Person-Flow Estimation with Preserving Privacy using Multiple 3D People Counters

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Abstract. The spread of mobile phones made it easy to estimate person-flow for corporate marketing, crowd analysis, and countermeasures for disaster and disease. However, due to recent privacy concerns, regulations have been tightened around the world and most smartphone operating systems have increased privacy protection. To solve this, in this study, we propose the person-flow estimation technique with preserving privacy. We use 3D People Counter which can record only the time and direction of passing people, a person's height, and walking speed, therefore it preserves privacy from the moment of collecting data. To estimate people's in-out data, we propose four methods and they use some of the sensor data above in different combinations. We compared these methods and the height-based method could estimate about 79% of the sensor data as in-out data. Additionally, we also created a system to interpolate in-out data into person-flow data and to visualize it. By using this method, we believe that it can be used for the purposes described in the beginning.

Keywords: Person-Flow Estimation · Privacy · 3D People Counter.

1 Introduction

There are many situations where person-flow data can be used in the real world. For example, in a shopping mall, shop owners can measure how long people stay in a place and which corridors are frequently visited to improve their sales. More recently, person-flow data has also been used to counter the coronavirus outbreaks by analyzing the number of people in public places.

To obtain person-flow data, we can use various methods described below. Global Positioning System (GPS) is the most well-known method to obtain a personal location and is used by some smartphone applications. On the other hand, mobile network operators collect their user's device location. Also, Wi-Fi packets or Bluetooth packets are useful to track a person's move. However, the operating system (OS) of modern smartphones has made it more difficult to get personal location data. For example, Android OS makes users possible to select when the application can use their location data [2]. Furthermore, several smartphones have a function to randomly set the MAC addresses when connecting to a Wi-Fi access point in the OS, therefore we cannot track people who have such a smartphone.

Moreover, many countries around the world are rethinking the protection of privacy. Particularly, in the European Union (EU), EU General Data Protection Regulation (GDPR) has been set in place [14]. The GDPR requires organizations that want to use personal location data for their services to treat them in the same way as personal information. However, in general, person-flow estimation requires the acquisition of personal location data from people's smartphones, therefore it is a problem to ensure their anonymity.

Based on this situation, in this study, we propose a person-flow estimation technique with preserving privacy by multiple 3D People Counters. Similar sensors and cameras have already become popular, but the sensor only collects people passing data and does not save stereo images captured. Therefore, unlike other techniques, this method can preserve privacy from the time collecting data. Using this sensor, we aim to estimate person-flow in any area where all gates have a sensor. If the area looks like a long rectangle and has only two gates at both short sides of the rectangle, we can estimate person-flow easily. However, many areas in the real world look like various shapes and have multiple gates in general, therefore it is difficult to estimate person-flow in such an area.

To solve this, we propose the three-step person-flow estimation method including in-out estimation, interpolation, and visualization. Firstly, we estimate the people's in-out data by analyzing the sensor data including passing time, person's height, and duration to go through the sensing area in four ways. The first in-out estimation method uses only passing time. The next method uses passing time and height. In this method, we can convert about 79% of the passing data to person-flow data and it seems to be the best in this paper. The third replaces people's height data with walking speed data, and the last uses all data, and we tried two strategies. After in-out estimation, we interpolate the in-out data into person-flow data to visualize realistically. We used the customized RVO2 Library [3] to interpolate person-flow data more realistic in that people in the area do not collide with each other and hit obstacles. Finally, we visualize the person-flow data using Harmoware-VIS and evaluate the effectiveness of the interpolation. As a result, we could estimate person-flow and visualize it in reality.

The contributions of the paper are followings:

- We defined the problem of how we estimate person-flow with preserving privacy.
- We proposed and implemented the method which has three steps including in-out estimation, interpolation, and visualization to solve the problem.
- We evaluated and confirmed the effect of the proposed method.

2 Related Work

2.1 Work about location acquisition techniques and person-flow estimation methods

Location acquisition techniques and person-flow estimation methods have already been widely studied and some of them are put to practical use. Here we introduce some of them and discuss the pros and cons of them.

GPS Generally, GPS estimates a personal location by calculating the propagation time of radio waves from three satellites or more. Thanks to the signal from satellites, its estimation error is a few meters outdoors anywhere on earth. However, we can rarely use GPS in rebar buildings or undergrounds because radio waves from satellites are greatly attenuated. Furthermore, GPS uses long length radio waves and requires 4 satellite signals to estimate location accurately. Therefore, to get continuous location data it consumes big electric power, and it results in a decrease of uptime of mobile devices.

Mobile Network We can estimate personal location by the strength of radio waves and the location of a mobile base station to which a mobile device is connected. Related to a person-flow estimation, the method above has been considered to be able to use a survey of traffic volume.

In the study by Ratti et al. [13], the usage data of mobile phones in an urban area was collected by mobile base stations chronologically. Then they estimated person-flow in the city by creating a heatmap of this data. Besides, they mentioned that results could provide a new approach to improve urban systems. In the study by Caceres et al. [7], they utilized a characteristic that a cell phone communicates to a base station when the phone enters or leaves the communication range of the station. Thanks to their method, they demonstrated that traffic data could be collected at a lower cost. In the study by Ng et al. [12], they estimated location data by focusing on the attenuation of a signal of mobile network in Hong Kong.

In general, these methods have a lower cost than others because most of them use existing equipment. However, they use privacy-sensitive data such as call histories possessed by a mobile network operator after anonymization. Therefore, if these data are not handled properly, it can be a big problem in terms of privacy protection.

Wi-Fi Packet Sensors In the study of Fukazaki et al. [8, 9], they conducted person-flow estimation by anonymized MAC address in prove requests from smartphones collected by multiple Wi-Fi packet sensors. However, because several people may have two or more smartphones, they compared people count from packet sensors with that from more reliable sensors to estimate more accurate person-flow only by packet sensors. In the study of Kawaguchi et al. [11], they also compared people count from packet sensors with that from cameras and examined a ratio of randomized MAC addresses to all MAC addresses collected by packet sensors individually. They concluded that these ratios seem to depend on the location of a sensor and will not change over time. Therefore, we can estimate person-flow only by packet sensors statically by examining environments of the location of a sensor in advance. In the study of Xu et al. [21] and Fukazaki et al. [9], they utilized the Received Signal Strength Indication (RSSI) value to estimate a more accurate location.

Bluetooth There are mainly two estimation methods using Bluetooth. The First is collecting an inquiry response packet from a smartphone to which a Bluetooth device sends a connection inquiry. In the study of Schauer et al. [15], they used the method above but the estimation accuracy of this method was lower than that of the Wi-Fi method because recent smartphones do not replay to a connection inquiry by default and it causes the decrease in detectable smartphones by Bluetooth.

The Second is collecting packets from a Bluetooth Low Energy (BLE) tag by multiple BLE scanner. In the study of Urano et al. [18, 19], they distributed BLE tags to event participants and tested the method. Furthermore, they proposed a tandem scanner to avoid packet loss and introduced three-point positioning and particle filter to improve estimation accuracy.

Person-Flow Camera There are many studies to improve obtaining person-flow using cameras. In the study by Bartolini et al. [6], they created robust people counting method to be able to be applied in buses. Their system can deal with vibrations, lighting fluctuations, and environmental variations. Also, Terada et al. [17] introduced a stereo camera to realize people counting in a crowd where a conventional method cannot deal with. In the study by Abuarafah et al. [5], they developed the crowd density estimation system using a thermal camera. On the other hand, Satyam et al. [16] created a robust crowd estimation method using texture features. Also, Ibrahim et al. [10] reviewed some optical flow techniques for motion estimation of crowd flow.

2.2 The position of this study in comparison with related work

Figure 1. shows the relation between our work and related works. We can track person-flow in wide areas by GPS and Mobile Network at a lower cost. However, the use of GPS is restricted by a modern smartphone OS. Also, location data from Mobile Networks contains a user's information like a phone number. Therefore, there is great concern about privacy when we use them for person-flow estimation. On the other hand, Wi-Fi and Bluetooth can collect only a user device's MAC address, therefore there is less concern about privacy. However, a tracking area is generally narrower than that by GPS or Mobile Network. Moreover, cameras may be able to track the narrowest area than other methods and the cost of equipment will be high if we install many cameras in order to cover a wide area.

In order to realize the person-flow estimation method which can be applied to a wide area and consider privacy, we introduce multiple 3D People Counters. This sensor only obtains photos of the head of people, therefore the sensitiveness of the privacy is considered to be lower than other methods. Also, the cost to use this method in a wide area seems to be better than a method that uses cameras installed in an entire area. The person-flow is estimated by examining the correlations of the sensor data, including a person's height which can be obtained by a stereo camera but not by a single-lens camera. It is expected

Fig. 1. Compared to related works.

that our works can be applied to commercial marketing in stores and disaster countermeasures.

3 Person-Flow Estimation in Open Space

3.1 Target Environment

In this paper, we aim to estimate person-flow in an area like Figure 2. A target area has multiple gates and thousands of people enter and leave the area from them every day. For example, a station, an underground mall, an airport terminal, and a shopping mall are one of them. If we can obtain person-flow data in such an area, there are many merits for us. For example, in a shopping mall, shop owners can measure how long people stay in a place and which corridors are frequently visited. These customer behavior data are useful to improve their sales. Also, there is much public transportation including trains, buses, and taxis at a station or an airport terminal, therefore we can estimate the time - series trend of usage of public transportation. More recently, person-flow data has also been used to counter the coronavirus outbreaks by analyzing the number of people in public places such as stations. Therefore, obtaining person-flow data in target areas is a significant problem.

3.2 Problem Definition

To estimate person-flow in an area like Section 3.1, we install 3D People Counters shown in Figure 3 and Table 1 at ceilings of every gates. Each sensor can collect a passing time, direction, person's height, and duration to go through the area.

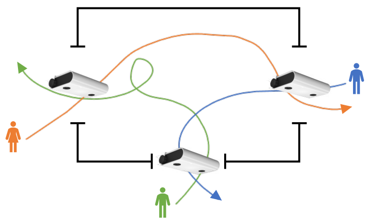

Fig. 2. The example of an estimation target area.

Fig. 3. 3D People Counter (VC-3D by Vitracom GmbH.)

However, sensor data is only passing data and does not represent a person-flow in the area. Therefore, we estimate people's in-out data by analyzing the correlations of some of the sensor data, including time, height, and duration. After estimation, we interpolate the in-out data into person-flow data in order to obtain what route do people walk in the area. Finally, we visualize the person-flow data to be able to be easily understood by a human and utilize for the aim described at the beginning of the introduction.

3.3 Procedure of Person-Flow Estimation

In this study, we estimate person-flow by following steps shown in Figure 4. First of all, 3D People Counters capture stereo images and analyze them to output sensor data. Sensor data consist of individual people data including when to pass the gate, how long to pass through the sensing area, the direction to which they passed, and their height. The captured images are discarded and not included in the sensor data. After that, we store the sensor data to our server in real-time and retrieve them for person-flow estimation lately.

Before estimation, we calibrate sensor data to eliminate the error derived from the condition of the installed place of a sensor and the characteristic of an individual stereo camera. To do this, we first shift all sensor's height data so that the average is the same value (in this paper, this value is 160.) Next, we align them so that the variance is the same (15 in this paper.)

Using calibrated data, we can estimate person-flow by our proposed method described in Section 4. To begin with, we estimate people in-out data from sensor data by four methods in Section 4.1. This procedure can also be conducted for

Table 1. The specification of 3D People Counter.

Installation height	2.4 to 6.0 m
Monitoring Area	up to 10.0 x 7.0 m
Counting Line	up to 5 lines
Power Supply	Power over Ethernet (PoE)

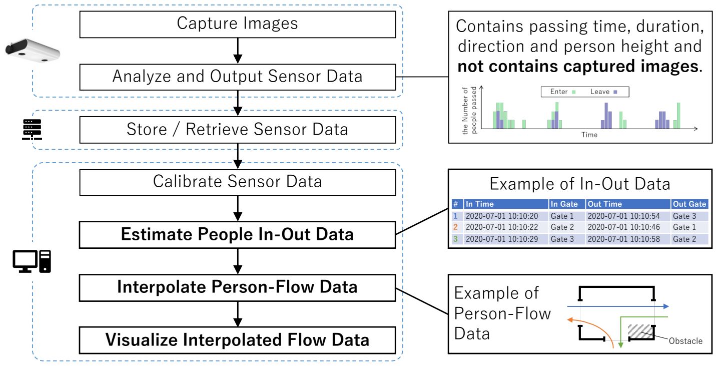

Fig. 4. Procedure of Person-Flow Estimation in this study.

non-calibrated real-time sensor data and results can be obtained with about 2-5 minutes delay (depends on the size of the area.) However, if we simply visualize the in-out data so that people walk in linear from an entrance to an exit, several of them may collide with each other or hit an obstacle. To solve this problem, we interpolate the in-out data into person-flow data so that each person in the area do not collide with each other and not hit an obstacle. Finally, we visualize the person-flow data.

4 Details of Proposed Method

4.1 In-Out Estimation

In our study, we propose mainly four methods for estimating in-out data in order to compare the conversion rate between sensor data and in-out data and the reliability of in-out data. Each method uses different data set from sensor data and their calculation cost are different from each other, therefore we should select the most cost-effective method among them when using them in a new area where we want to estimate person-flow. In the following sections, these methods will be explained respectively and the area like Figure 2 is the estimation target.

Method A: Using passing time and direction data In this method, we estimate in-out data by comparing the temporal changes in the number of people passing by each sensor. For example, in Figure 5, the sensor data shows that 10 people entered the area from the Sensor 1 gate around 10:10:00, 4 people left from Sensor 2 around 10:10:30, and 6 people left from Sensor 3 around 10:10:45. In addition, nobody enters or leaves the area between 10:10:00 and 10:10:50. Therefore, we estimate that 4 people move from the Sensor 1 gate to Sensor 2 in about 30 seconds and 6 people move from Sensor 2 to Sensor 3 in about 45 seconds.

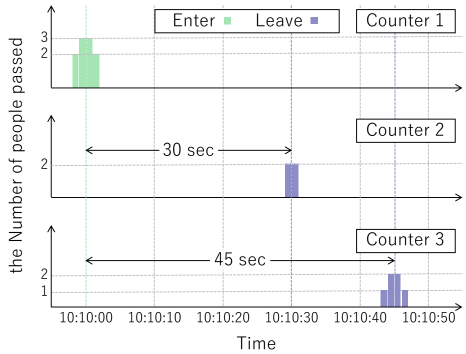

Fig. 5. The sample sensor data used in the method using passing time and direction data.

Method B: Using passing time, direction and person height data In this method, the each person's in-out data is estimated using the height of the passing person as a key. First of all, we roughly calculate the required time to move from one sensor gate to another in all combinations. In the calculation, we use the result from the previous section's method or the division of distances between gates and average human walking speed. Next, we determine the following time duration parameters for all sensor combinations. These parameters are used to eliminate the wrong flow which is too fast or slow for people to walk, thus we have not to determine them strictly.

- $d_{min(a \to b)}$: The minimum required time to move from Sensor a to Sensor b
- $d_{ave(a \to b)}$: The average required time to move from Sensor a to Sensor b
- $d_{max(a \to b)}$: The maximum required time to move from Sensor a to Sensor b

In addition, we introduce a fourth parameter h_d which represents the range that allows for height error. This is because although we calibrated height data, there are remaining errors that can never be eliminated. In our experience, this error is about 2 - 4 centimeter between entrance and leaving, therefore we use $h_d = 5[cm]$ in this paper. (For the convenience of explanation, the error with h_d [cm] or more is considered to be a different person.)

Finally, we define the Flow Reality Matrix (FRM) as the fifth parameter. The FRM is a matrix that defines how likely person-flow is to occur between each sensor. The value of each element of the FRM is defined as $fr_{a,b}$: the reality of occurrence of person-flow from the gate of sensor a to b. Each $fr_{a,b}$ is a value between 0 and 1 and the higher $fr_{a,b}$ is, the more likely it is to occur person-flow from sensor a to b. This matrix is defined from information known in advance about the target area in order to avoid estimation errors. For example, in a public place such as a station terminal, we define a smaller $fr_{a,a}$ value (same sensor) for all sensors because it is unlikely that people will enter and exit the same gate. We also reduce $fr_{a,b}$ for other gates that are eventually connected to the same destination.

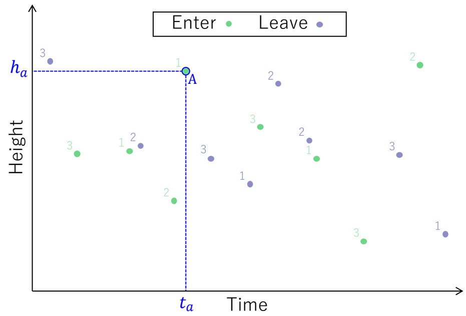

Fig. 6. The Graph showing time, height, direction of passing people.

Given the five parameters above, the estimation is conducted by the following steps.

1. Shown in Figure 6, we consider a graph of the time axis and height axis, and each point is classified by sensor No. and the color that represents entry or exit. For example, the Point A surrounded with a blue circle represents that a person whose height is h_a entered the target area from the Sensor 1 gate at the time of t_a.
2. For all points that represent entry to the area in Figure 6 (define as $P_1 ... P_m$ in chronological order), calculate the probability of the same person as all points that represent leaving from the area (define as $Q_1 ... Q_n$ in chronological order.) At this time, the score for the flow from P_i to Q_j is defined as $s_{i,j}$, and the passing time, height and sensor No. for P_i is defined as t_{P_i}, h_{P_i} and c_{P_i} respectively. (Therefore, $t_{P_1} \leq t_{P_2} \leq ... \leq t_{P_m}$ and $t_{Q_1} \leq t_{Q_2} \leq ... \leq t_{Q_n}$.) The calculation of $s_{i,j}$ is performed like below.
   (a) Define the degree of height similarity between P_i and Q_j as $h_{i,j}$ and calculate $h_{i,j}$ as below.

$$h_{i,j} = 1 - \left(\frac{min(|h_{P_i} - h_{Q_j}|, h_d)}{h_d} \right)^2 \tag{1}$$

   Note: Define the minimum value between a and b as $min(a, b)$.
   (b) For P_i and Q_j, let $t_{i,j}$ be the degree of probability that the flow from the Sensor c_{P_i} gate and Sensor c_{Q_j} can occur on the time basis. In addition, define following variables: $d_{i,j} = t_{P_i} - t_{Q_j}$, $d_{min} = d_{min(c_{P_i} \to c_{Q_j})}$, $d_{ave} = d_{ave(c_{P_i} \to c_{Q_j})}$, $d_{max} = d_{max(c_{P_i} \to c_{Q_j})}$ and calculate $t_{i,j}$ like below.

$$t_{i,j} = \begin{cases} 1 - \left(\dfrac{d_{ave} - d_{i,j}}{d_{ave} - d_{min}} \right)^2 & (d_{min} \leq d_{i,j} \leq d_{ave}) \\ 1 - \left(\dfrac{d_{ave} - d_{i,j}}{d_{ave} - d_{max}} \right)^2 & (d_{ave} \leq d_{i,j} \leq d_{max}) \\ 0 & (otherwise) \end{cases} \tag{2}$$

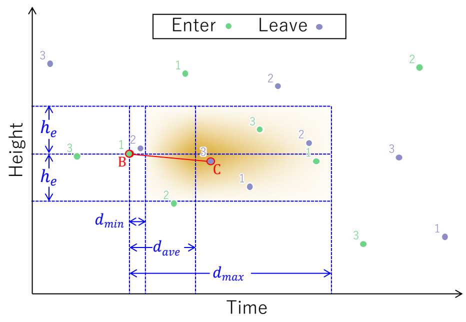

Fig. 7. The search of combinations of a entering data and a leaving data.

(c) Calculate $s_{i,j}$ as follows.

$$s_{i,j} = h_{i,j} t_{i,j} fr_{c_{P_i}, c_{Q_j}} \tag{3}$$

For example, the color density in Figure 7 is proportional to the score for Point B.

3. Using the score $s_{1,1}, ..., s_{1,n}, s_{2,1}, ..., s_{m,n}$ obtained above, explore combinations of P_i and Q_j from the perspective that each of them is considered to be right as a one person's entrance and leaving. First of all, we start exploration with $i = 1$ and do the following:
   - If P_i is already combined with any of Q_j, do nothing.
   - If $s_{i,j}$ is bigger than all of $s_{i,1}, s_{i,2}, ..., s_{i,j-1}, s_{1,j}, s_{2,j}, ..., s_{i-1,j}$, consider P_i and Q_j is the right combination and set $s_{i,1}, s_{i,2}, ..., s_{i,j-1}, s_{1,j}, s_{2,j}, ..., s_{i-1,j} = 0$.
   - If $s_{i,j}$ is smaller than any of above, do nothing.

   After that, repeat above with $i = 2$ and continue until $i = m$. Once finished, go back to $i = 1$ and repeat the whole procedure until a new combination will not be found in a procedure. In short, first priority is given to early entry, and the second priority is given to the height similarity and duration probability. For example, Point B in Figure 7 should be combined with Point C.

After exploration, the entry and leaving points in Figure 6 are combined like Figure 8. Using Figure 8, we can estimate the number of people who have moved to a specific entrance and exit and the time required to move between gates.

Method C: Using passing time, direction and walking speed data In this method, we replace person height in 4.1 with walking speed. Similary, define the walking speed of P_i as v_{P_i}, the degree of walking speed similarity between P_i and Q_j as $v_{i,j}$ and the range that allows for walking speed error as v_d. After that, calculate $v_{i,j}$ as following.

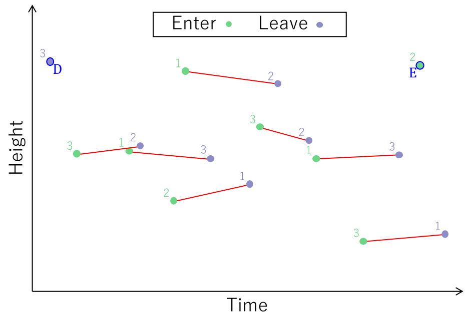

Fig. 8. The estimation result from Figure 6.

$$v_{i,j} = 1 - \left(\frac{min(|v_{P_i} - v_{Q_j}|, v_d)}{v_d}\right)^2 \tag{4}$$

Also, $s_{i,j}$ is calculated like Formula 3.

$$s_{i,j} = v_{i,j} t_{i,j} fr_{c_{P_i}, c_{Q_j}} \tag{5}$$

Method D: Using passing time, direction, person height and walking speed data In this method, we introduce two strategies: AND strategy and OR strategy. In AND strategy (hereinafter called "method D-1"), we use both height and walking speed as a condition to distinguish one person from another. Therefore, we calculate $s_{i,j}$ like below.

$$s_{i,j} = h_{i,j} v_{i,j} t_{i,j} fr_{c_{P_i}, c_{Q_j}} \tag{6}$$

On the other hand, in OR strategy (hereinafter called "method D-2"), we first use the method in 4.1 and use the method in 4.1 with remaining data. In other words, we use height data mainly and use walking speed data as backup.

4.2 Interpolation of People In-Out Data

After an in-out estimation, we can see when and how many people move between specific gates. However, we cannot determine what route did they walk in the area from in-out data. If we think that they walk linear in the area, several people may collide with each other and pass through an obstacle.

To solve this, we added the interpolation step before visualization and introduced a customized RVO2 Library [3] for interpolation. RVO2 Library is an open-source implementation of Optimal Reciprocal Collision Avoidance (ORCA) [20] formulation. ORCA guarantees that agents in the simulation (i.e. people) have collision-free navigation. In addition, we created the new feature to add or remove agents while the simulation is running by RVO2. This feature represents the people's entrance and exit in the target area.

4.3 Visualization

In this study, we developed the visualization system using Harmoware-VIS[1] in order to easily understand the estimated person-flow by a human. Harmoware-VIS is the Spatio-Temporal Visualization Library using Deck.GL being developed by our Laboratory. To make use of Harmoware-VIS, we also created Synerex [4] provider that import person-flow data created in Section 4.2 and send it to Harmoware-VIS. In addition, we customized the size of moving agents (i.e. people in the area) to be suitable for people.

5 Experiment

In this experiment, we compared four proposed in-out estimation methods to find which method is the best for the sensor data. The target area in this experiment is Access Plaza in Chubu Centrair International Airport shown in Figure 9. This plaza is connected to the train station, bus stops, taxi zone, the hotel, two airline terminals, and the parking and has an area of about 120 meters by 70 meters. We use one hour of data clipped from one day of calibrated sensor data. Also, we compared the visualization results between in-out data and interpolated person-flow data in order to validate the effectiveness of interpolation.

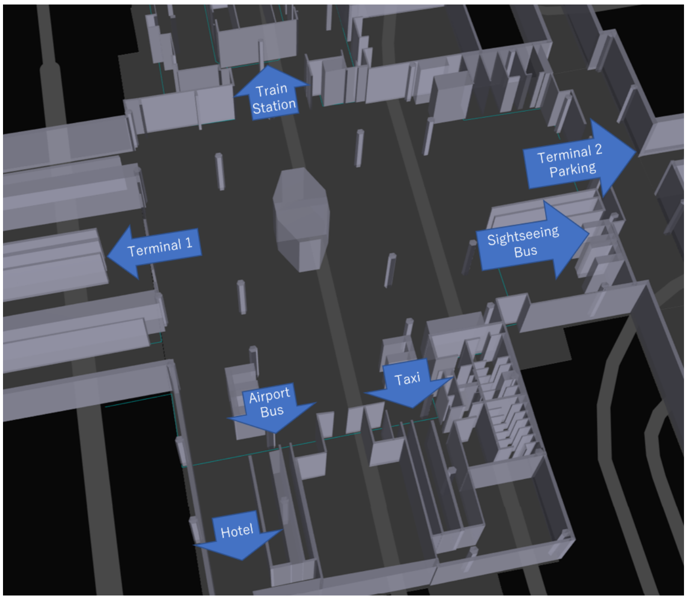

Fig. 9. Access Plaza in Chubu Centrair International Airport.

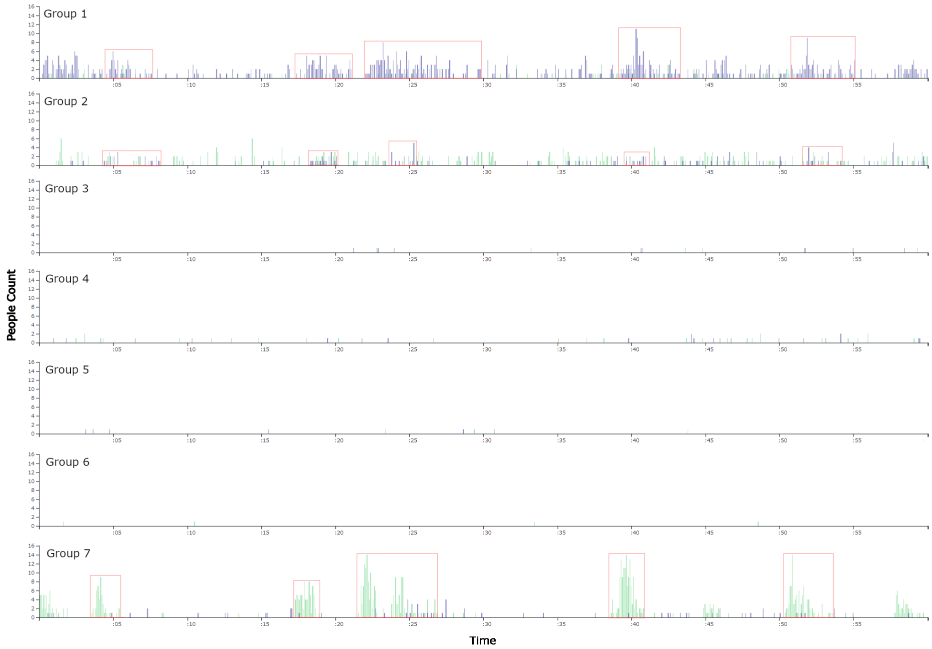

Fig. 10. The sensor data and estimation result by the method A.

5.1 In-Out Estimation in Open Space

In this experiment, we installed 20 people sensors in the target area and grouped them into 7 groups by directions.

The parameter for this experiment is described below. We set $d_{min(a \to b)}$, $d_{ave(a \to b)}, d_{max(a \to b)}$ using the distance between Sensor a to Sensor b (define as $dist_{a,b}$) as follows:

- $d_{min(a \to b)} = dist_{a,b}/5.5$ (five times faster than below.)
- $d_{ave(a \to b)} = dist_{a,b}/1.1$ (slightly slower than the average walking speed because there are obstacles in the real space.)
- $d_{max(a \to b)} = dist_{a,b}/0.55$ (two times slower than above.)

We also set $h_d = 5$, $v_d = 0.1$ and $fr_{a,b} = 1$ for all sensor pairs at first. (To confirm the effectiveness of fr, we change this parameter later and compare the estimation results.)

Method A: Using passing time and direction data Figure 10 shows the sensor data used in this method. In the figure, the exit count surrounded by red squares in Group 1 and 2 emerged after the entry count surrounded by red squares in Group 7 emerged. In addition, the exit count ratio between Group 1 and 2 is about 9:1. Therefore, we can estimate that 90% of people entered

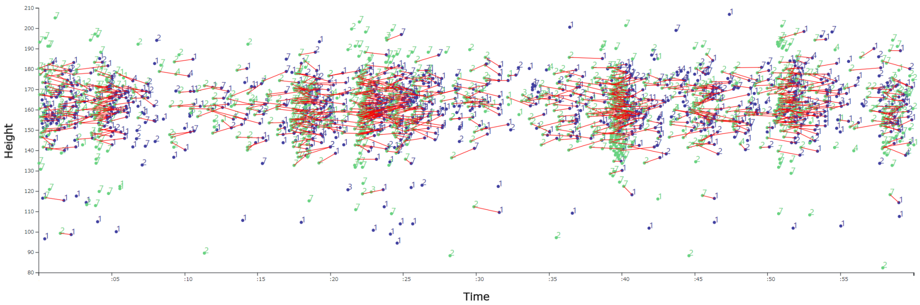

Fig. 11. The estimation result by the method B.

from Group 7 moved to Group 1 in about 30 seconds and 10% of them moved to Group 2 in about 60 seconds.

However, the data not surrounded by red squares have few changes in people count and it causes difficulty in estimation. For example, the data between :10 and :15 are mostly counted in Group 1 and 2, therefore we can estimate people entered from Group 2 moved to Group 1 but a duration to move between them can hardly be estimated. In addition, the data in Group 3-6 have too few people count for estimation.

Method B: Using passing time, direction and person height data Figure 11 shows the estimation result obtained from this method. In contrast to the previous result, we can estimate in-out data from the sensor data between :10 and :15. Furthermore, several data in Group 3-6 can also be converted to in-out data. In this method, we could convert about 78.6% of the sensor data to the estimated in-out data. The remaining sensor data seem to be derived from a sensor error or a person's behavior who stay in the area longer than we expected.

Method C: Using passing time, direction and walking speed data Figure 12 shows the estimation result obtained from this method. We expected that we can obtain similar results and conversion rates as the previous method because we use the same procedure with different sensor data. However, we could convert only 57.1% of the sensor data to the flow. This is because much data seem to be an error in the passing duration data. For example, several people walked faster than 10 m/s according to several sensor's data although common people cannot walk (run) at the speed. In addition, several person's walking speed was not be able to obtain from sensor data.

Method D: Using passing time, direction, person height and walking speed data In Figure 13 and 14, a radius of each entrance/leaving point represents the walking speed for the person.

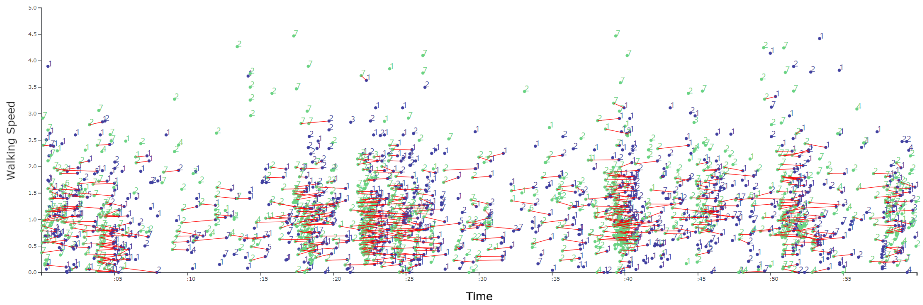

Fig. 12. The estimation result by the method C.

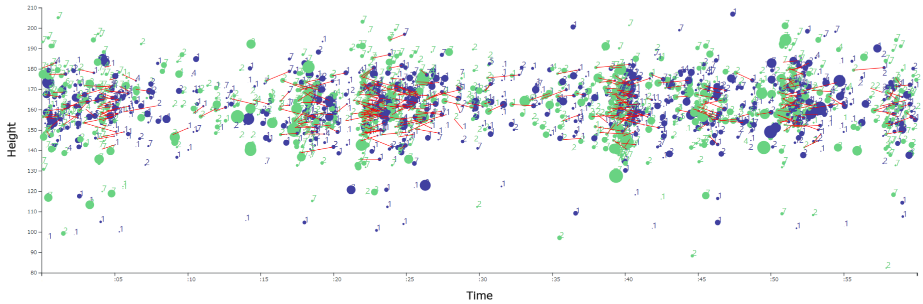

Fig. 13. The estimation result by the method D-1.

AND strategy (Method D-1) Figure 13 shows the estimation result obtained from this strategy. This strategy is the most strict one among other proposed methods, therefore we could only convert about 30.1% of the data. However, it seemed that 30% of people are more likely to move as estimated in-out data in real.

OR strategy (Method D-2) Figure 14 shows the estimation result obtained from this strategy. The conversion rate for this strategy is about 82.6%, therefore about 4% of the estimated in-out data is obtained from the previous method (using walking speed.) However, a height error for that flow is sometimes too big to consider the flow is occurred by the same person. Therefore, the estimation result of this strategy is a lack of reliability.

Introduction of Flow Reality Matrix As Described in Section 4.1, we introduced Flow Reality Matrix to reduce estimation miss. To confirm its effectiveness, here we set Flow Reality Matrix as follows:

– $fr_{a,a} = 0.25$ for all sensors (a flow between a same sensor)

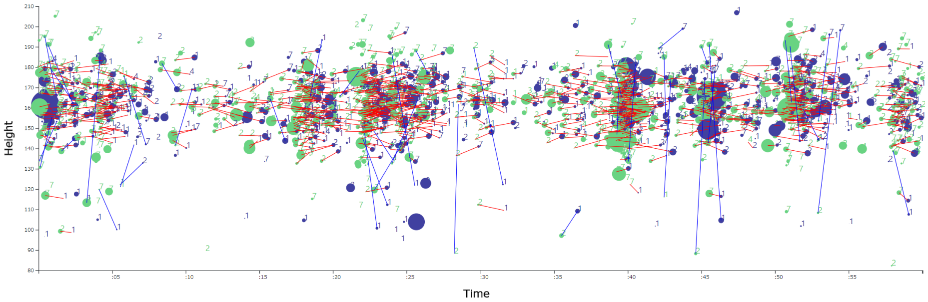

Fig. 14. The estimation result by the method D-2. (Blue lines in this figure represent person-flow estimated by walking speed.)

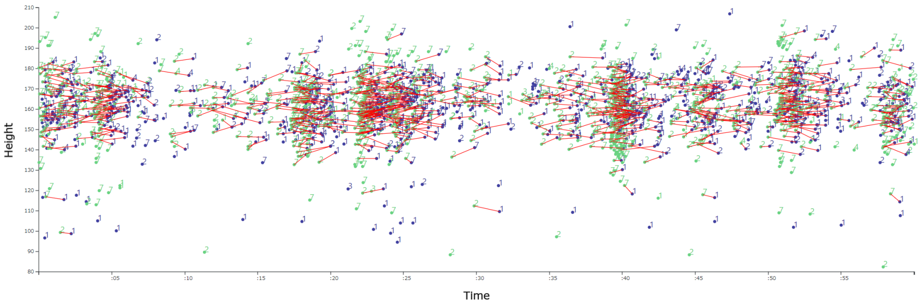

Fig. 15. The estimation result by the method using passing time, direction and person height with optimized Flow Reality Matrix.

- $fr_{a,b} = 0.5$ for a sensor pair in a same group (a flow between a same direction)
- $fr_{a,b} = 1$ for others

Using the parameter above, we conducted the estimation method using passing time, direction, and person height data. The estimation result of this is shown in Figure 15 and the comparison of In-Out table is shown in Table 2 and 3. It is said that several people who considered to enter and leave from the same Group if $fr_{a,b} = 1$ for all sensors were estimated to move between different Groups after the Flow Reality Matrix was changed. Therefore, the effectiveness of the Flow Reality Matrix is somewhat confirmed but we should check the validity of this by comparing it with the ground truth in-out data.

5.2 Interpolation and Visualization

We examined the effectiveness of interpolation by visualizing the interpolated result by Harmoware-VIS. Figure 16 shows frames clipped from the video of our

Table 2. The In-Out table from Figure 11.

In ＼ Out	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
Group 1	20	34	1	1	2		11
Group 2	257	8	2	1	1		20
Group 3	1	2					
Group 4	16	5					1
Group 5	2	1					
Group 6	2	1					
Group 7	339	74	4	14	3		14

Table 3. The In-Out table from Figure 15.

In ＼ Out	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7
Group 1	17	37	1	1	2		11
Group 2	259	6	2	1	1		20
Group 3	1	2					
Group 4	16	5					1
Group 5	2	1					
Group 6	2	1					
Group 7	341	74	4	14	3		11

previous visualization. The video frames start at the upper left and are arranged to the right, then go to the bottom left and end at the bottom right. Each green point represents people and the blue square is an obstacle. In this figure, one person is hit by the obstacle and several people hit each other. However, we cannot go through obstacles and not frequently hit other people in the real world.

In contrast to the above, Figure 17 shows frames of the visualization using interpolated data. People in this figure do not collide with obstacles and other people, therefore it is said that this visualization is more realistic than the previous one.

6 Conclusion

In this paper, we have proposed a method of person-flow estimation using multiple 3D People Counters. We have proposed four estimation methods to associate one's in-out data. Also, we have provided the interpolation and visualization method for the estimation result.

Using the second in-out estimation method, which uses passing time, direction, and person height data, we could have converted about 79% of the sensor data into people in-out data. Furthermore, Flow Reality Matrix could have reduced the in-out data that seems to be wrong to some extent.

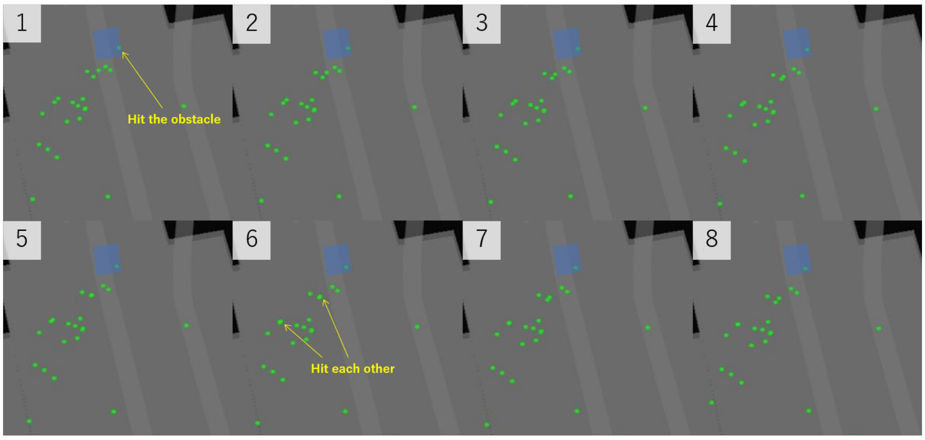

Fig. 16. The visualization result without interpolation by RVO2.

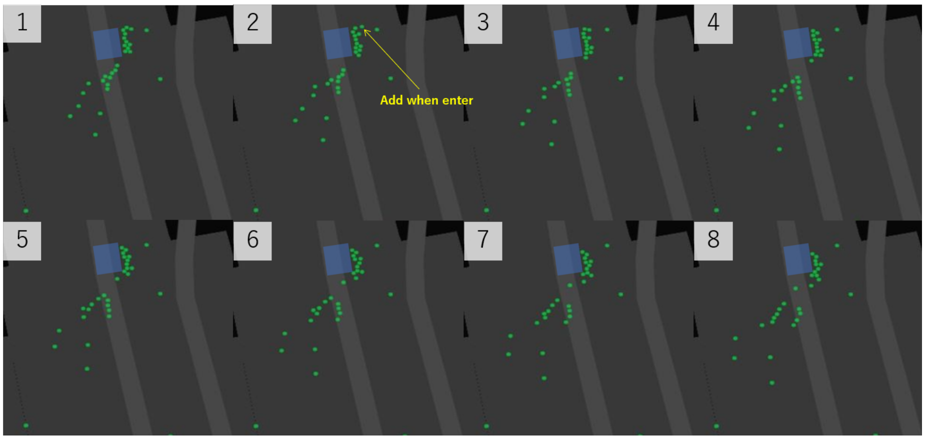

Fig. 17. The visualization result with interpolation by RVO2.

Also, we have customized the RVO2 Library to be able to add or remove agents as time goes by for interpolation. Finally, we have visualized the interpolated person-flow data by Harmoware-VIS.

However, it has been difficult to obtain accurate walking speed data, therefore it has been hardly possible to estimate person-flow accurately. In the future, we would like to examine a method of acquiring person-flow from walking speed.

In addition, we have been unable to evaluate the validity of the results of the person-flow estimation in this study because we were unable to prepare ground truth person-flow data. Also, we could not experiment in a very crowded situation due to COVID-19. In the future, we would like to evaluate the validity of the proposed method by collecting additional data and comparing it with data obtained by other methods such as a spherical camera.

As a future issue, we would like to estimate person-flow in more complicated places that have multiple areas and gates such as a shopping mall and an office. We think it can be done by connecting the results of in-out estimation data for all areas. Furthermore, we have already installed sensors in several contiguous areas and we are going to create the estimation system in such places.

Acknowledgement

This research is supported by the Commissioned Research of National Institute of Information and Communications Technology (NICT) and MIC SCOPE(No. 191506001).

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