proposed in [7], [25], and [26] to provide a social interpretation of pedestrian behavior and interactions. Other thread of research considered the detection of crowds and estimating their sizes such as the work presented [27], [28]. Group size and pedestrian counts are set as a background subtraction problem. In this setting, pedestrians count is estimated from the size of the region occupied by a set of pedestrians [29]. The current paper expands the state of the art of pedestrian group size estimation by providing a means to capture behavior commonality of pedestrians from their movement pattern. Such process is carried through by a dissimilarity measure on the structure of their speed profiles and with no prior learning requirement. **Table 1** provides a summary of the related work.

B. Automatic Walking Gait Detection

Traditionally, gait parameters and walking speed are collected based on manual measurements, through field or video observations. Gait information is proposed as descriptive attributes for human recognition [30]. Pedestrians are recognized by having a unique rhythm during walking that is periodic and oscillatory [31], [32]. Such propriety is exploited for the video based applications. The difference of the periodicity was a suitable feature used discrimination of pedestrian attributes [33], [34]. Effect of group size on walking speed was studied in [35] and [36]. In this research, it was shown that the mean walking speed decreases with increasing group size. Gait patterns can also reveal some knowledge beyond the information obtained from the simple analysis of speed profiles. For example, the variability and the stability of the gait can be measured for each individual. Those measures can characterize pedestrian attributes such as age, gender [37] and even pinpoint to certain health problems [38], [39].

III. Methodology

The proposed method for pedestrian group classification is shown in **Figure 1**. Pedestrian trajectories are tracked from video data using computer vision. Walking behavior similarity between nearby pedestrians is estimated, along with a selection of spatio-temporal measures. A graph based decision procedure is then applied to associate each pedestrian to groups and count the number of pedestrians in each group.

A. Pedestrian Tracking

A cluster-based appearance modeling and online tracking approach algorithm (MMTrack Algorithm) is used for detection of pedestrians in this study [40]. The MMTrack is a hybrid single pedestrian tracking algorithm that puts together the advantages of descriptive and discriminative approaches for tracking.

The tracking is complemented by a procedure for mapping from world coordinates to image plane coordinates using a homography matrix (a camera calibration process). The purpose of this calibration is to create a transformation that permits the recovery of real world coordinates (e.g., metric coordinates) from the pixel based coordinates of the video images. Such mapping between the real world and the image

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

TABLE I
OVERVIEW OF RESEARCH IN GROUP SIZE DETECTION

Ref	Features	Models and Tools	Applications	Data Sets	Crowd Density
Jacques et al., [19]	Spatial proximity, personal space and comfort level	Dynamic Voronoi Diagram	Groups detection and formation	Video based simulation	Low to Medium
Ge et al., [21]	Group "entitativity": Spatial proximity, relative speed, and direction.	Agglomerative clustering	Groups detection	Indoor and Outdoor Video Samples	Sparse to Medium
Sandikci et al., [22]	Similarity function based on Spatial proximity, relative speed and direction	Agglomerative clustering	Groups detection	Indoor and Outdoor Video sequences	Low to Medium
Mazzon et al., [25]	Relative speed, direction and acceleration	Social Force Model for group tracking	Groups Interaction and formation	Outdoor Video sequences	Low to Medium
Yu et. al, [26]	Facial recognition, proximity, relative motion	Graph-cut and modularity-cut	Social Groups Identification	One Location with multiple camera views	Low
Zhang et al., [27]	Geometrical features (blobs area perimeter) Image features (textures)	Statistical Learning. Non-linear Regression	Counting Pedestrians based on group sizes	Indoor and Outdoor Video sequences	Medium
Chan et al., [28]	Geometrical features (Segmentation area, perimeter). Image features (textures, internal edges)	Gaussian process regression	Crowd Size Estimation	Outdoor Video sequences	Medium
Kilamba et al., [29]	Geometrical features (blobs area, shape)	Group tracking using Kalman filter	Crowd Size Estimation	One Location with multiple camera views	Low to Medium

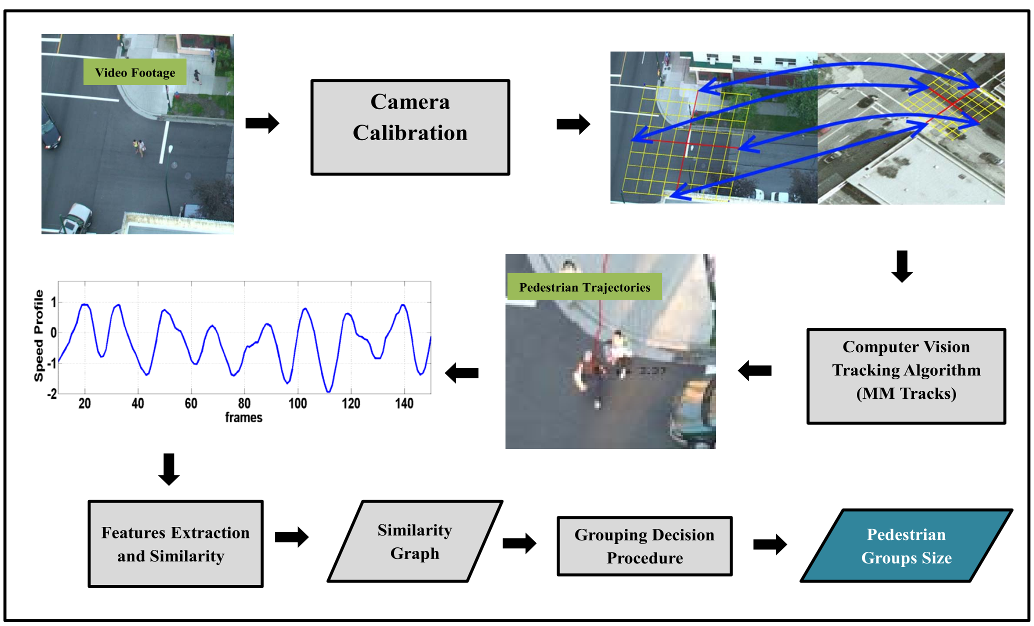


Fig. 1. Outline of the Pedestrian Group Count Methodology.

space lead to the correct collection of the tracked trajectory information such as positions and velocities of road-users such as pedestrians. The mapping is illustrated in **Figure 1**. Details and validation of the mixed feature camera calibration approach can be found in n [41].

Pedestrian walking trajectories are extracted, along the frames, by the video analysis as a finite set of 4-tuples:

$$R_j = \{(X_1, Y_1, Vx_1, Vy_1), \ldots\ldots\ldots,\ (X_i, Y_i, Vx_i, Vy_i), \ldots\ldots, (X_N, Y_N, Vx_N, Vy_N)\}$$

where X_i, Y_i are the spatial coordinates of the walking pedestrian R at frame i. Vx_i and Vy_i are the corresponding velocities at frame i. The speed profile (**See Figure 1**) is the

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

norm of the velocity vectors **V**x, **V**y and is defined as the time series: S = norm (**V**x, **V**y)

B. Similarity Measures

The motion process of a pedestrian, called ambulation, is composed of a sequence of steps. The length and frequency of those steps determine the walking speed. This walking speed is not uniform with regard to time. Rather, the pedestrian speed profile is composed of cyclic fluctuations repeated continuously over time (See illustration in **Figure 1**). The fluctuations correspond to every step taken by the pedestrian. The unique walking profile of a pedestrian is governed by its control of both the step length and the step frequency to navigate its surrounding. This paper introduces a dissimilarity measure to identify pedestrians exhibiting common walking behavior and estimate possible coupling between nearby pedestrians by examining the structure (i.e., fluctuations) of the speed profiles. Therefore, it is important to transform the time-series into a domain space, where the resemblance between the series is apparent. The proposed dissimilarity measure is based on the ordinal pattern analysis of time-series [42].

The ordinal analysis is a computational approach for revealing nonlinear dynamical characteristics that underlie time-series (e.g., a pedestrian walking profiles). Ordinal patterns capture the basic qualitative information (increasing and decreasing transitions) of the time- series and their frequency of occurrence (i.e., distributions) which can reveal properties of its dynamical structure. As a consequence, this process can differentiate between the different states of time-series. Therefore, by tracking the underlying dynamic of the walking movement and changes in those dynamics, it is possible to identify similarities in the structure of the walking behavior. The formal procedure of the ordinal analysis is summarized in the following steps [42], [43].

Step 1 (Embedding): Given a scalar time-series $\mathbf{T} = \{x(i), i = 1, \ldots, N\}$, an embedding is a reconstruction of an η-dimensional state space

$$\mathbf{X} = [\mathbf{X}_1, ..\mathbf{X}_i, .., \mathbf{X}_k].$$

$\mathbf{X_i}$ is said to be the i^{th} state of the system with

$$\mathbf{X}_i = [x(i), x(i+\tau), \ldots, x(i+(\eta-1)\tau)]$$

Where $i \epsilon \{1, \ldots, K\}$ $K = N-(\eta-1)\tau$. η and τ stand for the embedding dimension and delay time, respectively. If time-series is of length 100, with $\eta = 3$ patterns and $\tau = 2$, then there is 96 possible state tuple to analyze.

Step 2 (Ordinal Mapping): Let the η elements of $\mathbf{X}_i = [x(i), x(i+\tau), \ldots, x(i+(\eta-1)\tau)]$ be arranged in an increasing order:

$$[x(i+(r_1-1)\tau \leq x(i+(r_2-1)\tau \leq \ldots \leq x(i+(r_\eta-1)\tau]$$

then $\mathbf{X}_i$ can be uniquely mapped onto the η-tuple $r_i = (r_1, r_2, \ldots, r_\eta)$ rank pattern also called ordinal η-pattern Δ_i.

The ranks of this pattern sequence are indices organized in an ascending order representing the order (column) index of the element in state $\mathbf{X}_i$. It should be clear that r_i is one of the $\eta!$ permutations of the distinct symbols $(1, \ldots, \eta)$. For example, the pattern of the selected state with values [6, 11, 9] is (1, 3, 2). The reconstructed trajectory $\mathbf{X}$ in the η-dimensional space is represented by a symbolic sequence of ordinal patterns. In this sequence, each state $\mathbf{X_i}$ can be mapped onto one of the $\eta!$ permutations.

Step 3 (Rank-Frequency Distribution): Let Ω_Δ be the set of states in $\mathbf{X}$ having ordinal η-pattern Δ. The cardinality of Ω_Δ is then the occurrence count of Δ in the time-series and denoted as $\#_\Delta$. The distribution P_Δ is defined therefore as

$$P_\Delta = \#_\Delta / N - (\eta - 1)\tau$$

which is sorted in order of descending frequency to obtain the rank-frequency distribution P_Δ.

Step 4 (Dissimilarity Measure): The distance between the distributions to measure dissimilarity between two time-series, and this is given by [42]

$$Diss_{pe}(a, b) = \sqrt{(\frac{\eta!}{\eta! - 1})}\sqrt{(\Sigma_{i=1}^{\eta!}(P_{\underline{\Delta}a} - P_{\underline{\Delta}b})^2)}$$

where $P_{\underline{\Delta a}}$ and $P_{\underline{\Delta b}}$ represent the rank frequencies of the pedestrians a and b.

$Diss_{pe}$ is calculated between 0 and 1 where $Diss_{pe} = 0$, indicates that the rank–frequency ordinal patterns distribution in the two series is identical (e.g., curated synchronized walking). On the other hand, $Diss_{pe} = 1$ is obtained when walking behavior of two pedestrians is entirely different. The proposed dissimilarity measure considers only the states order relation of time-series, rather that the values of those states. This construction renders the dissimilarity measure robust against noise when compared with common time-domain similarity measures, where noise can significantly affect the comparison outcome

A set of features and distance metrics for measuring similarities of pedestrian trajectories are also considered alongside $Diss_{pe}$. The features include spatio-temporal measures such as spatial proximity based on the Euclidian distance, direction (curvature of motion) of travel and degree of alignment. The degree of alignment is defined as the standard deviation between the Euclidian distances, along with the walking space between nearby individuals.

C. Group Size Detection

The size estimation of pedestrian groups is cast as a top-down segmentation problem. Starting with an entire set of pedestrians in a common time period as a coherent group, the group splitting into subgroups is applied iteratively. The splitting decision procedure relies on the set of rules derived from the similarity measures. A graph-based implementation of this procedure is developed. The graph is built to identify unique groups and estimate their size automatically.

A connectivity graph G = (V,E,F) among pedestrians within temporal overlap windows is constructed. V is the set of vertices (each labeled with a pedestrian ID) and E is the set of edges potentially connecting vertices in V. A necessary condition for the two vertices v_i and v_j to be connected by an edge e_{ij} is that pedestrian i and j are temporarily together for an overlapping time window. F is a set of similarity constraint "f" on each edge defined as Boolean functions over

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

the speed profile structural dissimilarity measure, direction, mean distance and degree of alignment measures. An edge e_{ij} is cut between two vertices v_i and v_j if the similarity constraint f_{ij} do not satisfy predefined threshold criteria (i.e., when they have low similarity).

In this formalism, the group segmentation problem is cast as a graph partitioning problem. For a partition of the vertex set V, the vertices in a connected subset (connectivity graph) V_k have high similarity, and the vertices in two different connected subsets V_k, V_l have low similarity. $|V_k|$ is the number of nodes of the graph V_k. It corresponds to the size of the group k. A pedestrian is part of a group if it is connected with at least one of the existing group members. The graph is dynamically updated as individuals are leaving the scene and newer ones are entering. A pedestrian group is then removed from the graph if all its members are not tracked anymore. The reasoning over the lifetime of pedestrian motion profile approach is advantageous as it is tolerant to slight behavioral variations between members of the group. For example, a group of pedestrians is temporally dispersed as incoming pedestrians infiltrate it.

IV. Experiment Settings

A. Site Characteristics

The study location is a busy downtown intersection at Robson and Broughton Streets in downtown Vancouver, British Columbia. Robson Street is a northwest-southeast, two-way major street, with two lanes in each direction. Broughton Street is a northeast-southwest, minor two-way street, with one lane in each direction. Vehicular flows are controlled by flashing green signals along Robson Street, and by stop signs along Broughton Street, with no turning restrictions on either approach. The pedestrian crossing is allowed along all the four legs of the intersection, at any time across Broughton, and with actuated control across Robson. There is a downward grade in the northwest direction along Robson. This study will only focus on pedestrian movement along Robson Street (i.e. along northwest-southeast direction). The location was recorded for one hour chosen at a time when a sizable number of pedestrians were heading towards a summer event.

B. Data Collection: Ground-Truth

Ground truth data analysis is a valuable task to get insight on the properties of the available datasets before the classification process. The ground-truth labeling is applied to the video based on a good observers' judgment. While visual analyses can suffer from the shortfalls of mislabeling, the length of this video allowed for an elaborate careful review. Ground-truth based on three experts was provided to establish a labeling of each pedestrian in terms of group participation. Each pedestrian is associated with a group, and each group is given an *id*. Undetermined cases are excluded from the analysis, and each pedestrian is described by the manual observers in detail for comparison with automatically tracked events. The identification of groups was assessed based on proximity, social interaction, the direction of travel and walking speed preferences [14]. Interpersonal labeling variations were resolved through consistent revisions. The provided ground truth is, therefore, free from annotation errors.

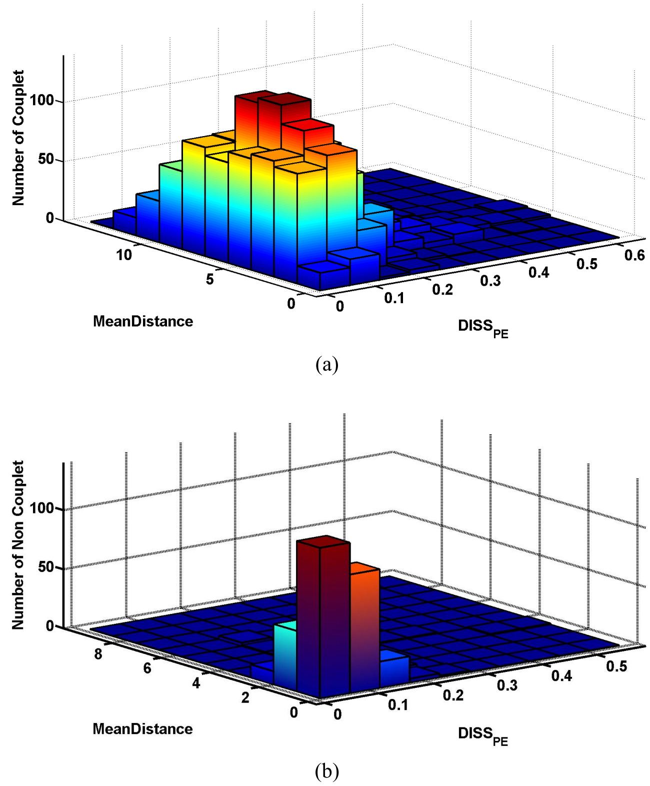


Fig. 2. Ground Truth Measures Distributions (Mean Distance in meter). (a) Pedestrians in Different Group. (b) Pedestrians in same Group.

To properly evaluate the accuracy of the methodology and the sensitivity analysis of the parameters, all the data are manually classified by the human observer. A total of 485 pedestrians is divided into single (122 pedestrians), 146 couples, 17 groups of three and 5 groups of four. However, it is observed that groups with over four individuals were usually split into subgroups. This split allows a configuration for more natural social interaction among the pedestrian in the group [7] while they walk. Similarity and distance measure were calculated for nearby pedestrians. An illustration of the ground-truth based on distance and speed profile structural dissimilarity $Diss_{pe}$ measures is shown in **Figure 2**. In general, the data points for pedestrians labeled as belonging to the same group are concentrated in a distinct region of the plot. In this region, the distance between individuals is small and lower dissimilarity in their walking profile. On the other hand, pedestrians that are associated with a different group tend to have a larger variation in their walking profile. Also, the inter-individual distance tends to vary from being close to further from each other.

Such difference is more pronounced through the significance test for the data shown in **Table 2.** The table provides a summary of the measure variables used in the analysis. 2399 pairs of pedestrians (tuples) were considered among which 2000 pairs consisting of pedestrians not associated with the same group and 399 pairs of pedestrians associated with the same group. (e.g., two set of couples walking nearby

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

TABLE II
FEATURES SIGNIFICANCE

Pedestrian Together	*Number of possible tuples*	*Mean Distance (meter)*	*Degree of Alignment*	*Dissimilarity Measure*
Yes	*399*	1.18[1.03]	0.361[0.59]	0.084[0.061]
No	2000	5.705[2.67] (<0.001)*	1.246[1.146] (<0.001)*	0.121[0.081] (<0.001)*

[ ] represents the standard deviation;
( ) represents the *p*-value of *t*-test;
* indicates statistically significant difference (at 95% confidence level) compared to the cell directly above.

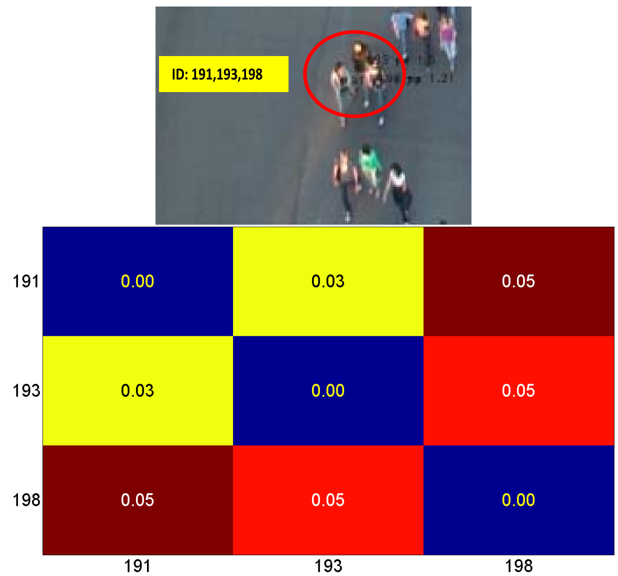
Fig. 3. Set of pedestrians walking nearby each other. Selected pedestrians and their dissimilarity matrix. Row and Colum labels are the IDs of the selected pedestrians.

each other will result in 6 pedestrian comparison tuples). There is a significant difference in mean distance, the degree of alignment between individuals. There are fewer distance variations between pedestrian in a similar group along with their travel as they tend to adjust their direction and movement according to their partners in the group. Compared to non-similar group tuples, pedestrian in the same group tend to have a significantly lower dissimilarity in speed behavior.

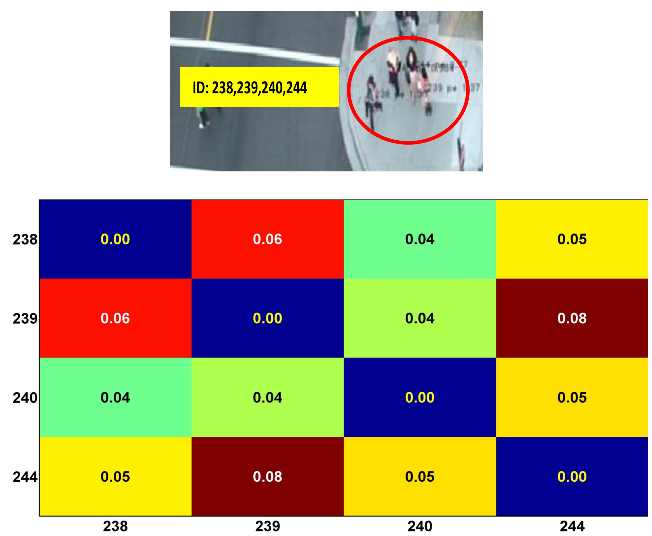
An illustration of pedestrians along to the dissimilarity measures, spatial information and speed profiles is presented in **Figure 3**. In **Figure 3,** pedestrians with ID 38 and 44 are walking in a group and have a dissimilarity measure Diss_{pe}

TABLE III
PARAMETERS OF THE CLASSIFICATION

Parameters	Selected Values
η (embedding dimension)	3
τ (delay time)	2
Distance	0.3 -2.2
$Diss_{pe}$	0.01-0.13



(a)



(b)

Fig. 4. Illustrative Examples of Pedestrian Grouping –Video snapshot with selected pedestrians and Dissimilarity Measure Matrix. (a) Group of 3 pedestrians. (b) Group of 4 pedestrians.

of 0.04. This value is the lowest among all the measured tuples. Pedestrian ID 43 is walking alone and has a higher Diss_{pe} when its speed profile is compared with all other pedestrians. While Diss_{pe} is low between pedestrians ID 38 and 47, they will not be grouped together given the spatial distance between them. A low Diss_{pe} value can be thought of as a necessary condition for grouping but not sufficient to be a stand-alone measure.

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

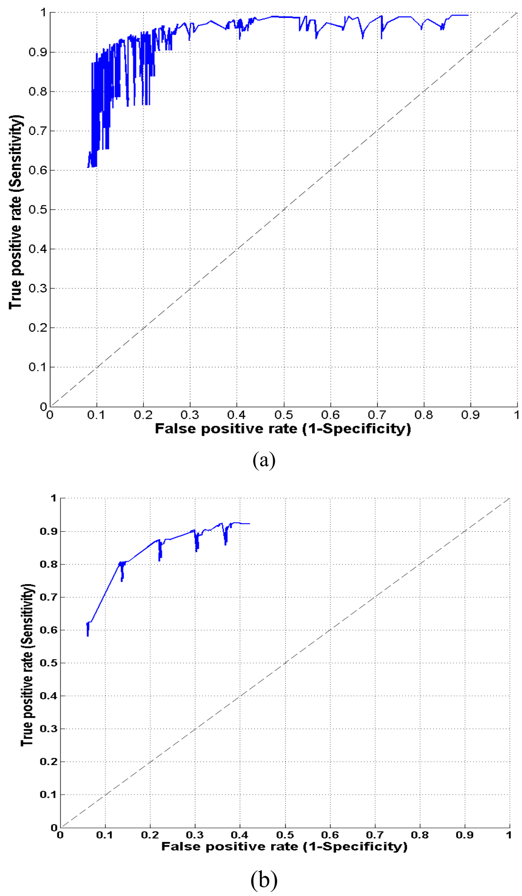


Fig. 5. Receiver operating characteristics analysis of grouping performance. (a) Single person evaluation. (b) Pairs in same group evaluation.

Pedestrian (ID 41) was lagging behind pedestrian (ID 40) due to ambulatory limitation. However, the two pedestrians were close and often interacted together while crossing. The pedestrians have a dissimilarity measure $\mathrm{Diss}_{\mathrm{pe}}$ of 0.06. Manual observations labeled them as pedestrians in the same group. **Figure 4.a** and**Figure 4.b.** illustrate two samples for pedestrian groups of size 3 and size 4, respectively. Low $\mathrm{Diss}_{\mathrm{pe}}$ is noticeable among members in the groups.

V. Performance Evaluation

The assessment of the proposed classification requires a review of the quality of different classifiers using a set of performance measures. Accuracy is a general measure of the classification performance; Kappa is a statistical validation test of the soundness of the method. The value of main parameters are provided in **Table 3**.

For sensitivity analysis, the *Distance* is varied from 0.3 to 2.2 meters, while $Diss_{pe}$ is ranged from 0.01 to 0.13. The first step is to assess how *good* the process in deciding whether two nearby pedestrians belong to the same group or not. The classification performance is visually evaluated by plotting the receiver operating characteristics (ROC) curves in **Figure 5**. The ROC curve quantifies the trade-off between the detection rate (the percentage of positive examples correctly classified as being in the same group) and the false-positive rate (the percentage of negative examples incorrectly classified as being in the same group). **Figure 5** compares the performance of the different classification runs with different features selections and different similarity based thresholds.

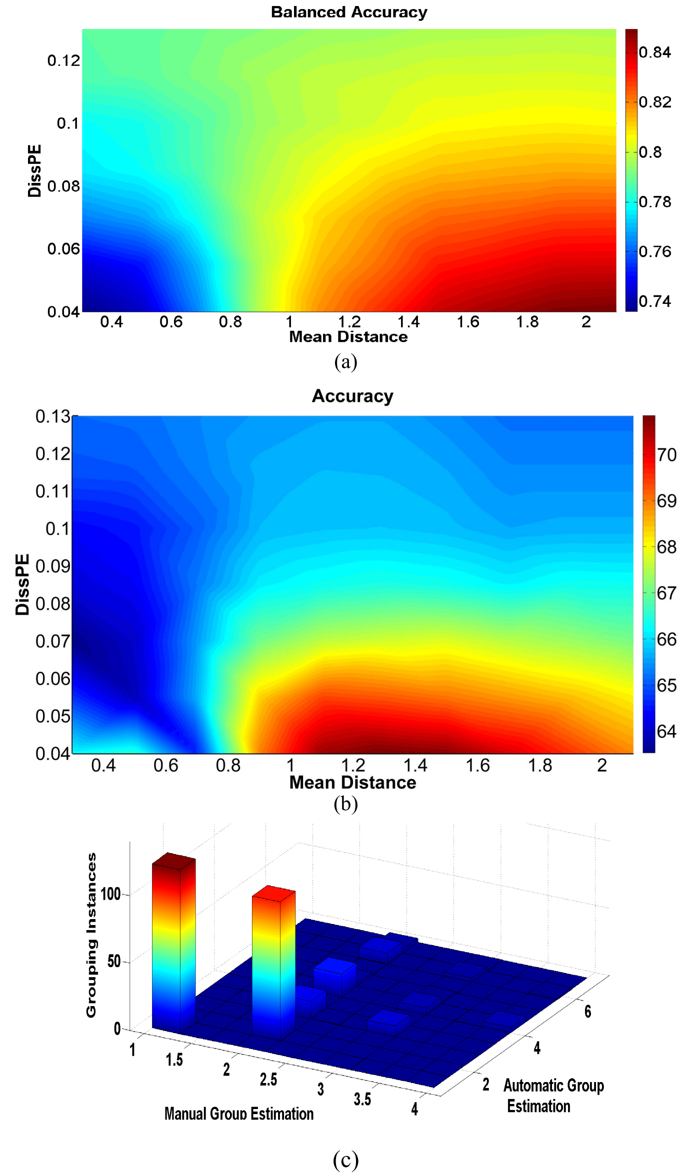
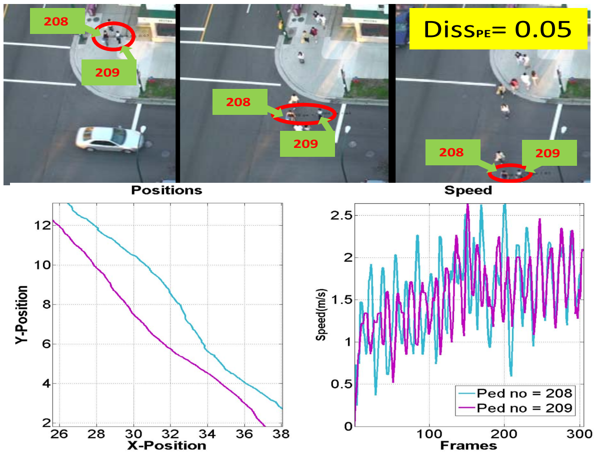


Fig. 6. Classification Evaluation. (a) Accuracy of pairs of pedestrian group associativity. (b) Accuracy of group size estimation. (c) Manual-automatic group counts.

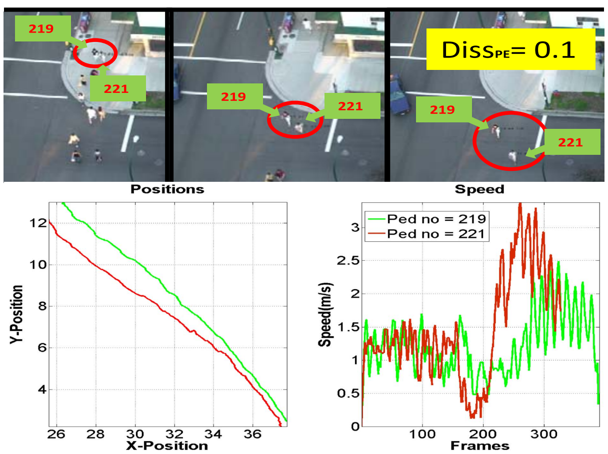
Figure 5.a demonstrates a true positive rate (i.e., identifying pedestrians walking alone as pedestrians belonging to groups of size one) of 90% at a false-positive rate (i.e., identifying pedestrian in the same group of size greater than one as pedestrians walking alone) of around 10%. **Figure 5.b** demonstrates a true positive rate (pedestrian in the same group classified as being in the same group) of 82% at a false-positive rate (pedestrians walking alone mislabelled as being together) of around 13%. The ROC evaluation demonstrates the inherent trade-offs of the classification process. In general, the choice of the "optimum" classifier is usually dependent on the target application.

Figure 6.a illustrates the variations in the classification accuracy with respect to the changes in the selected values of

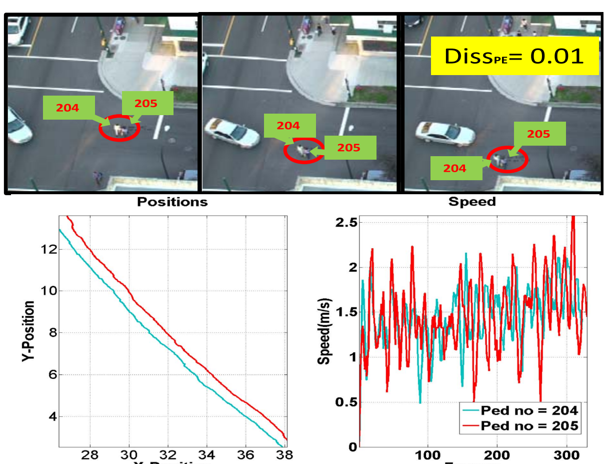
Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.



(a)



(b)



(c)

Fig. 7. Example of group behavior. (a) Two pedestrians in a group are split by incoming pedestrians before merging again to walk together. (b) Reaction of two pedestrians in group to an encroaching vehicle. (c) A different reaction of two pedestrians in group to an encroaching vehicle.

the $Diss_{pe}$ and the mean distance parameters[1]. The accuracy of pairs of pedestrian's group associativity is first evaluated with about 85 percent correct identification. Cohen's Kappa test is applied to test the statistical significance of the agreement between the automated counts and the ground-truth. The results were significant beyond what is expected by chance for all the cases as $\frac{\kappa}{\sqrt{Var(\kappa)}}$ exceeds the critical Z value (Z = 2.32 at a significance level of 99%). **Figure 6.b** demonstrates the accuracy of the group size estimation. An average classification of 71 percent is achieved with a maximum correct group classification of 77 percent is obtained at a distance of 1.3 meters and $Diss_{pe}$ of 0.04.

Figures 6.c provides a comparison between the manual and the automated counting outcome. Upon manually reviewing the video, few patterns are identified where the method fails to segment the pedestrian into the proper group number correctly. The most common error occurs when a temporary increase in density and the spacing between groups is reduced. Individuals waiting at the curb to cross are joined with additional pedestrians. When the pedestrians start crossing, crowd movement can be dominant, and neighboring groups are merged and start walking together. Another pattern is related to the splitting of groups due to incoming pedestrians flow. In such condition, pedestrians in the same group split and individually negotiate the influx of incoming pedestrians.

An illustrative example, where two pedestrians are walking together and then split is shown in **Figure 7.a** Another interesting phenomenon is when single individuals walk in tandem adjusting their speed to the leading individual while maintaining a small but consistent interpersonal distance. In such case, the procedure erroneously identifies individuals as belonging to a similar group. Varying reaction to safety critical situation is observed in several instances. For example, in **Figure 7.b**, the reaction of the two individuals to an encroaching vehicle was different leading to one pedestrian starting running while its partner is just increasing the walking speed. A higher $Diss_{pe}$ value identified such diversion in movement behavior. On another example, the couples in **Figure 7.c** reacted together and similarly to the encroaching vehicle. In such instance, a very low $Diss_{pe}$ value was calculated.

VI. Summary

The presented research is a step forward towards understanding group behavior. The detection of groups was performed in low to moderate dense pedestrian facilities using automated video analysis. The analysis demonstrated a significant difference in the walking behavior of pedestrians belonging to the same group compared to pedestrians walking closely but in different groups or just walking alone. Such findings relied on common measures such as temporal and spatial proximity along with the newly introduced speed profile structural dissimilarity measure. The new dissimilarity measure contributed notably to the understanding of pedestrian group behavior and the relationship between individuals in a crowd.

The results are promising; however, it is necessary to extend the current experimentation to larger data sets to ensure a more rigorous evaluation of the method. There are also some limitations to consider. The analysis does not adopt a proper definition of moderate pedestrian density. It would be

[1]Color bars and scales illustrate the performance. The scale (color) from 0 (dark blue) to 1 (dark red) corresponds to 0% to 100% in performance.

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

noteworthy to apply the classification to crowds with varying densities and interactions. This task would help to identify the shortcomings of the method with respect to the density bifurcation. Such phenomenon can be observed when small groups cease to exist during overcrowding and global crowd pattern emerges [44]. A direct extension of the current research is the study of the evolving nature of splits and formation of groups under varying densities [45]. The analysis does not incorporate pedestrian attributes. It is reported that the social relationship and hierarchy between individuals in the group command the speed and the group patterns and arrangements. Counting those factors can provide insight into the reaction of pedestrians in groups to hazards and safety events.

A better understanding of walking behavior is central to evaluating walking conditions such as comfortability and efficiency [46]. Gait analysis is a microscopic-level analysis which allows proper estimates of objective walking measures such as stride frequency and stride length for different population segments. Considering those parameters for studying group behavior analysis will be part of the future research [47]. Other potential applications for this research include the evaluation of standard guidelines for group movement behavior [48], [49] (e.g., intersection crosswalk clearance times [50]) and the calibration of pedestrian simulation models [51]. Group classification across different cultures is another problem to consider. For example, in many western cultures, individuals that know each other travel side-by-side rather than one behind the other as in some other cultures. Identifying discriminative measures between those group cultures would, then, be useful. Also, addressing the optimum camera setup for high quality pedestrian data collection is an important research task. Applying the current method to a wider variety of datasets with varied angles and illuminations can lead to improvements in the evaluation of the method.

REFERENCES

[1] D. C. Duives, W. Daamen, and S. P. Hoogendoorn, "State-of-the-art crowd motion simulation models," *Transp. Res. C, Emerg. Technol.*, vol. 37, pp. 193–209, Dec. 2013.

[2] W. Zeng, P. Chen, H. Nakamura, and M. Iryo-Asano, "Application of social force model to pedestrian behavior analysis at signalized crosswalk," *Transp. Res. C, Emerg. Technol.*, vol. 40, pp. 143–159, Mar. 2014.

[3] C. G. Keller and D. M. Gavrila, "Will the pedestrian cross? A study on pedestrian path prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 2, pp. 494–506, Apr. 2014.

[4] T. Gandhi and M. M. Trivedi, "Pedestrian protection systems: Issues, survey, and challenges," *IEEE Trans. Intell. Transp. Syst.*, vol. 8, no. 3, pp. 413–430, Sep. 2007.

[5] W. Xia, J. Zhang, and U. Kruger, "Semisupervised pedestrian counting with temporal and spatial consistencies," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 4, pp. 1705–1715, Aug. 2015.

[6] A. F. Aveni, "The not-so-lonely crowd: Friendship groups in collective behavior," *Sociometry*, vol. 40, no. 1, pp. 96–99, Mar. 1977.

[7] M. Moussaïd, N. Perozo, S. Garnier, D. Helbing, and G. Theraulaz, "The walking behaviour of pedestrian social groups and its impact on crowd dynamics," *PLoS ONE*, vol. 5, no. 4, p. e10047, 2010, doi: 10.1371/journal.pone.0010047.

[8] A. M. Cheriyadat and R. J. Radke, "Detecting dominant motions in dense crowds," *IEEE J. Sel. Topics Signal Process.*, vol. 2, no. 4, pp. 568–581, Aug. 2008.

[9] D. J. T. Sumpter, R. P. Mann, and A. Perna, "The modelling cycle for collective animal behaviour," *Interface Focus*, vol. 2, no. 6, pp. 764–773, 2012.

[10] K. Ismail, T. Sayed, and N. Saunier, "Automated analysis of pedestrian-vehicle conflicts context for before-and-after studies," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2198, no. 1, pp. 52–64, 2010.

[11] M. Zaki, T. Sayed, A. Tageldin, and M. Hussein, "Application of computer vision to diagnosis of pedestrian safety issues," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2393, no. 1, pp. 75–84, 2013.

[12] K. Rio and W. H. Warren, "The visual coupling between neighbors in real and virtual crowds," *Transp. Res. Procedia*, vol. 2, pp. 132–140, Oct. 2014.

[13] W. Ge, R. T. Collins, and B. Ruback, "Automatically detecting the small group structure of a crowd," in *Proc. Workshop Appl. Comput. Vis. (WACV)*, Dec. 2009, pp. 1–8.

[14] D. T. Campbell, "Common fate, similarity, and other indices of the status of aggregates of persons as social entities," *Behavioral Sci.*, vol. 3, no. 1, pp. 14–25, 1958.

[15] K. Ismail, "Application of computer vision techniques for automated road safety analysis and traffic data collection," Ph.D. dissertation, Dept. Civil Eng., Univ. British Columbia, Vancouver, BC, Canada, 2010.

[16] M. Enzweiler and D. M. Gavrila, "Monocular pedestrian detection: Survey and experiments," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 31, no. 12, pp. 2179–2195, Dec. 2009.

[17] S. Nedevschi, S. Bota, and C. Tomiuc, "Stereo-based pedestrian detection for collision-avoidance applications," *IEEE Trans. Intell. Transp. Syst.*, vol. 10, no. 3, pp. 380–391, Sep. 2009.

[18] Y. Zhang, D. Yao, T. Z. Qiu, L. Peng, and Y. Zhang, "Pedestrian safety analysis in mixed traffic conditions using video data," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 1832–1844, Dec. 2012.

[19] J. C. S. Jacques, Jr., A. Braun, J. Soldera, S. R. Musse, and C. R. Jung, "Understanding people motion in video sequences using Voronoi diagrams," *Pattern Anal. Appl.*, vol. 10, no. 4, pp. 321–332, Oct. 2007.

[20] C. McPhail and R. T. Wohlstein, "Using film to analyze pedestrian behavior," *Sociol. Methods Res.*, vol. 10, no. 3, pp. 347–375, 1982.

[21] W. Ge, R. T. Collins, and R. B. Ruback, "Vision-based analysis of small groups in pedestrian crowds," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 34, no. 5, pp. 1003–1016, May 2012.

[22] S. Sandıkcı, S. Zinger, and P. H. N. de With, "Detection of human groups in videos," in *Advanced Concepts for Intelligent Vision Systems*. Berlin, Germany: Springer-Verlag, 2011, pp. 507–518.

[23] Z. Yücel, F. Zanlungo, T. Ikeda, T. Miyashita, and N. Hagita, "Modeling indicators of coherent motion," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2012, pp. 2134–2140.

[24] S. Pellegrini, A. Ess, and L. Van Gool, "Improving data association by joint modeling of pedestrian trajectories and groupings," in *Computer Vision—ECCV*. Berlin, Germany: Springer-Verlag, 2010, pp. 452–465.

[25] R. Mazzon, F. Poiesi, and A. Cavallaro, "Detection and tracking of groups in crowd," in *Proc. 10th IEEE Int. Conf. Adv. Video Signal Based Surveill. (AVSS)*, Aug. 2013, pp. 202–207.

[26] T. Yu, S.-N. Lim, K. Patwardhan, and N. Krahnstoever, "Monitoring, recognizing and discovering social networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2009, pp. 1462–1469.

[27] J. Zhang, B. Tan, F. Sha, and L. He, "Predicting pedestrian counts in crowded scenes with rich and high-dimensional features," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 4, pp. 1037–1046, Dec. 2011.

[28] A. B. Chan, Z.-S. J. Liang, and N. Vasconcelos, "Privacy preserving crowd monitoring: Counting people without people models or tracking," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2008, pp. 1–7.

[29] P. Kilambi, E. Ribnick, A. J. Joshi, O. Masoud, and N. Papanikolopoulos, "Estimating pedestrian counts in groups," *Comput. Vis. Image Understand.*, vol. 110, no. 1, pp. 43–59, Apr. 2008.

[30] M. Ekinci, "Automatic gait recognition by multi-projection analysis," in *Proc. IEA/AIE*, Annecy, France, 2006, pp. 500–509.

[31] A. Crowe, M. M. Samson, M. J. Hoitsma, and A. A. van Ginkel, "The influence of walking speed on parameters of gait symmetry determined from ground reaction forces," *Hum. Movement Sci.*, vol. 15, no. 3, pp. 347–367, Jun. 1996.

[32] H. Mori, N. M. Charkari, and T. Matsushita, "On-line vehicle and pedestrian detections based on sign pattern," *IEEE Trans. Ind. Electron.*, vol. 41, no. 4, pp. 384–391, Aug. 1994.

[33] J. Yoo, D. Hwang, and M. Nixon, "Gender classification in human gait using support vector machine," in *Advanced Concepts for Intelligent Vision Systems*. Berlin, Germany: Springer-Verlag, 2006.

[34] M. H. Zaki and T. Sayed, "A framework for automated road-users classification using movement trajectories," *Transp. Res. C, Emerg. Technol.*, vol. 33, pp. 50–73, Aug. 2013.

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.

[35] H. Hediyeh, T. Sayed, M. H. Zaki, and K. Ismail, "Automated analysis of pedestrian crossing speed behavior at scramble-phase signalized intersections using computer vision techniques," *Int. J. Sustain. Transp.*, vol. 8, no. 5, pp. 382–397, 2014.

[36] S. Li *et al.*, "Automated collection of pedestrian data through computer vision techniques," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2299, no. 1, pp. 121–127, 2012.

[37] M. H. Zaki and T. Sayed, "Using automated walking gait analysis for the identification of pedestrian attributes," *Transp. Res. C, Emerg. Technol.*, vol. 48, pp. 16–36, Nov. 2014.

[38] H. B. Menz, S. R. Lord, and R. C. Fitzpatrick, "Acceleration patterns of the head and pelvis when walking on level and irregular surfaces," *Gait Posture*, vol. 18, no. 1, pp. 35–46, Aug. 2003.

[39] P. Terrier and F. Reynard, "Effect of age on the variability and stability of gait: A cross-sectional treadmill study in healthy individuals between 20 and 69 years of age," *Gait Posture*, vol. 41, no. 1, pp. 170–174, Jan. 2015.

[40] B. Y. S. Khanloo *et al.*, "A large margin framework for single camera offline tracking with hybrid cues," *Comput. Vis. Image Understand.*, vol. 116, no. 6, pp. 676–689, Jun. 2012.

[41] K. Ismail, T. Sayed, and N. Saunier, "A methodology for precise camera calibration for data collection applications in urban traffic scenes," *Can. J. Civil Eng.*, vol. 40, no. 1, pp. 57–67, 2013.

[42] G. Ouyang, C. Dang, D. A. Richards, and X. Li, "Ordinal pattern based similarity analysis for EEG recordings," *Clin. Neurophysiol.*, vol. 121, no. 5, pp. 694–703, May 2010.

[43] C. Bandt and B. Pompe, "Permutation entropy: A natural complexity measure for time series," *Phys. Rev. Lett.*, vol. 88, no. 17, p. 174102, 2002.

[44] D. Duives, W. Daamen, and S. Hoogendoorn, "Influence of group size and group composition on the adhered distance headway," *Transp. Res. Procedia*, vol. 2, pp. 183–188, Oct. 2014.

[45] S. Bandini, M. Mondini, and G. Vizzari, "Modelling negative interactions among pedestrians in high density situations," *Transp. Res. C, Emerg. Technol.*, vol. 40, pp. 251–270, Mar. 2014.

[46] S. Kim, J. Choi, S. Kim, and R. Tay, "Personal space, evasive movement and pedestrian level of service," *J. Adv. Transp.*, vol. 48, no. 6, pp. 673–684, Oct. 2014.

[47] H. Hediyeh, T. Sayed, and M. H. Zaki, "The use of gait parameters to evaluate pedestrian behavior at scramble phase signalized intersections," *J. Adv. Transp.*, vol. 49, no. 4, pp. 523–534, Jun. 2015.

[48] M. Iryo-Asano, W. K. M. Alhajyaseen, and H. Nakamura, "Analysis and modeling of pedestrian crossing behavior during the pedestrian flashing green interval," *IEEE Trans. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 958–969, Apr. 2015.

[49] L. Chen and C. Englund, "Cooperative intersection management: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 2, pp. 570–586, Feb. 2016.

[50] W. Ma, Y. Liu, and K. L. Head, "Optimization of pedestrian phase patterns at signalized intersections: A multi-objective approach," *J. Adv. Transp.*, vol. 48, no. 8, pp. 1138–1152, Dec. 2014.

[51] M. Hussein and T. Sayed, "Microscopic pedestrian interaction behavior analysis using gait parameters," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2519, no. 1, pp. 28–38, 2015.

Mohamed H. Zaki received the Ph.D. degree from the Hardware Verification Group, Concordia University, Montreal, in 2008. He studies road-users behavior and interactions through the microscopic analysis of travel data. A long-term goal is to understand the rules that govern the travel behavior of pedestrian and cyclists to improve sustainability in the era of intelligent transportation systems. He has joined the Bureau of Intelligent Transportation Systems and Freight Security, The University of British Columbia, in 2010, as a Post-Doctoral Fellow, and then a Research Associate.

Tarek Sayed is currently a Professor and a Distinguished Scholar with the Department of Civil Engineering, The University of British Columbia. His transportation engineering research has been focused on three main areas: to improve road safety analysis and evaluation techniques; to improve the level of knowledge associated with the safety implications of traffic operations and highway design; and developing and evaluating intelligent transportation systems to increase the efficiency of traffic. He is a fellow of the Engineering Institute of Canada, the Canadian Academy of Engineering, and the Canadian Society for Civil Engineering.

Authorized licensed use limited to: Tsinghua University. Downloaded on October 14,2020 at 04:05:24 UTC from IEEE Xplore. Restrictions apply.