Visualizing Congestion at Mass-Gathering Events with Proximity-Based Networks

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***Abstract*—Infectious diseases are typically transmitted through close contact with infected persons. The effective management of overcrowding is a crucial issue for events with a large number of attendees. Since the COVID-19 outbreak, analyzing people flow to recognize pedestrian behavior and walking patterns have been attracted studies. Visualizing crowded high-risk situations for infection at large gatherings is a complex task. It requires an approach that can effectively represent both spatial and temporal features while ensuring that the visibility of walking paths is not significantly compromised. To address these issues, we propose a novel approach for visualizing proximity as a network that represents the distance relationship between pedestrians. We developed the visualization system linking three components: Proximity Network, the walking paths of selected pedestrians from the network, and the temporal statistics of pedestrian traffic. Users of this system can freely select a group of pedestrians from Proximity Network and observe the paths of the selected pedestrians. This procedure enables better visibility of walking paths and an understanding of their spatio-temporal characteristics because only a smaller number of paths are drawn. This paper presents our case study of the proposed method for visualizing pedestrian proximity using real-world people flow data collected at an event site.**

***Index Terms*—Visualization, People flow, COVID-19.**

I. Introduction

People have been expected to avoid the “three Cs” (closed spaces, crowded places, and close-contact settings) in response to the outbreak of COVID-19, and to keep any necessary outings or travel short to reduce physical contact with others. These requests are based on the idea that infectious diseases spread through contact with infected persons. For that reason, mass-gathering events such as sports events or music concerts held under such circumstances, reducing overcrowding has been an important issue. Therefore, the analysis of pedestrian movement has been an actively discussed topic.

There have been various methods for measuring the people flow including capturing video images via cameras and obtaining data from GPS. We can obtain various insights regarding human behavior patterns and walking conditions by analyzing the people flow data. Such insights can be applied in various fields, including tourism, urban planning, disaster prevention, marketing, and others. For example, we can use it to improve the layout of merchandise in shopping malls [17] or to identify problems with evacuation routes during disaster drills [10]. Thus, the analysis of people flow supports our daily lives. As a result, numerous studies for analyzing human traffic have been presented.

There have been several methods for visualizing congestion. Alia et al. [1] represented the crowded areas with heatmaps. Wang et al. [19] visualize an undirected graph with walkways as edges and intersections as nodes. Each node is assigned a resistance that indicates how much energy a pedestrian might need to navigate through that node. However, conventional methods do not identify the walking paths of the persons involved in the congestion. Regarding infectious diseases, a particular warning situation is the proximity of the pedestrian groups and stagnated flow. On the other hand, there are few methods for the visualization of the people flow based on the proximity.

Based on these backgrounds, we specifically focus on the “proximity status” of individuals in our analysis. In addition, we develop a method that visualizes the proximity and the walking paths of proximate persons to observe characteristics with a high risk of infection. This method constructs a single visualization space by linking the following three components. (Figure 1)

- **Proximity Network:** A network generated by representing pedestrians as nodes and connecting pedestrians who have proximity by edges (Figure 1(a)).
- **Proximity Path:** Walking paths of pedestrians specified in Proximity Network (Users can click on nodes to select drawing targets) (Figure 1(b)).
- **Pedestrian Statistics:** Bar chart representing the number of pedestrians per second (Figure 1(c)).

We can get an overview of how proximity among individuals is taking place by observing Proximity Network. Furthermore, we can discover the clusters of pedestrians' proximity in the network and the patterns of their walking paths.

The remainder of this paper is organized as follows. Section 2 introduces related work on the visualization of pedestrian paths and the analysis of the people flow during an outbreak. Section 3 presents the detail of the proposed technique. Section 4 introduces case studies using the people flow before and after the spread of infection to observe differences. Section 5 summarizes this paper.

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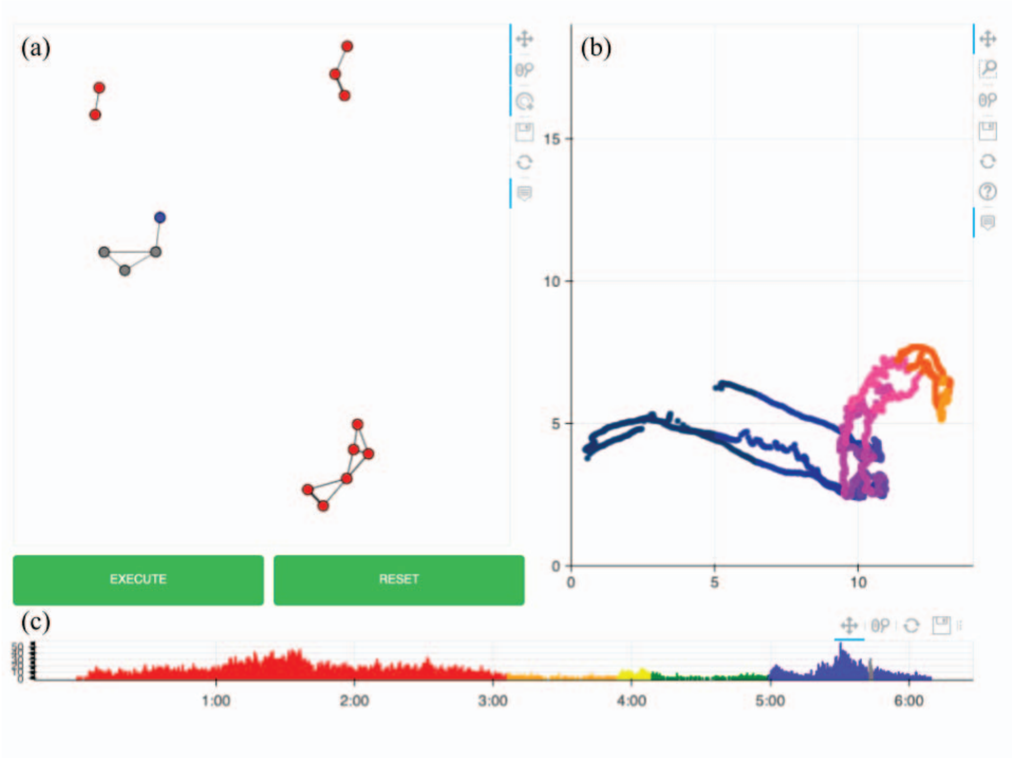


Fig. 1: Visualization system of pedestrian walking behavior
(a)Proximity Network. (b)Proximity Path. (c)Pedestrian Statistics.

II. Related Work

A. Visualization of walking paths

There are numerous methods to visualize pedestrian walking behavior. However, visualization techniques specialized to a huge amount of data are required because the people flow information often contains large-scale spatial-temporal data.

One of the typical ideas for visualizing such data is applying spatial-temporal 3D visualization. McArdle et al. [11] proposed a visualization method that represents spatial-temporal information by drawing a walking path with a space-time cube (STC). Andrienko et al. [3] proposed a "trajectory wall" as an extension of space-time cubes. This approach needs to tackle visual cluttering as the number of pedestrians increases and the need for manipulation to observe features.

Another idea is linking multiple visualization components to represent such complex data. It is difficult to visualize all features in a single static visualization component, so it is better to correlate features that can be represented on multiple visualization components together. As a linked visualization approach, Guo et al. [7] developed a composite visualization tool to analyze patterns of various moving vehicles, by adopting not only direct drawing of trajectories on maps, but also other visualization methods including piled polyline charts, scatterplots, and parallel coordinates plots. Additionally, Fukute et al. [6] proposed a method that simultaneously displays major routes classified by spectral clustering and temporal changes in flow rate per clustered routes using the ThemeRiver technique. As an experimental approach to investigate this issue, Wielebski et al. [20] conducted a comparative experiment of features from visualizations of the same walking path information using six different methods.

Visualization of moving objects has a serious problem of comprehensibility due to the visual cluttering as the number of moving objects increases. Several methods have been reported that apply clustering, sampling, or character-coding to a set of paths to draw characteristic paths. Based on this idea, Andrienko et al. [2] proposed an interactive clustering method for trajectories and visualized popular walking patterns on maps. Yabushita et al. [22] proposed a method for summarizing and visualizing people flow by approximating walking paths on a two-dimensional grid and drawing bundles of similar walking paths with a large number of people walking. Guo et al. [8] classified walkers' trajectories according to their speed and direction, and also developed a system to visualize important trajectories using meaningful colors based on HSV model. Miyagi et al. [12] presented a visualization technique that firstly compresses the people flow datasets by a character-coding method and then applies natural language processing methods to extract movement patterns and classify walking paths. Tsuchida et al. [18] developed a visualization system that firstly represents the distribution of walking speed and then provides an interaction mechanism to specify user-interested subregions and display paths only through the specified subregions.

Though there have been a lot of visualization techniques for the paths of pedestrians, there have been a small number of methods focusing on the proximity of the pedestrians. As an example, Gupta et al. [9] visualized relationships among a small number of pedestrians and places where multiple persons stayed at the same time. Differently from such studies, our method aims to visualize only the paths of pedestrians related to infection caused by the proximity and to visualize the features of both time and space by linking three visualization methods.

B. People flow and COVID-19

With the outbreak of the COVID-19 infection, there have been various studies related to the analysis of the people flow, including the effects of restrictions on movement due to measures such as emergency declarations on the people flow [16] [4] and comparisons of human behavior patterns before and after the spread of infection [5] [21].

Physical distancing is one of the most effective infectious disease control measures. Rezaei and Azarmi [14] developed a system to detect violating physical distancing in real-time from image data acquired by surveillance cameras. Moritz et al. [13] measured the number of contacts during concerts held under three different scenarios: (1) No restrictions (the pre-pandemic setting), (2) moderate restrictions (checkerboard pattern seating, twice as many entrances as in (2)), and (3) strong restrictions (pairwise seating with 1.5 meters interspace to the next pair, four times as many entrances as in (1)), to investigate the risk of infection during large events. The results showed that scenarios (2) and (3) resulted in a strong reduction in contacts.

The infection spreads through contact with infected individuals. Therefore, it is effective to avoid high density situations to reduce the opportunities for people to come into contact with each other and limit the spread of infectious diseases [15]. Thus, it is important to observe the proximity of pedestrians; however, there have been a small number of visualization methods for the people flow based on proximity. Our method differs from conventional methods in that it emphasizes the process of narrowing down the walking paths with a high risk of infection through visualizing proximity status.

III. Processing Flow of the Presented Visualization System

This section presents the processing flow of the proposed system consisting of the following three steps: people flow measurement, extraction of proximity, and visualization.

A. People flow measurement

We measure the people flow using LiDAR, a remote sensing technology that uses laser light to measure distances. Privacy protection is a concern if the people flow data is measured by a camera and human faces are therefore taken. On the other hand, LiDAR only stores the distance and angle to the target object, thus people flow data can be measured without storing personally identifiable information. Figure 2 shows an example of measurements by LiDAR.

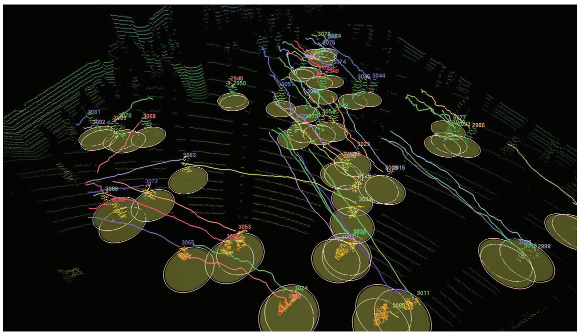


Fig. 2: A screen of LiDAR when measuring the people flow.

We record time, pedestrian ID and coordinates through the measurement. The paths of pedestrians can be reproduced by concatenating the coordinates of pedestrians with the same ID in chronological order.

B. Extraction of proximity information

The method detects pairs of pedestrians that have been in close proximity to each other for a certain period of time, based on the coordinates of pedestrians that appear at the same time. In this study, "proximity" is defined as the state in which two pedestrians have been within a certain distance for a certain period of time. We defined two meters as the threshold distance based on the definition of physical distance in Japan. In addition, we defined 60 seconds as the threshold period of time because there has been an illustrative case of infection occurring through one to two minutes of contact with an infected person [23].

C. Visualization

The proposed visualization system consists of three linked visualization components: Proximity Network, Proximity Path, and Pedestrian Statistics (Figure 1). This subsection describes a detailed implementation of each visualization component.

1) Proximity Network: This component visualizes the proximity status as a network consisting of nodes corresponding to pedestrians and edges connecting pedestrians that are in proximity as shown in Figure 1(a). Only pedestrians that meet the proximity condition appear as nodes. Edges become thicker as the contact duration increases, and the colors of nodes depict the time when the pedestrian is walking.

2) Proximity Path: By specifying a set of pedestrians from the network described in Section III-C1, the walking paths of the specified pedestrians are drawn as shown in Figure 1(b). One path corresponds to one pedestrian. Here, the display space of this component has the same aspect ratio as the space where the people flow data was measured. Users can observe the paths of specified pedestrians in detail since a smaller number of the paths are drawn while avoiding visual cluttering. Furthermore, the colors of the walking paths depict when a pedestrian walked there during the total walking time of the specified pedestrians. This allows users to understand situations where the walking paths are close at a certain period.

3) Pedestrian Statistics: The number of pedestrians observed at each time point is displayed as a bar chart as shown in Figure 1(c). The vertical line shows the number of pedestrians and the horizontal one shows the time. Pedestrian Statistics uses the same color-coding as in Figure 1(a) based on the time period. Meanwhile, the time during which specified pedestrians were walking is displayed in gray as shown in Figure 1(c). This allows users to understand the position of the time when specified pedestrians were walking in the entire dataset. Moreover, users can understand the relationship between the occurrence of proximity and the number of pedestrians.

IV. Case Study

This section presents an example analysis of the people flow measured before and after the spread of COVID-19 using the proposed method. The goal of this case study is to detect changes in the movements of persons before and after the spread of infectious diseases.

A. Dataset

We measured the people flow in the stadium, assuming a sporting event as a mass-gathering event. It is estimated that the concourse is particularly crowded because the spectators can move around freely, so we installed the measurement instrument in a part of the concourse. As a result, we prepared three datasets for [Before the pandemic] from 2019, and three datasets for [With the pandemic] from 2020. All measurements were carried out continuously for six hours, from before the start of the game until its completion.

Table I shows the approximate number of pedestrians included in each dataset that compares before and after the outbreak of the COVID-19 infection. The datasets are sorted by date of data measurement. Remark that it is possible to count the same pedestrian multiple times as different ones since the LiDAR cannot assign the same ID to a pedestrian again when it goes outside the measurement range and then comes back.

TABLE I: Approximation of pedestrian traffic.

Before the pandemic	(a)	(b)	(c)
	27000	70000	44000
With the pandemic	(d)	(e)	(f)
	3000	4000	4000

B. Result

This subsection introduces visualization results of the data measured at the stadiums, as shown in Table I.

Fig. 3: Different phases of the game in five colors.

On the day the measurements were taken, a soccer game was being played at the stadium, so the color of the nodes in Proximity Network (Figure 1(a)) and Pedestrian Statistics (Figure 1(c)) was divided into five colors based on the phase of the soccer game (Figure 3). Difference colors represent the phase of the match in Figure 3.

1) Proximity occurrence.: Figure 4 shows an example of Proximity Network, while Figure 5 shows an example of Pedestrian Statistics from the measurement data of (a) to (f).

As a result of Proximity Network, the nodes of Before the Match (Red nodes) appeared more than in other phases. On the other hand, the nodes of After the Match (Blue nodes) appeared relatively rare, even though the number of pedestrians is about the same as Before the Match. This appearance indicates that spectators went home promptly after the match both "Before the pandemic" and "With the pandemic". Furthermore, there are orange, yellow, and green nodes corresponding to the proximity that appeared during the match "Before the pandemic", but not "With the pandemic". This appearance indicates a decrease in the number of spectators leaving their seats during the game. We assume three possible reasons for this change in the spectators. Firstly, it could be due to the prohibition of eating food in the venue during the measurement period of "With the pandemic". The spectators can usually buy meals at food stands in the concourses of the stadiums we have measured. However, the food stands were closed for infection control. Secondly, it could be just due to the attitude of the spectators. During the period of "With the pandemic", a cap was imposed on the maximum number of spectators in the stadium. Therefore, the spectators in the venue might be enthusiastic soccer fans, indicating that they might focus on the game during the match.

2) The size of proximity group: We have drawn the walking paths of the proximity groups that Figure 4(b) contains. First, we draw a small group of 2 to 3 persons, as shown in Figure 4(b)(1).

The result shown in Figure 6(a) indicates that their walking paths are similar in time and route, which suggests that the small group of pedestrians might be acquaintances.

On the other hand, in Figure 6(b), the paths of Figure 4(b)(2) exhibit few commonalities, while a high frequency of

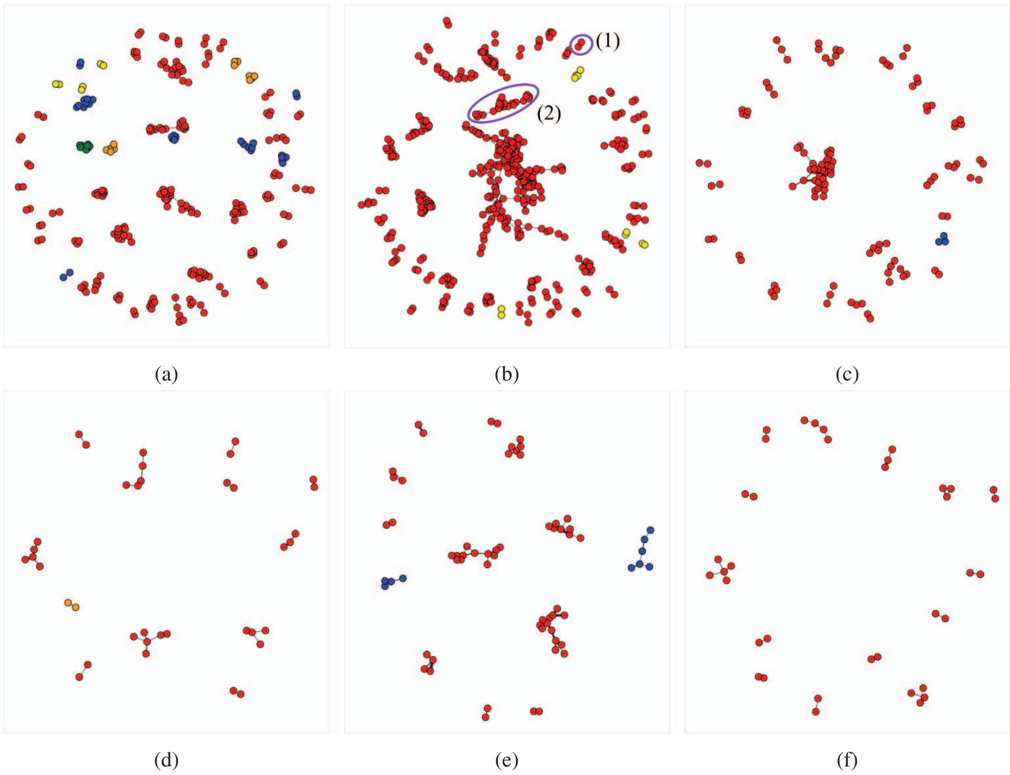


Fig. 4: Visualization results of Proximity Network.

proximity occurs within a certain range. Thus, their proximity is probably unintended. Figure 4(b) contains a gigantic proximity community of more than 100 pedestrians. This group is formed by the overlapping unconscious contacts of small groups. This means that pedestrians associated with such large groups possibly have unknowingly come into contact with infected. Therefore, we need to be on the lookout for the occurrence of such groups in terms of infectious diseases. On the other hand, the sizes of the proximity groups were not very large after the spread of COVID-19. This result suggests that in addition to the small number of pedestrians, spectators had the awareness to keep their distance from others.

V. Conclusion

This paper proposed a system to visualize the characteristics of the people flow with a high risk of infection by focusing on the proximity state. This method tackles the visibility issue by extracting pedestrians in close proximity from large-scale people flow data and by drawing only the walking paths of user-specified pedestrians. This feature facilitates the discovery of walking path characteristics related to infection.

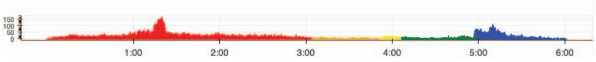
In Section IV, we presented the visualization results of measured data before and after the outbreak using the proposed method. The results show that the occurrence of proximity was significantly reduced and the sizes of the proximity groups got smaller after the outbreak.

Future issues of this study are the following.

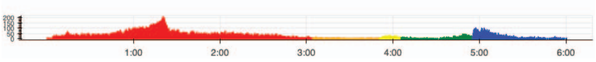
- Applying people flow data measured under other conditions.
- Improvement of network layout and drawing methods.
- Automatic recommendation of features to be observed
- Validate infection control measures based on the findings of the proposed method.

We applied the data measured before and after the outbreak as a visualization example in this study. It would be possible to compare changes in walking routes due to conditions such as weather or days of the week, by applying the people flow data measured under other conditions. It can also be applied to data measured at other locations to see how the structure of the building affects the people flow. In addition, we would like to improve the layout algorithm of Proximity Network because the current implementation does not represent spatial information. When dealing with larger data sets, there is an increasing need to extract spatio-temporal information from Proximity Network to gain a comprehensive understanding of the proximity situation at a glance.

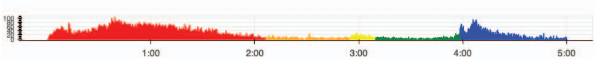
Furthermore, automatic recommendation system of features to be observed can be a significant help to users when using this visualization system. Our future work includes the development of an algorithm that detects anomalies and indicates when and where they are occurring for the above



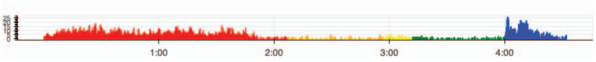
(a)



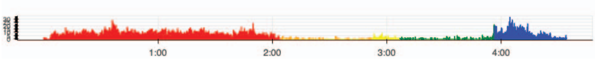
(b)



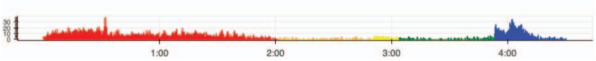
(c)



(d)

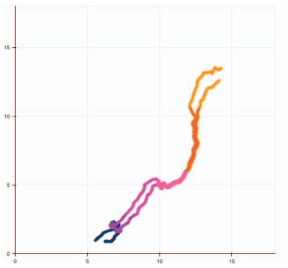


(e)

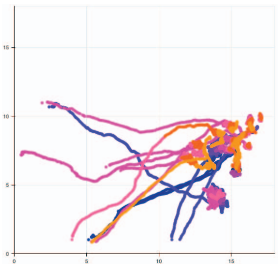


(f)

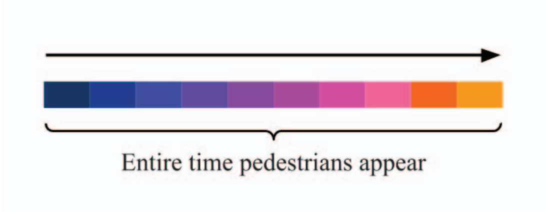
Fig. 5: Visualization results of Pedestrian Statistics.



(a) Figure 5(b)(1)



(b) Figure 5(b)(2)



(c) Color map of trajectory

Fig. 6: Visualization results of Pedestrian Path.

purpose.

Finally, we can devise infectious disease control measures based on the information obtained from the visualization system. The proposed system can be applied to the people flows obtained from crowd simulation. Therefore, we can compare changes in pedestrian movement between the measured data and the simulated data with the infection control measures developed.

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