

Pedestrian Dynamics at Transit Stations: An Integrated Pedestrian Flow Modelling Approach

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Abstract The objective of this chapter is to explore an integrated modelling framework that captures pedestrian walking behaviour in congested and uncongested conditions and covers different traffic dynamics caused by complex geometric and operational characteristics such as those observed in transit stations. The integrated modelling framework is built using concepts from the Social Force model, behavioural heuristics, and materials science. Pedestrian trajectory data provided by the Delft University of Technology were used to test the validity of the aforementioned modelling framework. A simulation study showed that the model reproduces realistic trajectory patterns in an environment similar to that at the Foggy Bottom METRO station in Washington, D.C, USA.

1 Introduction and Motivation

Pedestrians play an increasingly important role in the traffic scenes of the modern world. This role is particularly important in urban areas, such as Washington D.C., where pedestrians often dominate the traffic flow [3]. By accurately modelling pedestrian behaviour, design of civil infrastructures may be improved by increasing the number of pedestrians who can safely flow through the corresponding geometric components (i.e. pedestrian infrastructure capacity). Of particular interest is the flow of pedestrians through public transit stations [1, 6, 12]. Transit stations must be able to hold large numbers of travellers while also allowing pedestrians to move safely and efficiently from one location to another. Accurately modelling pedestrian behaviour

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through transit stations allows identifying areas with critical densities that might be dealt with through changing the corresponding geometric features or through offering some level of control (pre-timed or real time). Many models of pedestrian behaviour have been previously suggested, however, a relatively recent review of crowd models suggested that model usability is highly dependent on the application for which the model was originally developed [4]. In this chapter, the model is intended to be used for crowd management and control for the Washington, DC METRO system. As such, the model must be able to accurately show high-density situations, run in real time, and consider the complex nature of human decision making. Although some existing pedestrian models are computationally efficient, these models frequently capture one-to-one interactions and fail to consider the complexities of decision making that occur in crowded conditions [9, 11].

The objective is to accurately and efficiently model pedestrian operational behaviour (focusing on walking behaviour), using a combination of the Social Force model [7], the behavioural heuristics model [10], and concepts from materials science such as multi-body potential molecular interactions [5]. The resulting integrated model (IM) rules are programmed in a JAVA simulation platform constructed by the authors. Realistic parametric values were initially taken from the literature and later calibration efforts were conducted using experimental data obtained by the Transport and Planning Department at the Delft University of Technology. The basic manual calibration was aimed to reproduce the observed densities in a bidirectional flow experiment. Afterwards, simulations were run to look into the reproducibility of trajectory patterns observed in 4 additional experiments. After this introduction, Sect. 2 presents the model itself, including a description of the models formulation and basic calibration. Section 3 contains an analysis of the results obtained from model simulation related to the 5 experimental scenarios previously described in addition to an exploratory study on simulating pedestrian movements in a transit station. In Sect. 4, the paper concludes and suggests future research recommendations.

2 Model Formulation and Calibration

In this section, some IM related details are explained, beginning with the formulation framework, which specifies the aspects of the suggested model that were adapted from other sources as well as the method by which they were combined. Afterwards, the calibration efforts that were undertaken for this model are described.

The motivation behind offering the suggested integrated modelling framework is the hope that the resulting formulation will benefit from the attraction/repulsive force concepts offered by the social force models (offering realistic one-to-one interactions), the flexibility of the behavioural heuristics (incorporating multiple psychological and physiological pedestrian characteristics) and the theoretical foundation from materials science. Accordingly, the basic interaction between ‘bodies’ (i.e. pedestrians or obstacles) is adapted from the Social Force model [7]. The Social Force model essentially uses Newtonian physics to describe how pedestrians move.

The model defines attractive and repellent forces which push and pull pedestrians along their path of motion. On the other hand, the behavioural heuristics model utilised in this paper considers that pedestrians take advantage of their eyesight and cognitive perception of their surrounding environment to determine which direction is the most efficient to reach their local destination (i.e. operational navigation) [10]. Finally, an essential concept from materials science is incorporated; this concept states that molecular interactions can be well modelled by taking into account directly neighbouring molecules. This greatly simplifies the complexity of the calculations since not all surrounding objects need to be considered. This conceptual hypothesis is to be tried in this paper: when applied to pedestrian dynamics, this concept implies that accurately modelling pedestrian behaviour requires ‘social force’ calculations not only between the two closest bodies (i.e. pedestrians or obstacles), nor all surrounding bodies, but rather between multiple bodies (i.e. multi-body potential interactions) within the corresponding field of view [5]. In our model, based on the findings of the research conducted in materials science [5], the closest three other pedestrians/obstacles are taken into account when determining a specific pedestrians course of action. It should be noted that this number may be a parameter to be calibrated depending on surrounding traffic conditions.

Given the aforementioned modelling framework, manual calibration was conducted using a bidirectional flow experiment data set provided by TU Delft (Fig. 1c). A more detailed review of these experiments is provided by [2]. From this data, macroscopic information such as average flows and densities were extracted. The mean and standard deviation of the pedestrians speed in the experimental data (assuming a normal distribution) was applied to the modelled pedestrians as their desired speed.

The density from the model was recorded at every time step and compared to the actual density recorded in the data. In this case, the density consists of the number of pedestrians in the entire walking area (40 m^2). These density recordings taken from the data were used to determine how closely the model was representing the experimental results on a macroscopic level. The resemblance between the experimental data (i.e. observed density) and the model output (i.e. simulated density) was measured based on a simple relative error term expressed as the absolute (positive) difference between the two values (i.e. observed density simulated density) divided by the observed data (i.e. observed density). The parameter values in the model were changed using a tabu-search approach in order to reproduce results similar to those seen in the experimental data. The error resulting from the density comparisons is 24.6% error for the IM approach. Such error is outside the acceptable error ranges [8] despite the low density values recorded; the integrated model still obtained the lowest error if compared to the BH and SF models implemented by the authors.

Section 3 describes the numerical results gathered from simulation, including a comparison between the experimental data and the integrated approach model output for 5 scenarios: a unidirectional flow scenario, a bidirectional flow scenario, a crossing scenario, a wide bottleneck scenario and a narrow bottleneck scenario. The simulation study is further extended to explore some trajectory patterns produced by the integrated model at a transit station.

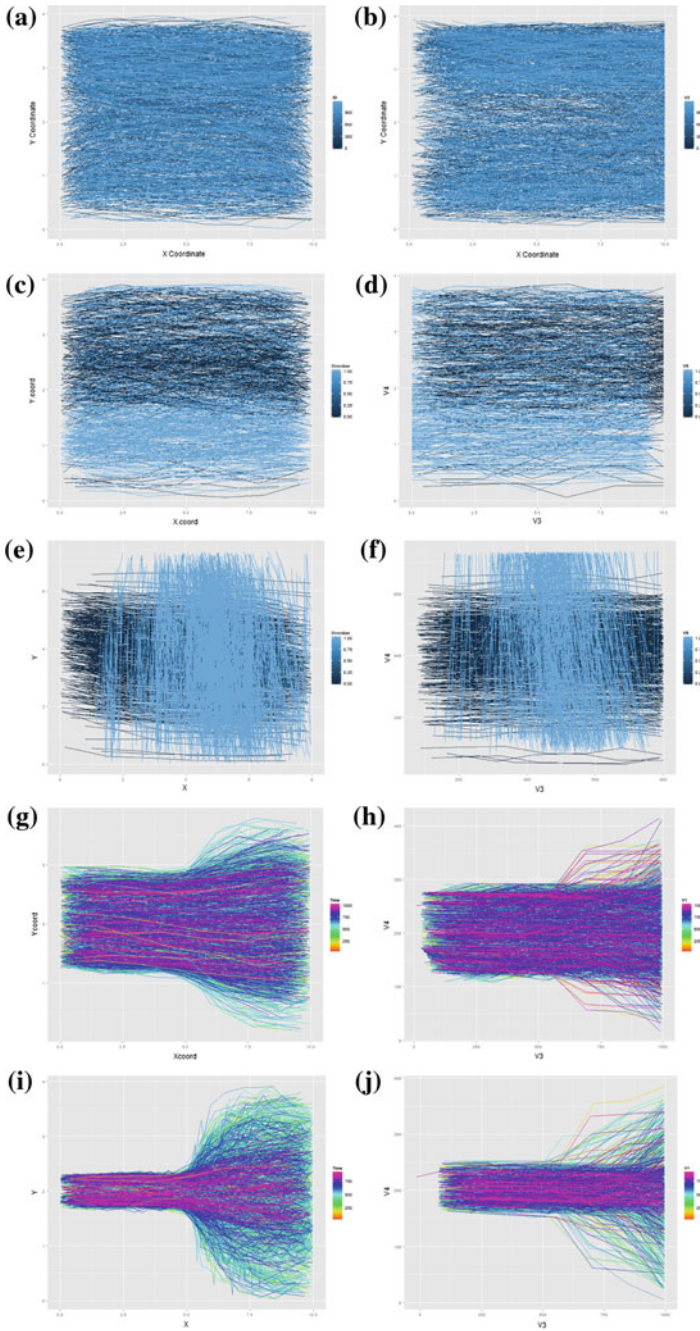


Fig. 1 Comparison of data and model trajectory results for 5 experimental scenarios. Unidirectional flow: data (a), model (b); bidirectional flow: data (c), model (d); crossing flow: data (e), model (f); wide bottleneck: data (g), model (h); narrow bottleneck: data (i), model (j)

3 Simulation

Figure 1 presents a trajectory comparison between experimental data gathered by TU Delft and the corresponding trajectories that were gathered from the IM model (using the parameters that produced the lowest error). From the top, the images show: one directional flow, two directional flow (left to right in blue and right to left in black), crossing (right to left in black and top to bottom in blue), wide bottleneck (colours based on entrance time: red most recent and orange yellow, less recent), and narrow bottleneck. The sharp changes in direction seen in the IM trajectories are due to the 1 second time step that has been employed. Aside from this obvious difference, there are numerous similarities between the experimental trajectories and the simulated trajectories. The one directional flow indicates consistency in the area occupied by pedestrians. In the two directional flow situation, in addition to matching in terms of area occupied by pedestrians (i.e. area mainly occupied by pedestrians moving from right to left—black trajectories—versus area occupied mainly by pedestrians moving from left to right—blue trajectories), the simulation suggests lane formation similar to that seen in the data, although this phenomena cannot be definitively observed with all of the trajectories plotted at once. The simulated pedestrians in the crossing scenario are also seen to have similar trajectory patterns as those observed in the experiment. It seems there is a major crossing area and a minor crossing area towards the left of the corresponding plots). The last two scenarios illustrated in the figure correspond to bottlenecks. The simulated wide bottleneck scenario provides more similarities with the observed trajectories if compared to the narrow bottleneck scenario; such results at this exploratory level of the study is somewhat expected due to the increasingly complex interactions that occur at narrow bottlenecks [8]. In both simulated bottleneck results, the funnelling effect can be seen as the pedestrians fan outwards before entering the bottleneck area. The experimental results from the narrow bottleneck show sharp zig-zagging trajectories from pedestrians travelling on the outermost edge of the funnel shape who are attempting to enter the central area, whereas the simulation shows these trajectories as smooth. The zig-zagging seen in Fig. 1i is caused by the swaying effect, which is visible at low speeds, and occurs when pedestrians shift their weight from their right foot to their left foot.

Since the IM is ultimately intended to be used at the Washington DC METRO system, a simulation was conducted based on the layout of the station at Foggy Bottom. In the corresponding scenario, it was assumed that pedestrians entered the platform from the escalator near the right side of Fig. 2a (descending escalators) as well as from train doors. Pedestrians were able to leave the platform via the more centrally located escalator (ascending escalators) as well as by entering train doors. The simulation was conducted with pedestrians entering from the escalator at a uniform arrival rate.

Figure 2a shows the simulated trajectory data with the train doors and escalators shown. Figure 2b is a density plot, which shows the areas with the highest ‘congestion’, which correspond primarily to waiting areas. The darkest areas in

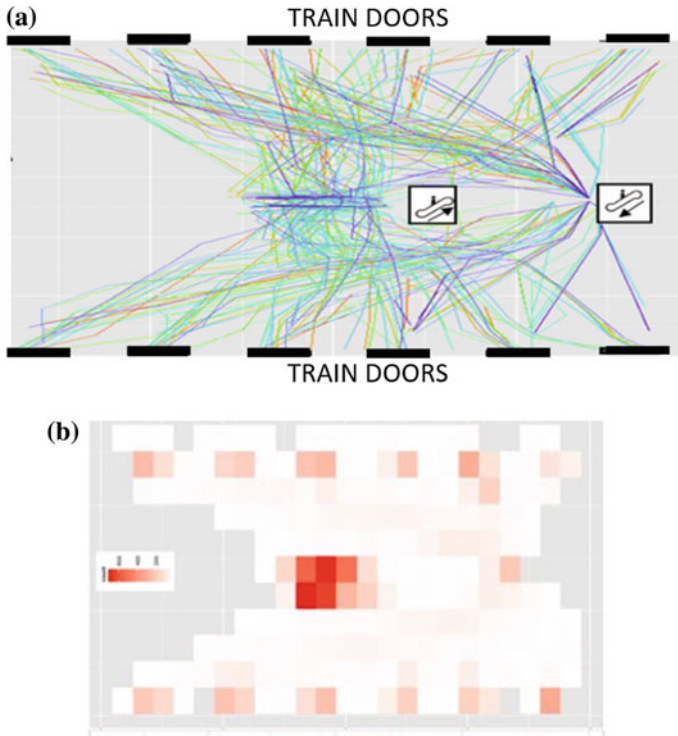


Fig. 2 Transit scenario results: simulated trajectories at transit station (a); density distribution for transit simulation (b)

Fig. 2b indicate areas in which pedestrians have spent prolonged periods of time (more than 1 s). These dark points correspond to waiting areas, such as those located near train doors where pedestrians who have descended on the escalator are awaiting their train and the area in front of the escalator where pedestrians are waiting to exit the station. The pedestrians waiting for the escalator are experiencing delays due to congestion, which may be mitigated by crowd control, whereas the pedestrians waiting near the train doors are waiting for their train to arrive, which is controlled by the train scheduling. The highest density area occurs near the escalator that leads from the platform to the stations exit, where pedestrians can be seen queuing. This result is expected, especially considering trains from both directions arrived at the same time. This causes a queue to build up in front of the escalator as pedestrians await their turn to leave. This result resembles the real-world lane formation, which shows pedestrians queuing in straight lines (rather than half a circle) before entering the escalator. This queuing is shown by the green and red points in front of the escalator in Fig. 2a. Although the transit simulation cannot be numerically verified by empirical data at this stage (the same traffic patterns observed in real-life are observed in the simulation), the results appear to accurately reflect basic densities and crossing

areas on the station platform. These results, in addition to the proximity between the empirical data and the simulation results shown above (Fig. 1), indicate that the IM approach is well-suited for performing in transit situations, and further work should be conducted to reinforce this indication.

4 Conclusions

Pedestrian modelling faces numerous challenges, ranging from covering heterogeneity among the behaviour of individuals to a lack of commonly used datasets. These difficulties affect models in different ways the heterogeneity of pedestrians contributes to the non-existence of a single model that can accurately describe all types of scenarios, and the lack of common data sets contributes to different approaches taken by authors to validate their models. Furthermore, there is a lack of commonly accepted calibration and validation methods as well as a lack of agreement on which phenomena and behaviours a model should be able to capture, which adds to the difficulty of verifying that a particular model is working well. Although the pedestrian modellers ultimate goal, of being able to realistically simulate all types of situations with a single model, has not yet been reached, there are many models which are capable of reproducing specific situations. One such model has been presented here. The IM approach is intended to be used in high-density situations, and this paper discusses the initial calibration and validation efforts that have been taken towards achieving that goal. In order to further improve this model, experimental data gathered in high-density situations will need to be used for calibration. Additionally, a sensitivity analysis must be conducted, in addition to more intensive calibration efforts, in order to verify that the IM approach is capable of simulating all types of scenarios that are seen in transit stations. Future calibration efforts will consist of a thorough macroscopic and microscopic calibration in addition to specifying individual pedestrian information, such as sight angle and distance. The primary future goal identified by the authors of this paper is to collect data from high-density experiments, which will be invaluable to this model, as well as to other models with similar objectives.

Acknowledgements This material is based upon work partially supported by the George Washington University Facilitating Funds (UFF). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the university. The authors would like to thank the Transport and Planning Department at the Delft University of Technology (TU Delft) for providing the different trajectory data used in this study.

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