

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

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## Abstract

In our previous field experiments [1], we observed a discrepancy between physical congestion, indicated by density, 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 a scheme 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.

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## 1 Introduction

In daily life, the most common scenario is normal egress, where pedestrians have lower urgency to reach the destination and are regarded to have different behaviors from the pedestrians under emergencies [2]. In this case, besides the egress efficiency, it is also important to build more enjoyable pedestrian walking environments in order to provide better services and attract more users. Therefore, research on pedestrian comfortability under the normal egress scenario is also significant.

However, we found that previous studies are deficient in determining appropriate indicators to reflect the perceived congestion and comfortability of pedestrians after a broad review. When handling with the comfortability of pedestrians on a smaller scale, pedestrian level-of-service (LOS) has been widely applied. The most commonly applied LOS standard is Fruin's LOS, which classifies the service level into six categories based on pedestrian flow characteristics, including density, velocity, and flow rate [3]. The LOS is established on the premise

of the pedestrian fundamental diagrams, which depict the mutual relations between the three traffic diagrams including velocity, density, and flow rate [4]. In particular, the monotonic negative correlation between density and velocity has been empirically validated using the Voronoi density [5]. However, other previous studies on pedestrian dynamics have indicated that the velocity does not always have a monotonic correlation with the density [6]. In addition to the decreasing trend where low density corresponds to high velocity, the steady trend where low density surprisingly corresponds to low velocity was also observed. This phenomenon, which we name the low-density-low-velocity phenomenon, was considered to be caused by pedestrians who chose to wait or walk slowly to avoid collisions with pedestrians in front of them.

Focusing on these low-density-low-velocity pedestrians, we performed field experiments with pedestrian trajectories tracked to measure the physical congestion and the questionnaires to record the psychological congestion of pedestrians

in [1]. Comparison results show that the low-density-low-velocity pedestrians perceived high congestion, which means the low physical congestion corresponds to high psychological congestion. In turn, we find that the gap between the desired walking velocity and the actual velocity can be the key to 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:

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

where  $\mathbf{v}_i(t)$  indicates the velocity of pedestrian  $i$  at moment  $t$ ,  $\mathbf{p}_i(t)$  indicates the corresponding pedestrian position, and  $\Delta t$  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 personal 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:

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

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.  $N_i(t)$  represents the number of pedestrians including himself/herself within the possessed region.

## 3 Sensing data

The sensing was performed at the 2F concourse at JR-East (East Japan Railway Company) Shinjuku Station. The whole sensing was permitted by JR-East, and performed by Denso Wave Incorporated (Denso) from 7:00 to 10:00 AM on July 4th, 2023. In more detail, Denso performed the sensing, data transmission, and data processing procedures. We got the processed sensing data (hereinafter referred to as sensing data) for the analysis of pedestrian movements.

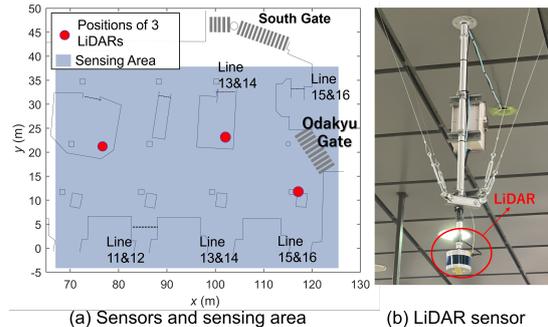


Fig.1: Sensing location, sensors, and sensor positions.

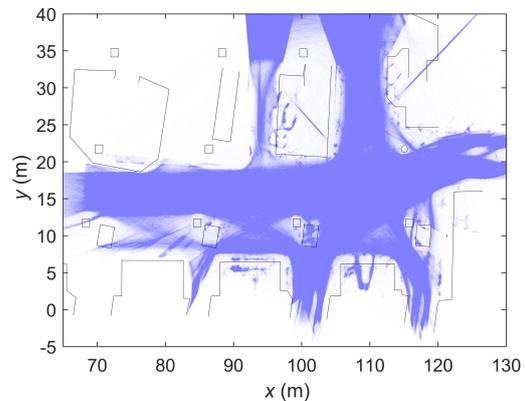


Fig.2: Trajectories of passengers by LiDAR sensor.

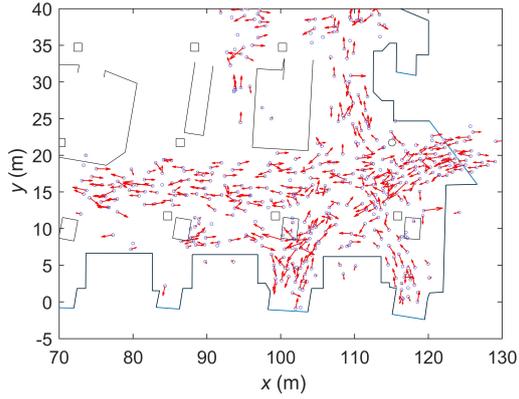


Fig.3: Velocity at 8:30 am.

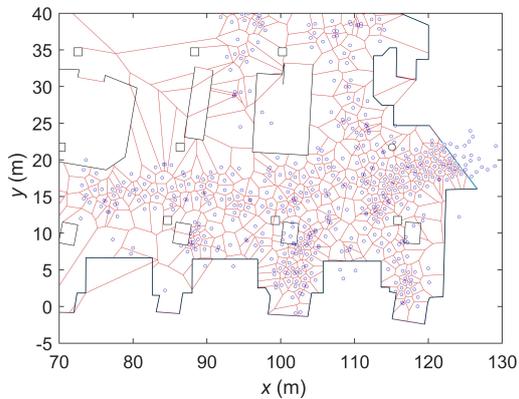


Fig.4: Voronoi density at 8:30 am.

The sensor positions and sensing objects are shown in Fig. 1(a). Three LiDAR sensors (Velodyne, VLP-16) were installed on the ceiling at a height of around 2.5 m as shown in Fig. 1(b). The sensing area (blue range in Fig. 1(a)) covers around  $55 \times 40 \text{ m}^2$ .

## 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 direction and speed value of the velocity. The red polylines in Fig. 4 indicate the Voronoi boundary. For each pedestrian point, the polylines surround-

ing compose its personal space, and the personal density can be calculated as the reciprocal of the personal space.

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.

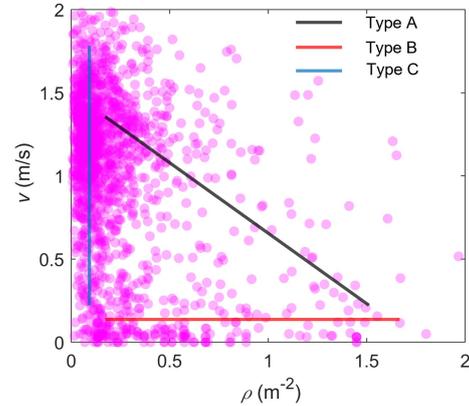


Fig.5: Different trends in the fundamental diagram.

The three different types may reflect different pedestrian movement features as well as underlying psychologies. Type A is a natural trend that when pedestrians want to leave, higher pedestrian density could hinder pedestrians from walking at their desired speed, thus shows a higher-density-lower-velocity trend. Type B is a low-density-low-velocity trend that representing some pedestrians who are not or less motivated to walk. One possibility is that pedestrians prefer to wait for former pedestrians to leave to avoid congestion before the exit. The other possibility is that pedestrians only stand there with a desired speed as zero. Therefore, even the density is low, the corresponding velocity is also low. Type C is a low-density-diversified-

velocity trend, which indicates that pedestrians have different free speed under low density situations. This is also related to the passenger behavior during morning rush hours at train stations. Passengers who are in a hurry will walk at a much higher speed than those who are not.

### 4.3 Discussion on the perceived congestion of pedestrians

In our previous experimental research, we propose that the perceived congestion derives from the gap between the desired speed and the actual speed. In the sensing data of subway station, the different trends of the fundamental diagram indicates more diversified desired speed. Therefore, we would discuss on how to measure the perceived congestion of pedestrians.

For a certain pedestrian, with the trajectory data tracked, the desired speed can be regarded as the highest speed when his density is low (e.g.  $\leq 0.5$  m/s). Nevertheless, the desired speed can change due to pedestrians' different motivations. For instance, a pedestrian stand still for several time steps will begin to walk after achieving his/her purpose. Therefore, to recognize the change of desired speed, clustering on the velocity data should be performed to distinguish different motivations. This analysis can help obtain the perceived congestion of each pedestrian. Besides, by taking spatial average, evaluation of geometrical layouts can also be performed.

## 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. 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 a scheme 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.

## 6 Acknowledgement

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