Invited Paper

Analysis and Visualization of Large-Scale Pedestrian Flow in Normal and Disaster Situations

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Abstract

In recent years, many human-tracking techniques that use images, lasers, and RFID processing have been proposed for analyzing pedestrian trajectories. In normal situations, such research can be used in marketing support and information provision and safety management linked to pedestrian flow. In disaster situations, it can be used to aid the formulation of disaster response plans and evacuation guidance and to measure the state of damage. In this paper, we extract pedestrian flow using stereo cameras and propose a method for comparing and visualizing pedestrian flow measured over an extended period of time. We confirm the effectiveness of the proposed method from the results of an experiment in which we analyze pedestrian flow measured using a stereo camera over a long period of time at an office complex near Akihabara Station. Recently, people obtain a large amount of information via SNS (social networking service) and this information influences human behavior. Lastly, we clarify this influence by visualizing the flow of SNS information and pedestrians.

Key words: Human tracking, Analysis of pedestrian flow, Visualization, Stereo camera

1. Introduction

Typically, research on techniques of human tracking and trajectory extraction for analyzing pedestrian trajectories in a real environment has been performed in experimental environments. In recent years, however, this research has been performed in natural environments. These techniques are general purpose and can be used in various applications including for security at (railroad) crossings¹⁾²⁾ and airports³⁾⁴⁾, pedestrian-trajectory analysis in a shopping complex⁵⁾⁶⁾, employee management in manufacturing and service industries⁷⁾, detection of wandering patients in a nursing home for the elderly⁸⁾⁹⁾. Furthermore, in addition to these normal applications, in earthquake-prone Japan, the analysis of pedestrian flow can be applied for the purpose of measuring the state of damage and issuing evacuation guidance during earthquakes (Fig.1).

To analyze pedestrian trajectories, we installed four stereo cameras in a restaurant row which is located in the office complex “UDX” located beside the Akihabara station in Tokyo, Japan. Our system has been recording pedestrian trajectories during business hours since February of 2008 (see camera extracts in Fig.2 and schematic diagram of UDX in Fig.3). In this office

(a) Normal situations

(b) Disaster situations

Fig. 1 Use of flow lines in normal and disaster situations.

complex, office workers go down using the downward escalator, and general visitors go up using the upward escalator for lunch and dinner.

The technique proposed herein incorporates techniques to determine headcounts in a crowded environment, such as the use of cameras¹⁰⁾¹¹⁾, RFID tags¹²⁾, and lasers¹³⁾. However, these techniques can only be used

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Fig. 2 Extracted pedestrian trajectories. The upper left shows the entrance connected with Akihabara Station, the upper right shows the second-floor passage, the lower left shows the upward escalator on the third floor, and the lower right shows the downward escalator.

Fig. 3 Floor guide of UDX. The arrows show recording pedestrian trajectories.

to collect data over several hours or days, but cannot be used to analyze pedestrian-trajectory data collected over long periods of time, and in particular not on the timescale of a year. To acquire data over a year-long period, robust hardware and software is required, and methods are needed for efficiently representing pedestrian trajectories obtained from the large number of images collected every day. For the experiment performed in UDX, about 21,000 pedestrian trajectories were observed per day from four cameras. Our system is recording only the text files of three-dimensional head position, not image files from the viewpoint of privacy. The text files showing trajectories collected over a year are about 100G [Byte] in size.

In this paper, we introduce a novel framework in which to analyze pedestrian flow over a long period of time. This method consists of three main parts. The first part consists of a framework for extracting pedestrian trajectories that use fuzzy clustering. The next part efficiently represents pedestrian flow over a long period of time using mixture models (a set of similar trajectories will hereinafter be referred to as a flow).

Fig. 4 Ubiquitous Stereo Vision (USV) device. Three base lines (5, 10 and 18 [cm]) and two angles of field (71.5 and 96.6 [degree]) of a stereo camera are prepared depending on the various purposes.

The last part analyzes the pedestrian flow expressed by the mixture models so that our system can compare pedestrian flows between two different time periods or from two different places, and it visualizes the pedestrian flow over a long period of time¹⁵⁾. The efficiency of the proposed method is evaluated by analyzing and visualizing pedestrian flow from images obtained from over a one-year period from a real office complex. When the Great East Japan Earthquake hit Japan in 2011, Tokyo was affected by train stoppages and people were not able to return to their homes on the day of the earthquake. In this experiments, we analyze pedestrian flow in both normal situations and during the Great East Japan Earthquake.

In addition, due to the rapid spread of SNS, human behavior is now influenced by information circulating on SNS websites. During the Great East Japan Earthquake, information was diffused as people continuously posted messages informing others that the facility used in the study was accepting people who could not return to their homes and about the state of train operations. In the final section of the paper, we analyze SNS information and pedestrian flow, identify the relationship between these variables using visualization, and discuss future works.

2. Extraction of Pedestrian Flow

We introduce a method for extracting pedestrian trajectories from a disparity image that is obtained by a stereo camera using fuzzy clustering¹⁴⁾. Next, similar trajectories are grouped together into the pedestrian flow using a competitive learning.

2.1 Ubiquitous Stereo Vision

Our research group is developing hardware and software for a stereo camera called the “Ubiquitous Stereo Vision (USV)” camera, which can be used universally

Fig. 5 Input images obtained using the USV. In the disparity image, a bright pixel shows large disparity (close to the camera).

Fig. 6 Coordinate system. This system is calibrated to the $X - Z$ plane, which is parallel to the floor.

for people tracking, as shown in Fig.4. The USV camera can calculate a 640×480 disparity image that occupies 2 bytes/pixel at 15 FPS from the stereo image using the field-programmable gate array (FPGA) board. Because the FPGA board calculates the disparity image, 100% of the computer's CPU power can be spent on post processing. An example of (a) a texture image and (b) a disparity image obtained from the USV is shown in Fig.5.

Assuming the projection camera is a pinhole camera, the disparity image can be restored to points in the three dimensions $\mathbf{X}_{x,y} = (X_{xy}, Y_{xy}, Z_{xy})$ using the disparity d of pixel (x, y) . To simplify the calculations, the coordinate system $\mathbf{X}$ is calibrated to the $X - Z$ plane, which becomes parallel to the floor. Each disparity value is calculated by template-matching its corresponding local domain in the stereo images, because of which the disparity value contains a noise component with a matching miss. Thus, we consider that a proximity domain in a two-dimensional image is a proximity domain even after the restored three-dimensional image is created. Each surrounding length of $\mathbf{X}_{x,y}$, $\mathbf{X}_{x+1,y}$, and $\mathbf{X}_{x,y+1}$ is calculated. If the length is below a threshold value, the average of the coordinates is projected on the floor and the value is stored in object $\mathbf{x}_i = (X, Z)$, as shown in Fig.6. The $\times$ symbol means that the perimeter length is shorter than the threshold. Human regions in the image are constructed by using

Fig. 7 Flow of the tracking method. The k -means method is used for initial step clustering, and the c -means fuzzy method is used for final step clustering.

the $Y > 0$ pixels. Next, we explain the method for clustering objects $\mathbf{x}_i = (X, Z)$ for people tracking.

2.2 Two-stepped Fuzzy Clustering for Human Tracking

To solve a tracking problem, it is important to effectively use time-series information, which is done in the present research by introducing hierarchical predictions into two-stepped clustering. Furthermore, ambiguous division is possible also when two or more clusters adjoin by using fuzzy clustering, which extends the k -means method. Bezdek, who proposes fuzzy clustering¹⁶⁾, called the extended method of the k -means method the c -means method. In this paper, fuzzy clustering is called the c -means method and the k -means method is distinguished as a method without fuzzy character. Although various techniques, such as kernel method¹⁷⁾, etc.¹⁸⁾, are proposed regarding fuzzy clustering, the valuation function becomes complicated. In this paper, the simple c -means method is used to reduce computational complexity.

This method for clustering human regions in the images follows a two-stepped clustering approach. First, according to the initial clustering algorithm, middle clusters $\mathbf{w}_j$ ($j = 1, 2, \dots, N$) consist of objects $\mathbf{x}_i$ ($i = 1, 2, \dots, M$). Next, human regions $\mathbf{v}_k$ ($k = 1, 2, \dots, C$) are extracted from middle clusters by using the final clustering algorithm. The flow of this two-stepped approach is shown in Fig.7. The results of clustering are used as the initial value for processing the next image. Furthermore, the cluster velocity calculated by the final clustering is used as the initial value for the initial clustering process of the next image. We explain the two-stepped clustering approach in detail below.

(1) Initial Step Clustering

Initial clustering forms middle clusters using each ob-

ject $\mathbf{x}_i$. The k -means method is used for initial clustering instead of the c -means method (fuzzy clustering)¹⁶⁾ because, if the number of objects increases, the computational complexity of the c -means method also increases. The initial clustering algorithm is as follows:

[STEP1–1]: Each object $\mathbf{x}_i$ belongs to the nearest cluster $\mathbf{w}_j$ which is created from the previous image. If there is no cluster within the threshold distance Th_k , a new cluster $\mathbf{w}_{N+1}$ is created.

[STEP1–2]: The center of gravity of each cluster is calculated. A cluster that does not contain an object is deleted.

[STEP1–3]: STEP2–1 of the final clustering algorithm is executed.

The use of the k -means method may lead to a minimization problem of the valuation function

$$J_k = \sum_{i=1}^M \sum_{j=1}^N (u_{ij}) \|\mathbf{x}_i - \mathbf{w}_j\|^2, \quad (1)$$

where u_{ij} is the function that assigns each object $\mathbf{x}_i$ ($i = 1, 2, \dots, M$) to the nearest cluster $\mathbf{w}_j$ ($j = 1, 2, \dots, N$). The function u_{ij} is

$$u_{ij} \in \{0, 1\}. \quad (2)$$

(2) Final Step Clustering

The final clustering algorithm is used to extract human regions $\mathbf{v}_k$ from middle clusters $\mathbf{w}_j$. The algorithm uses the c -means method, which can resolve ambiguous expressions. A particular person can be accurately tracked, even if he or she is approached by another person, by using an ambiguous expression. Fuzzy clustering is a minimization problem of the equation

$$J_c = \sum_{j=1}^N \sum_{k=1}^C (u_{jk})^m \|\mathbf{w}_j - \mathbf{v}_k\|^2, \quad (3)$$

which means that equation (1) is more general compared with equation (3). Furthermore, to convert this valuation function to a fuzzy function, u_{ij} in equation (2) is extended to a membership function as follows:

$$u_{jk} \in [0, 1]. \quad (4)$$

If m approaches 1, it indicates a near-correct determination assumption. Moreover, the fuzzy capability will be enhanced if m is high, $m = 2$ is suitable and is used in the present work. The final clustering algorithm is as follows:

[STEP2–1]: When the distance between each middle cluster $\mathbf{w}_j$ and the last cluster $\mathbf{v}_k$ created from the previous frame, is less than the threshold Th_c , $u_{jk}^{(t)}$

Fig. 8 Typical pedestrian trajectories extracted from images. Escalator and an entrance become start/end points.

of the t -th frame is calculated by

$$u_{jk}^{(t)} = \left[\sum_{l=1}^C \left(\frac{\|\mathbf{w}_j - \mathbf{v}_k^{(t-1)}\|^2}{\|\mathbf{w}_j - \mathbf{v}_l^{(t-1)}\|^2} \right)^{\frac{1}{m-1}} \right]^{-1}. \quad (5)$$

However, the following equation defines u_{jk} of the middle cluster, which has the same centroid as the last cluster:

$$u_{jk}^{(t)} = \begin{cases} 1, & \|\mathbf{w}_j - \mathbf{v}_k^{(t-1)}\|^2 = 0 \\ 0, & \|\mathbf{w}_j - \mathbf{v}_k^{(t-1)}\|^2 \neq 0 \end{cases}. \quad (6)$$

A new cluster $\mathbf{v}_{C+1}$ is created if there is no cluster within the threshold distance Th_c .

[STEP2–2]: The centroid of each cluster is calculated by using equation (7). If a cluster contains fewer elements than the threshold value, the cluster is deleted.

$$\mathbf{v}_k^{(t)} = \frac{\sum_{j=1}^M (u_{jk}^{(t)})^m \mathbf{w}_j}{\sum_{j=1}^M (u_{jk}^{(t)})^m}. \quad (7)$$

[STEP2–3]: The next frame image is acquired for processing and the control returns to STEP1–1 of the initial clustering algorithm. However, the velocity $\Delta \mathbf{v}_k = \mathbf{v}_k^{(t)} - \mathbf{v}_k^{(t-1)}$ is calculated and each initial cluster belonging to $\mathbf{v}_k$ is updated by adding it to $\mathbf{w}_j$.

Because sequential information can be used effectively in clustering, the calculated velocity of a cluster is used as the prediction value for the next cluster. In addition, because fuzzy clustering permits ambiguous clusters, each cluster is deleted when the number of elements in it is either 0 or less than the threshold value.

Fig. 9 Example of flow amount. In panel (a), the blue lines show the number of movements from 2F to 3F. The red lines show the number of movements from 3F to 2F. In panel (b), the blue lines show the number of movements from 4F to 2F. The red lines show the number of movements from 2F to 4F.

2.3 Clustering for Pedestrian Flow

The start point and the end point of the resulting human trajectory $\mathbf{v}_k^{(t)}$ are selected as the basis for clustering features. These features are clustered using the Learning Vector Quantization (LVQ) algorithm¹⁹⁾ which is a basic competitive learning networks. Fig.8 shows an example of the clustering results. These extracted trajectories can be expressed as “up from 2F to 3F,” “down from 4F to 2F,” and so on by defining each cluster as “2nd floor (2F)” and “3rd floor (3F)”. In this paper, these expressions are referred to as pedestrian flow.

Fig.9 shows a specific pedestrian flow observed during work days of a particular month. The horizontal axis represents time, and the vertical axis represents the headcount for the given flow. In this paper, we refer hereinafter to the difference in the daily headcount of the specific flow as the “flow amount,” as given by the function $p(x)$, where x denotes time.

3. Mixture Model of the Flow Amount

3.1 Estimation of Mixture Distribution Parameter

In general, people have lunch at noon, and dinner in the evening. When pedestrians move according to the time of day, the pedestrian flow is expressed using the normal-mixture distribution of the following equation, as shown in Fig.10:

$$p(x; \theta) = \sum_{i=1}^M \pi_i N(x; \mu_i, \sigma_i^2), \quad (8)$$

$$N(x; \mu_i, \sigma_i^2) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp \left\{ -\frac{(x - \mu_i)^2}{2\sigma_i^2} \right\}, \quad (9)$$

where θ denotes the mixture distribution parameter and is obtained from a particular mixture proportion π_i , mean μ_i , and variance σ_i^2 of the probability density

Fig. 10 Mixture model expression for the flow amount. There are $M = 8$ mixture distributions for (a), and $M = 7$ for (b).

function. It is easy to estimate θ from the given model number M and sample x_j ($j = 1, \dots, N$) using the maximum-likelihood estimation. Thus, θ is estimated using the expectation-maximization algorithm (EM algorithm) that uses an iterative method for calculation. The iterative method of the EM algorithm, which uses the normal mixture distribution, is explained below.

• Expectation step:

The probability that sample x_j belongs to the k -th mixture distribution is given by

$$w_{kj}^{(t)} = \frac{\pi_k^{(t)} N(x_j; \mu_k^{(t)}, \sigma_k^{2(t)})}{\sum_{i=1}^M \pi_i^{(t)} N(x_j; \mu_i^{(t)}, \sigma_i^{2(t)})}. \quad (10)$$

• Maximization step:

The mixture distribution parameter is updated in the following equation:

$$\pi_k^{(t+1)} = \frac{1}{N} \sum_{j=1}^N w_{kj}^{(t)}, \quad (11)$$

$$\mu_k^{(t+1)} = \frac{1}{N \pi_k^{(t+1)}} \sum_{j=1}^N w_{kj}^{(t)} x_j, \quad (12)$$

$$\sigma_k^{2(t+1)} = \frac{1}{N \pi_k^{(t+1)}} \sum_{j=1}^N w_{kj}^{(t)} x_j^2 - \mu_k^{(t+1)^2}. \quad (13)$$

This method facilitates efficient compression of the flow amount data and can also be used to analyze the flow amount. The analysis done to compare and visualize over a long period of time is explained in detail in Section 4.

3.2 Estimation of Number of Mixtures

When the number M of mixture components is large, it is possible to approximate the flow amount with high precision, but it becomes difficult to interpret the significance of the distribution. Thus, M is determined according to an Akaike's information criterion (AIC)²⁰⁾. The AIC is a measure of the goodness of fit of an estimated statistical model, and is given as

$$AIC = 2k - 2 \ln(L), \quad (14)$$

where k is the number of parameters in the statistical model and L is the maximized value of the likelihood function for the estimated model.

In general, the model becomes complex and although the log likelihood can be increased by increasing the number of free parameters, M need not be increased. The AIC is a measure of these trade-offs. The AIC value is small when there is a favorable trade-off between the complexity and the error margin of the model. In this paper, we select the minimum AIC model to express the flow amount. There are three free parameters — π_i , μ_i , σ_i — per distribution in this problem, however, it is necessary to restrict π_i to satisfy the condition $\pi_1 + \pi_2 + \dots + \pi_M = 1$, in the framework of AIC that is characterized by the following equation:

$$AIC = -2\{L(x; \theta) - (3M - 1)\}. \quad (15)$$

The number M of mixture distributions of the mixture component with the smallest AIC is selected.

Fig.10 shows an example of the expression of the flow amount for different mixture distributions created using the proposed method. In both figures, the solid line denotes the observed flow amount, and the short dashed line denotes the estimated result obtained using the proposed method. The two results agree well with each other.

4. Analysis and Visualization of Pedestrian Flow

It is important for a facilities manager to be aware of the comparative results of the flow amount in an office complex to measure the effect of an advertisement, an event, etc. Moreover, when a facilities manager wants to know the change in the flow amount over a long period of time, it is important to present results that are easy to understand. In this section the method of comparing and visualizing the flow amount is clarified.

4.1 Comparison of Pedestrian Flow

Because the degree of similarity is very high between the different flow amounts collected over the long term as shown Fig.9, it can be assumed that only minor change occurs in the daily flow amount. Moreover, because a large amount of data is acquired every day, an approximate statistical analysis method is required, as opposed to a detailed analysis. We also assume that the mixture component number does not change for the observed flow amount.

The method of comparing two flow amounts such as the flow amount $p_a(x)$ over a period A and the flow amount $p_b(x)$ over a period B, is described here. First, the number of mixtures M_{ab} and θ_{ab} are calculated about $p_{ab}(x) = \{p_a(x) + p_b(x)\}/2$ using the method described in Section 3. Next, using the EM algorithm described in Section 3.1, θ_a of period A and θ_b of period B are calculated using the number of mixtures M_{ab} and the initial value of θ_{ab} .

After estimating the mixed distribution parameter over periods A and B with the method just described, we can determine whether the time for every distribution is early or late by comparing the obtained μ_i values and whether the number for every distribution increased or decreased by comparing the π_i and σ_i values.

4.2 Visualization of Pedestrian Flow

The visualization of the flow amount for a long period of time, such as n days $\{p_1(x), p_2(x), \dots, p_n(x)\}$, is described here. First, the mixture numbers $\hat{M}$ and $\hat{\theta}$ are calculated about $\hat{p}(x) = \frac{1}{n} \sum_{i=1}^n p_i(x)$ with the proposed method. Next, using the EM algorithm, θ_i of $p_i(x)$ ($i = 1, \dots, n$) is calculated from the number of mixtures $\hat{M}$ and the initial value $\hat{\theta}$.

After estimating the mixing parameter over the period $1 \sim n$, we determine whether the time for every distribution is early or late by arranging μ_i ($i = 1, \dots, n$) and whether the number of every distribution increases or decreases by arranging π_i and σ_i ($i = 1, \dots, n$).

5. Experimental Results in Normal Situations

We measured the pedestrian flow in an office complex using the proposed method, then compared the pedestrian flow amount between two different periods or at two different places. Moreover, the pedestrian flow amount over a long period of time is represented. In this experiment, x of $p(x)$ takes on discrete values at intervals of 15 min. The processing time was from 10:00 to 23:00 (business hours). Moreover, M ranged from 1 to 20, and was chosen on the basis of the minimum AIC.

5.1 Evaluation of Extracted Pedestrian Flow

To evaluate the flow amount extracted using the proposed tracking method, the flow amount is compared with a headcount accomplished by manually viewing the collected data. If the threshold Th_L , which determines whether to project a three-dimensional point on a floor, is small, the region extracted as a person becomes small. On the contrary, when Th_L becomes large, many mistaken corresponding points are included. Next, we

Table 1 Comparison of automatic headcount and manual headcount.

From To	12:00 12:15	12:15 12:30	12:30 12:45	12:45 13:00	error (%)
2F→3F True	66 (65)	120 (123)	45 (45)	49 (54)	2.06
2F→4F True	67 (66)	149 (144)	262 (242)	326 (312)	3.26
3F→4F True	36 (31)	56 (54)	89 (85)	93 (90)	2.83

set $Th_L = 20\sqrt{10} \simeq 63$ [mm], so that the human region might be correctly extracted. As the conditions for making a new cluster, we adopted $Th_c = 20\sqrt{720} \simeq 537$ [mm] and $Th_k = 20\sqrt{150} \simeq 245$ [mm], for which good experimental results were obtained.

Because the maximum number of people were in the passage during lunchtime, a headcount of the people in the passage was taken every 15 min during lunchtime (12:00 ~ 13:00). The results are shown in Table 1. 2F→3F represents the number of people that go from 2F to 3F. The upper value in the table cell represents the headcount determined by the USV, and the lower value in parenthesis represents the actual headcount performed manually. These results show that the average measurement error is about 3%, and a high rate of extraction has been achieved by the proposed method. In addition, the root mean square error (RMSE) between the real position and the estimated position is 8.93 [cm].

A computer with an Intel Pentium M 1.6G [Hz] CPU and a 1G [Byte] memory was used for these calculations. Because a projection calculation to a floor plane takes 30 [msec], and a clustering calculation takes about 3 [msec] per frame, the proposed technique is quite fast.

5.2 Experiment Comparing Pedestrian Flow

Next, we compare the trajectories collected over a long period using the proposed method. The results of the comparison are shown in Fig.11. Each set of readings has two graphs which express flow amounts over two different period or at two different place. In addition, tables in Fig.11 show how the numbers change or the time change for every distribution. The item with no description gives the movement from 2F to 3F.

Fig.11 (a) compare the flow amount for Monday and Friday over the same time period (March 1–31, 2009). We find that the number of people on Friday is higher than that for Monday in all time zones, and there is a significant increase in the flow amount after dinner. The peak observed on Friday nights is about 30 minutes later than on Monday nights. Fig.11 (b) shows the

flow amount during an event held on October 25 (Saturday) 2008 and on a holiday in October 2008 when no event occurred. The results show that, although the event does not influence the night-time increase in the headcount, it causes an increase in the headcount during the daytime. Fig.11 (c) shows the flow amount during an event held on October 4 (Sunday) 2009 and on Sunday in October 2009 when no event occurred. We find the event does not influence increase the flow amount. Moreover, we installed the guidance signboard of restaurant row in front of the Gallery on the fourth floor. Fig.11 (d) shows the increase of flow amount from comparing before and after installation.

Figs. 11 (e) and (f) compare the flow amount during shiny versus rainy weekdays and shiny versus rainy holidays, respectively. When it rains on weekdays, the flow amount increases, and when it rains on a holiday, the flow amount decreases. The reason for this is that many general visitors use the office complex on holidays, and there are many office workers on weekday. Also, office workers choose this restaurant row because they do not need an umbrella. In addition, rain has a greater influence on the flow amount during the day than the night, and when it rains, it is clear that there occurs a delay. Fig.11 (g) shows the flow amount for weekdays and holidays for the period of October 1 to November 30, 2008. On holidays, there is a high flow amount and the peak time is later compared to weekday. Because this office complex is near Akihabara, which is known as “Electric Town” and has offices on the upper floors, we attribute these results to the fact that there are many general visitors on holidays and many office workers on weekdays in the office complex. Fig.11 (h) shows the flow amount between 4F to 2F for March 3, 2009. Because this office complex has offices above the fourth floor, it is possible that these results reflect the traffic of office workers going from the office to the restaurant and then returning to their office. These graphs also provide evidence that lunchtime lasts about 30 to 40 min.

5.3 Visualization Experiment

The pedestrian flow amount over a long period of time was represented using the proposed method, and the processing time was business hours for this experiment.

Fig.12 (a) shows a result for Sunday and Fig.12 (b) shows a result for Tuesday. Movement from 2F to 3F means that a visitor went into the restaurant. The flow amount on Sunday contains two distributions; lunch (at

Dist.	1	2	3	4	5	6
Num.	+10	+107	+10	+57	+411	+22
Time	+5	-4	-13	-2	+25	+35

(a) Monday (left) and Friday (right) on 2009/3/1-31

Dist.	1	2	3	4	5	6
Num.	+121	+186	+46	-24	+57	± 0
Time	+18	+22	+33	+14	+3	+12

(b) Holiday on 2008/10/1-23 (left) and 10/25 (right)

Dist.	1	2
Num.	-76	+18
Time	+4	-2

(c) Sunday on 2009/10/5-31 (left) and 10/4 (right)

Dist.	1	2	3	4	5	6	7	8
Num.	-7	+81	+217	+19	+24	+17	-13	-32
Time	+39	-12	-35	+0	-2	-2	+12	-13

(d) Down from 4F to 3F on before(2009/9/17) and after(2009/9/30) guidance signboard installation

Dist.	1	2	3	4	5	6
Num.	-7	+161	-5	-3	+73	+24
Time	+3	+7	+13	+23	-1	+9

(e) Shiny day (left) and rainy day (right) on working day of 2009/3/1-31

Dist.	1	2	3	4	5	6	7
Num.	+12	-274	-144	-69	-97	-30	-12
Time	+6	+12	-3	+2	+7	+7	+2

(f) Shiny day (right) and rainy day (left) on holiday of 2009/3/1-31

Dist.	1	2	3	4	5	6
Num.	+56	+139	+132	+175	+76	-8
Time	+78	+30	+38	+24	-7	-5

(g) Working day (left) and holiday (right) on 2008/10/1-11/30

Dist.	1	2	3	4	5	6	7
Num.	+36	+169	+18	-7	-80	-227	-23
Time	+8	+30	+40	+21	-30	-22	+3

(h) Down from 4F to 2F (left) and up from 2F to 4F (right) on 2009/3/3

Fig. 11 Comparison of different flow amounts. Gaussians from which the flow amount is composed are mixture distributions. Tables show the change in the number of people and relative time. “Dist.” means the distribution number. “Num.” shows the difference between the number of pedestrians from the right period and the left period, and “Time” shows the time difference in minutes.

13:21) and dinner (at 18:28), as shown in Fig.13 (a). Because the two distributions are strongly correlated, we deduce that the density of people is influenced by the weather and the events of the day. On a typical Sunday,

the office complex is more crowded during lunchtime than during dinnertime, but it is also crowded during dinner on Sundays before a public holiday (Happy Monday). In particular, it is crowded during the vacations

(a) Visualization of movement from 2F to 3F on Sunday

(b) Visualization of movement from 2F to 3F on Tuesday

Fig. 12 Visualization of the flow amount in the office complex over a long period of time.

called Golden Week (GW), Silver Week (SW), the middle of the summer vacation (BON) and at the end of the year. Furthermore, it is clear that the office complex is highly congested every year at the end of March and in early June. In addition, we believe that correlations between public events and the flow amount can also be clarified by investigating the dates of nearby public events.

On February 3, 2008, there were few visitors because of snowy. Rain and snow on a holiday decrease the number of visitors. In addition, a multiple homicide occurred in the pedestrian area in front of the Akihabara station on June 8, 2008, resulting in seven deaths, and this event shocked the nation. Following this incident, the pedestrian density decreased sharply, then slowly recovered over a two-month period. Moreover, it is clear that the recovery of normal traffic for the evening period took even longer than it did for the daytime period. By visualizing the pedestrian flow on weekdays, we also find that this incident had a larger influence on weekdays than on Saturday.

Fig.13 shows the mixture expression from 2F to 3F for Sundays and Tuesdays. We find that Tuesday has eight distributions, and we see from Fig.13 (b) that, on Tuesdays, it is crowded at lunchtime (12:19, 13:39) and

(a) Movement from 2F to 3F on Sunday

(b) Movement from 2F to 3F on Tuesday

Fig. 13 Mixture expression on Sunday and Tuesday. The underlying Gaussians are the mixture distributions.

at dinnertime (18:22, 19:43). If events on the crowded lunchtime (March 11, August 5, 2008; July 7, November 17, 2009), the crowded dinner time (March 18, June 10,

2008; February 10, April 28, August 4, 2009), and the crowded both time (May 27, December 2, 2008; August 25, 2009; January 26, 2010) are investigated, it could be possible to understand the ways to increase the flow amount and effective events.

6. Experimental Results during Disasters

6.1 The Great East Japan Earthquake

At 14:46 on March 11, 2011, a large earthquake of magnitude 9.0 struck off the northeast coast of Japan. This large-scale earthquake, known as the Great East Japan Earthquake, measured intensity 7 (on the 7-point Japanese scale) in Kurihara, Miyagi Prefecture and lower and upper 6 across a wide area from Tohoku to north Kanto. Furthermore, major tsunami warnings were issued over a wide area from the Pacific coast of Hokkaido to coast of Ibaraki. Rising above 20 meters, the giant tsunami caused enormous damage along the Pacific coast of Tohoku.

The earthquake was also felt in Tokyo, measuring upper 5 around Akihabara station. The earthquake triggered a wave of train stoppages and traffic congestion, paralyzing the transportation network. According to a newspaper article published on April 9, approximately three million people, unable to return to their homes, slept in evacuation centers and stations throughout the region.

6.2 Comparison of Pedestrian Flow before and after the Earthquake

Fig.14 shows the results of the comparison between the average pedestrian flow during the one-month period before the earthquake and pedestrian flow after the earthquake. The graphs on the upper left in (a) to (f) express the flow amount on certain days of week during the month before the earthquake and the graphs on the upper right express the flow amount on the day of the earthquake (and the following two days).

Fig.14 (a) shows the results of the comparison between the flow amounts up from 2F to 4F. Under normal circumstances, a flow line of people moving from the restaurants on the second floor to the offices on the top floor can be observed. Usually, an elevation of flow amount occur around lunch time; however, hardly any occur in the evening. These flow line levels appear to consist of seven distributions. Since the first three distributions occur before the time of the earthquake, there are no significant differences in the number of people or timing before and after the earthquake. However,

on the day of the earthquake, the number of people at the fourth distribution at 15:43 is zero. This result shows that no people moved up to the fourth floor after the earthquake struck (at 14:46). On the other hand, in the last two distributions at 19:26 and 21:01, increases of 153 and 387 people can be observed. An irregular movement of people occurred because the facility provided a place to stay for people who could not return to their homes on the day of the earthquake.

Fig.14 (b) shows the movement line up from 2F to 3F and expresses the flow of pedestrians visiting the facility from outside to eat. Since the characteristics of the flow line levels differ significantly before and after the earthquake, it is difficult to compare them using the method presented in this paper; however, as with (a), on the day of the earthquake the number of people at around 4 pm was close to zero and increased dramatically at around 6 pm. Due to the influence of train stoppages, the final distribution occurred almost one and a half hours (84 minutes) later than usual.

The flow line down from 3F to 2F shown in Fig.14 (c) expresses the movement of people leaving the facility after eating. On the day of the earthquake, the third distribution occurred immediately after the earthquake at 14:49, 43 minutes later than the usual time of 14:06. Generally, high-rise buildings are structurally robust, so during the earthquake, there were broadcasts advising that it was safer to stay inside the building than to go outside; however, people could be seen to panic and make their way outside. Furthermore, in both (a) and (b), the number of flow lines immediately after the earthquake at around 4 pm was zero. Under normal circumstances, the number of flow lines increases when shops close at around 11 pm; however, on the day of the earthquake, many people decided to return home earlier. On the day of the earthquake, Japan Railway trains were suspended until the end of the day; however, a subway line with a station near Akihabara resumed operations at 20:43, enabling people to return home early. Subsequently, other subway lines gradually began to resume operations, and at 23:32, train services resumed on the Tokyo Metro Hibiya line, which has a station at Akihabara. Information about these train stoppages was shared via broadcasts throughout the office complex.

Fig.14 (d) shows the results of the comparison of the number of flow lines up from F2 to F3 on Saturdays before the earthquake and the day after the earthquake (March 12, Saturday). These flow lines represent the

Fig. 14 Comparison between the number of flow lines before and after the earthquake.

movement of people from outside the facility to the restaurant area. The Saturday data consists of two distributions, one in the morning and one in the afternoon. Due to the influence of the earthquake, the morning and afternoon distributions fell by 863 and 907 people, respectively. Furthermore, according to Fig.14 (e), the influence on the number of people on the Sunday two days after the earthquake was smaller than that on the Saturday; however, there were still fewer people than usual.

Until when did the decrease in pedestrian flow due to the influence of the earthquake continue? To confirm this, we compared the data from the long Golden Week holidays before the earthquake, in May 2010, with that from the Golden Week holidays after the earthquake, in May 2011. The results are shown in Fig.14 (f). A com-

parison of the data for May 3 to May 5, 2010, and May 3 to 5, 2011, reveals that, two months after the earthquake, pedestrian flow had increased over and above the level for the previous year. Although a straight-forward comparison is not possible due to factors such as weather and urban development in the surrounding area, after falling sharply immediately after the earthquake, the flow of pedestrians recovered with time.

6.3 Visualization of Pedestrian Flow before and after the Earthquake

Next, we used the proposed method to visualize pedestrian flow on Fridays, Saturdays, and Sundays during the period from January 4, 2011 to April 30, 2011, including the day of the earthquake and the following two days. The results are shown in Fig.15. The graphs show the data for Fridays, Saturdays, and Sun-

(a) Visualization of Friday data

(b) Visualization of Saturday data

(c) Visualization of Sunday data

Fig. 15 Long-term visualization for the four-month period in which the earthquake occurred.

days from top to bottom. The Friday data consists of three distributions. The two days on which many people visited the office complex, February 11 and April 29, were national holidays. On these national holidays, the number of people at 14:55 was higher than usual. On the day of the earthquake (March 11), the 19:33 distribution increases due to the increase in the number of people who could not return to their homes due to train stoppages. On March 18 the following week, although the daytime flow line remains unchanged, there is an extremely low number of pedestrians around dinner time. The level of pedestrian flow rapidly returned to normal from April. Furthermore, from April, the number of people on Saturdays (b) and Sundays (c), which had fallen sharply immediately after the earthquake, rapidly returned to normal.

7. Information Flow in Virtual Space and Pedestrians Flow in Real Space

In modern society, the flow of information via SNS and other online methods is closely linked to the flow

Fig. 16 Number of twitter posts including the keyword “UDX” on the day of the earthquake. **Fig. 17** Number of twitter posts including the keyword “JR” and keywords related to the subway on the day of the earthquake.

of pedestrians in real space. On the day of the earthquake, the office complex in Akihabara opened its doors to people who could not return to their homes, and as a result, information to that effect was diffused via Twitter as a wave of messages were posted on SNS websites. These included posts such as, “The UDX office lobby is a good option for people in Akihabara who can’t get home. It’s warm and there’s a convenience store and a coffee shop. They have security guards here too so it’s safe,” and “It’s true that UDX has opened its doors. It’s warm and there are toilets as well.”

The number of posts on Twitter containing the name of the facility on the day of the earthquake is shown in Fig.16. The blue line shows the number of tweets, the green line the number of retweets, and the red line the total of the two. Furthermore, in order to return home, people required information about the train conditions. Fig.17 (a) and (b) show the change in the number of posts on Twitter containing the keyword “JR (Japan Railway)” (a) and keywords related to the subway (b). These information flow patterns display similar characteristics to the patterns of pedestrian flow. Since people decided to come to or return home from the facility on the basis of this information, the flow of information is closely linked to the flow of pedestrians.

On March 26, 2010, a symbolic incident that served to highlight the close relationship between the flow of information and the flow of pedestrians occurred around Takeshita Street in Harajuku. At around 16:20, someone released information that a certain artist would per-

Fig. 18 Crowds of people flocking to Takeshita Street (<http://twitpic.com/1az6wc>).

form a surprise concert on Takeshita Street. This information was diffused via SNS websites such as Twitter. Although the information was a false rumor, people believed it and crowded into Takeshita Street, resulting in the situation shown in Fig.18 and prompting the dispatch of helicopters and ambulances. To avoid such incidents in the future, it is important to conduct research focusing on how information and pedestrian flow are transmitted.

Now we are recording not only pedestrian flow in Akihabara but also tweets containing the keyword “Akihabara”²¹⁾. Fig.19 (a) shows the number of passers-by at office complex in March, 2014. The x -axis shows the day of the month and the y -axis shows the number of people. The graph reveals that, on March 8 and 16, 2014, the days on which Akihabara experienced high activity on twitter, and more people passed the measurement location in Akihabara. In particular, the event that generated increased twitter activity on March 16 was held right at the office complex in which pedestrian flow was being measured.

In order to view the correlation between pedestrian flow at the office complex UDX and the number of tweets containing the keyword “Akihabara”, the total number of tweets containing the keyword “Akihabara” posted during the period of time in which pedestrian flow was measured (9:00–23:00) is presented for each day of the month in Fig.19 (b). We identified the

(a) Number of people in Akihabara UDX

(b) Number of tweets containing the keyword “Akihabara”

Fig. 19 Number of people in Akihabara and number of tweets containing the keyword “Akihabara”.

Fig. 20 Correlation diagram between the number of people and the number of tweets.

five days in March with the highest number of people and the five days with the most tweets containing the keyword “Akihabara” and found that the four days of March 8, 16, 21, and 29 were included in both of the above, revealing that a high number of pedestrians passed through the Akihabara facility on the days in which Akihabara was experiencing high activity on Twitter. Furthermore, the results of correlation analysis of the number of tweets containing the keyword “Akihabara” and the level of pedestrian flow are shown in Fig.20. On this graph, a linear approximation function is drawn, with the x -axis showing the number of tweets and the y -axis showing the level of pedestrian flow. The correlation coefficient for the two variables was 0.7313, indicating a strong correlation.

Thus, by analyzing not only the movement of data in virtual space but also the movement of people in real space, it is thought that more useful results about the

diffusion of information can be obtained; however, detailed analysis of this relationship will be left for future research. For example, it should be possible to prevent the spread of false rumors by constructing a model that describes how information in virtual space influences pedestrian flow in real space.

8. Conclusion

In this paper, we propose a human tracking method that uses fuzzy clustering and a method for comparing and visualizing the pedestrian flow over a long period of time that uses the EM algorithm and the AIC. The proposed method also significantly compresses the data load generated by observing the flow amount by expressing the change in the flow amount with mixture distributions. Efficiency of the proposed method was evaluated by analyzing the pedestrian flow observed in an office complex near Akihabara station for more than a year. The proposed method generates useful information for managers, such as an information regarding the effect on pedestrian traffic of a public event, and the relationship between weather and pedestrian density. Using a method for comparing pedestrian flow during the Great East Japan Earthquake, we observed the state of people who could not return to their homes on the day of the earthquake and the situation in which people began returning home as subway services resumed.

Future work will include the differentiation between men and women and between adults and children, an estimation of the gaze of tracked pedestrian, and pedestrian identification between separate cameras. Moreover, by analyzing not only the movement of data in virtual space but also the movement of people in real space, it is thought that more useful results about the diffusion of information can be obtained. If these works achieve its aims, a more useful analytical service will be available for building managers.

References

- 1) Daisuke Hosotani, Ikushi Yoda and Katsuhiko Sakaue: "Development and Long-Term Verification of Stereo Vision Sensor System for Controlling Safety at Railroad Crossing", ICVS 2009, Lecture Notes in Computer Science, 5815, pp.154–163 (2009)
- 2) Seh-Chan Oh, Gil-Dong Kim, Woo-Tae Jeong and Young-Tae Park: "Vision-based object detection for passenger's safety in railway platform", International Conference on Control, Automation and Systems (ICCAS), pp.2134–2137 (2008)
- 3) V. Atienza-Vanacloig, J. Rosell-Ortega, G. Andreu-Garcia and J. M. Valiente-Gonzalez: "People and Luggage Recognition in Airport Surveillance Under Real-Time Constraints", International Conference on Pattern Recognition (ICPR), (2008)
- 4) David Thirde, Mark Borg, Josep Aguilera, Horst Wildenauer, James Ferryman, Martin Kampel: "Robust Real-Time Tracking for Visual Surveillance", EURASIP Journal on Advances in Signal Processing, ID 96568 (2007)

- 5) Jeffrey S. Larson, Eric T. Bradlow and Peter S. Fader: "An Exploratory Look at Supermarket Shopping Paths", International Journal of Research in Marketing, 22, 4, pp.395–414, (2005)
- 6) Takayuki Kanda, Dylan F. Glas, Masahiro Shiomi, Hiroshi Ishiguro, Norihiro Hagita: "Who will be the customer?: A social robot that anticipates people's behavior from their trajectories", International Conference on Ubiquitous Computing (UbiComp), pp.380–389 (2008)
- 7) T. Fukuhara, R. Tenmoku, T. Okuma, R. Ueoka, M. Takehara and T. Kurata: "Improving service processes based on visualization of human-behavior and POS data: A case study in a Japanese restaurant", Serviceology for Services, pp.3–13, 2014.
- 8) Marie Chana, Daniel Estèvea, Christophe Escribaa, Eric Campoa: "A review of smart homes —Present state and future challenges", Computer Methods and Programs in Biomedicine, 91, 1, pp.55–81 (2008)
- 9) Weiming Hu, Xuejuan Xiao, Zhouyu Fu, Dan Xie, Tieniu Tan, Steve Maybank: "A System for Learning Statistical Motion Patterns", IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), 28, 9, pp.1450–1464 (2006)
- 10) Gianluca Antonini and Jean Philippe Thiran: "Counting Pedestrians in Video Sequences Using Trajectory Clustering", IEEE Trans. on Circuits and Systems for Video Technology, 16, 8, pp.1008–1020 (2006)
- 11) Wongun Choi, Caroline Pantofaru and Silvio Savarese: "A general framework for tracking multiple people from a moving camera", IEEE Trans. on Pattern Analysis and Machine Intelligence, 35, 7, pp.1577–1591, (2013)
- 12) Bao Xu and Wang Gang: "Random sampling algorithm in RFID indoor location system", Proc. of the Third IEEE International Workshop on Electronic Design, Test and Applications, pp.168–176 (2006)
- 13) H. Zhao and R. Shibasaki: "A novel system for tracking pedestrians using multiple single-row laser-range scanners", IEEE Trans. on Systems, Man and Cybernetics, Part A: Systems and Humans, 35, 2, pp.283–291 (2005)
- 14) M. Onishi and I. Yoda: "Dynamic Trajectory Extraction from Stereo Vision using Fuzzy Clustering", IEIJ Trans. EIS, 128, 9, pp.1438–1446 (2008) (in Japanese)
- 15) M. Onishi and I. Yoda: "Comparison and Visualization Method of Pedestrian Trajectories in a Complex Office for a Long Period", IEICE Trans. on Information and Systems, J93-D, 4, pp.486–493, (2010) (in Japanese)
- 16) James C. Bezdek: "Pattern Recognition with Fuzzy Objective Function Algorithms", Advanced Applications in Pattern Recognition, Plenum Press (1981)
- 17) R. Inokuchi and S. Miyamoto: "Kernel Methods for Clustering: Competitive Learning and c-Means", International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 14, 4, pp.481–493 (2006)
- 18) K. Honda and H. Ichihashi: Regularized Linear Fuzzy Clustering and Probabilistic PCA Mixture Models. IEEE Trans. on Fuzzy Systems, 13, 4, pp.508–516 (2005)
- 19) T. Kohonen: "Learning Vector Quantization", Self-Organizing Maps, pp.203–217 (1997)
- 20) H. Akaike: "A new look at the statistical model identification", IEEE Trans. on Automatic Control, 19, 6, pp.716–723 (1974)
- 21) M. Onishi and M. Muta: "Development of Digital Signage Contents Using Microblogging Service", IEICE Trans. on Information and Systems, J97-D, 12, pp.1839–1842, (2014) (in Japanese)

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