ウェーブレット変換と機械学習を用いた雑踏密度の推定

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概要

群集を適切に誘導したり、公共施設のデザインを設計する際には、その空間における群集密度を測定することが重要である。しかしながら、従来のビデオカメラによる群集密度の測定は、取得データを機械的に扱うことが難しいことから、コストのかかる方法だと考えられる。そこで、歩行者の所持するタブレットセンサーを用いた、新しい群集密度推定手法を開発した。センサーからのデータに対し、ウェーブレット解析と機械学習を適用することで、各時点における局所密度を推定することができた。

Wavelet analysis of pedestrian gyroscope data to estimate crowd density using machine learning

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Abstract

The density of a crowd is an important factor that affects the speed at which a crowd can be guided to less crowded spaces or the design of public facilities such as airports, intersections and event venues. However, it is time-consuming to measure crowd densities via video data because this type of data is not easy to handle automatically. Therefore, we developed a new method for estimating crowd densities by using tablet sensor data from pedestrians. By applying wavelet analysis and machine learning to the data, we can estimate the local density at each moment.

1 Introduction

Crowd density, which affects the degree of comfort and mobility of pedestrians, is a key factor in the design of public facilities such as airports, intersections and event venue. From the perspective of efficiency, it is necessary for managers of these facilities to measure the crowd density.

In response to the demands of society, crowd dynamics in public areas have been actively studied to determine the relationship between building construction and crowd density. In previous research, a video camera has been directed at crowds, and some interesting features of crowds have been revealed by analysing the recorded data. This measurement method, which is analysed after the video data has been recorded the data, has frequently been used. It is effective for investigating the state of crowds in detail [1, 2].

However, this measurement method is time-consuming because the video images need to be processed to deal with camera distortions, use predefined geometric settings and track the trajectories of pedestrians. In addition, the area that can be recorded is usually limited by the design of the facilities or privacy laws.

Therefore, to reduce the analysis time required for this task, we propose a simple and fast method to estimate crowd densities. Our method only needs the angular velocity of the torso of pedestrians such that the data we need to analyse comprise of simple time series, which also enables better protection of the pedestrians' privacy. After we obtain the angular velocity, the data are preprocessed by frequency analysis using the continuous wavelet transform (CWT). Finally, we estimate the local density [3] by applying machine learning to the pre-processed data. In our method, the data are simple enough to be analysed in real time so that it could be used for Internet of things services in the near future.

The rest of this paper is organised as follows. Section 2 describes the experimental setup and acquired data. In Section 3, we explain the CWT. In Section 4, we introduce the k-nearest neighbour (k-NN) algorithm and the types of input data. In Section 5, the results of density estimation are shown. Finally, we conclude the paper in Section 6.

2 Experiment

To investigate how pedestrians behave in crowds, we conducted real experiments, as depicted in Fig. 1(a). The experiments were conducted in a square area that has one entrance in the middle of one side and one exit in the middle of the opposite side. The length and width of the room were both 4.8 m, while the widths of the entrance and the exit were both 0.4 m. A video camera was installed over the rooms to record the entire experimental process. Note that the video data were only used for observation and not in the analysis. A snapshot of the experiment is shown in Fig. 1(b).

We instructed some participants with yellow caps, which designated as 'crowd members' to walk randomly in the square area. The number of the crowd members was varied from 0 to 40 in increments of 5. In contrast, a participant with a red cap, which we designated as a 'passer', entered the area and passed through the crowd members after a start signal was given. The passer was equipped with a tablet to measure the angular velocity of his/her torso (Fig. 2). By repeating the trial while changing the number of crowd members, we obtained one-dimensional (1D) time series data of the passer's angular velocity (Fig. 3).

We conducted similar experiments with different participants on two different days, which we called exp 1 and exp 2 (Table 1).

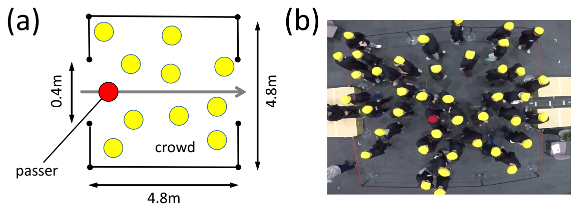

Fig 1: (a) Schematic diagram of the experiment. (b) Snapshot of the experiment.

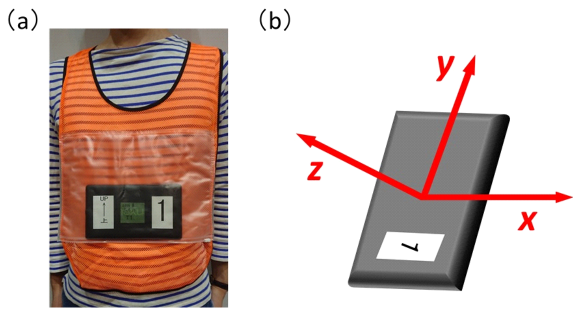

Fig 2: (a) Passer with a tablet. (b) Coordinates of the gyroscope sensor in a tablet. Using the gyroscope data with respect to the x-axis, we can track the rotation of the torso of the passer.

3 Continuous Wavelet Transform (CWT)

The continuous wavelet transform (CWT) [4] is an analysis tool that incorporates the concepts of both time and frequency. We considered that a time series x_n, with equal time spacing $\delta t =$

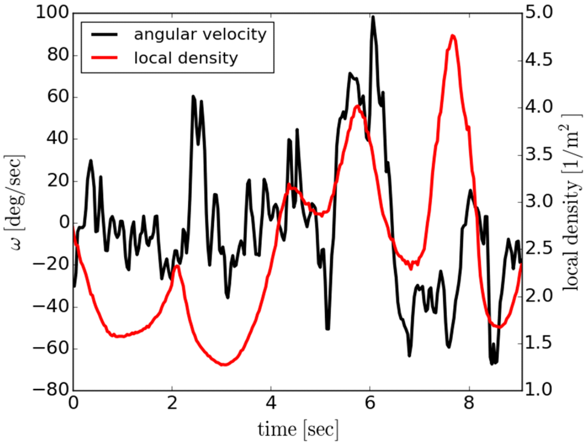

Fig 3: Experimental data from one trial. The black curve represents the angular velocity of a passer and the red curve represents the local densities around the passer. Note that we regarded the density distribution, which is referred in the previous paper [3], as the local density.

Number of crowds	Global density [/m^2]	exp 1 trials	exp 2 trials
0	0.0434	20	-
5	0.260	20	-
10	0.477	20	30
15	0.694	20	-
20	0.911	20	30
25	1.13	20	-
30	1.35	40	30
35	1.56	40	-
40	1.78	40	-

Table 1: Overview of the experiments.

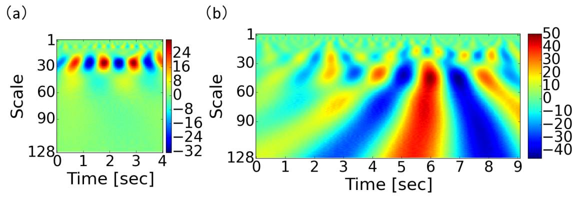

Fig 4: Scalogram of the gyroscope data from one trial in a crowd of (a) 0 crowd members and (b) 40 crowd members. Note that the data of exp 1 were used. A larger scale leads to a lower frequency of the wavelet function.

1/30 [sec] and localised time index $n = 1 \cdots N$. In addition, we used the wavelet function $\psi(\eta)$, where η is a non-dimensional time parameter. Hence, the CWT coefficient of a discrete sequence x_n was defined as

$$W_n(s) = \sum_{n'=1}^{N} x_{n'} \left(\frac{\delta t}{s}\right)^{1/2} \psi^* \left[\frac{(n'-n)\delta t}{s}\right], \quad (1)$$

where s represents the scale and $*$ is a symbol which represents complex conjugate. The scale is proportional to the inverse of fourier frequency. Moreover, the normalization of ψ is considered in this definition. We used the morlet wavelet as ψ;

$$\psi_(\eta) = \pi^{-1/4} e^{i\omega_0\eta} e^{-\eta^2/2}, \quad (2)$$

where we set $\omega_0 = 5$. In our case, we applied the CWT to the experimental data of each trial and used only the real part of the $W_n(s)$. By varying s and varying n, we obtained scalograms that plot the amplitude of an arbitrary part of x_n versus the scale, as shown in Fig. 4. Note that the scale s is varied within $\{s \mid 1 \leq s \leq 128 \ \wedge \ s \in \mathbb{Z}\}$. Thus, the gyroscope data of each trial were compressed into a plot that contains information for both time and frequency.

4 Method

4.1 Vectorisation

The shape of the input for the regression algorithm is preferably 1D data; thus, we needed to vectorise the scalogram. We defined the wavelet coefficient $\mathbf{W}_n$ as

$$\begin{aligned}\mathbf{W}_n = [&W_{n-15}(1), W_{n-15}(2), \cdots, W_{n-15}(128)\\ &, W_{n-14}(1), \cdots, W_{n-14}(128), \cdots W_n(1), \cdots\\ &, W_n(128), \cdots, W_{n+15}(1), \cdots, W_{n+15}(128)]^T.\end{aligned} \quad (3)$$

Here, the density of the wavelet coefficient $\rho(\mathbf{W}_n)$ is a mean of the local densities during $[n-15,\ n+15]$, where the local density is referred as the density distribution in the previous research [3]. Note that the density of the wavelet coefficient $\rho(\mathbf{W}_n)$ ranged from 0.318 to 5.31 in our experiment. In addition, the number of $\mathbf{W}_n$ is $N-30$ in a trial, where n was varied from 16 to $N-15$.

4.2 Machine learning and density estimation

We used the k-nearest neighbour (k-NN) algorithm [5] to estimate crowd density, which is a non-parametric method for regression. Our method is composed the following two steps:

Learning

By using datasets of exp 1, we calculated wavelet coefficients $\mathbf{W}_n$ and the densities of the datasets ρ as learning data. Note that the density $\rho(\mathbf{W}_n)$ is considered as a function of $\mathbf{W}_n$. The number of the learning data was 45962.

Prediction

By using datasets of exp 2, we calculated wavelet coefficients $\mathbf{W}'_n$ as test data. We calculated the Euclidean distance between $\mathbf{W}_n$ and $\mathbf{W}'_n$. We extracted the k nearest learning datasets to $\mathbf{W}'_n$, and then the mean value of the density $\rho(\mathbf{W}_n)$ of the k learning datasets is the predicted density $\rho_{\mathrm{pred}}(\mathbf{W}'_n)$ of the test dataset. Note that $k=31$ in this study. The number of the test data was 12110.

5 Density estimation

We estimated the performance of the algorithm using the MRE, which is frequently used to measure the differences between the predicted values and the observed values. The MRE is defined as

$$\mathrm{MRE} = \frac{\sum \frac{\left|\rho_{\mathrm{true}}(\mathbf{W}'_n)-\rho_{\mathrm{pred}}(\mathbf{W}'_n)\right|}{\rho_{\mathrm{true}}(\mathbf{W}'_n)}}{N_{\mathrm{all}}}, \qquad (4)$$

where $\rho_{\mathrm{true}}(\mathbf{W}'_n)$ is the true density of the test data and N_{all} represents the number of $\mathbf{W}'_n$. Note that $\rho_{\mathrm{true}}(\mathbf{W}'_n)$ is calculated in the same way as the calculation of $\rho(\mathbf{W}_n)$.

We also applied the raw velocity $[v_n]$ and raw angular velocity $[\omega_n]$ to our estimating method for comparison with the case of $\mathbf{W}_n$, by changing $\mathbf{W}_n$ into $[v_n]$ and $[\omega_n]$. Table 2 shows the MRE of the density estimation for each feature type. It shows that the estimation obtained by the wavelet coefficient has a lower MRE than those obtained by other features. In particular, the estimation by the wavelet coefficient is better than that by the velocity even though the velocity is considered to be closely related to crowd density. In addition, it is easier to measure the angular velocity than the velocity. Thus, it can be said that the wavelet transform of the angular velocity was effective in our estimation algorithm.

Feature	MRE [%]
raw velocity	48.4
raw angular velocity	75.9
wavelet coefficient	36.2

Table 2: Results of the regression.

Moreover, we extracted the learning and test data from different participants so that this algorithm would be less influenced by the differences of individual passers. From the point of view of applying this method for the general public, its robust performance is important.

6 Conclusion

We developed a new method for estimating crowd density, which is low cost because only angular velocity is necessary.

In this study, we asked the participants to walk at random in the experiments. We need to further verify the performance of our method in real situations using empirical data in the future.

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