AN ANALYSIS OF CROWDS FLOW CHARACTERISTICS BY USING LASER RANGE SCANNERS

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KEY WORDS: Laser scanning, Sensor, Computer Vision, Feature extraction, Spatial Planning, Machine vision

ABSTRACT:

Recently, according to growth and concentration of population in urban area, congested situations at several railway stations in rush hour become a serious social issue. Therefore, designing the station more comfortably for the passengers has been desired. In other words, in order to mitigate the congested situations, a method measuring crowds flow characteristics should be developed. In this paper, we propose a people tracking method for wide and high density situations by using multiple laser range scanners. Additionally, we try to analyze the crowds flow characteristics such as traffic volume, traffic density, degree of intercrossing, velocity, and directionality. Then, we detect several prominently congested areas. In order to evaluate our proposed system, an experiment at Japan railway station was conducted. The accuracy of people tracking shows over 80% in rush hour. Based on the obtained trajectories, the density and direction distribution of the trajectories are calculated by using Kernel Density Estimation method. Furthermore, based on the variance of moving direction and traffic volume, we define a degree of intercrossing in each flow, and then the prominently congested areas are highlighted. Finally, we conclude our proposed system will be efficient to mitigate a congested situation and improve the usability of the public space such as railway station, exhibition hall, or shopping mall.

1. INTRODUCTION

In public space such as railway station, museum, exhibition hall or shopping mall, to measure people behaviour or flows becomes increasingly important for several reasons, e.g., floor planning, mitigation of congestion, detection of suspicious person for security, alignment of advertising messages, etc. Especially, at the concourse of railway station, congested situation in rush hour becomes a serious social issue. Therefore, an automatic people tracking system has been desired, which achieves with high accuracy even if the target space is wide and congested. Conventional researches trying to track multiple pedestrians had almost used CCD camera (Haritaoglu, 2000; T. Zhao, 2004; Curio, 2000). However, camera has some disadvantages, which are affected by illuminating disturbance, narrow viewing angle, and a problem of personal privacy. Therefore, we try to exploit multiple laser range scanners. Moreover, in order to extract the characteristics of pedestrians' behaviour or people flow, several methodologies had proposed, such as Semantic Scene Model (Makris, 2005), Acitivity Map (Demirdjian, 2002), and other algorithms (Hu, 2006; Brandle, 2006; Grimson, 1998; Stauffer, 2000). However, conventional researches had targeted at few persons and relatively narrow space, so that almost researches have not dealt with much congested situation e.g. a railway station. In this paper, we propose a method to track pedestrians robustly for a congested situation and to analyse crowds flow characteristics such as traffic density, walking direction, walking velocity, a degree of intercrossing, and those relativity. Finally, we describe an experimental result conducted at concourse of railway station in Japan.

2. METHODOLOGY

2.1 Outline of Laser Range Scanner

In order to track multiple pedestrians, single-row type laser range scanner, LMS200, by SICK corp. is exploited. It measures a range value between sensor and surrounding objects by calculating a time of flight of a reflected laser pulse, and it scans horizontal plane of 180 degrees by rotating an inner mirror. The laser scanner has high angle resolution (0.5 degree) and high scanning rate (37.5Hz). It uses an eye-safe laser beam (safety class 1) with 905nm wavelength. The laser beam covers a maximum range of 30m, and the range error is within 4cm. The advantages of laser range scanner are to obtain range value actively (light is not necessary), and it has wide field of view. In this paper, in order to cover a wider area and mitigate occlusions, multiple laser scanners are installed on a floor at 20cm height, and scan horizontally to aim at pedestrians' feet as shown Figure 1, 2. Therefore, obtained data consist with same horizontal level. Each laser scanner is controlled by a client computer, and the client computers are connected to a server one by using LAN. The obtained range data are gathered to the server through the network on the real time basis.

Figure 1. Sensor alignment scanning pedestrians' feet

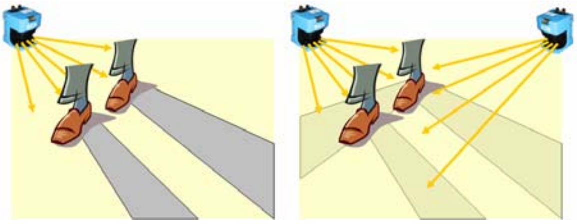

Figure 2. Mitigation of occlusion by using multiple laser range scanners

2.2 People Tracking

2.2.1 Calibration

In order to integrate each laser scanner's local coordinate system to common one, Helmert transformation is conducted for each coordinate system. Since each laser scanner is installed that scans at same horizontal plane, the overlapping measurement data by other sensors corresponds to same shapes. By referring this information, the transformation of shift and rotation is conducted manually by integrating the redundant common shapes' features.

2.2.2 Background Subtraction

Obtained range data contains both moving objects (e.g. pedestrians' legs) and static objects (e.g. walls, poles, etc.). When a certain amount of frames are stored (e.g. 512 frames), a histogram of the range value at each sampling angle is calculated. Since the mode value in the histogram can be regarded as static objects, the range standing for the mode value is registered as a background object. By iterating this process for all sampling angles, a background image is obtained. In order to extract only moving objects, range data near from background value (e.g. within 30cm) are subtracted.

2.2.3 Tracking

People tracking is achieved by conducting spatio-temporal clustering. Firstly, By regarding a certain laser point within moving objects as the first centre point, nearby points from the centre point are searched (e.g. within 15cm). Similarly, by regarding the already searched point as the next centre point, same process is iterated until nearby points are not found. Additionally, in a previous frame, nearby points from current searched points are searched as well. If clustered points are found in a previous frame, previous cluster's ID is inherited to the current cluster. Otherwise, new ID is registered to the new cluster. By extending same cluster's centroid from previous frames, the time-series people positions are obtained.

2.3 Crowds Flow Detection

2.3.1 Probability Density Distribution of Crowds Flow

Based on the trajectories data obtained by above mentioned processes, several properties of crowds flow characteristics are extracted, which are main stream paths, the average and variance of the vectors, traffic density, velocity variance, and those spatial distributions. Particularly, we describe the crowds flow characteristics as a probability density distribution by using kernel density estimation method (KDE). The KDE is defined as follows.

$$p(\mathbf{x}) = \frac{1}{nh^d}\sum_{i=1}^{n} K\left(\frac{\mathbf{x}-\mathbf{x}_i}{h}\right) \tag{1}$$

where $p(\mathbf{x})$ = probability density function
$\mathbf{x}$ = feature vector of the obtained trajectories
$K(\ )$ = kernel function
n = the number of data
h = bandwidth of the kernel function
d = dimension of the feature vector

In this paper, the feature vector of the probability density is defined as (x, y, angle). This means the calculated probability density corresponds to the traffic volume at the site (x, y) and the walking angle. Therefore, the higher value of $p(\mathbf{x})$ corresponds to higher populated site in the flow directions. To learn the probability density $p(\mathbf{x})$, we calculate equation (1) by using the trajectories' vertices (x, y, angle). As the kernel function, Gaussian kernel is adopted as follows.

$$K(\mathbf{x}) = \frac{1}{(2\pi)^{d/2}}\exp\left(-\frac{1}{2}\mathbf{x}^T\mathbf{x}\right) \tag{2}$$

where $\mathbf{x}$ = feature vector of the obtained trajectories
d = dimension of the feature vector

2.3.2 Extraction of Congested Area

In order to extract prominently congested areas, the target area is divided as same interval 2-dimentional grid. Then, we define an index of congestion at each cell as follows.

$$C = -\sqrt{\bar{x}^2+\bar{y}^2}\int p(x,y,a)da \tag{3}$$

where C = an index of congestion
x, y = position of trajectories' vectors
a = angle of trajectories' vectors
$p(x,y,a)$ = probability density mentioned above
$\bar{x}, \bar{y}$ = average vector calculated as follows

$$\bar{x} = \frac{\int \cos a \cdot p(x,y,a)\,da}{\int p(x,y,a)\,da} \tag{4}$$

$$\bar{y} = \frac{\int \sin a \cdot p(x,y,a)\,da}{\int p(x,y,a)\,da} \tag{5}$$

Firstly, an average vector $(\bar{x}, \bar{y})$ of the feature vector within each grid cell is calculated by equation (4, 5). The length of the average vector stands for a kind of variance of angles. Therefore, in the case that the length shows near zero, the directional vectors include a variety of directions, so that it can be assumed as congested area. Contrary, in the case that the length shows near one, the directional vectors have almost same directions, i.e. the crowds flow can be regarded as not congested. Finally, we define an index of congestion as a product of a traffic volume and negative value of length of the average vector as shown equation (3).

2.3.3 Expression of Time Series Transition

Since crowds flow pattern changes at every moment, it is necessary to adjust the time interval how previous frames should be dealt with (e.g. a minute, an hour or a day). In order to adjust time interval flexibly, a leaky bucket algorithm is applied. For example, if we need to assess the trajectories in the past 10 seconds, an additional value of one KDE process is defined as 10, and the added value is subtracted 1 at every seconds. Therefore, the probability density will be zero after 10 seconds, so that we can adjust the time interval by adjusting the additional value and subtracting value. Accordingly, if some pedestrians pass at same position and direction, the probability density is higher than other places.

3. EXPERIMENTAL RESULTS

3.1 Overview of Experiment

In order to test our proposed system in a real environment, we conducted an experiment at a concourse of railway station in Japan. The dimension of the measurement area is about 60m x 30m (Figure 3). In this experiment, we exploited 8 laser scanners to cover entire target area. In rush hours, over 200 pedestrians occupy the concourse as shown Figure 4.

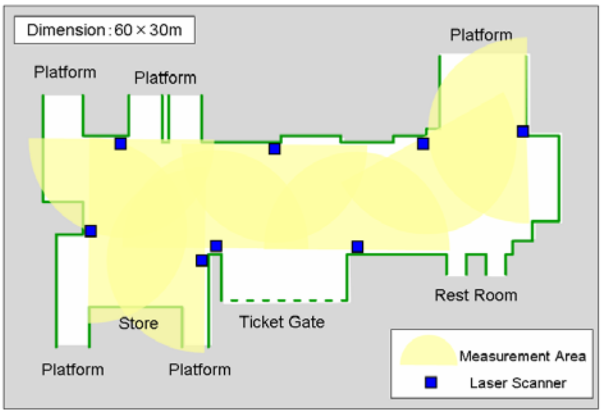

Figure 3. Layout of 8 laser range scanners

Figure 4. An image of experimental site

3.2 Results of Tracking Pedestrians

Figure 5 shows a result of tracked 69 persons. The line symbols stand for the obtained trajectories. The validation period is selected from 7:00 AM to 7:05 AM including congested and not congested situation. We assess the tracking accuracy as the ratio of the number of trajectories tracked from entrance to exit completely. In relatively congested period from 7:00 to 7:02, the tracking accuracy is 81.2%, and in unoccupied period from 7:02 to 7:05, the accuracy is 88.9%. Conventional researches using CCD camera could not achieve these accuracy and successive tracking in wide space and high congested situation.

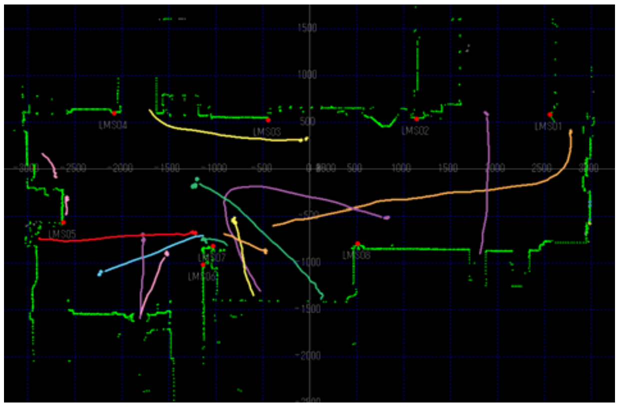

Figure 5. Tracking result (non-congested period)

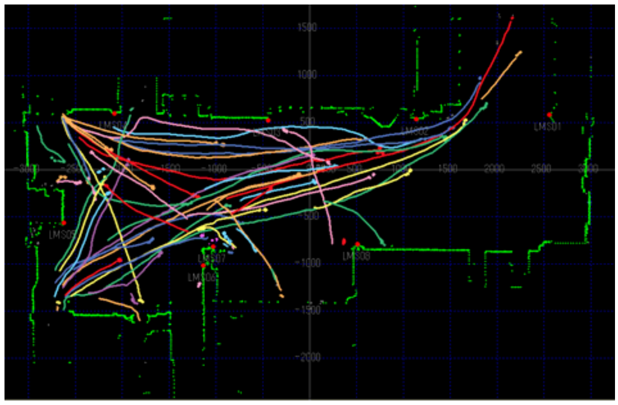

Figure 6. Tracking result (congested period)

3.3 Results of Crowds Flow Detection

Figure 7 shows a result of visualization of calculated crowds flow as a probability density distribution. The sampling data period is selected from 7:00 AM to 7:10 AM. In this figure, z axis corresponds to the value of probability density or the likelihood. In other words, the probability density is in proportion to the traffic density. The color of crowds flow stands for the direction that pedestrians walked most frequently. Figure 8 stands for a result that shows prominently congested areas. The highlighted areas show where the calculated congestion index mentioned in section 2.3.2 is over a certain threshold. These all processes are achieved on the real-time basis.

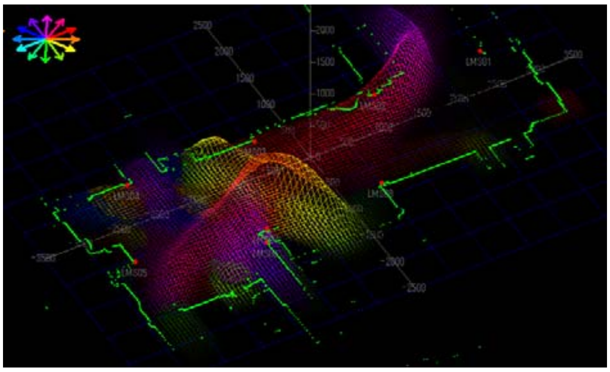

Figure 7. Calculated probability density distribution

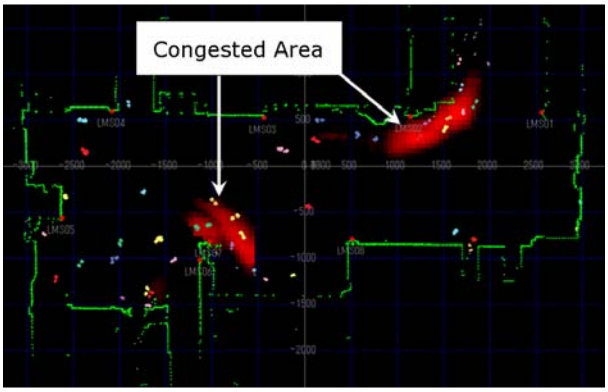

Figure 8. Extracted prominently congested area

3.4 Statistics of Walking Characteristics

On the basis of tracking results, the relationships between walking speeds, angle of pivoting are derived. Figure 9 denotes the scatter plot for angle of pivoting v.s. walking speeds. As the result of Figure 9, the data have almost 2 clusters that one shows low walking speed but angle of pivoting has large variance, and the other shows the range from 0.5 to 2.0 of walking speed and relatively small variance. We found when pedestrians change their walking directions, pedestrians slow down their walking speed.

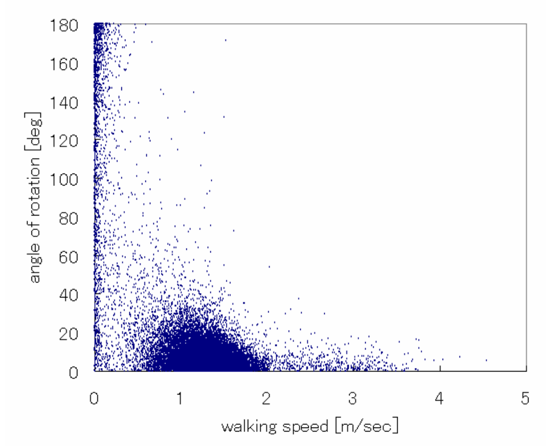

Figure 9. Scatter plot of angle of pivoting v.s. walking speed

4. CONCLUSION

In this paper, a people tracking method by using multiple laser range scanners is proposed, which is relatively robust than cameras in congested situation. Moreover, based on the obtained trajectories, crowds flow characteristics such as traffic density, walking velocity and directionality, a degree of intercrossing, and those relativity are analyzed as the probability density by using kernel density estimation method. Additionally, by calculating the uniformity of trajectories' directions and the traffic volume, prominently congested areas are extracted. Finally, we conclude our proposed method should be effective to analyze crowds flow characteristics on the real-time basis even if the target space is relatively wide and congested situation such as railway station or shopping mall.

REFERENCES

Brandle, N., Bauer, D., Seer, S., 2006. Track-based Finding of Stopping Pedestrians - A Practical Approach for Analyzing a Public Infrastructure, *Proc. of the IEEE ITSC*, pp.115-120.

Curio, C.. Edel brunner, J., Kalinke, T., Tzomakeas, C., Von Seelen, W., 2000. Walking pedestrian recognition, *IEEE Trans. Intelligent Transportation Systems*, vol.1, no.3, pp.155-163.

Demirdjian, D., Tollmar, K., Koile, K., Checka, N., Darrell, T., 2002. Activity maps for location-aware computing. *Proc. of IEEE Workshop on Applications of Computer Vision*.

Grimson, W.E.L., Stauffer, C., Romano, R., Lee, L., 1998. Using Adaptive Tracking to Classify and Monitor Activities in a Site, *CVPR98*, pp.22.

Haritaoglu, I., Harwood, D., Davis, L. S., 2000. W4: Real-time surveyllance of people and their activities, *IEEE Trans. PAMI*, vol.22, no.8, pp.809-830.

Hu, W., Xiao, X., Fu, Z., Xie, D., Tan, T., 2006. A System for Learning Statistical Motion Patterns, *IEEE Trans. PAMI*, vol.28, no.9, pp. 1450-1464.

Makris, D., Ellis, T., 2005. Learning Semantic Scene Models from Observing Activity in Visual Surveillance, *IEEE Trans. SMC Part B*, vol.35, pp.397-408.

Stauffer, C., Grimson, W.E.L., 2000. Lerning Patterns of Activity Using Real-Time Tracking, *IEEE Trans. PAMI*, vol.22, no.8, pp.747-757,

Zhao, H., Shibasaki, R., 2005. A real-time system for monitoring pedestrians, *Proc. of IEEE Workshop on Applications of Computer Vision.*

Zhao, T., Nevatia, R., 2004. Tracking multiple humans in complex situations, *IEEE Trans. PAMI*, vol.26, no.9, pp.1208-1221.