CSCE 2013 General Conference - *Congrès général 2013 de la SCGC*

Montréal, Québec
May 29 to June 1, 2013 / *29 mai au 1 juin 2013*

Exploratory Data Analysis for Calibration of Pedestrian Models

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Abstract: Empirical data of human crowd is essential to study pedestrian behaviour. Pedestrian data under different circumstances is required to validate and assess the predictive power of pedestrian modelling tools. Different types of pedestrian data, microscopic or macroscopic, are required for different applications of pedestrian modelling. However, few pedestrian data is available in the literature. In this paper, some microscopic and macroscopic data extracted from video recordings in three different locations: Downtown Vancouver (Canada); Duisburg- Essen University (Germany); and O-train station, Ottawa (Canada) are reported. One of the videos is recorded from a controlled experiment and the two others are recorded from natural pedestrian movements. Findings of this paper can be used as benchmarks to analyze pedestrian behaviour in similar situations.

1. Introduction

Study of human dynamics is of great application and significance in transportation engineering and urban planning. Design or operation assessment of pedestrian facilities, crowd management, and improving pedestrian safety are some of the areas where understanding of pedestrian behaviour is required. Lack of appropriate and reliable data is one of the greatest challenges in analyzing pedestrian behaviour. Detailed microscopic and macroscopic pedestrian data are required in order to estimate and validate pedestrian models. Pedestrians do not behave similarly under different circumstances. Since most of pedestrian issues and safety problems occur in critical conditions, such as high density crowd, monitoring pedestrians in those situations would be of great help to transportation designer and planners. Empirical data is usually extracted from video recordings of human movements. In some cases, controlled experiments are conducted to study pedestrian behaviour in specific conditions. The relatively low cost associated with video recording compared to manual data collection and the detailed data that can be provided from a wide field of view makes this method an effective way to collect data (Ismail *et al.* (2010) [1]).

Different pedestrian-related data is required for different applications of pedestrian modelling. On one hand, in microscopic modeling approaches each pedestrian is acted as an agent and his/her behaviour is studied separately (e.g. Robin *et. al* (2009) [2]). These models deal with behaviour of individuals including changing in agent's direction or speed, interactions between them, and navigation around obstacles. Therefore the required data is microscopic including speed and direction of individuals. On the other hand, in macroscopic approaches the behaviour of a crowd as a whole is of interest (e.g. Helbing,(1998) [3]). Hence the extracted data has to contain information about aggregate traffic characteristics such as flow, average speed, and density.

There is few real empirical data in the literature in the context of pedestrian dynamics. The objective of this paper is to provide some microscopic and macroscopic pedestrian data to be used as benchmarks for better understanding of pedestrian dynamics and performance assessment of related modeling tools.

The data was extracted from three different real-world video recordings of pedestrian crowds in different situations. One of the videos was conducted in controlled conditions and other two were recorded in natural environments. The process of extracting data from all of these videos was performed manually.

2. Data Collection

The data used in this study was collected in 3 different locations: 1.Downtown Vancouver, Canada, 2. Duisburg- Essen University, Germany, 3. O-train Station, Ottawa, Canada. In this section, the process of collecting and preparing data for each of these locations is described.

2.1. *Downtown Vancouver Data*

This data was collected from actual pedestrian movements in downtown Vancouver, British Columbia at the intersection of Robson and Broughton streets (Ismail *et. al* (2009) [4]). The video was recorded during late afternoon capturing the pedestrian movements to and from a large firework event happening at the same time in the nearby area and therefore contains high pedestrian volumes. The video was recorded from the 29th floor of a building that faces the mentioned intersection. A frame extracted from this video is shown in Figure (1).

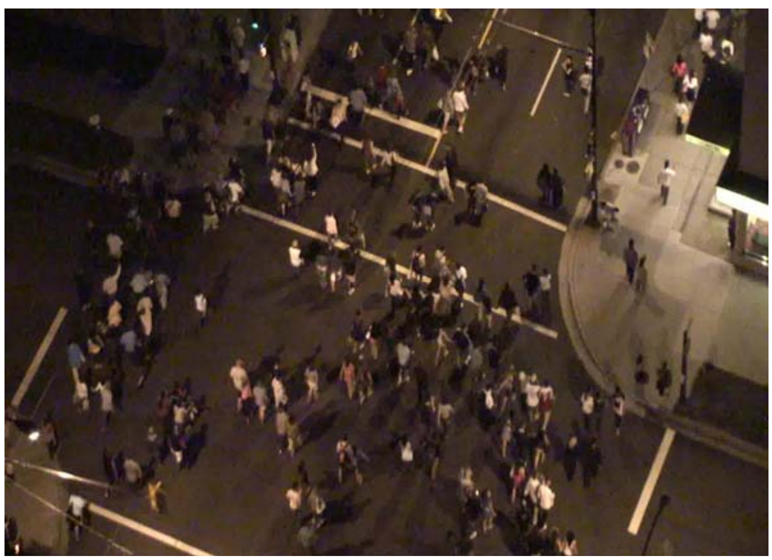

Figure 1: A frame from Vancouver scenario

Larger portion of pedestrians in this crowd were walking in groups rather than walking alone. The term 'group' is used in its socio-psychological sense referring to people who are socially bounded. This may arise when family members or friends walk together on purpose. Those aggregate of people who walk close to each other by chance and without any social ties are not considered group mates. Groups of two to five people were observed in this crowd (majority of them consist of two people).

A one-minute video sequence was selected to extract microscopic data from pedestrian movements. Trajectories of pedestrians at crosswalks and along a main street that was closed for vehicle traffic were extracted using a manual pedestrian tracking method. Camera calibration was performed using the method described in Ismail *et. al* (2013) [1] to project the coordinates of each observation from the image planes to world coordinates and generate pedestrian trajectories. Data for 238 pedestrians was collected. A total of 4186 positions were observed. Data was extracted with a time interval of 15 frames (0.5 seconds).

The speed and direction data for each pedestrian was derived from the successive observed positions of the pedestrian in the walking plane. Let P_t be the position of the pedestrian in time *t*, such that $P_t = (x_t, y_t)$, the direction and speed were calculated based on the following equations:

$$D_t = P_t - P_{t-0.5},$$
$$dir_t = D_t / \| D_t \| \qquad \text{(eq.1)}$$
$$V_t = \| D_t \| / 0.5$$

where D_t is the displacement of the pedestrian during two successive observations. dir_t and V_t are direction and speed of the pedestrian respectively. Observations were made every half a second (time step= 0.5sec).

A direction of 90° indicates no change in pedestrian's movement direction. In other words it shows that the pedestrian's centerline of movement for that observation overlaps direction vector of the pedestrian. Negative angles (larger than 180°) were removed from the data. These angles are caused either by some errors in manual tracking or may represent some rare situations when the pedestrian walked backwards.

In addition to the microscopic information, some macroscopic data was also extracted from Vancouver video recordings. Part of video was used for density and flow measurements. The duration of the video is 247 seconds and density and flow was manually measured in an area of approximately 10 by 10 meters. The defined area was considered in the middle of the space that had been closed to vehicle traffic and was used for pedestrian passing only (Figure (2)). Multiple snapshots with the rate of 2 frames per second, 494 snapshots in total, were provided to manually count the number of pedestrians inside this area.

The video was played in slow motion mode for each 5 seconds and the number of people crossing the boundary lines was counted within this time duration. The total number of people crossing each line within these 4 minutes is shown in Figure (2). The main flow moves from line A towards line B and almost no flow passes in the opposite side (from B heading towards A) and from D to C. Flow from C to D is negligible compared to the high pedestrian flow moving from A to B. As the passing flow was measured within different 5 seconds, the data for density was also averaged out every 5 seconds, so that the fundamental diagram can be reported based on the data of density and flow. The flow passing through line A towards line B is used to generate fundamental diagram.

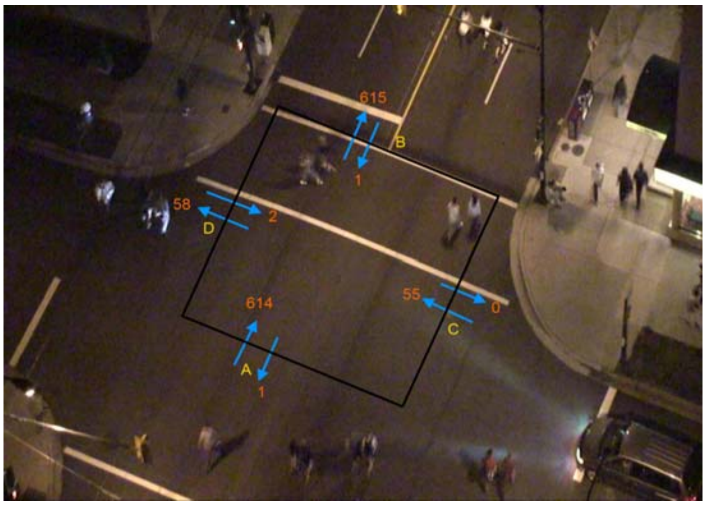

Figure 2: Area used for flow and density count

2.2. Duisburg Data, Germany

This data was collected at the campus Duisburg in Duisburg- Essen University, Germany. Kretz *et. al*. (2008) collected the data to study pedestrian flow through bottleneck [5]. They conducted a controlled experiment with 94 participants who walked through a bottleneck with a depth of 40 centimeters trying to represent a normal walking situation (non-panic). The experiment repeated with ten different widths of the bottleneck including 40, 50, 60, 70, 80, 90, 100, 120, 140 and 160 centimeter. For each bottleneck width multiple runs was performed (three runs for most of the bottleneck widths). The video was recorded from the top. A snapshot from the video recordings of a bottleneck width of 1 meter is shown in Figure (3).

Figure 3: A snapshot from German data

This data is used in this study to measure the interpersonal distances between pedestrians in high density situations. Adequate space is required both laterally and longitudinally to avoid physical contacts. The required lateral spacing is defined by the width of the human body (shoulder) together with allowance for body sway and longitudinal spacing is identified by pacing distance plus perception and reaction times. Based on the aforementioned factors, Fruin (1971) [7] has considered a lateral space of 28 to 30 inch (71 to 76 cm) and a longitudinal spacing of 8 to 10 ft (2.5 to 3 m) resulting in a minimum personal area of 20 to 30 ft^2/pr (2 to 3 m^2/pr) to move comfortably and to avoid contacts with others in unhindered walking situations. The personal space of a walking pedestrian is different from personal space in stationary situation. Pedestrians require larger distance in front while walking to avoid collisions [8].

However, the size and the shape of the personal space are continuously changing based on the crowd density and the travel speed of the pedestrian [6]. Interpersonal distance decreases as the density increases. Much smaller personal areas are perceived in crowded situations where movement is restricted, resulting in less freedom of motion. Fruin suggested a minimum desirable occupancy of 5 to 10 ft^2/pr (0.5 to 1 m^2) where physical contact with others is avoidable. According to Bandini *et. al* (2012) [8] 40x40 cm is the space individuals occupy in high density conditions. Jelić *et. al*. (2012) [9] suggest that in high density situations people walk in lockstep and the distance they keep from each other turns into the distance they move forward with steps they take.

Snapshots from the recorded videos were created with the rate of two frames per second. The head coordinates of each pedestrian in each of these images were stored using Matlab and then were converted from pixel coordinates to metre coordinates. The distance between each pedestrian and pedestrians in his/her surrounding environment in each frame was calculated using these coordinates.

2.3. *O-train Data, Ottawa*

This data was collected from O-Train station at Carleton University; Ottawa, Canada during the time the train stops at the station to load/unload passengers. Videos were recorded during November 2012 and purposefully at morning times (between 8 to 9 a.m) when the train is almost full with students heading to school. Therefore, when arriving at Carleton University the prevalent direction of movement is out-flow from the train. No or very few in-flow was observed. The camera was set on the fifth floor of one of the campus buildings (Minto Center) which overlooks the station and provides a good view of southbound trains arriving at Carleton. Six videos of train arrivals to the station were recorded. Video recordings started and ended with arrival and departure of the train and each of them was between 90 to 150 seconds long. A snapshot of the video is shown in Figure (4).

Figure 4: A snapshot of O-Train data, Ottawa

The observed train has 3 exit doors, annotated in Figure 4 with letters A, B, and C. Width of each door was measured to be 1.30 metres. Each video was played in slow motion mode and number of passengers passing each door every 5 seconds was counted. The egress time for each door was measured. Egress time is defined as the total time from the first to the last passenger passing the door.

3. Discussion of the Results

Summary of the obtained data is reported in this section.

3.1. *Downtown Vancouver Results*

Two examples of manually tracked pedestrian trajectories are shown in Figure (5).

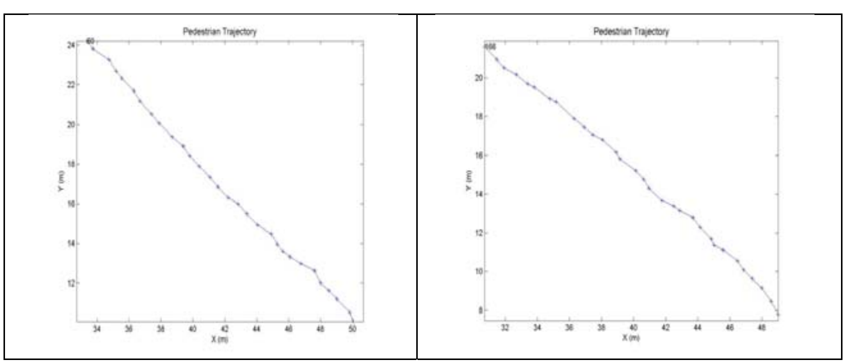

Figure 5: Examples of pedestrian trajectories (axes are x and y world coordinates)

Histogram of observed speeds is illustrated in Figure (6). Some of the speed statistics are reported in Table (1). Speed values are expressed in (m/s). Maximum observed speed is 3.74 m/s.

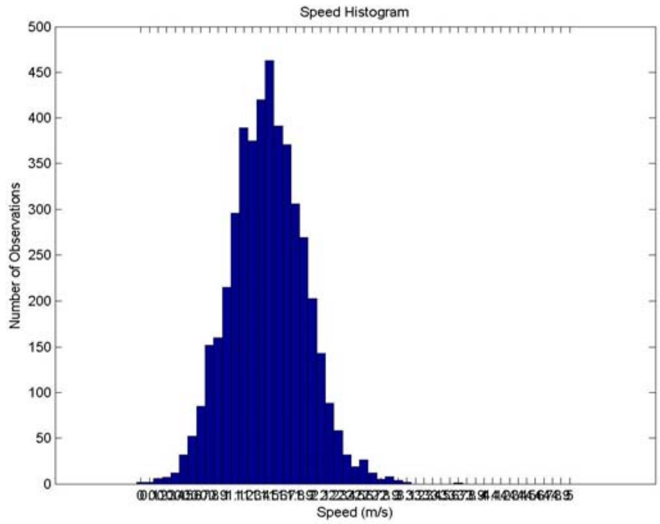

Figure 6: Speed Histogram

Table 1: Speed Statistics.

Max observed speed	3.7403
Min observed speed	0.1162
Average speed	1.475
Standard Deviation	0.43231
Most frequent observed speed	1.5
Median of speed data	1.4703

The speed data for people walking in groups and those walking individually are reported in Table (2) and Figure (7). Mode and average speed for group members is slightly smaller than individual pedestrians as expected. However, as the number of observations for group members is approximately three times higher than number of observed speeds for individual pedestrians we cannot come to a general conclusion based on this data.

Table 2: Speed data for people in group and individual pedestrians

	People in group	Individual pedestrians
Max observed speed	2.9947	3.7403
Min observed speed	0.1162	0.46168
Average speed	1.4665	1.5305
Standard Deviation	0.42615	0.46723
Mode	1.5	1.6
Median	1.4654	1.5083

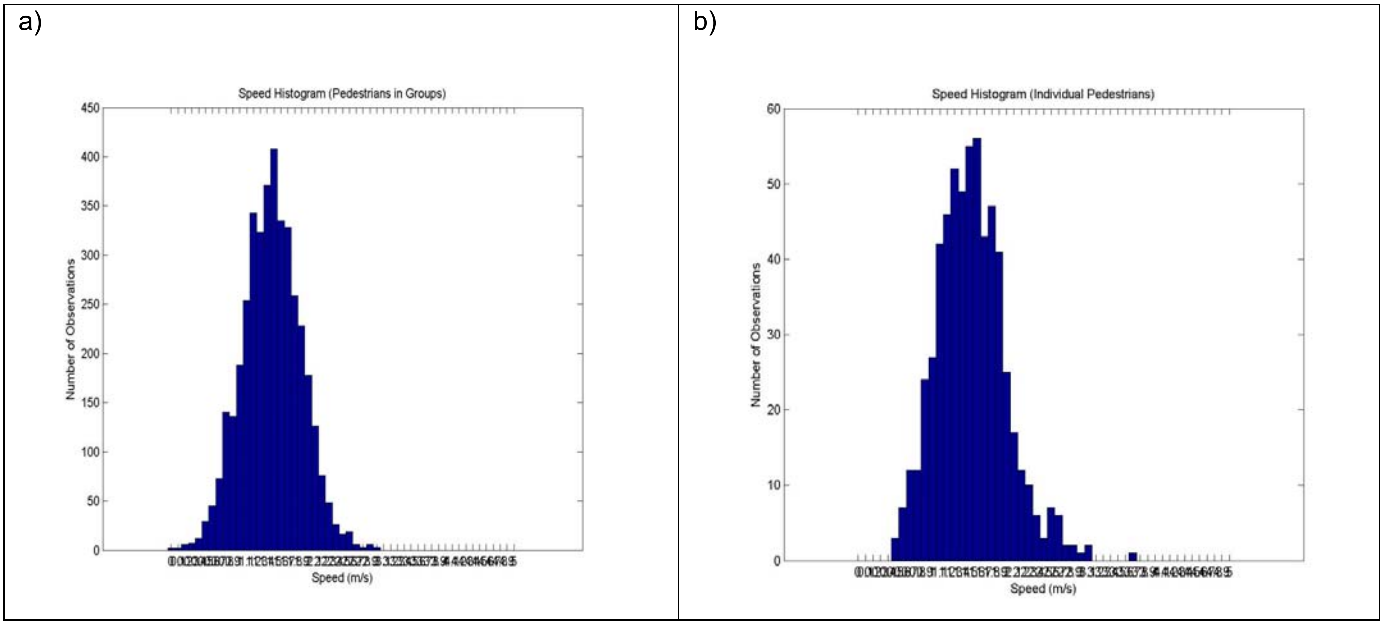

Figure 7: Speed Histogram of (a) people in group (b) individuals

Directions of pedestrians have been divided into ranges of angles which represent small, moderate, or high change in movement direction along pedestrian trajectories. The angle ranges are as follows:

$$\begin{cases} 60° <= \text{Dir} <= 120° & \text{no / small direction change} \\ 0° <= \text{Dir} < 30° \;\; \textbf{or} \;\; 150° < \text{Dir} <= 180° & \text{moderate direction change} \\ 30° <= \text{Dir} < 60° \;\; \textbf{or} \;\; 120° < \text{Dir} <= 150° & \text{high direction change} \end{cases}$$

Figure (8) shows that pedestrians tend to keep their direction and only few cases of high change in movement direction have been observed.

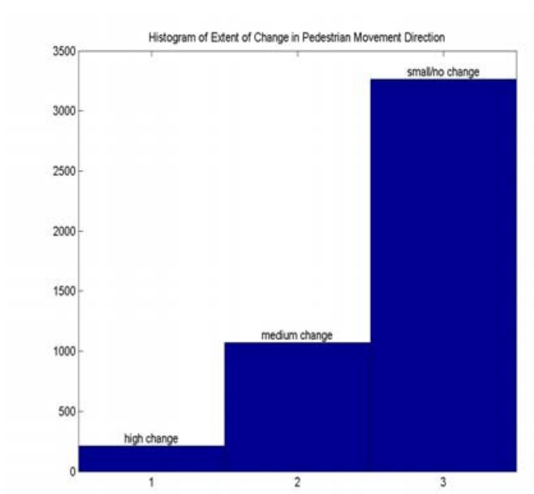

Figure 8: Observations of different extent of change in movement direction

The same approach has been performed for group members and individual pedestrians and similar results are obtained in both cases. No significant difference has been observed in the behaviour of the two categories (group members and individuals) regarding this behaviour. 4.5%, 23.52%, and 71.79% made high, moderate, and small direction change respectively in the sample of group members and 5.68%, 23.91%, and 70.40% made high, moderate, and small direction change respectively in individual pedestrian population.

Regarding the macroscopic data, the graph of flow (passing line A in Figure (2)) over time, density of the defined area over time, and the fundamental diagram (density-flow) are shown in Figure (9). All the values are measured for the duration of 5 second. The density values do not undergo a significant change in this data and therefore no clear trend is observed in density-flow diagram for this data.

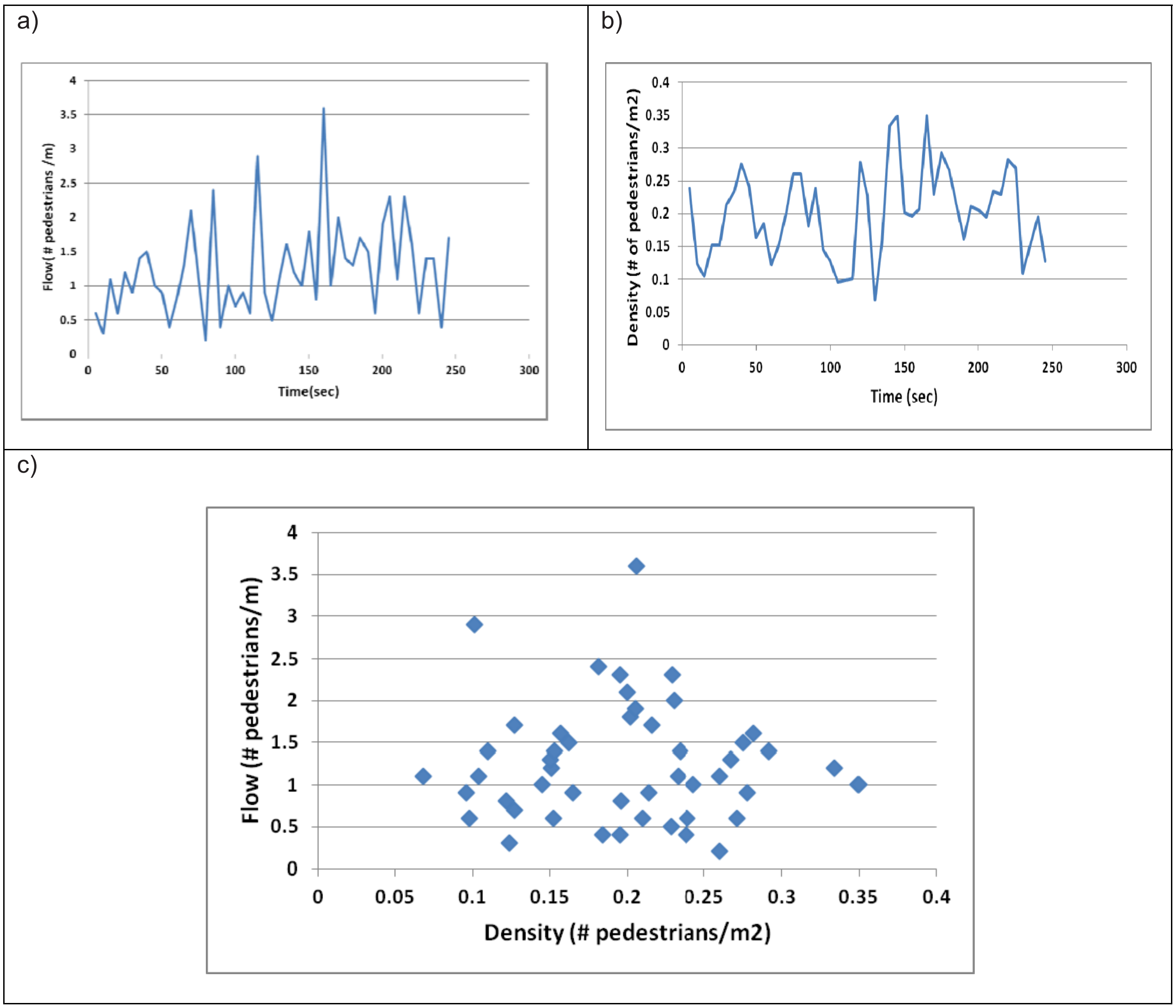

Figure 9: a) Flow over time (every 5 sec) , b) Density over time, c) Density-Flow Diagram

3.2. *Duisburg Results*

The minimum and percentile values of interpersonal distances in different videos are reported in Table (3).

Table 3: Interpersonal distances measured in different videos.

Video name	Min	10th percentile	15th percentile	20th percentile
60_2	25.03145	37.87927	39.42852	41.53046809
60_3	16.83409	32.28428	35.13379	36.69667
70_2	23.26457	33.13534	34.81745	36.56606
70_3	21.80617	33.23945106	35.74100319	37.35759574
80_2	19.85119	31.37789	32.8052	35.64998
80_3	22.27853	30.02971	33.0368	34.84323
90_2	25.81579	33.34727	34.59417	36.15964
90_3	19.81809	33.61177	35.52916	37.50382
100-2	21.36683	33.48621	35.34473	37.61279
100-3	22.13687	30.58	32.21	34.69
120_2	21.13355	33.24232	35.24474	36.62913
120_3	23.03381	32.83289	35.87485	37.66919
140_2	26.3967	33.82457	36.0613	37.51445106
140_3	24.50136	32.85681	35.67494	36.88506
160_2	23.91513	33.5635	36.75273	38.34523
160_3	21.96545	33.25394	36.38373	38.308
average	22.4468488	33.03407632	35.28956957	37.12258218

Table 4: Interpersonal distances with respect to the angle between the direction of movement and position of the other pedestrian

angles (degree)	Num of Observations	Min	10th percentile	15th percentile	20th percentile
0-5	281	27.68975	30.76795	33.17065	35.22795
5-10	259	31.7793	34.81345	36.4889	38.19625
10-15	283	30.69055	34.8786	36.79445	38.795
15-20	254	30.8235	35.675	37.34205	38.8638
20-25	309	30.8083	36.0791	38.7545	41.12505
25-30	343	32.57935	36.4223	38.44435	40.2194
30-35	336	31.8422	36.1194	38.45265	40.32905
35-40	382	31.0885	36.7768	39.06395	41.43224
40-45	332	32.73405	37.7031	40.1542	41.9936
45-50	359	31.10775	36.7801	38.9367	40.8512
50-55	302	31.23455	35.06615	36.8817	39.2618
55-60	245	31.3693157	33.993157	36.325578	38.69252
60-65	214	32.3602631	34.641578	36.067	37.25015
65-70	191	34.0506315	35.913052	37.485263	39.32047
70-75	214	33.6979	36.2658	37.38825	38.0433
75-80	216	29.1494117	32.4135882	34.095117	35.38035
80-85	195	29.3813888	32.566777	35.419777	36.75744
85-90	215	31.0454210	33.144368	34.912315	36.17610

Table (4) indicates the observed interpersonal distances with regard to the angle between the pedestrian's direction of movement and position of nearby pedestrians. Angle 90° shows the lateral distance and angle 0° shows the longitudinal distance the pedestrian maintains with other pedestrians. Each value reported in this table is the average of the values obtained for different videos.

Looking at the values in the tables above one can conclude that in high density situations interpersonal distance is not a function of the angle between pedestrians, that is, the distance a pedestrian keeps with other nearby people does not depend on whether they are arranged in lateral or longitudinal directions. In addition, a value between 35 to 40 centimeters can be selected as a distance threshold between pedestrians in high density situations.

3.3. *O-train Results*

Figure (10) shows the relation between total number of passengers that leave the train and egress time. Expectedly, egress time increases as the number of passengers increases. A line has been fitted to data and results of ANOVA test implies that there is a significant relationship between two variables which can be well explained by this line. The value of R-square obtained is 0.83. Line of best fit is also shown in figure (10).

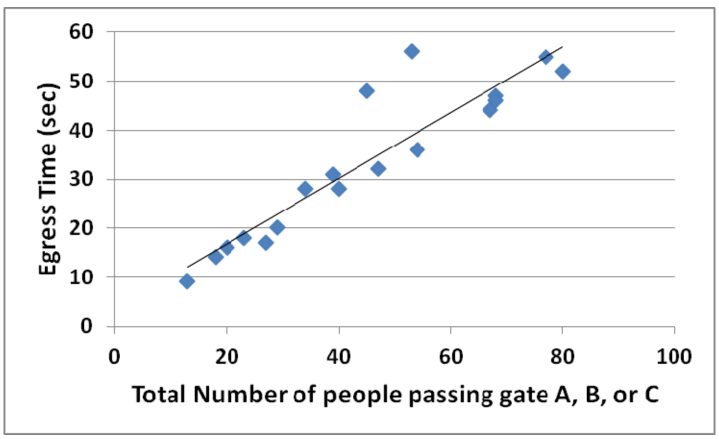

Figure 2: Relation between number of people passing the door and egress time

The time it takes to unload the train is not sufficient enough to observe adequate change in flow over time for each door. Figure (11) displays the observed flows passing doors A, B, or C for the time interval of 5 seconds. Maximum flow is 7.7 p/m with the most frequent observed value of 6.15 p/m for the time interval of 5 seconds.

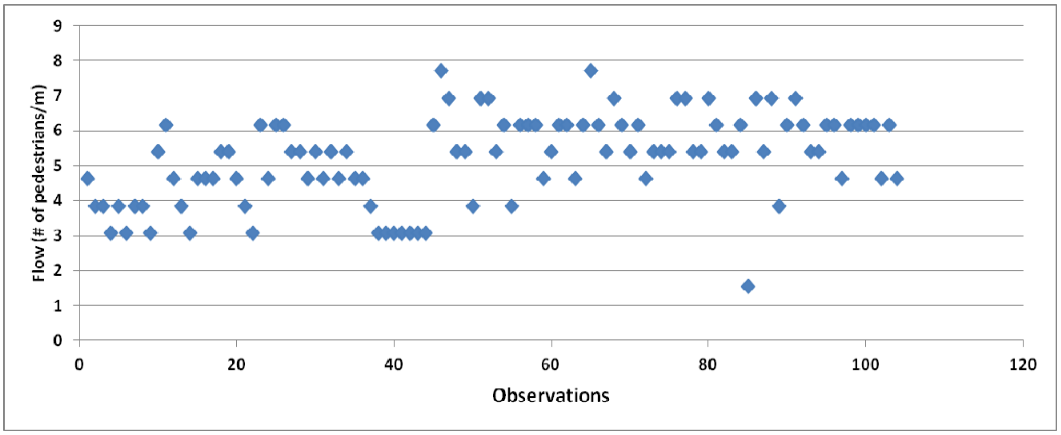

Figure 11: Observed flows every 5 seconds

4. Conclusion

A common practice to validate and assess the performance of modeling tools is to compare between numerical results obtained from these tools and real-world data. The literature suffers from the lack of pedestrian data required for this purpose.

This paper presents some microscopic and macroscopic pedestrian data collected in different circumstances. Microscopic data such as speed and direction are reported. It has been observed that pedestrians tend to maintain their direction while walking. Few observed high variation of movement in their trajectory can be the result of interaction with other pedestrians or obstacles in their ways. Moreover, speed and direction behaviour of pedestrians in groups and individuals are studied for the sake of comparison. Furthermore, a range of acceptable values for the minimum interpersonal distance between pedestrians in high density situations has been selected. The relationship between egress time and number of people passing through a bottleneck in high density situation is found. Finally, values of pedestrian flow passing through a bottleneck in highly crowded situation (O-train data) have been reported. All of these data are of great significance in transportation studies and can be used as benchmarks for validation or estimation of pedestrian behaviour models. The data gained through this study is one of the few available pedestrian data in the literature.

References

1. [1] K. Ismail, T. Sayed, and N. Saunier, “A methodology for precise camera calibration for data collection applications in urban traffic scenes".Canadian Journal of Civil Engineering, Volume 40, Number 1, January 2013 , pp. 57-67(11).
2. [2] T. Robin, G. Antonini, M. Bierlaire, and J. Cruz, “Specification, estimation and validation of a pedestrian walking behaviour model,” *Transportation Research Part B: Methodological*, vol. 43, no. 1, pp. 36–56, Jan. 2009.
3. [3] D. Helbing, “A Fluid Dynamic Model for the Movement of Pedestrians,” *Arxiv preprint condmat9805213*, vol. 6, pp. 391–415, 1998.
4. [4] K. A. Ismail, T. Sayed, and N. Saunier, “Automated Collection of Pedestrian Data Using Computer Vision Techniques,” *Transportation Research Board Annual Meeting Compendium of Papers*, p. 23p, 2009.

5. [5] T. Kretz, A. Grünebohm, and M. Schreckenberg, “Experimental study of pedestrian flow through a bottleneck,” *Journal of Statistical Mechanics: Theory and Experiment*, vol. 2006, no. 10, pp. P10014–P10014, 2006.
6. [6] J. J. Fruin, *Pedestrian planning and design*, Metropolitan Association of. Urban Designers and Environmental Planners, New York, 1971.
7. [7] S. Bandini, A. Gorrini, L. Manenti, and G. Vizzari, “Crowd and Pedestrian Dynamics: Empirical Investigation and Simulation,” *measuringbehaviour.org*, vol. 2012, pp. 308–311, 2012.
8. [8] I. Karamouzas, P. Heil, P. Van Beek, and M. Overmars, “A predictive collision avoidance model for pedestrian simulation,” *Motion in Games*, pp. 41–52, 2009.
9. [9] A. Jelić, C. Appert-Rolland, S. Lemercier, and J. Pettré, “Properties of pedestrians walking in line: Stepping behaviour,” *arXiv preprint arXiv: …*, pp. 1–8, 2012.
10. [10] A. Johansson, D. Helbing, H. Z. Al-Abideen, and S. Al-Bosta, “From Crowd Dynamics to Crowd Safety: A Video-Based Analysis,” *Advances in Complex Systems*, vol. 11, no. 04, pp. 497–527, 2008.
11. [11] W. Daamen, "Modelling Passenger Flows in Public Transport Facilities," PhD thesis,TRAIL Thesis Series, no. T2004/6, Delft University Press, Delft, 2004.