PEDESTRIAN DENSITY ESTIMATION SYSTEM USING TIME-SPATIAL IMAGE (TSI) PROCESSING AND SHORT-TERM MOTION VECTOR

E. UA-AREEMITR, W.H.K. LAM and A. SUMALEE
Department of Civil and Environmental Engineering,
The Hong Kong Polytechnic University, China
Email: ekalux.uaareemitr@polyu.edu.hk

ABSTRACT

Estimation of pedestrian density and/or area occupation on a real-time basis is quite challenging to be implemented automatically, economically and accurately. The traditional data collection approach is labor-intensive and time-consuming. Alternative image processing approaches required a high computational resource to extract and track pedestrians accurately. This paper introduces a real-time area occupation system using Time-Spatial Image (TSI) processing and short-term motion vector which can be performed on the real-time basis without using large amounts of processing resources from pedestrian extraction and tracking. TSI is an image of numerous lines against time. The proposed system will estimate TSI from a virtual detection line. After a short time period, the detection lines can be constructed as TSI. In this research, the camera are installed in the observation area on a gantry with a top-down view, 90 degrees to the horizontal axis, to avoid the pedestrian privacy issue. The proposed system will estimate multiple TSIs at the same period from different virtual detection lines location within the observed location. The study exploit the attributed of the direction of pedestrian height within the TSI to estimate the short-term individual pedestrian direction so called short-term motion vector. The proposed system pedestrian density result will be validated with the density estimated from perspective transformation. The results are shown as pedestrian density in term of area occupation based on the inflow and outflow at the observed location.

Keywords: pedestrian flow estimation, pedestrian area occupation estimation, short-term motion vector estimation, Time-Spatial Image (TSI) processing

1. INTRODUCTION

Pedestrian data extraction technique is one of necessary keys for understanding the pedestrian behavior in pedestrian facilities and the facilities efficiency and safety evaluation (Hoogendoorn et al. 2003). The pedestrian behavior within the location indirectly indicates the facilities performance. Therefore, the facility performance at the observing location can be renovated for a new design to support pedestrian demand or for planning similar pedestrian facility economically. Traditionally, the pedestrian data extraction can be collected by human survey. The collected result demonstrates the pedestrian counting at the observing location. Using human afford on data gathering can be undeniable that the data set is not involves bias. Since, human manual data collection sometime has variety of data quality. Each data collectors may have different decision making in the ambiguous situations. However, machine vision can be adopted to make those situation results certain and standardized.

Visual-based automatic pedestrian data extraction technique, nowadays, are mainly focused on pedestrian trajectory and counting. This approach is widely used for pedestrian survey nowadays. The approach basically implemented from background subtraction (Hoogendoorn et al. 2003 and Tekmono et al. 2001) and motion vector (Fardi et al. 2006 and Velastin et al. 1994). The image processing based applications are vulnerable for the unstable light condition. Furthermore, motion tracking from background subtraction involved excessive computational power. The motion tracking system requires the pedestrian tracking in every frame of the video source. The computational cost would be overabundant. Therefore, the image processing technique that can handle the various light conditions and consume less computational cost could be one of the best solutions for pedestrian data extraction which is Time-Spatial Image (TSI) processing.

The TSI was firstly introduced by Albiol et al. (2001). Albiol implement the technique to estimate train passengers counting. The technique demonstrated that it requires less memory storage comparing to the motion tracking approach since the technique transform the video source into the image of a certain time as TSI. Li et al. (2008) estimate urban traffic state at the observing junction. Whenever the traffic light is green the vehicle shape in the TSI will be shorten since the moving vehicles require less occupation time in the virtual detection line. On the other hand, the red light traffic make vehicle to stop for a certain time. Therefore, the vehicle in TSI of the red light traffic is expanded along the time axis due to the vehicle stop at the virtual detection line. Yue (2009) introduced TSI for vehicle counting or flow estimation. The approach introduced by Yue counts each vehicle under the free-flow state traffic condition since each vehicle is quite distinguish to each other vehicle. Lee and Kim (2012) propose TSI for mass pedestrian data extraction. Using motion vector on the virtual detection line for indicate the direction of pedestrian.

The TSI demonstrate potential of estimating pedestrian macroscopic information is promising based on Lee and Kim (2012) approach. However, our research will extend Lee and Kim research to investigate on angle of virtual detection line setting and pedestrian flow density estimation.

2. METHODOLOGY

The proposed system can be categorized into several procedures as can be seen in Figure 1. The system has to define the virtual detection line properly. The well-defined virtual detection line will be used for TSI generating. The TSI can be directly used for flow estimation using blob coloring and feature extraction. For the location dimension correction, the system has to define the location area to perform the perspective transformation. In order to estimate density, pedestrian inflow and pedestrian outflow are adopted for estimating the pedestrian density.

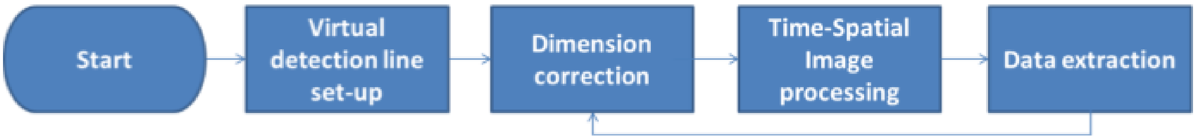


Figure 1. Flow of the system framework

2.1 TSI Characteristics and Virtual detection line set-up

The camera setting can be seen in the Figure 2a top down to the observing area. There are some attribute in the TSI. Whenever the detection line is set closer to middle of the image the pedestrian shape is quite suitable for counting as Figure 2c. On the other hand, the detection line is assigned close to the edge of the image as Figure 2b and Figure 2d. The individual pedestrian direction is obviously seen due to the reality of three dimensions. The each pedestrian has unique characteristic involves pedestrian body width, body depth and body height. The lower part of the body will appear first in the detection line when the pedestrians walk into detection zone, an area including 3 detection lines. The upper body part will appear first when the pedestrian leave the detection zone. Therefore, this study will focus on the TSI generated from the near edge of the video frame as detection line 1 and 3.

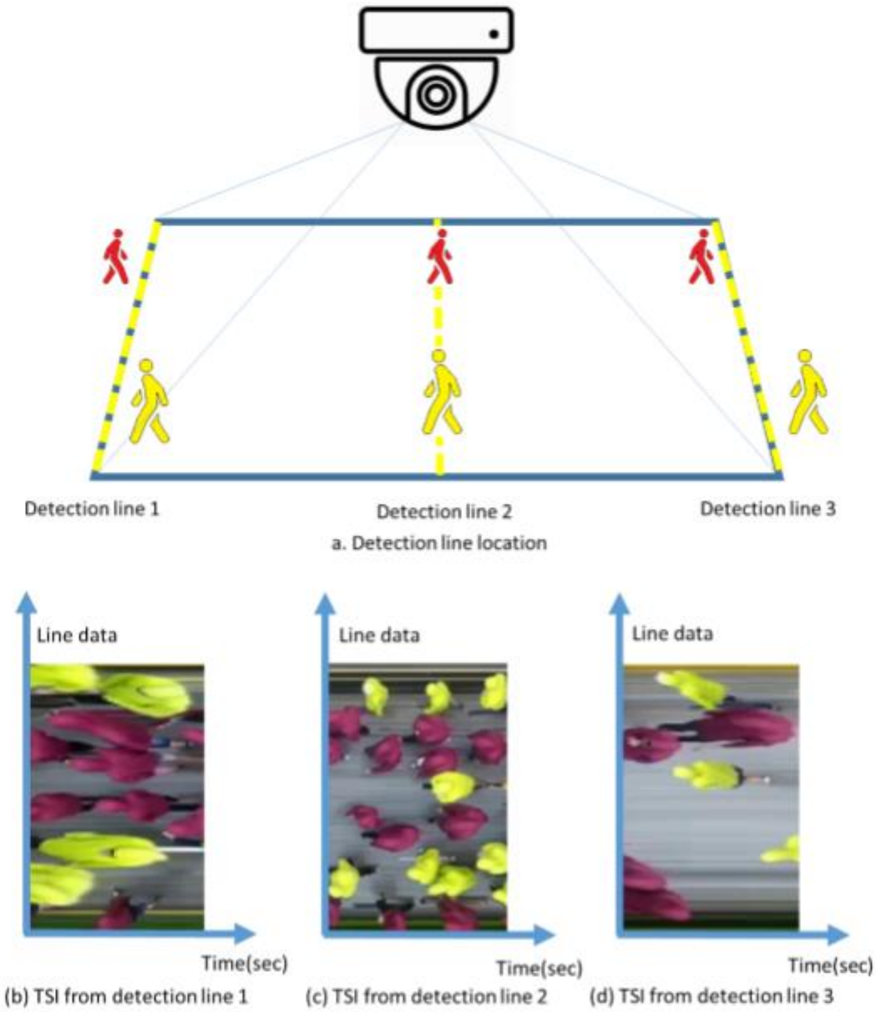


Figure 2. (a) Detection line location setup, (b) TSI from Detection line 1, (c) TSI from detection line 2 and (d) TSI from detection line 3

The location this study used for the data extraction can be seen in Figure 3. It is an experimental site size of 4 m width and 5.25 m length. The image processing technique called Time-Spatial Image (TSI) processing is a special technique for transforming video period into an image. The TSI is a two dimensions image represents as line data axis and time axis. The TSI generating sequence and it result as in Figure 4.

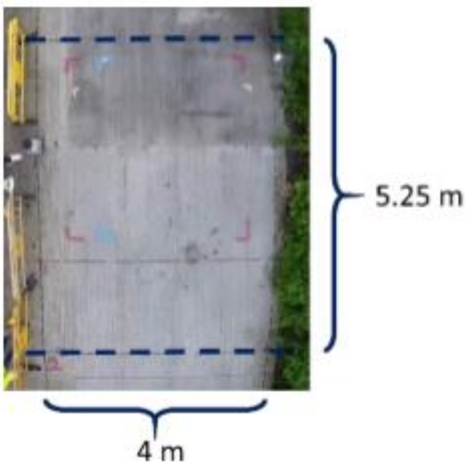


Figure 3. Experiment site location characteristic.

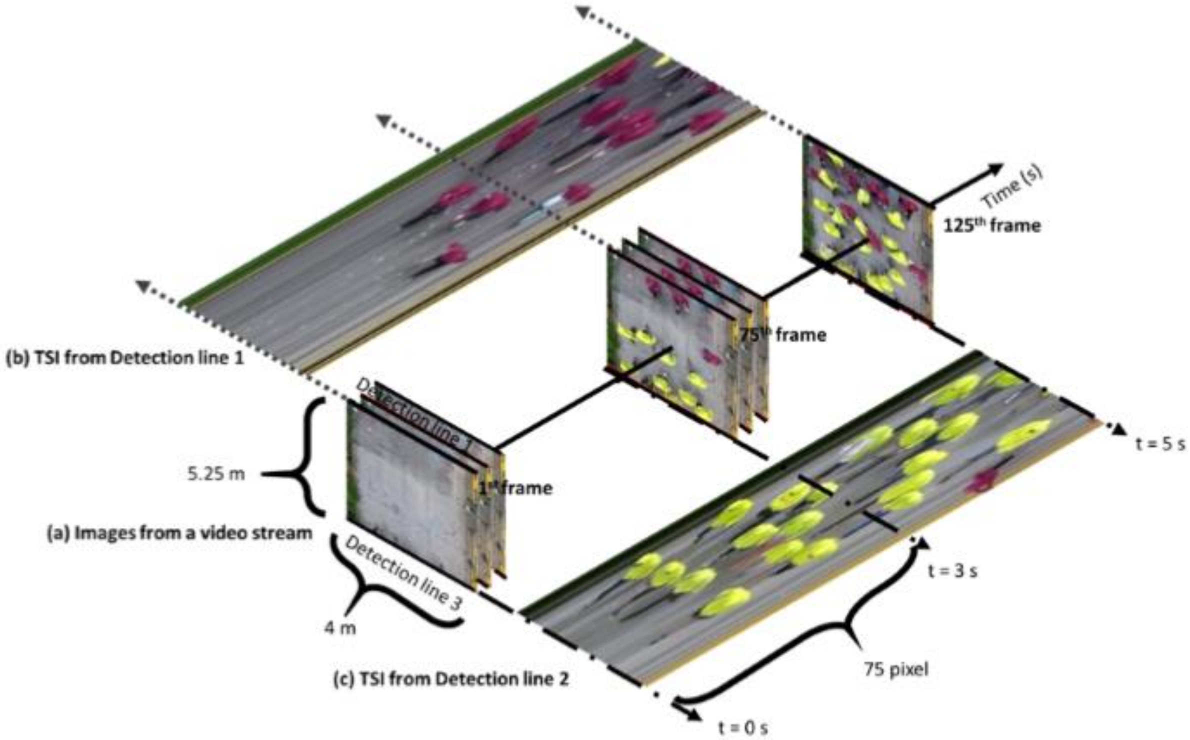


Figure 4. TSI generating sequence and TSIs of the pedestrian (a) images from a video stream, (b) TSI from Detection line 1 and (c) TSI from Dectection line 2

A video stream consists of numerous recorded images at each time period. The number of images in a second can be determined by frame per second (fps) unit. For an example, a video of 25 fps has 25 recorded images in one second. As depicted in Figure 4a, the virtual detection lines can be assigned covered the observing area for pedestrians detection. There are two detection lines assigned one at the top as detection line 1 and one at the bottom as detection line 2 of the images from a video stream.

In each frame, a line will be collected by the detection line. The collected lines will be used for constructing TSI. The TSI result of 5 seconds from detection line 1 and detection line 2 can be represent as Figure 4a and Figure 4b respectively.

2.2 Flow estimation using TSI processing

Pedestrian flow can be estimated by TSI processing. The TSI is a transformed image from a short period of time. Therefore, the TSI is the image or time period as depicted in Figure 4b and Figure 4c. The amount of pedestrian in the TSI can be directly used for calculate pedestrian flow. The average pedestrian flow (ped/s), $\overline{q_t}$, is the a number of pedestrian that passing though the location for a certain time t as (1) and (2).

$$\overline{q_t} = \frac{\sum_{i=1}^{C} P_{t,i}}{C} \quad (1)$$

$$P_{t,i} = \left(\sum_{j=0}^{n} (p_j) - \boldsymbol{\varepsilon}_{\mathbf{t-1}}\right) \quad (2)$$

While $P_{t,i}$ is number of pedestrian within the TSI (ped) at time period t. i denotes index of TSI. j represents index of pedestrian. The amount of pedestrian in the TSI and number of TSI is n (ped/s) and C respectively. P_j is the pedestrian at index j in TSI i. $\boldsymbol{\varepsilon}_{\mathbf{t-1}}$ is the counted pedestrian at time period $t-1$ that appear in the time period t due to the pedestrian was at the detection line between 2 TSI generating periods for minimizing duplicate counting. Basically, the amount of pedestrian that appeared in the TSI is flow. The core component is how can system extract and count pedestrian in TSI. Image processing will be used for extraction pedestrian from TSI.

2.3 Density estimation using pedestrian inflow and outflow

Pedestrian density can be estimated by detection zone pedestrian inflow and outflow counting as (3). TSIs generated from detection line as Figure 4b and Figure 4c can be used for estimating density by (4).

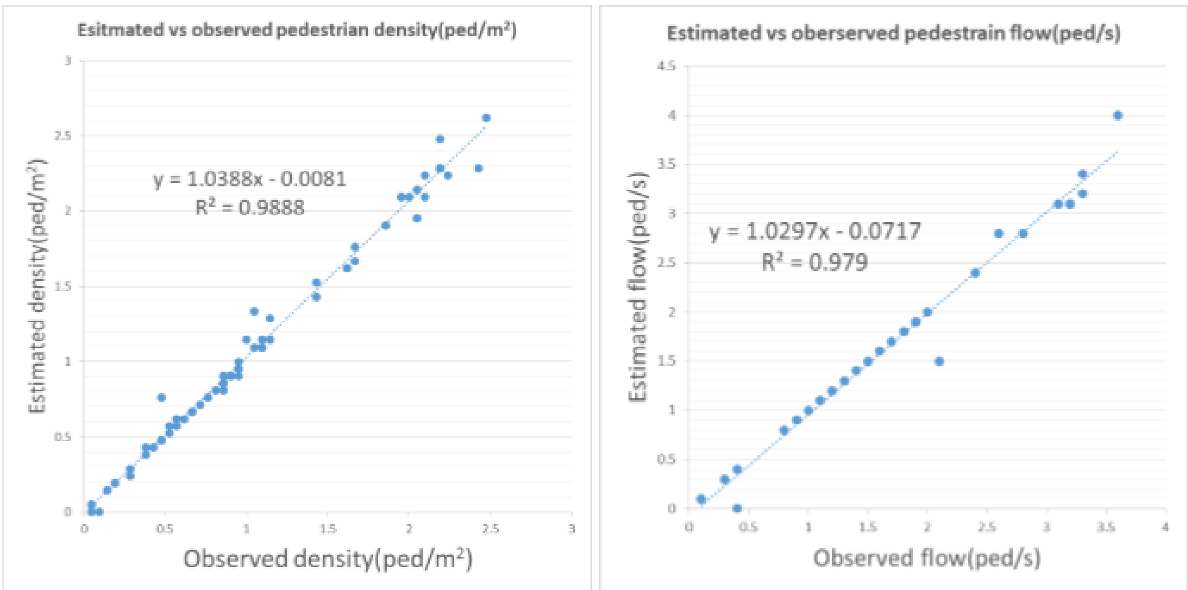
$$k_t = \frac{q_{in} - q_{out}}{a} \tag{3}$$

$$k_t = \frac{P_{d1,in} + P_{d2,in} - P_{d1,out} - P_{d2,out}}{a} \tag{4}$$

While k_t is density at time period t (ped/ m2). q_{in} and q_{out} denotes inflow pedestrian counting(ped) and outflow pedestrian counting(ped) respectively. a is a detection area (m^2) of a constant detection zone width. P is the pedestrian counting (ped). $d1$ and $d2$ denotes detection line 1 and detection line 2 respectively. in and out represents pedestrians direction as into detection zone and leaving detection zone respectively. The pedestrian direction as mentioned on the previous section can be estimated using the pattern matching for each direction.

3. EXPERIMENTAL RESULT AND DISCUSSION

In this research, the pedestrian video data collected from the pedestrian experiment. Based on the data, the pedestrian walking in two directions, the red shirt pedestrians direction is always opposite with the green shirt pedestrians. The amount of pedestrians varies from 40 to 80. The duration of the each data is approximately 20 second per experiment. The system result can be seen in the following Figure 5.



(a) (b)

Figure 5. Accuracy of estimated against observed (a) pedestrian density and (b) pedestrian flow

From Figure 4, the system result is quite accurate within range 0 to 1 ped/m2. However, most of the estimated density is underestimated from 1 to 2.5 ped/m2. This is caused by the pedestrian is extremely close to each other. The image processing for pedestrian recognition might considered the 2 pedestrian that interconnected in TSI as a pedestrian. The result MAPE and r-squared is equal to 0.034 and 0.9888 respectively. For the pedestrian flow estimation, the MAPE and r squared is 0.024 and 0.979 respectively. The major cause of the pedestrian flow estimation is quite the same to the density which is the group of pedestrians walked very close to each other.

The source of the flow estimation is accurate due to the fact that the system calibrate and adjust the flow directly between 2 consecutive TSIs. The system reduce error significantly when considering the pedestrian duplicate counting from pedestrian who walked in between the TSI construction period which his/her head will be separated for 2 consecutive TSI as ε_{t-1} in (2). For the pedestrians that very close to each other, the further image processing such as pattern matching or pedestrian type classification can be used for the future accuracy enhancement. Therefore, the result accuracy is solely based on the image processing to extract and count each pedestrian from a TSI. The fundamental pedestrian flow density diagram is illustrated as the following Figure 6.

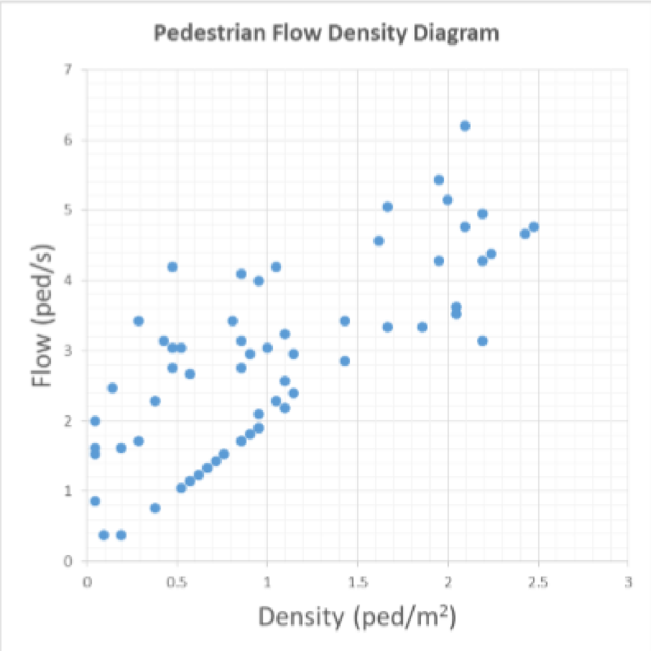


Figure 6. Pedestrian flow density diagram

4. CONCLUSION AND FUTURE WORK

TSI processing with short term motion vector can be practically used for pedestrian data extraction. The proposed system is quite useful for pedestrian automatic data collection. The data can be used for pedestrian facility management and evaluation with some additional image processing.

For the future works, TSI processing can be improved by several aspects such as image processing aspect for enhancing the pedestrian shape within TSI for accurate pedestrian extraction, pedestrian flow theory aspect and pedestrian cell transmission model aspect in multidirectional in super network scale.

The data set this research was using is from the control experiments. The pedestrians in the video data were wearing fixed shirt colors. In order to make TSI usable in real-world situation, the future works need to be done. Therefore the head feature recognition and extraction is essentially needed to be focus on. Moreover, The Time-Spatial Video processing for the better flow for data extraction since the system doesn't need to separate video into TSI.

The pedestrian flow and density results accuracy using TSI processing can be enhanced by integrating the pedestrian flow theory. The pedestrian flow theory can be adopted for understanding the pedestrian flow and adjusted TSI processing to process the current situation precisely.

In major scale, TSI processing is one of suitable tools for extraction pedestrian network such as in Central elevated walkway in Hong Kong Island. The system can evaluate the pedestrian density and flow in the elevated walkway in real-time basis. Therefore, pedestrian cell transmission model in multi directional can be investigated in the future research in various aspects including economic aspect, transportation aspect and computer vision aspect.

5. ACKNOWLEDGEMENT

The work described in this paper was jointly supported by research grants from the Research Grants Council of the Hong Kong Special Administrative Region (Project No. PolyU 5243/13E) and the Research Committee of the Hong Kong Polytechnic University (Project No. 1-ZVFJ).

6. REFERENCES

Hoogendoorn, S.P., Daamen, W. and Bovy, P.H.L. (2004) Extracting Microscopic Pedestrian Characteristics from Video Data, TRB annual meeting.

Teknomo, K., Takeyama, Y. and Inamura, H. (2001) Tracking system to automate data collection of microscopic pedestrian traffic flow, *Proceeding of The 4th Eastern Asia Society For Transportation Studies*, Hanoi, Vietnam, Vol. 3 no 1, pp. 11-25.

Velastin, S.A., Yin, J.H., Davies, A.C. and Vicencio-Silva, M.A. (1994) Automated measurement of crowd density and motion using image processing, *The 7th International Conference on Road Traffic Monitoring and control*, London, England, pp. 127-132.

Fardi, B., Seifert, I., Wanielik, G. and Gayko, J. (2006) Motion-based pedestrian recognition from a moving vehicle, *Proceedings of the IEEE on Intelligent Vehicles Symposium*, Tokyo, Japan, pp. 219 -224.

Albiol, A., Mora, I. and Naranjo, V. (2001) Real-time high density people counter using morphological tools, *IEEE Transaction on Intelligent Transportation System*, Vol. 2, pp. 204-218.

Li, L., Chen, L., Huang, X., and Huang, J. (2008) A traffic congestion estimation approach from video using time-spatial imagery, *Intelligent Networks and Intelligent Systems*, Vol. 1, pp. 465-469.

Yue, Y. (2009) A traffic-flow parameters evaluation approach based on urban road video, *International Journal of Intelligent Engineering and Systems*, Vol. 2, pp. 33-39.

Lee, G.G. and Kim, W.Y., (2012) Measuring Pedestrian Traffic Using Feature-Based Regression in the Spatiotemporal Domain, *International Journal of Control, Automation, and System*, pp. 328340.