Evaluating the gap between the physical and psychological congestion of pedestrian flow

Xiaolu Jia[1], Claudio Feliciani[1], Sakurako Tanida[1], Daichi Yanagisawa[1], Katsuhiro Nishinari[1]

[1] Department of Aeronautics and Astronautics, The University of Tokyo.

Abstract

In our previous field experiments [1], we observed a discrepancy between physical congestion and perceived congestion. Pedestrians exhibited a strategy of walking at low speeds even in low-density areas to avoid potential collisions ahead. However, it remained uncertain whether this low-density-low-velocity behavior occurred in daily life. In this study, we collected trajectory data from a train station using LiDAR sensors to analyze the density and velocity patterns of real passengers. The sensors tracked pedestrian positions, enabling us to capture local velocity and density at each moment. Our findings confirm the existence of low-density-low-velocity pedestrians in daily life. Additionally, we identified a low-density-diversified-velocity trend, emphasizing the complexity and heterogeneity of pedestrian behavior. Based on these observations, we propose an approach to estimate perceived congestion among pedestrians. These insights contribute to the creation of more comfortable walking environments by understanding the nuanced dynamics of pedestrian movement.

1 Introduction

Building walking environments with less congestion has been the main objective of pedestrian management. Congestion can be classified into physical and psychological categories. In previous research, the physical and psychological congestion has been regarded as the same. However, we found the discrepancy between physical and psychological congestion from previous crowd experiments [1]. Hereinafter, we would introduce the main indicators for both the physical and psychological congestion, and then explain the reason for their difference.

Concerning physical congestion, macroscopic indicators, such as pedestrian level-of-service (LOS) based on flow characteristics-density, velocity, and flow rate [2]; vorticity-based congestion numbers, measuring alignment at local areas [3]; and pedestrian entropy, gauging movement smoothness [4], assess the overall crowd dynamics. However, we specifically concentrate on microscopic physical congestion experienced by individual pedestrians to facilitate a comparison with their psychological congestion.

To evaluate the congestion of each pedestrian, the most common indicators are personal density and velocity. In previous research, the personal density and velocity have been considered consistent because of their monotonic negative correlation [2, 5], and are applied to evaluate the psychological congestion, i.e., discomfort, of pedestrians.

However, experimental results show that the velocity does not always have a monotonic correlation with the density [6]. Another trend indicating that the velocity remains constant despite the variation in density was observed. This is due to the low-density-low-velocity pedestrians who choose to wait or walk slowly to avoid collisions with pedestrians in front of them.

The inconsistency between density and velocity impacts their different effectiveness in indicating psychological congestion. Our field experiments, which involved tracking pedestrian trajectories to measure physical congestion and administering questionnaires to record psychological congestion [1], revealed that low-density-low-velocity pedestrians perceived high congestion. This implies that low physical congestion corresponds to high psychological congestion, making velocity a superior indicator to density in gauging psychological congestion.

However, the low-density-low-velocity is only observed in field experiments, where the walking motivations of pedestrians are different. Therefore, we would examine the density-velocity fundamental diagram in real life by analyzing the sensing data at a train station, and analyze the features of real passengers.

2 Velocity and density

Here, we introduce the methods to measure personal velocity and local density for further numerical analysis.

Generally, the method of calculating pedestrian velocity is self-explanatory. Velocity is defined as the rate of change of pedestrian position with respect to time, which was calculated using Equation 1:

$$\boldsymbol{v}_i(t) = \frac{d\boldsymbol{p}(t)}{dt} = \frac{\boldsymbol{p}_i(t+\Delta t) - \boldsymbol{p}_i(t-\Delta t)}{2\Delta t}, \quad (1)$$

where $\boldsymbol{v}_i(t)$ indicates the velocity of pedestrian i at moment t, $\boldsymbol{p}_i(t)$ indicates the corresponding pedestrian position, and Δt indicates the time gap used to measure velocity. Here, we applied $\Delta t = 0.2$ s for calculation.

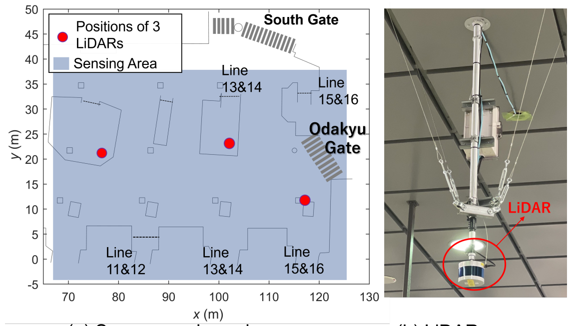
As to the density of an individual, the peripersonal space (PPS) has been applied to indicate the region that a pedestrian can manipulate [7]. It is believed that the more the PPS is occupied, the less the mobility will be, and the higher his/her personal density will be. In this paper, we apply the Voronoi diagram [5] to represent this PPS. An illustration of the Voronoi diagram of pedestrians can be seen in Fig. 4, which we will introduce in Sec. 4. The density of a certain pedestrian can be expressed using Equation 2:

$$\rho_i(t) = \frac{1}{A_i(t)}, \quad (2)$$

where $\rho_i(t)$ indicates the local density of pedestrian i at moment t. $A_i(t)$ represents the area of the Voronoi cell that pedestrian i actually possesses.

3 Sensing data

The sensing was conducted on the 2F concourse of JR-East (East Japan Railway Company) Shinjuku Station. The entire sensing operation was authorized by JR-East and executed by Denso Wave Incorporated (Denso) between 7:00 and 10:00 AM on July 4th, 2023. Details about the sensor appearance, sensor locations, and sensing environments can be observed in Fig. 1. The obtained pedestrian trajectories from the sensors are shown in Fig. 2.



(a) Sensors and sensing area (b) LiDAR sensor

Fig.1: Sensing location, sensors, and sensor positions.

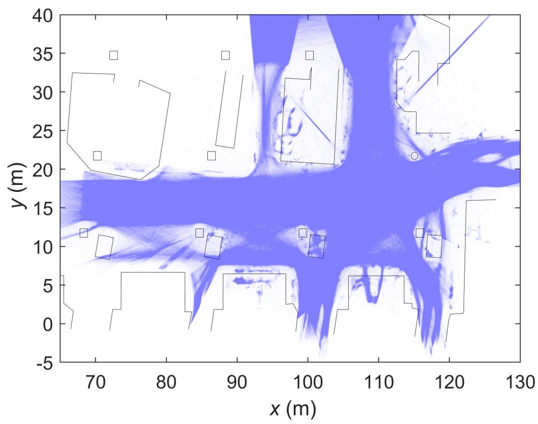


Fig.2: Trajectories of passengers by LiDAR sensor.

4 Results analysis

4.1 Results of density and velocity

The velocity and density at 8:30 am are selected and illustrated in Fig. 3 and Fig. 4. The black lines represent inner and outer boundaries (walls, elevators, pillars, etc.). The blue circles represent pedestrians. The red arrows in Fig. 3 indicate the velocity including the direction and speed value. The red polylines in Fig. 4 indicate the Voronoi boundary. For each pedestrian point, the polylines surrounding compose its personal space, and the personal density can be calculated as the reciprocal of the personal space as shown in Eq. 2.

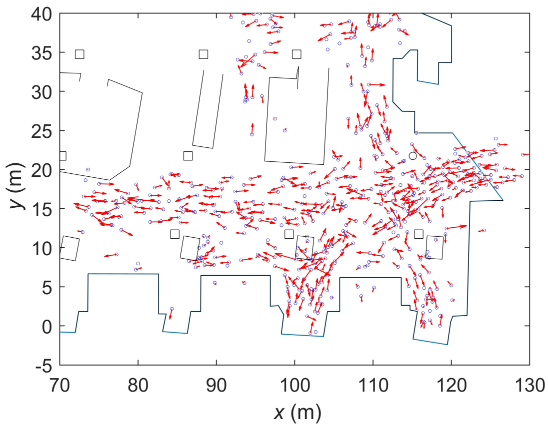


Fig.3: Velocity at 8:30 am.

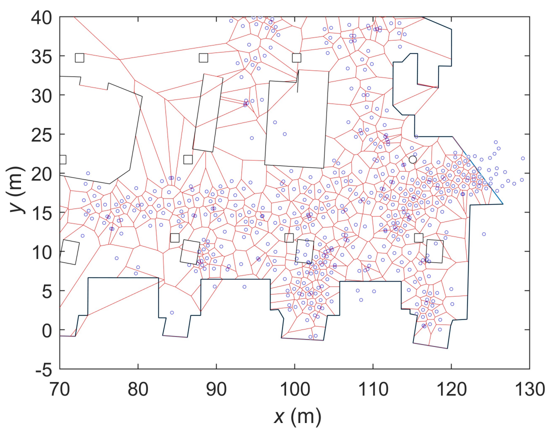


Fig.4: Voronoi density at 8:30 am.

Accordingly, the velocity and density of each pedestrian at each moment can be calculated, and the correlation between personal velocity and density can be obtained.

4.2 Fundamental diagram

The density-velocity fundamental diagram is shown in Fig. 5. Each scatter represents the density-velocity pair of a certain pedestrian at a certain moment. We observe three types of variation trends. Type A is the typical monotonically decreasing trend, Type B is a horizontal trend, and Type C is a vertical trend.

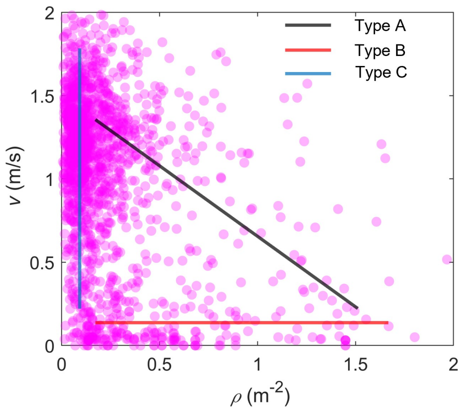


Fig.5: Different trends in the fundamental diagram.

The three distinct types may reflect varying pedestrian movement features and underlying psychologies.

Type A represents a natural trend wherein higher pedestrian density impedes individuals from walking at their desired speed when trying to leave, resulting in a higher-density-lower-velocity trend.

Type B exhibits a low-density-low-velocity trend, suggesting that some pedestrians are either not motivated or less inclined to walk. This could be attributed to a preference for waiting until the area clears to avoid congestion near the exit. Alternatively, pedestrians in this category may simply stand with a desired speed of zero. Consequently, even when the density is low, the corresponding velocity remains low.

Type C displays a low-density-diversified-velocity trend, indicating that pedestrians exhibit varying free speeds under low-density situations. This observation is particularly relevant to passenger behavior during morning rush hours at train stations. Individuals in a hurry tend to walk at significantly higher speeds compared to those with less urgency.

4.3 Discussion on the perceived congestion of pedestrians

In our previous experimental research, we proposed that perceived congestion stems from the gap between the desired speed and the actual speed. The analysis of subway station sensing data highlights diverse trends in the fundamental diagram, signifying a wider spectrum of desired speeds. As a result, we intend to explore the measurement of pedestrians' perceived congestion through the following approach.

For an individual pedestrian, utilizing the tracked trajectory data, the desired speed can be considered as the highest speed when their density is low (e.g., $\leq$ 0.5 m/s). However, the desired speed may vary due to different motivations among pedestrians. For instance, a pedestrian who remains stationary for several time steps may commence walking after accomplishing their purpose. Therefore, to discern changes in desired speed, clustering on velocity data is necessary to identify various motivations. This analytical approach assists in capturing the perceived congestion of each pedestrian.

While this approach necessitates future validation through a comparison of physical and psychological congestion, we anticipate that this paper will serve as a reminder for a more meticulous quantification of psychological congestion.

5 Conclusion

Our study explores the intricate relationship between pedestrian density and velocity. Analyzing LiDAR sensor data from a train station, we unveil the low-density-low-velocity phenomenon, where pedestrians opt for slower speeds in less crowded areas, possibly to avoid congestion. Furthermore, the density-velocity fundamental diagram reveals three trends: Type A (monotonically decreasing), Type B (low-density-low-velocity), and Type C (low-density-diversified-velocity).

To estimate perceived congestion, we propose an approach considering the gap between desired and actual speeds, clustering velocity data for different motivations, and spatial averaging for layout evaluation. This challenges conventional beliefs and provides insights for designing pedestrian-friendly environments to enhance daily walking experiences.

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