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Measuring "Nigiwai" From Pedestrian Movement

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ABSTRACT The analysis of the movement of people in a shopping area with the aim of improving marketing is an important research topic. Many conventional methods are dependent on the density of people in the area, which is easily estimated by counting the people entering or exiting the area. However, a high density does not always mean an increase in activity, as certain people are simply passing the area at a given time. The primary goal of this study was to introduce a set of indicators for measuring the bustle of the area, which we call "Nigiwai," from pedestrian movement by using an analogy from classical kinematics. Such indicators can be used to measure the impact of promotional events and to optimize the design of the area. Our novel indicators were evaluated with simulated pedestrian scenarios and were demonstrated to distinguish shopping scenarios from those in which people move around without shopping successfully, even when the latter scenarios had much higher densities. The indicators were computed solely from the pedestrian trajectory, which can easily be obtained from ordinary sensors using deep learning-based techniques. As a demonstration with real data, we applied our method to a video of a street and provided a visualization of the indicators.

INDEX TERMS People flow analysis, surveillance system, multi-agent systems.

I. INTRODUCTION

The analysis of pedestrian behavior has become an active research topic. In addition to traditional qualitative methods that rely on factors such as inquiry, quantitative methods have become increasingly prevalent owing to the advances in the collection and processing of big data (see Section II). Quantitative analysis may lead to a drastic improvement in designing areas such as shopping malls and streets. Quantitative metrics offer a measure for assessing or predicting the effect of a marketing strategy, such as a promotional event. By using these metrics, the arrangements of shops and paths can be optimized to increase the activity of shoppers. An effective evaluation indicator for shopper activity is required to achieve these goals. Although the sales data or inquiry surveys of shoppers may provide substantial information, these are usually difficult to obtain. However, the trajectories of people are relatively easy to determine owing to the rapid development of algorithms and devices for pedestrian tracking [4]. In particular, deep learning-based methods [3] and sensing devices such as LiDAR sensors [26] have made the accurate, real-time collection of pedestrian movement possible [26].

The density of people in a certain area could be selected as an indicator to quantify the bustle or activity of the area. However, the density alone cannot determine whether people engage in certain activities in the area or only pass the area on their way to another destination (Figure 1). We are interested in quantifying the activities of people rather than how crowded the area is. Therefore, we introduce the concept of the *Nigiwai* of the area, where Nigiwai is the Japanese term for a bustle of people. Although there is no consensus on the rigorous definition of Nigiwai, we make the following assumptions:

1) The Nigiwai of an area is an amalgamation of the Nigiwai defined for the places and pedestrians in the area.

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(a) (b)

FIGURE 1. (a) The area is filled with people; however, their purpose does not involve any activity in the area; instead, they are traveling to other destinations (photo courtesy of www.pxfuel.com). (b) These people have visited the area to engage in shopping and sightseeing activities (photo courtesy of Dieter Karner CC BY 2.0).

2) The Nigiwai for a place or person is determined by the interaction thereof with other people nearby.
3) A person contributes to the Nigiwai if she/he has a purpose for being in the place and participates in a certain activity happening there.

According to our assumptions, a person who is simply passing the place to visit another place is not considered as creating Nigiwai, whereas a person engaged in shopping or a group of people gathered together should be assumed as contributing to Nigiwai.

Based on the above principles, we introduce a set of indicators to measure Nigiwai in Section III. To define the indicators, we rely only on the trajectories of people, and not on other information such as personal and sales data. The indicators are demonstrated to discern a simulated shopping street with shoppers from the same street full of passersby, revealing a higher value for the former. There are two key concepts underlying the proposed method. The first concept considers the relative velocity as well as the distance between pedestrians and from region of interest (ROI) points such as shop locations. In this manner, our indicators take into account the interactions among people. The use of the relative velocity in addition to distances is analogous to classical kinematics, in which not only positions but also their derivatives are used as independent variables for the system modeling. The relative velocity allows us to distinguish people passing one another from people walking together, which cannot be achieved by simply observing the relative positions. Note that, on a street with a crowd of people moving in one direction, the relative velocity among them is expected to be small. However, this is only true in the long-term average, whereas the relative velocity between two strangers who are close and who are walking in the same direction naturally fluctuates owing to physical and psychological reasons. Therefore, our indicators are still expected to discern a group of people walking together from a group of strangers walking in the same direction, which is indeed confirmed with the simulation presented in Section IV-B.

The second concept is to consider the *local* quantities first and to define the global indicators for the area as the aggregation of the local indicators. This results in a finer, localized, targeted, and easily interpretable metric for the analysis and visualization (Section IV-B). Based on these concepts, we define local Nigiwai indicators, which measure the contribution of each person or place to the Nigiwai. The indicator for a person can be viewed as the level of participation of that person in the activity taking place in the area. The indicator for a place estimates, for example, the level of attractiveness of a shop. Our principle is that the global (or total) Nigiwai of an area is an aggregation of the local Nigiwai created by each pedestrian and ROI in the area.

The contributions of this work can be summarized as follows:

- We propose an indicator that measures the contribution of each person to the Nigiwai in the area. The same indicator for an ROI measures the degree of attraction of people to the place (for example, a shop).
- We evaluate our indicators with simulated pedestrian trajectories in different settings. We show that our indicators can clearly distinguish a scenario in which people are shopping from one in which people are simply passing.
- We demonstrate our method with real pedestrian trajectories extracted from a surveillance camera by employing an existing deep learning-based tracking algorithm.
- We reveal that our indicators are robust against mis-tracking of people. This robustness is important for real applications, as even state-of-the-art tracking techniques suffer from non-negligible mis-tracking rates.

An outline of the proposed method[1] is depicted in Figure 2.

II. RELATED WORK

People flow analysis has become an active research area as a basic tool in numerous applications, including visual

[1] Our codes are available at https://github.com/shizuo-kaji/Nigiwai

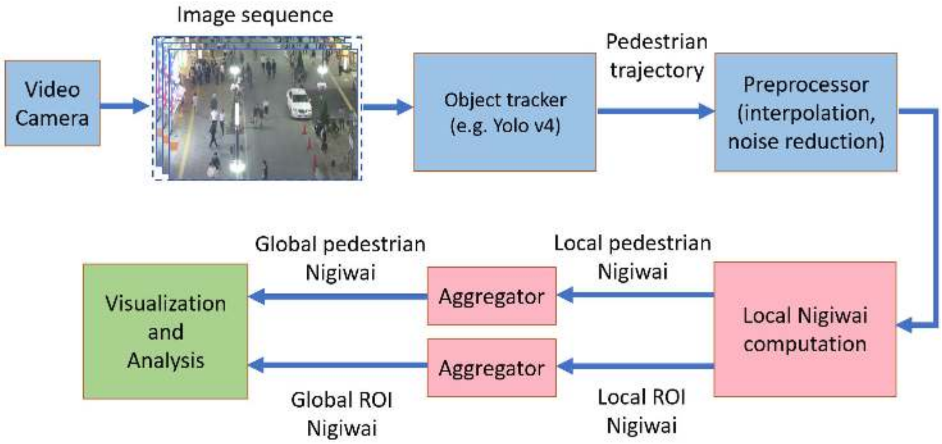


FIGURE 2. An outline of the proposed method. Standard or existing techniques were used for the phases presented in blue boxes, whereas the pink boxes indicate the contributions of our study..

surveillance [16], crowd management [7], and public space design [8]. People flow analysis can be categorized as two types in terms of the scale.

The macroscopic monitoring of the people flow in a large area can provide a source of information for urban planning, disaster response, and emergency preparation. For this purpose, a statistical summary consisting of many people and a long duration is considered rather than individual pedestrian behavior. For example, in [21], abnormal events such as disasters and road accidents were detected in a large area by analyzing mass GPS data. In [1], a smart platform for monitoring the people flow on a large campus was introduced, in which Wi-Fi tracking and environmental parameters such as the CO concentration, temperature, and humidity were used. The people flow prediction in a large urban area was achieved by using cellular data in [5].

In contrast, people flow analysis in small areas focuses on individual pedestrian trajectories, which is relevant to our present work. One of the main research topics in this direction is the clustering of pedestrians [18]. Certain clustering techniques use the Euclidean distance [14] to determine groups, and others additionally take into account the velocity and orientation [9]. Numerous motion-based methods have been proposed for detecting pedestrian behavior in a group. For example, in [24], a potential model was introduced to determine the probability distributions of the relative distance and motion between two interacting people in a group. This work was extended in [22] by applying the same method to larger groups and with different densities of people. An interesting fact regarding the relation between the group motion velocity and surrounding people density was noted in [23], where it was reported that individuals walk faster than a group of two, and similarly, a group of three walk slower than a group of two. In [25], a method was presented for analyzing the pedestrian dynamics in groups based on their intrinsic properties, and it was demonstrated that the velocity and size of the group were affected by the gender, age, and height of its constituents. The interaction among pedestrians was studied in [20] by identifying groups and estimating the intensity of the interactions between people. In [19], a method was proposed for identifying the social relations between pedestrians in a group based on their motion trajectories and velocity, as well as the height differences between group members. These studies placed greater focus on the mechanics of the individuals and groups, which was reflected in their trajectories, but not on the effect they produced on the entire area.

In addition, some studies have focused on pedestrian motion in shopping areas. In [17], pedestrian paths in a hypermarket were collected and analyzed by interviewing the shoppers, who were asked to draw their routes during their shopping after they had completed their shopping. In [12], laser detectors were used to collect pedestrian movement paths in a shopping mall and video cameras were used to capture their head motions and eye gaze. Based on these data, shoppers were manually grouped into three categories—randomly walking, walking straight, and finding their way—and then analysis was conducted for each category. In [10], a system for analyzing the shopper activity was introduced using a depth camera. First, the person's head was detected and tracked. Then, shopper interaction with the products was detected by analyzing the person's movement within the shelf zone. In [13], a system for forecasting the customer navigation in an indoor retail area was introduced. Designated devices were installed in each cart and basket for obtaining the shopper paths, and the customer attraction level for different products was predicted by learning Hidden Markov Models. Note that these methods require expensive data collection equipment or process, including inquiry, head and eye tracking, designated shopping carts, manual labeling, and training models. In contrast, our method utilizes only ordinary surveillance cameras. Moreover, the previous studies mainly targeted indoor scenarios. Our goal in this paper is different from the previous studies in that we aim at providing quantitative information of the shopping behavior (Nigiwai) in both indoor and outdoor shopping areas based only on pedestrian motion without any training data.

III. NIGIWAI INDICATORS

Our model is based on the distances and relative velocities between agents, where an agent may represent a pedestrian or an ROI (such as a shop). We assume that the pedestrian trajectory data are provided as a set of tuples (x, i, t), where $x \in \mathbb{R}^2$ are the two-dimensional coordinates of the pedestrian with ID i at frame t. The input trajectory is interpolated if necessary, so that for any t and i, x is known if pedestrian i exists in the area at frame t. Let N_t be the set of pedestrians that exists at frame t and N_{ROI} be the set of ROI points, that is, the fixed locations that do not depend on t. (For example, Figures 4 (d) and (e) present the configurations of the ROI points for a simulated scene: one is uniformly distributed and the other is placed at shop locations.)

The Euclidean distance between agents i and j is denoted by $d_{i,j,t} = |x_{i,t} - x_{j,t}|$, where $x_{i,t} \in \mathbb{R}^2$ are the coordinates of agent i at frame t. To reduce the effect of noise in the tracking position, we use the moving average distance $\tilde{d}_{i,j,t}$, which is defined by

$$\tilde{d}_{i,j,t} = \alpha d_{i,j,t} + (1-\alpha)\tilde{d}_{i,j,t-1}, \tag{1}$$

where $0 \leq \alpha \leq 1$ is a hyperparameter that is selected depending on the strength of the noise. If one of the moving agents (i or j) does not exist in the previous frame $(t-1)$, $\tilde{d}_{i,j,t}$ is taken to be $d_{i,j,t}$. Similarly, the absolute relative velocity is defined by

$$\tilde{v}_{i,j,t} = \beta v_{i,j,t} + (1-\beta) v_{i,j,t-1}, \quad v_{i,j,t} = \frac{|\tilde{d}_{i,j,t} - \tilde{d}_{i,j,t-1}|}{\Delta t}, \tag{2}$$

where $0 \leq \beta \leq 1$ is a hyperparameter for the moving average and Δt is the interval of the frames.

The local Nigiwai indicator for a pedestrian or an ROI $i \in (N_t \cap N_{t-1}) \cup N_{ROI}$ has the following form:

$$Nig_L(i,t) = \sum_{j \in (N_t \cap N_{t-1}) \setminus \{i\}} w_j f(\tilde{d}_{i,j,t}, \tilde{v}_{i,j,t}), \tag{3}$$

where $f(\tilde{d}_{i,j,t}, \tilde{v}_{i,j,t})$ is a non-negative real-valued function that decreases with respect to both variables, and w_{ij} is the weight that is pre-assigned according to the characteristics of i and j. The weights w_{ij} may be constant for all pairs of i and j, but additional information (such as the age of the pedestrians) can be used if available. The rationale behind Eq. (3) is as follows: When two people (or a person and a shop) are close, they are assumed to contribute to creating Nigiwai *only when* their relative velocity is small. Thus, for example, two people walking together contribute to Nigiwai, but two people passing by do not. Similarly, a person stopping near a shop contributes to Nigiwai, whereas one passing by the shop does not. The local Nigiwai indicator for a pedestrian ($i \in N_t$) measures the degree of participation of that person in the activity taking place in the area. The local Nigiwai indicator for an ROI ($i \in N_{ROI}$) reflects the attractiveness of the place to people; it identifies the places or shops which people visit and where they spend more time when compared with other places or shops.

In the remainder of this paper, we focus on the following particular form:

$$\begin{aligned}
f(\tilde{d}_{i,j,t}, \tilde{v}_{i,j,t}) &= h(\tilde{d}_{i,j,t}) \cdot g(\tilde{v}_{i,j,t}) \\
h(\tilde{d}_{i,j,t}) &= \exp(-\tilde{d}_{i,j,t}/W_d) \\
g(\tilde{v}_{i,j,t}) &= \frac{1}{(\tilde{v}_{i,j,t}/W_v + 1)^2} \\
Nig_L(i,t) &= \sum_{j \in (N_t \cap N_{t-1}) \setminus \{i\}} h(\tilde{d}_{i,j,t}) \cdot g(\tilde{v}_{i,j,t}) \\
&= \sum_{j \in (N_t \cap N_{t-1}) \setminus \{i\}} \frac{\exp(-\tilde{d}_{i,j,t}/W_d)}{(\tilde{v}_{i,j,t}/W_v + 1)^2},
\end{aligned} \tag{4}$$

where $W_v, W_d > 0$ are hyperparameters. Note that both h and g are decreasing functions. The parameter W_v controls the weight of the relative velocity term For example, with a small value of W_v, the relative velocity will have a greater effect on the Nigiwai score, whereas with $W_v = \infty$, $g(\tilde{v}_{i,j,t})$ has a constant value of one regardless of the relative velocity, and hence, the model simply becomes a density estimation around the agent. Similarly, W_d controls the weight of the distance.

Two global scores for the duration from t_s to t_f are defined based on the local Nigiwai score determined for each pedestrian or ROI, as follows: The global pedestrian Nigiwai is defined by

$$Nig_G^P(t_s, t_f) = \frac{1}{t_f - t_s + 1} \sum_{t=t_s}^{t_f} \sqrt{\sum_{i \in N_t} Nig_L(i,t)}, \tag{5}$$

where the local pedestrian Nigiwai are aggregated over time. As the number of interacting pairs of pedestrians is quadratic in the number of pedestrians, the square root is taken after summing all Nigiwai scores for the pedestrians at each frame.

The global ROI Nigiwai is defined by

$$Nig_G^R(t_s, t_f) = \frac{1}{(t_f - t_s + 1)|N_{ROI}|} \sum_{t=t_s}^{t_f} \sum_{i \in N_{ROI}} Nig_L(i,t), \tag{6}$$

where the local Nigiwai at ROI points $Nig_L(i, t)$ are averaged over time and the number of ROI points.

IV. EXPERIMENTS AND ANALYSIS

In this section, we analyze the effectiveness and robustness of the proposed method based on the evaluation of the Nigiwai indicators using both simulated and real data.[2] In Section IV-A, the simulation scenarios used in our experiments are described. In Section IV-B, we demonstrate that

[2]The codes and the data used in the experiments are available at https://github.com/shizuo-kaji/Nigiwai

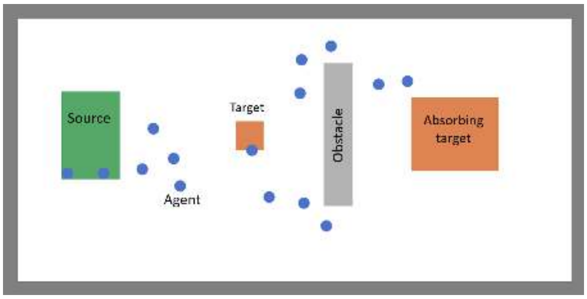


FIGURE 3. Basic elements in Vadere simulator. ***Agent*** represents a pedestrian, ***source*** produces pedestrians, ***target*** attracts pedestrians, ***absorbing target*** represents an exit of pedestrians, and ***obstacle*** is avoided by pedestrians.

the proposed indicators can successfully distinguish between the simulated pedestrian trajectories of shoppers and numerous passersby. We discuss the role of the hyperparameters. In particular, setting one of them to infinity reduces the model to one that is concerned only with the local density of the pedestrians; we demonstrate that this reduced model cannot distinguish shoppers from passersby, thereby proving the advantage of our method. In Section IV-C, the robustness of the proposed method is evaluated against the mis-detection of pedestrians. In Section IV-D, we present the verification of the proposed method by applying it to pedestrian trajectories extracted from real video samples.

A. PEDESTRIAN SIMULATION

The simulated trajectories were produced by an open-source crowd simulator known as Vadere[3] [6]. In our study, we used the Optimal Steps Model [15] to create the pedestrian movement. The basic components for constructing a scene are depicted in Figure 3.

Using the Vadere simulator, we designed two specific scenario types for pedestrian movements: *shopping scenarios* and *passing scenarios*. In the former, we emulated people shopping in a mall or shopping street, whereas in the latter, we emulated people passing by the same mall or through the street. For example, Figure 4 (a) depicts a shopping street, with many small shops on both sides of the street. Figure 4 (b) shows a shopping scenario based on the base region in (a), whereas (c) presents a passing scenario in the same base region. In the shopping scenario, people move between shops, taking different paths. The entrance to the street is modeled with sources and the exit to the street is modeled with special targets with an absorbing facility. In a shopping scenario, shops are simulated using targets with different waiting times. For each shop (target), the waiting time represents the probability of this shop attracting people and them staying therein. In a passing scenario, people are guided to move from the entrance to the exit directly, without visiting any shops.

We demonstrate that the shopping and passing scenarios could be distinguished using the proposed Nigiwai model, even when the number of total pedestrians was much higher in the passing scenarios.

[3]https://gitlab.lrz.de/vadere/vadere

B. COMPARISON OF SIMULATED SHOPPING AND PASSING SCENARIOS

In this section, the distinction between the passing and shopping scenarios is evaluated. Several simulated scenarios were used, in which the proposed Nigiwai indicators were computed and compared for the passing and shopping scenarios. The hyperparameters for all simulated scenarios were assigned as $W_v = 0.01$, $W_d = 4$, $\alpha = 0.9$, and $\beta = 0.9$.

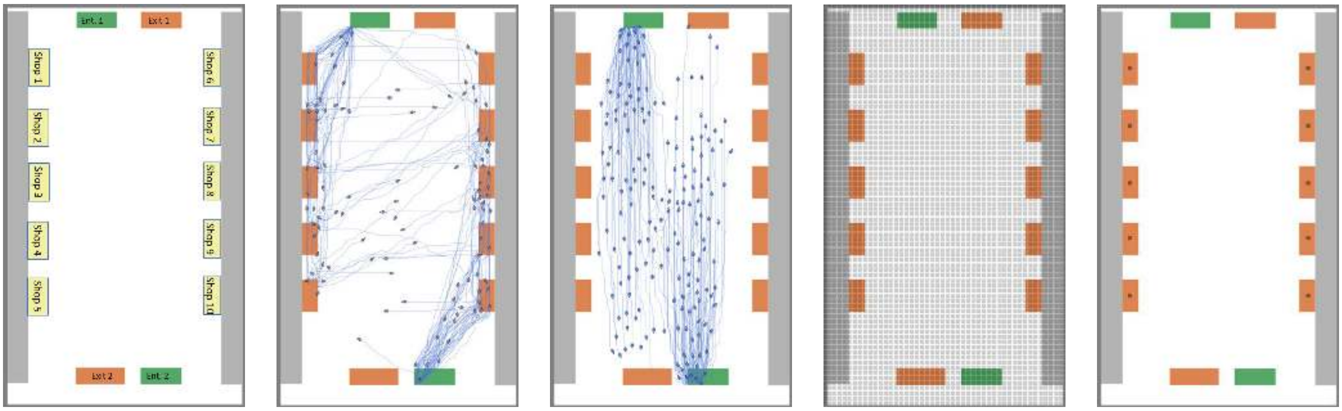
1) SCENARIOS WITH THE SAME NUMBER OF PEDESTRIANS

To evaluate the performance of the proposed method, we started by using scenarios with the same number of people. To this end, we designed shopping and passing scenarios for a shopping street, as illustrated in Figure 5, in which pedestrians move circularly around a middle barrier, without a new person entering or exiting for a certain period. Specifically, pedestrians enter at the same rate for 200 frames in both scenarios, following which they stop entering for the next 100 frames. During this time (the final 100 frames), the number of people in both scenarios is the same. In the shopping scenario, targets are used to simulate shops with different attraction probabilities and different waiting times, where pedestrians are attracted to these targets with different paths (Figure 5 (a)). In the passing scenario, targets are used to guide pedestrians to walk circularly, without stopping at any shops (Figure 5 (b)). The proposed Nigiwai indicators were evaluated as follows:

To compute the local Nigiwai for pedestrians, Eq. (4) was applied considering only the moving agents (pedestrians), following which the global pedestrian Nigiwai could be obtained using Eq. (5). Figure 6 (a) depicts the global pedestrian Nigiwai in each frame versus the time (frame number) for the shopping and passing scenarios. The right and left axes represent the global pedestrian Nigiwai and pedestrian number in each frame, respectively. Note that both scenarios had the same increasing people rate and the number of people was fixed from frames 200 to 300. It is obvious from this figure that the Nigiwai score in the shopping scenario was always higher than that in the passing scenario.

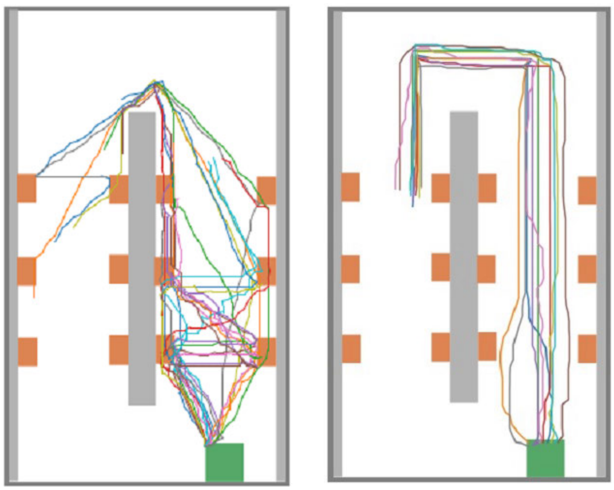
To determine the local place Nigiwai, Eq. (4) was used to compute the Nigiwai score at the ROI points, where 48×80 points were selected in both scenarios, similar to those in Figure 4 (d). Figure 6 (b) presents a comparison between the two scenarios according to the global ROI Nigiwai (Eq. (6)) in each frame. The shopping scenario achieved a higher score than the passing one.

Moreover, by aggregating the ROI scores in a period, we could identify the most attractive places for pedestrians during that period. Figure 7 provides an example of aggregating the ROI scores for the shopping scenario from frames 200 to 300, in which a stronger red color indicates a more attractive region. In this example, we assigned three different waiting times to the simulation shops. A shop with a



(a) (b) (c) (d) (e)

FIGURE 4. (a) Example of a shopping street, (b) pedestrian trajectories in a shopping scenario, (c) pedestrian trajectories in a passing scenario, (d) uniformly placed ROIs, and (e) ROIs placed at selected shops.

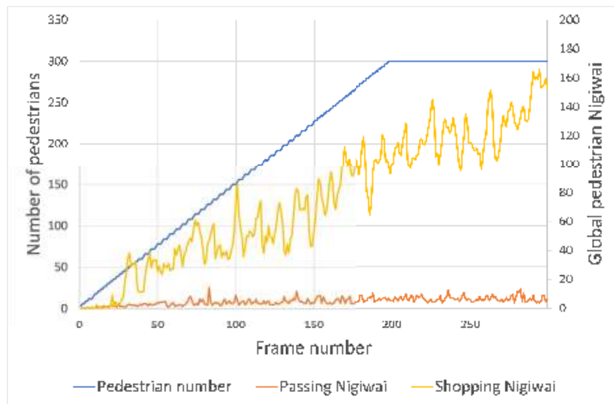


(a) (b)

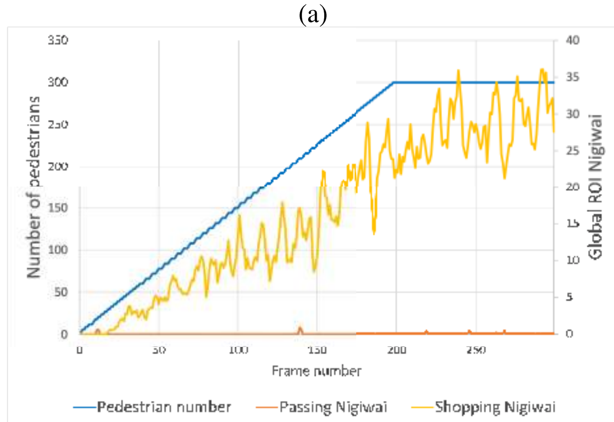
FIGURE 5. Trajectory samples of (a) shopping and (b) passing scenarios. The pedestrians move circularly, without a new person entering or exiting.

TABLE 1. Global pedestrian/ROI Nigiwai for the shopping and passing scenarios with different numbers of people.

Number	Global pedestrian Nigiwai		Global ROI Nigiwai	
of people	Passing	Shopping	Passing	Shopping
100	2.82	23.53	0.005	7.33
300	6.84	124.62	0.060	28.57
500	8.58	528.77	0.168	124.23
700	10.89	760.93	0.450	191.14



(a)



(b)

FIGURE 6. Comparison between the Nigiwai of the shopping and passing scenarios with the same number of people. (a) Global pedestrian Nigiwai in each frame. (b) Global ROI Nigiwai in each frame.

long waiting time activated more ROIs around it, as indicated in the figure.

To compute the global Nigiwai indicators in a certain period, we used Eqs. (5) and (6) to obtain the global Nigiwai for the pedestrians (Nig_G^P) and ROIs (Nig_G^R) from frames 200 to 300, respectively. Different numbers of people were employed in both scenarios. Specifically, the global Nigiwai indicators were estimated for scenarios with 100, 300, 500, and 700 people. For simplicity, we use, for example, shopping-100 to indicate the shopping scenario with 100 people. Table 1 summarizes the global indicators for these numbers of people in both scenarios. Notably, Table 1 demonstrates that the Nigiwai score (Nig_G^P or Nig_G^R) for shopping-100 was higher than that for passing-700. This indicates that the proposed global indicators could distinguish

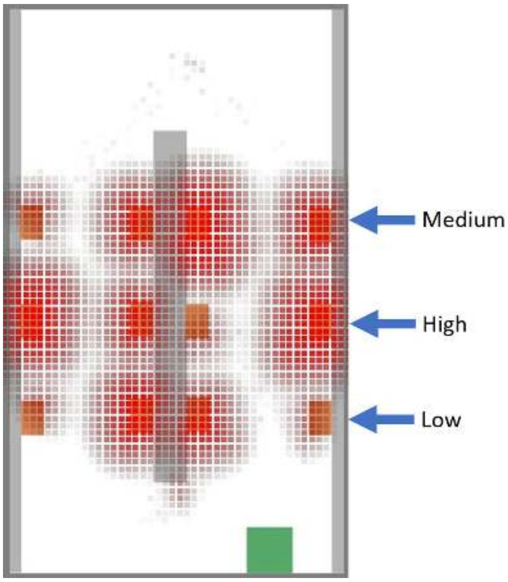


FIGURE 7. **Calculation of the attraction level of each ROI by aggregating its Nigiwai score over time. The ROIs at the shop locations had a high Nigiwai, and three attraction levels corresponding to three different waiting times can be observed.**

between the shopping and passing scenarios even though the number of people in the passing scenario was higher than that in the shopping scenario. In the following sections, we focus on the global ROI Nigiwai (Nig_G^R), which we simply refer to as the global Nigiwai.

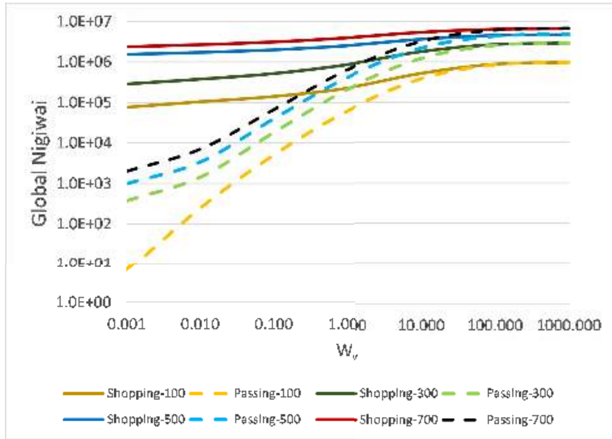
To investigate the effect of changing the hyperparameters W_v and W_d, we computed the global Nigiwai scores under different values of W_v and W_d. Figure 8 (a) presents the effects of varying W_v, with $W_d = \infty$, on the distinction between the passing and shopping scenarios. For $W_v < 0.1$, we could clearly distinguish between all passing and shopping scenarios whereas setting $W_v \geq 100$ eliminated the effect of the relative velocity, and the distinction between passing and shopping scenarios became ambiguous. Figure 8 (b) depicts the results of using $W_v = 0.01$ and changing W_d. According to these graphs, we selected $W_v = 0.01$ and $W_d = 4$ in all of the simulation experiments.

One of the key concepts of the proposed model is taking into account the relative velocities between agents. To illuminate this point, we compared the proposed model with a similar model without using the relative velocity term. We compared our Nigiwai indicators with those defined by Eqs. (7) and (8), which were obtained by inserting $W_v = \infty$ into Eq. (4).

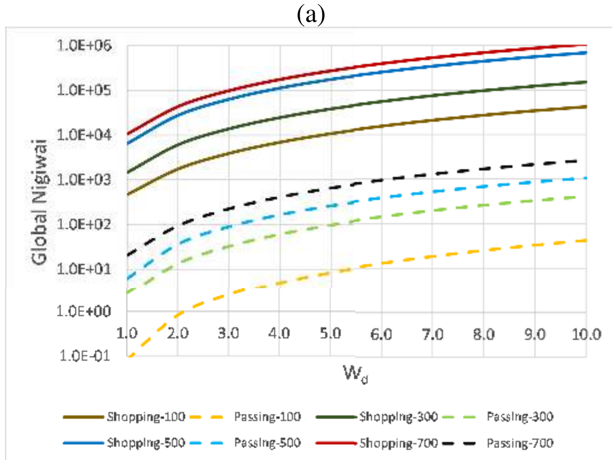
$$Den_L(i,t) = \sum_{j \in (N_t \cap N_{t-1}) \setminus \{i\}} \exp(-\tilde{d}_{i,j,t}/W_d) \tag{7}$$

$$Den_G^R(t_s,t_f) = \frac{1}{(t_f - t_s + 1)|N_{ROI}|} \sum_{t=t_s}^{t_f} \sum_{i \in N_{ROI}} Den_L(i,t) \tag{8}$$

These indicators depend only on the relative positions of the agents, and we refer to them as the local and global density-based models, respectively. Figure 9 compares the results of the proposed method and those obtained by the density-based model. The scale is normalized such that the maximum score is 1 in the two plots. It is obvious from this figure that our method outperformed the density-based model.



(a)



(b)

FIGURE 8. **Relation between variation of hyperparameters and Nigiwai score for different passing and shopping scenarios: (a) varying W_v with $W_d = \infty$ and (b) varying W_d with $W_v = 0.01$.**

As a visualization example, we present the snapshot results when using the proposed and density-based models in Figure 10. As indicated in (a) and (b), when applying the proposed method to the shopping scenario, the ROI points had high Nigiwai scores only at the shops around which pedestrians spent a certain period. In the passing scenario, all ROI points had low scores (not red). However, according to Figures 10 (c) and (d), the density-based model yielded similar ROI scores around the pedestrians in both the shopping and passing scenarios; therefore, it could not distinguish between them.

2) SCENARIOS WITH VARYING PEDESTRIAN NUMBERS

To assess the validity of our method in a more realistic setting, we conducted two experiments with pedestrians entering and exiting during each scenario. In the first experiment,

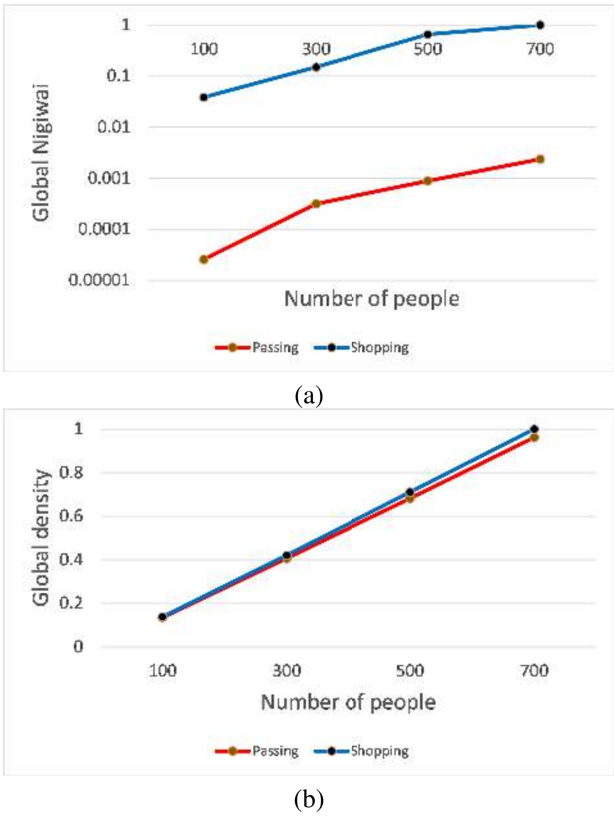


FIGURE 9. **Comparison between the proposed and density-based models according to their distinction between the passing and shopping scenarios. (a) Proposed model. (b) Density-based model. The two scenarios were clearly distinguished with the proposed model.**

shopping and passing scenarios for a shopping street were created, as illustrated in Figures 4 (b) and (c), respectively. These scenarios had a different number of pedestrians in each frame; however, we ensured that the instantaneous number of people in the passing scenario was always higher than that in the shopping scenario (by increasing the entering rate in the passing scenario). Figure 11 presents the comparisons between the global Nigiwai in both scenarios (right axis). The instantaneous number of pedestrians in each frame is represented by the left axis. Two values of W_v were tested: 0.01 and ∞, as illustrated in (a) and (b), respectively. In the case of using $W_v = 0.01$, that is, assigning a high weight to the relative velocity, the shopping scenario always had a higher Nigiwai when compared with that of the passing scenario, whereas with $W_v = \infty$ (density-based model in Eq. (7)), the passing score was higher than the shopping score. It is clear from Figure 11 (b) that both the shopping and passing density curves increased proportionally to the curves corresponding to their number of pedestrians, indicating that the number of pedestrians had a strong impact on the computation of the score in this case.

In the second experiment, the Supermarket scenario that was presented in [6] was employed, which simulated people shopping in a supermarket. Shelves were simulated using targets with different waiting times. For the passing scenario, we made certain modifications to the shopping scenario by

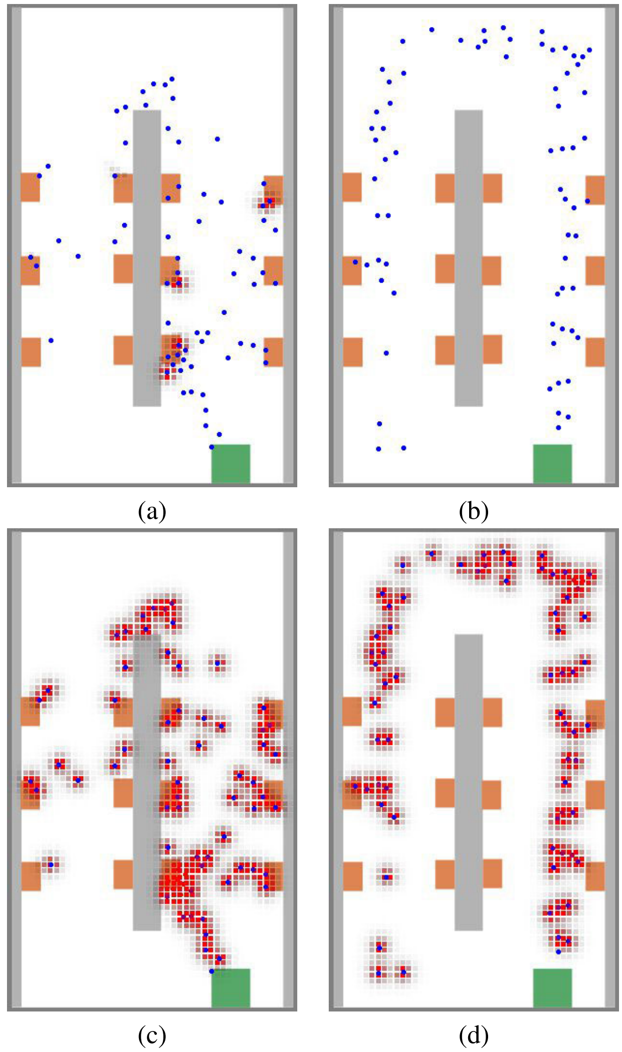
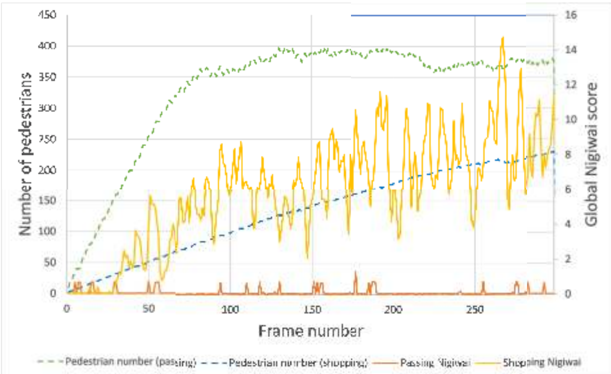


FIGURE 10. **Snapshots from the simulation scenarios, where pedestrians are represented by blue circles and high ROI scores are indicated in red. (a) and (b) ROI scores for the shopping and passing scenarios, respectively, using the proposed method. (c) and (d) A repetition of (a) and (b) when applying the density-based model. When using the proposed method, the ROIs had high scores only in the shops; however, the density-based model yielded similar scores in the shopping and passing scenarios.**

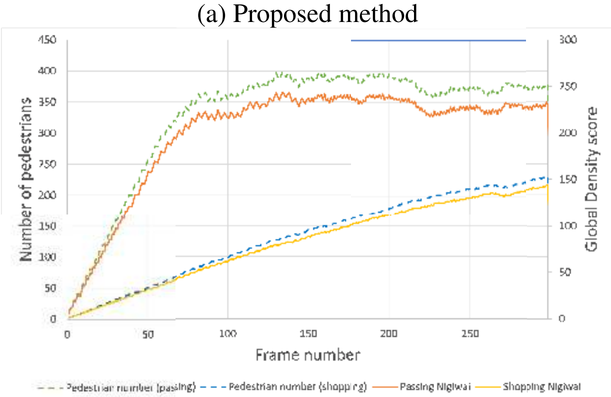
removing all waiting times for the targets and guiding people to walk around in the supermarket, without going to a specific shelf. Figures 12 (a) and (b) present the path images for the two scenarios. A comparison of the Nigiwai indicators for the two scenarios is provided in Figure 12 (c). The global Nigiwai was computed in both scenarios, whereas the number of people in the passing scenario was always kept higher than that in the shopping scenario. We can observe that the variety of paths was greater in the shopping scenario, and accordingly, the density might be lower; the Nigiwai score was always higher in the shopping scenario.

C. ROBUSTNESS AGAINST TRAJECTORY DISCONTINUITY

In real-world situations, the ideal pedestrian trajectories such as those obtained by the Vader simulator cannot



(a) Proposed method

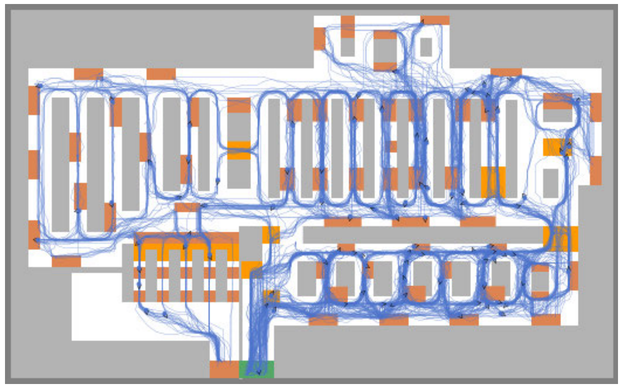


(b) Density-based model

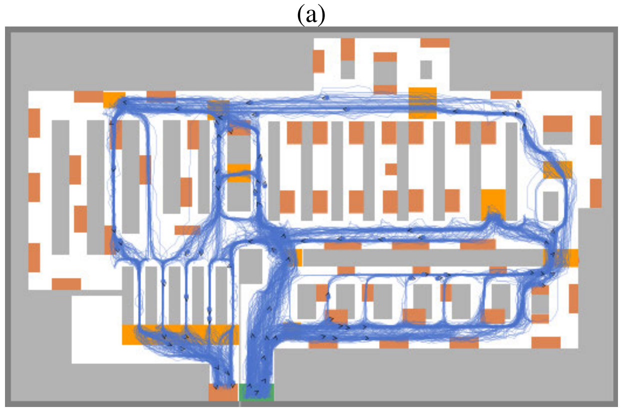
FIGURE 11. Comparison between shopping and passing scenarios shown in Figure 4, with different numbers of pedestrians. (a) Proposed method ($W_v = 0.01$). (b) Density-based model ($W_v = \infty$). In the latter, the score was strongly correlated with the number of pedestrians.

be determined. Therefore, one of the most important issues was to evaluate the proposed method under different mis-detection and mis-tracking levels. If a person is mis-detected in a frame, the ID label of the person does not exist in this frame, whereas if a person is mis-tracked, the ID label is changed to a new value. To evaluate the effects of the above on the results of the proposed model, the global Nigiwai scores were computed for the shopping-100 and passing-700 scenarios with simulated mis-detection and mis-tracking. We applied two levels of mis-detection and mis-tracking. In level 1, we randomly removed the ID of each pedestrian for 10% of their existing duration to simulate mis-detection, and we randomly changed each pedestrian ID to a new ID to simulate mis-tracking. In level 2, we repeated the above steps twice.

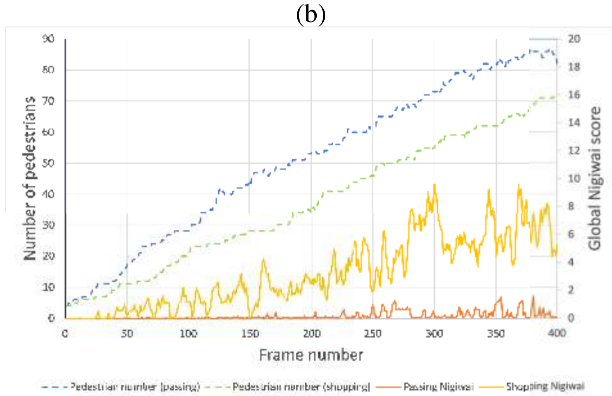
The simulation for each level of mis-detection and mis-tracking was performed 20 times for a single original trajectory data point. Figure 13 uses a violin plot to compare the global Nigiwai distributions of the passing-100 and shopping-700 scenarios under the two mis-detection and mis-tracking levels. The variation was not very large and the Nigiwai scores of the two scenarios could be clearly differentiated.



(a)



(b)



(c)

FIGURE 12. Example of a supermarket simulation. (a) and (b) Samples of pedestrian paths for shopping and passing scenarios, respectively. (c) Comparison between global Nigiwai scores for the two scenarios with regard to the number of pedestrians.

D. TRAJECTORY EXTRACTED FROM REAL VIDEO

We applied the proposed method to the MOT16-03 and MOT16-04 videos [11] as a demonstration with real data. The pedestrians in these videos were detected using a deep-learning-based object detection algorithm YOLO v4 [2] with publicly available codes.[4] To match the scaling of this video, we set $W_v = 0.1$, $W_d = 1$, $\alpha = 0.5$, $\beta = 0.1$, and $\gamma = 0.5$, where γ is a hyperparameter for estimating the moving average of the local Nigiwai indicator.

[4]https://github.com/AlexeyAB/darknet

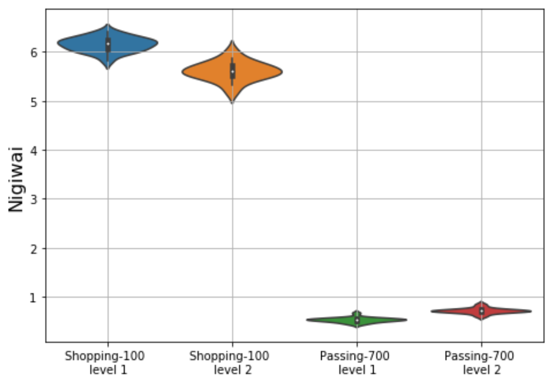
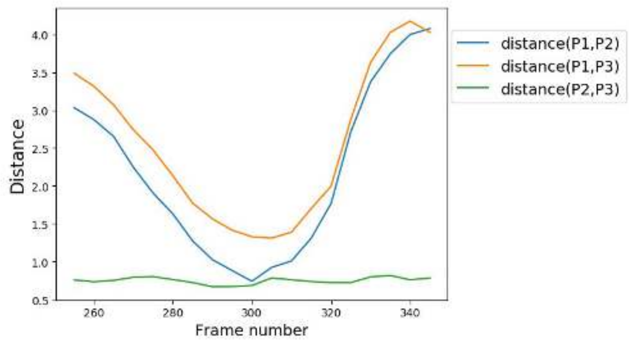


FIGURE 13. **Comparison between Nigiwai of the shopping-100 and passing-700 scenarios. Two levels of mis-detection and mis-tracking were applied. At each level, the violin plot presents the Nigiwai distribution for 20 iterations.**

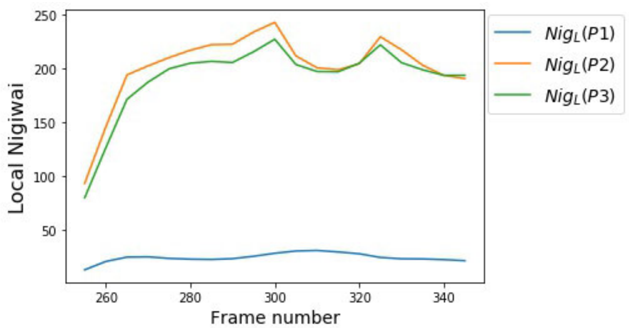
First, we computed the local Nigiwai for the pedestrians as per Eq. (4). Examples of visualizing the pedestrian Nigiwai are presented in Figure 14 (a, c, and e), where red indicates a high Nigiwai score (a supplementary video is also provided). As illustrated in this figure, people walking in groups had a higher Nigiwai score than individual pedestrians. This result matched with that mentioned before; that is, the Nigiwai activity is increased when people are in groups as opposed to individual pedestrians. To demonstrate the advantages of the proposed model when compared with the density-based model (Eq. (7)), we present the results of using the density-based model for the same frames in (b, d, and f) respectively, where $W_v = \infty$. It can be observed from these figures that the pedestrian scores were only dependent on the relative distances between them, regardless of whether they were individual pedestrians or moving in groups.

To illustrate further, we present the Nigiwai scores for three specific pedestrians, shown in Figure 14 (e and f), and compare their scores using the proposed and density-based models. The three pedestrians are labeled as P1, P2, and P3,

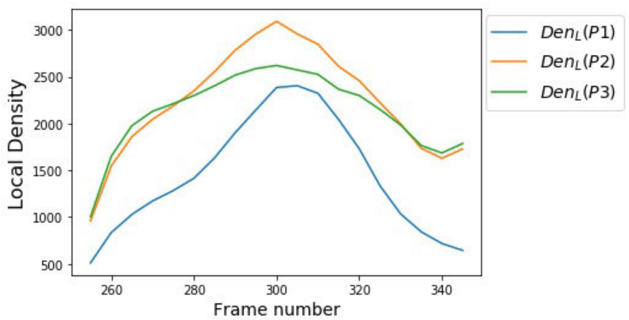
FIGURE 14. **Application of proposed and density-based models to MOT16-03 (a-d) and MOT16-04 (e-f) videos, where the red color indicates a high score. The images in the left column (a, c, and e) represent the proposed results and those in the right column (b, d, and f) represent the density-based results. Note that the proposed method yielded high scores for persons in a group rather than for individual pedestrians, whereas the density-based method did not. Detailed comparisons for three pedestrians, shown in (e) and (f), are provided in Figure 15..**



(a) Relative distances



(b) Proposed method



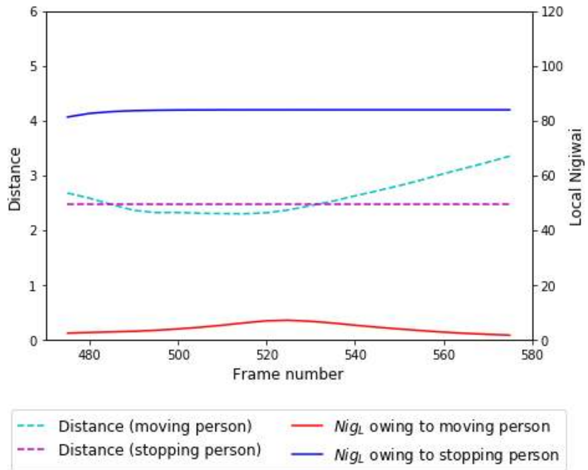
(c) Density-based model

FIGURE 15. Comparison of the proposed and density-based models using the three pedestrians shown in Figure 14 (e, f) as a case study. Note that P2 and P3 are walking together, whereas P1 is walking individually in the opposite direction. (a) Relative distances between the three persons. (b) Nigiwai scores using $W_v = 0.1$. (c) Scores using the density-based model ($W_v = \infty$).

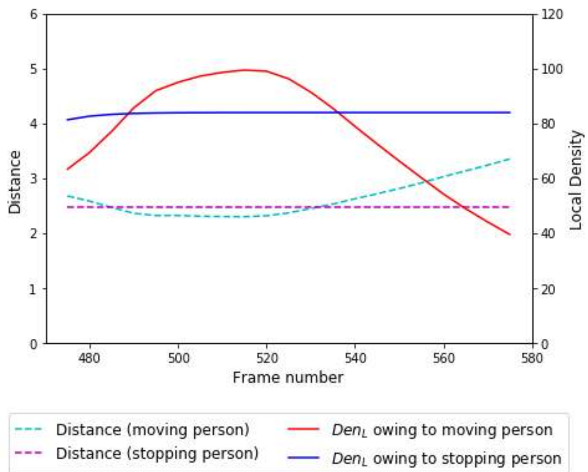
where P2 and P3 are walking together while P1 is walking individually in the opposite direction. Figure 15 (a) depicts the three relative distances between them. The Nigiwai scores using $W_v = 0.1$ for the three pedestrians are indicated in Figure 15 (b). It can be noted that the three pedestrians were very close to each other around frame 301 (Figure 15 (a)); however, the Nigiwai of P1 was small compared to the Nigiwai of P2 or P3. Figure 15 (c) depicts the use of the density-based model, where $W_v = \infty$. In this case, we note that P1 had a high score around frame 301 owing to the small relative distances to P2 and P3. This also supports our claim that the incorporation of the relative velocity into our model is important in quantifying Nigiwai.

Finally, we compared the contributions to the local Nigiwai score at an ROI point by two persons, as illustrated in

(a) MOT16-04 (Frame 455)



(b) Proposed method



(c) Density-based model

FIGURE 16. Comparison of the Nigiwai contributions of a person stopping in front of a shop and another passing by the shop (ROI). (a) Sample frame showing the two persons in blue bounding boxes, where the ROI point is indicated by the center of the green circle. (b) Nigiwai contribution of each person using the proposed method ($W_v = 0.1$). (c) Contribution of each person using the density-based model ($W_v = \infty$). The distance to the ROI is presented by the left axis.

Figure 16 (a), where one had stopped at the front of a shop and the other was passing by. An ROI point at the front of this shop is represented by the center of the green circle. The local Nigiwai at this point was computed considering only these two persons, using $W_v = 0.1$. The result was compared with the score obtained when using the density-based model ($W_v = \infty$). Figure 16 (b) presents the Nigiwai component owing to each person when using $W_v = 0.1$. The relative distance between each person and the ROI point is indicated on the same graph. It can be noted that a stationary person always contributed a higher value to the ROI Nigiwai than a moving person, regardless of their distances from the shop. Figure 16 (c), where $W_v = \infty$, indicates that the contribution score of the moving person was increased around frame 515 because this person was closer to the shop than the stationary person. We can conclude that with the proposed method, the stationary person contributed more to the Nigiwai of the shop than the person passing by, whereas the density-based model determined the score based on the relative distances of the people from the shop, without considering whether they were passing by or had stopped in front of it.

V. CONCLUSION

A set of novel evaluation indicators for the shopping activity (Nigiwai) in a shopping area have been introduced. Our indicators are computed solely from the pedestrian trajectories, which can easily be obtained with surveillance cameras. The proposed method uses both the distances and relative velocities between agents, which enables the finer structures of the pedestrian activities to be captured. Evaluations with simulated pedestrian trajectories demonstrated that the proposed method could successfully discern scenarios with shoppers from those with passersby, even when the latter had a higher number of pedestrians. Moreover, the proposed method exhibited high robustness against mis-detection and mis-tracking in the simulations. We also verified our method using real data. We first extracted the pedestrian trajectories with an existing algorithm, and our indicators were calculated and visualized with the extracted trajectories. In a subsequent study, we will investigate the correlation between our indicators and other indicators such as sales by using real data collected from a shopping street. Our study has some limitations that are worth noting. Appropriate values of the parameters W_v and W_d depend on the scale and frame rate of the sampled trajectory data, and the geometry of the area. Heuristic calibration may be required before the indicator is applied to a specific setting. Although our indicators effectively evaluate different people flows at the same place or areas with similar shapes and sizes, it is not suitable for deducing absolute Nigiwai scores, which can be used to compare people flows measured in different areas.

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