OpenPTDS Dataset: Pedestrian Trajectories in Crowded Scenarios

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Abstract. Pedestrian simulation is an important approach for engineers to evaluate the safety issues of metro buildings. Although there exist many works of pedestrian evacuation, it is still lacking of rich evacuation data to calibrate simulation models. To overcome this problem, we conducted several real-life pedestrian experiments and create a data set named OpenPTDS. Fundamental speed-density diagram is drawn to show its feasibility. To promote further research and applications, the source data is shared at https://github.com/my-HenryS/multi-agent-simulation.

Keywords: pedestrian trajectory, dataset, speed-density diagram

1 Introduction

Pedestrian model has long been a problem faced by many government officers, physicists, and computer scientists. From the perspective of pedestrian model granularity, current works can be divided into two classes: macroscopic models and microscopic models based on a simple or complex topology. The two resolution models can be applied to situations such as tall buildings [1, 2], cities [3, 4], airports, and subway stations, with the goals of evacuation guidance, finding exits [1, 2], or evacuation training [5].

Although there exist many studies addressing the problem of pedestrian modeling, validation practice is not scrutinized because lacking of rich pedestrian data. Currently we have three open datasets including Campus Dataset [12], ETH Dataset [13], UCY Dataset [14]. Campus Dataset is developed by Robicquet A et al. [12]. Its scenario is mainly campus streets, where people density is small. ETH Dataset is proposed by Pellegrini et al. in multi-object tracking. Its main scenario is library and includes about 750 persons‘ trajectories. UCY Dataset is designed by Lerner A et al. [14]. It includes two scenarios and 786 pedestrians. All these datasets are useful, but they have common problems such as low resolution, small frame rate, unavailable obstacle information et al. And they are normally lacking evacuation scenarios.

To tackle this problem, we carried out several pedestrian evacuation and counterflow experiments with Beihang university students. By collecting data using recent high resolution cameras, we recorded detailed video sequences and then build a dataset to help to build pedestrian evacuation and walk behavior models.

2 Pedestrian trajectory datasets

We tracked crowd information including evacuation and crosswalk counterflow. From March to October 2017, in the new main building of the Beihang University, we designed and participated in manifold real life experiments, using video recording experiments, and tracking each pedestrian track information using the target tracking algorithm. A dataset including pedestrian trajectories was formed, which can be used in evaluation of the trajectory prediction method.

The data set related statistics are as follows:

- There are two types of scenes including indoor evacuation and crosswalk convection. There are different obstacles and exit widths under each scenario.
- Two situations including competitive and non-competitive.
- A total of 33 experiments.
- The number of pedestrians in each experiment was 26.
- 30 frames per second (FPS), resolution 1920*1080.

2.1 Scenarios in datasets

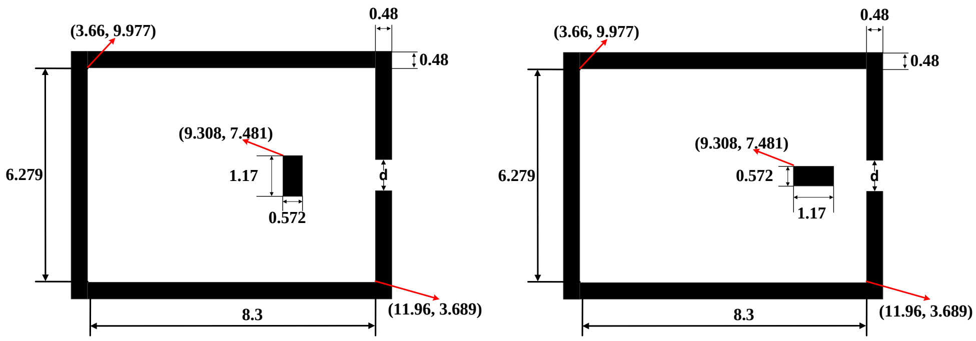
The data collected in this study include two types of scenes: room evacuation and crosswalk. In the former scenario, the crowd was assumed to evacuate from the exit. Pedestrians show a series of movements such as obstacle avoidance, moving with dense crowd, and escaping from the exit. In the crosswalk, the population is divided into two parts, which are separated at a distance, simulating pedestrians on both sides of the crosswalk ready for a serial intersection. In the process of crosswalk, pedestrians will follow suit and avoid pedestrians. The head of the experimental individual carries a hat of different colors to help trajectory tracking.

Fig. 1. Experiment scenarios. Left is counterflow in crosswalk. Right is room evacuation.

2.1.1 Setting of evacuation scene in indoor evacuation

The setting of the indoor evacuation escape experiment mainly consists of three attributes, such as the position of the obstacle, the width of the escape exit and the movement state of the pedestrian. There are two possible values for each attribute. The set of scene data sets for the same set of attributes contains three experiments, and the initial position of the pedestrian is different in each experiment. So for the escape scenario, the dataset contains 24 experiments.

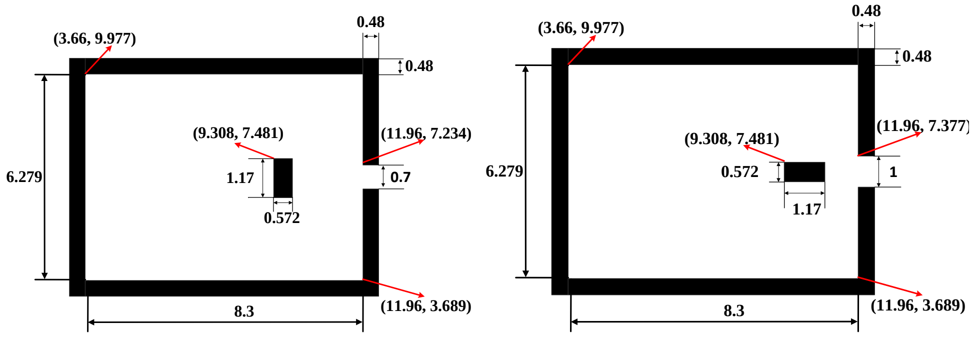
There are two types of obstacles, one is horizontal and vertical, the other is parallel to the exit direction, while the exit direction is opened to the right under video recording. We specify that the lower left corner of the scene is a coordinate origin (0, 0) and the coordinate system is set up, then the transverse obstacle is a rectangle with (9.308m, 7.481m) as the upper left top, the length and width of 1.17m and 0.572m respectively; the longitudinal obstacle is the upper left apex with (9.724m, 7.234m), and the length and width of the 0.572m and 1.17m rectangles respectively.



(a) Lateral obstacle (b) Horizontal obstacle

Fig. 2. Scenarios of various obstacles.

There are two experimental settings for the escape scene: wider and narrower doors. The wide gate scene is 1.0m, and the narrow gate is 0.7m. The crowd escape in the wide door scene is more fluent than the narrow gate, and the difference characteristics of the pedestrian's movement behavior under different congestion can be obtained through different gate width settings.



(a) narrow gate scene (b) wide door scene

Fig. 3. Scenarios of various exit widths.

In the indoor evacuation experiment, there are two types of pedestrians, emergency and non-emergency, which simulate the fierce scramble and congestion of pedestrians and the state of pedestrians in their daily life. In order to simulate the emergency, we were given an experiment to give the volunteers through the export to reward (Bonus), making the experimenter willing to travel at a rate beyond the normal pace, and to produce crowding and space competition similar to escaping in the exit.

Figure 4 shows the escape behavior of pedestrians in an emergency. The pedestrians will rush to the escape exit in the scene at a higher speed and form close crowds as shown in Figure 5 at the exit.

Fig. 4. A pedestrian escape scene in an emergency

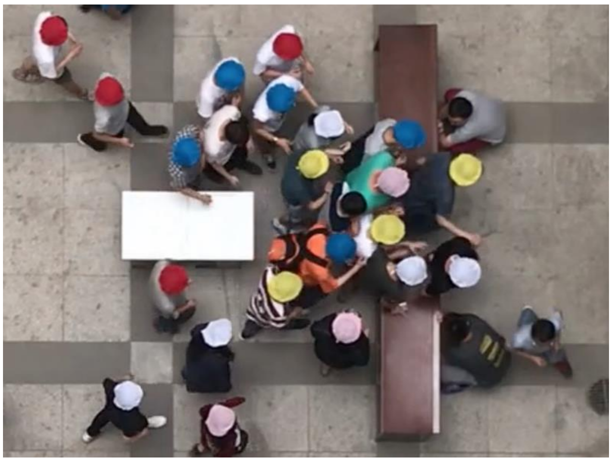


Fig. 5. The crowding of pedestrians at the door

In addition, in order to verify the impact of the barrier distance on the escape, we moved the lateral obstacle near the gate to move 0.923m, and at the gate width of 1m, we did an emergency and non emergency escape experiment, as shown in Figure 6.

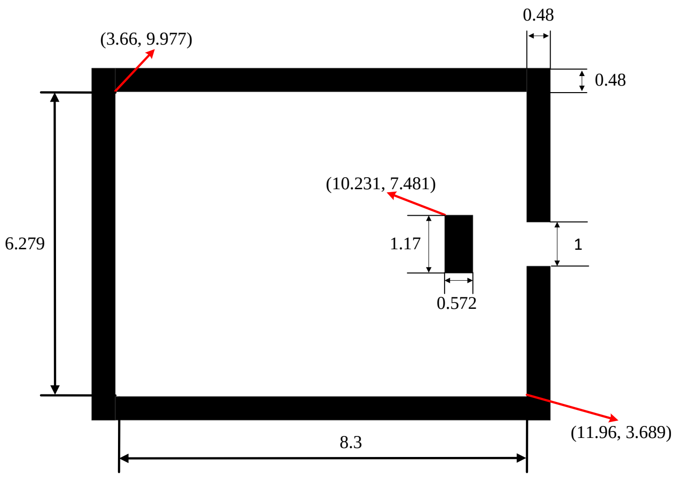


Fig. 6. The scene of the obstacle near the door

3.1.2 Setting of crosswalk convective scene

The crosswalk convective data set shows the movement of pedestrians at the two sides of the intersection. There are 4 experiments for the emergency convective scene and 3 non-emergency convective scenes.

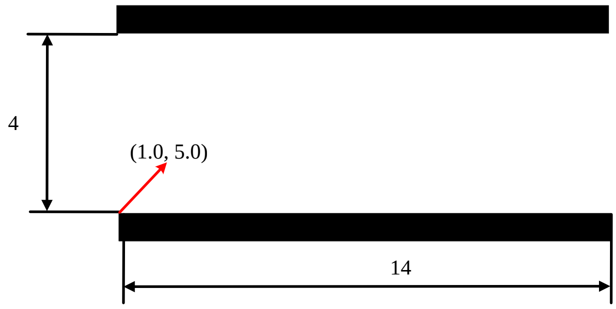


Fig. 7. Crosswalk convection experiment

3.2 Datasets numbering rule

We have numbered each set of experiments in the dataset so as to facilitate data set management and data processing. We define a set of experiments with the following attributes: the large class of scenes, the scene properties (the location of the obstacles, the size of the exit), the state of the pedestrians' motion (emergency / non emergency), the experimental group number.

Table 1. Numbered naming rules.

number	Scene category	Obstacle position	Gate size	motion states	Group number
#	evacuation 0	Lateral obstacle 0 Longitudinal obstacle 1 The lateral barrier is close to the gate 2	Narrow gate 0 Wide gate 1	Non-emergency 0 Emergency 1	0, 1, 2…
	crosswalk 1	non 0	non 0	Non-emergency 0 Emergency 1	0, 1, 2…

For example, for pedestrian trajectory data of "indoor escape scene - vertical obstacle wide door emergency third experiments", the serial number is #01012. For the "convective scene non-emergency first experiment", its serial number is #10000.

3.3 A brief description of track tracking method

The pedestrian trajectory in this dataset is obtained from the target tracking software developed by the laboratory. The author is involved in data acquisition. The software can use the KCF target tracking algorithm [20] and MDNet [21] to track the pedestrian trajectory, and the pedestrian trajectory can be obtained after the initial frame selection is desired. The KCF algorithm has a fast tracking speed and can be traced in real time, but it is easy to be disturbed, and the pedestrian tracking effect in the field of vision is poor when the population density is large; the tracking speed is slow with MDNet, and the recognition speed is generally 3 frames per second, but the accuracy rate is significantly higher than that of the KCF algorithm. Therefore, in the data tracking of this data set, the authors select the KCF algorithm to track the trajectory of pedestrians in the non-competitive scene, and use the MDNet algorithm to track the pedestrian trajectory in the competitive experimental scene.

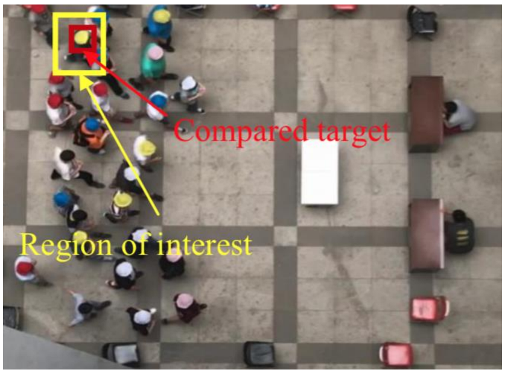


Fig. 8. Schematic diagram of KCF algorithm

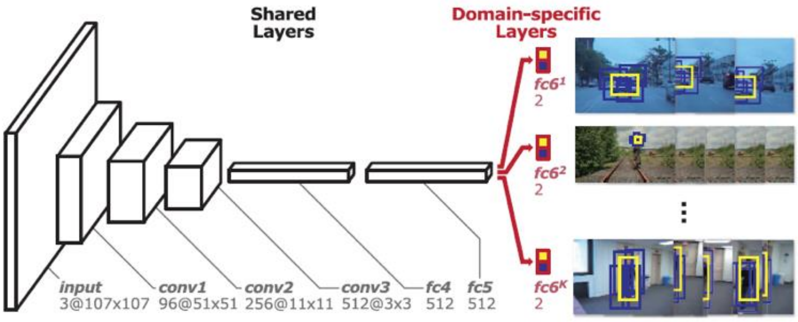


Fig. 9. Schematic diagram [21] of MDNet network structure

3.4 Data format

The trajectory data measured in real life experiments are arranged as the data format shown in Table 2.

Table 2. Data format examples

SNo	PNo	PosX	PosY	FrameNo

…	.	..	..	…
#01010	5	9.23	6.11	65
…	.	..	..	…

As shown in Table 2, SNo represents the scene number (Scene Number), PNo means the pedestrian number (Pedestrian Number), PosX, and PosY represent the X axis and Y axis of the position coordinates respectively, and the FrameNo represents the frame number. Because the frame rate of video capture is known, we can clearly get the time from which the pedestrian position is recorded from the frame number. At the same time, if we need to get pedestrian speed information, we can get the speed value by comparing the position of pedestrians between two adjacent frames by difference method. It is important to note that the same pedestrian in a different scene (SNo) is not the same pedestrian in a real life experiment, only to distinguish the different pedestrians in the same scene, but this does not affect the learning of the data set in the post prediction method, because the prediction model proposed in this study will focus on the pedestrian perception of the environment. In general, there is no need to consider the performance of pedestrians in different experiments.

3.5 Analysis of the authenticity of data sets

In the study, Weidmann [22] et al. Analyzed the macroscopic behavior of pedestrian flow, including the speed density relationship of pedestrian flow. Ma Y et al. In her research, [9] selected the regional density density relationship of 2m*2m, which was the most concentrated population density, and compared it with Weidmann empirical formula. The results of the Ma study show that the Weidmann velocity density empirical formula is more effective in the lower pedestrian density than in the hourly density, and the gap between the density and the real situation is larger at high density, and our data set also verifies this. Figure 10 is a pedestrian velocity density graph at the exit of the exit scene in an indoor evacuation scene. In this case, we find that when the density is less than 6 people /m2, our data set is more consistent with the empirical formula, while in high density, the average velocity decreases with the increase of density. Although the average velocity is more than the empirical value given by the Weidmann formula, its empirical values are less than 0, and our velocity density data is consistent with the study of Ma Y et al. So it can prove the rationality of the macro behavior of the dataset.

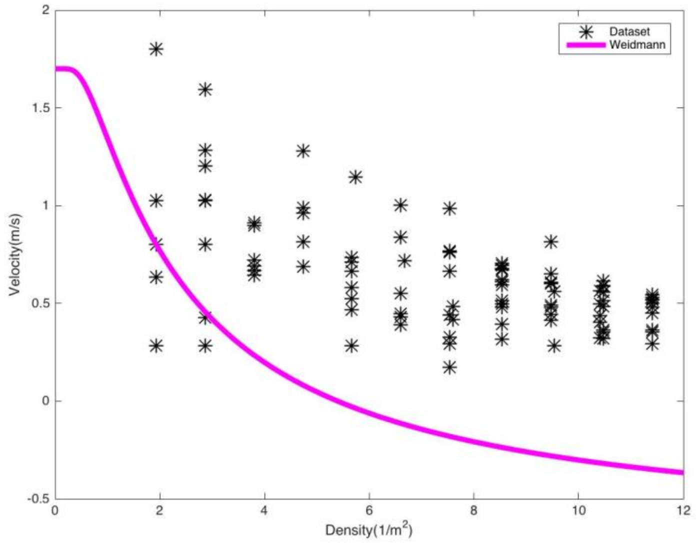


Fig. 10. Velocity density relation diagram at the exit

In microscopic behavior, pedestrian movement research is generally analyzed from the perspective of self-organization [23]. From the corresponding convection experiments in Fig. 7, we can observe the channelization and following behavior of the crowd. From the comparison between emergency and non-emergency experiments, we can find the crowding behavior of pedestrians at the escape exit when competing with each other. In some experiments, we can also observe that pedestrian escape is the faster-is-slower effect, that is, the evacuation time of a group of people who want to escape quickly in the fierce competition is slower than the non-competitive people. To sum up, this dataset reflects the movement behavior of the crowd well from the macro and micro level.

5 Conclusion

This paper presents a pedestrian evacuation dataset which includes 33 experiments. Competitive and non-competitive scenarios are included. The data is evaluated with the fundamental speed-density diagram and shared at https://github.com/my-HenryS/multi-agent-simulation. We hope this data set can help researchers carry out further validations of more accurate pedestrian trajectory prediction models.

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