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Estimating pedestrian volume using Street View images: A large-scale validation test

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ABSTRACT

Pedestrian volume is an important indicator of urban walkability and vitality. Hence, information on pedestrian volumes of different streets is indispensable for creating healthy, pedestrian-oriented cities. Pedestrian volume data have traditionally been collected through field observations, which has many methodological limitations, e.g. time-consuming, labor-intensive, and inefficient.

Assessing pedestrian volume automatically from Street View images (SVIs) with machine learning techniques can overcome such limitations because this approach offers a wide geographic reach and consistent image acquisition. Nevertheless, this new method has not been rigorously validated, and its accuracy remains unclear.

In this study, we conducted a large-scale validation test by comparing pedestrian volume extracted from SVIs with the results from field observations for more than 700 street segments in Tianjin, China. A total of 4507 sampling points along these street segments were used to collect SVIs.

The results demonstrated that using SVIs with machine learning techniques is a promising method for estimating pedestrian volumes with a large geographic reach. Automated pedestrian volume detection could achieve reasonable (Cronbach's alpha ≥ 0.70) or good (Cronbach's alpha ≥ 0.80) levels of accuracy. It is worth noting that various factors of SVIs and street segments may affect the accuracy. SVIs with higher image quality, larger image size, and collection times closer to the targeted periods produced more accurate results. The automated method also worked better in areas with high pedestrian volume and high street connectivity.

1. Introduction

Recent developments in urban big data and machine learning have provided us new data sources and an interdisciplinary approach to understand urban phenomena (Ruppert, 2013). For instance, in the past, information on perceived of built environment characteristics (e.g., urban greenery and aesthetics) or residents' travel behavior (e.g., walking, cycling) were often manually collected through surveys or field observations. Recent urban big data have provided effective means to collect such environmental and behavioral data on a large geographical scale. Hence, urban big data can advance urban studies, especially in the areas of walkability and healthy cities (Rzotkiewicz, Pearson, Dougherty, Shortridge, & Wilson, 2018).

Rapid global urbanization over recent decades has led to a fundamental change in people's lifestyle and a rapid expansion of urban populations. The United Nations estimates that nearly 70% of the world's population will live in cities by 2050 (United Nations, 2018). Moreover, urban residents have experienced rapid declines in physical activity levels, with roughly one-third of urban adults in the world being physically inactive (Hallal et al., 2012). Compelling evidence demonstrates that regular physical activity, such as walking and cycling, has an array of health benefits, including the reduced risk of obesity and chronic illness, and improved physiological and psychological health (I.-M. Lee et al., 2012; Sallis, Floyd, Rodriguez, & Saelens, 2012; Wang et al., 2019).

As the most common form of physical activity, walking can be easily

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incorporated into daily life, and it has additional environmental and social benefits, such as reducing private vehicle use, mitigating traffic congestion and air pollution, and encouraging social interaction (Giles-Corti et al., 2013; Lu, Xiao, & Ye, 2017; Nazelle et al., 2011; Yin, 2017). Many seminal urban planning theories aims to facilitate walking and pedestrian activities, by well-designed city image (Lynch, 1960), streets (Jacobs, 1961), and public open spaces (Whyte, 1980). Recent planning theories, such as smart growth and neourbanism, explicitly aim to promote walking and active living through various design strategies, such as mixed land use, compact development, well-connected streets, and the provision of pedestrian destinations (Durand, Andalib, Dunton, Wolch, & Pentz, 2011; Giles-Corti et al., 2013).

To provide sustained support for researchers and planners who aim to create walkable and healthy cities, it is necessary to assess pedestrian volume, and other walking behaviors constantly. Assessing pedestrian volumes in different streets or areas can help researchers to evaluate walkability and to discern how built environment characteristics affect walking behaviors (Ewing & Clemente, 2013). In the past, pedestrian volume has been typically collected with pedestrian counts on sites. However, field observation is inherently subject to significant limitations, such as high demand for manpower and cost, and small study areas. Street View image services from companies such as Google, Baidu, and Tencent provide high-resolution, geocoded, streetscape images in many global cities (Rzotkiewicz et al., 2018). Researchers can use Street View images (SVIs) in conjunction with machine learning techniques to extract new built environment characteristics and behavioral data (Shapiro, 2017; Ye et al., 2018; Ye, Zeng, Shen, Zhang, & Lu, 2019). For example, this automated approach has been used to assess levels of social and physical disorder (Badland, Opit, Witten, Kearns, & Mavoa, 2010; Rundle, Bader, Richards, Neckerman, & Teitler, 2011), the presence or absence of public facilities (Clarke, Ailshire, Melendez, Bader, & Morenoff, 2010; Kelly, Wilson, Baker, Miller, & Schootman, 2013; Wilson et al., 2012), and the degrees of urban greenness (Li et al., 2015; Lu, Sarkar, & Xiao, 2018). Recent research has suggested that SVIs is a promising and effective alternative for assessing pedestrian volume (Yin, Cheng, Wang, & Shao, 2015). To our knowledge, the accuracy of this new method has not been rigorously tested yet. Therefore, it remains unclear whether SVIs and machine learning techniques can offer a reliable approach to assess pedestrian volume with acceptable accuracy.

In this study, we conducted a comprehensive validation test by comparing the automated pedestrian volume extracted from SVIs with field observation for 701 street segments in Tianjin, China. More importantly, we identified the optimal parameters of SVIs and street features to achieve the highest level of agreement with field observation data. The SVIs parameters we considered included image source, collection time, and image quality. The street features included street length, pedestrian volume, and street connectivity. Our study contributed to the development of an innovative and efficient method to collect pedestrian volume data for any location covered by SVIs worldwide. More importantly, this study can help researchers and planners to create healthy cities and promote physical activities by identifying which areas have high or low pedestrian activity, and by highlighting which built environment characteristics facilitate or hinder walking in the long run.

2. Literature review

2.1. The importance of walking

The last few decades have witnessed a substantial decline of engagement in physical activity by urban residents, and this decline has serious effects on the population's health (Koohsari, Badland, & Giles-Corti, 2013; I.-M. Lee et al., 2012). A global survey indicated that 31% of the world's urban population fails to meet the recommendation of 150-min moderate to vigorous physical activity per week (Hallal et al., 2012). Many developing countries such as China and India have undergone rapid urbanization, which has contributed to the decline in physical activity, and increased the risk of many chronic diseases (Ng, Howard, Wang, Su, & Zhang, 2014; Ng, Norton, & Popkin, 2009). For instance, the average physical activity level of urban adults in China fell by 32% between 1991 and 2006 (Ng et al., 2009). Physical inactivity is the fourth leading cause of death worldwide, and it exerts substantial healthcare and financial burdens in many societies (Kohl et al., 2012). Strong evidence indicates that 6–10% of all deaths from non-communicable diseases (such as coronary heart disease or type II diabetes) can be attributed to physical inactivity (I.-M. Lee et al., 2012; Sallis et al., 2012).

Walking is arguably the most common and pervasive type of physical activity. Walking requires no special skills or equipment, and it can be incorporated into the daily routines of urban residents of all ages (Tudor-Locke, Bittman, Merom, & Bauman, 2005). In addition, walking has significant environmental and social benefits, such as reducing congestion and greenhouse gas emissions and improving social cohesion and urban livability (Yin, 2017). Many researchers and public health officials have taken a keen interest in building walkable communities and promoting walking behavior. New urban land use and transport planning policies have increasingly aimed to increase walking and mitigate dependency on automobiles (Babb & Curtis, 2015). Promoting walking underpins the many urban planning theories, which link increased rates of walking to the general vitality of urban life (Southworth, 2005). Jane Jacobs deemed walking, at both the district and street levels, as an essential source of urban vitality (Jacobs, 1961) and urged that streets should be used throughout the day, by various people and for various activities (Jacobs, 1961). Her theory influenced the birth of both new urbanism and smart growth theory. Similarly, the understanding and encouraging of walking activities in cities and public spaces complements the goals of urban theories regarding the image of the city (Lynch, 1960) and the quality of public space (Whyte, 1980). Therefore, monitoring walking activities with indicators such as pedestrian volume can provide sustained support for researchers and planners to promote walking behavior.

2.2. Previous studies of the relationship between the built environment and walking

Promoting walking has become a public health priority worldwide (WHO, 2010). Researchers have increasingly recognized that interventions to promote walking must address not only personal attitudes and preferences through education but also structural factors of the built environment (Brownson et al., 2008; Yin & Wang, 2016). Some reviews have offered firm evidence that the characteristics of the built environment can promote or hinder walking behavior (Heath et al., 2006; McCormack & Shiell, 2011; Owen, Humpel, Leslie, Bauman, & Sallis, 2004; Saelens & Handy, 2008).

The features of the built environment that affect walking behavior can be measured at both the macro-scale (neighborhood level, e.g., land use mix, street connectivity) and the micro-scale (street level, e.g., sidewalk and road characteristics). Most studies have focused on macro-scale features because built environment features are most easily captured and measured using geographic information systems (Chudyk, Winters, Gorman, McKay, & Ashe, 2014). The macro-scale built environment has been measured and characterized by using the D variables of density, diversity, design, destination accessibility, and distance to transit (Boer, Zheng, Overton, Ridgeway, & Cohen, 2007; Ewing & Cervero, 2010; Frank et al., 2006; Frank, Saelens, Powell, & Chapman, 2007; Marshall & Garrick, 2010; Smith et al., 2008; Xie, An, Zheng, & Li, 2018). In essence, urban residents tend to walk more in compact neighborhoods with mixed land use, in areas with finer-grained street networks, in areas that are closer to transit stations, and in places with more pedestrian destinations (Ewing & Handy, 2009). Furthermore, micro-scale built environment characteristics also affect walking behavior (Yin, 2017). Previous empirical studies have tentatively suggested that aesthetics, safety from crime and traffic all affect the frequency and duration of walking (Duncan, Spence, & Mummery, 2005; Owen et al., 2004; Parra et al., 2011; Shigematsu et al., 2009; Wallmann, Froboese, & Bucksch, 2011).

2.3. Street View imagery in walkability studies

Advances in the fields of big data and computational science have stimulated research on the associations between built environments and walking. These advances have provided new methods for collecting environmental and behavioral data, especially at the micro-scale street level (Rzotkiewicz et al., 2018).

Some researchers have used SVIs to develop built environment assessment tools, such as walkability assessment tools (Cain et al., 2014; Emery, Crump, & Bors, 2003; Hoehner, Ivy, Ramirez, Handy, & Brownson, 2007; Troped et al., 2006) or the Pedestrian Level of Service tool (Asadi-Shekari, Moeinaddini, & Zaly Shah, 2013; Jaskiewicz, 2000; Talavera-Garcia & Soria-Lara, 2015). Several recent studies have developed new Internet-based audit tools that use Google SVIs to assess built environment features. For example, Google SVIs were used to identify target areas for improving pedestrian access (Griew et al., 2013), to assess environmental features related to dietary and physical activity in neighborhoods (Bethlehem et al., 2014), to assess the physical environment along cycling routes to schools (Vanwolleghem, Van Dyck, Ducheyne, De Bourdeaudhuij, & Cardon, 2014), and to conduct virtual audits of neighborhood environments (Bader et al., 2015). Google SVIs have also proved useful for investigating the relationships between crimes and the physical features of urban residential environments (He, Páez, & Liu, 2017), and for addressing the challenges faced by people with disabilities (Ahmetovic, Manduchi, Coughlan, & Mascetti, 2017). In addition, some studies have used Google SVIs to assess specific aspects of built environment features such as green space (Li et al., 2015), open skies (Yin & Wang, 2016), safety (He et al., 2017; Naik, Philipoom, Raskar, & Hidalgo, 2014), and traffic signs (Campbell, Both, & Sun, 2019). Several studies have used these desk-based audits to evaluate the effects of built environments on walking (Clarke et al., 2010; Griew et al., 2013; Rundle et al., 2011) and cycling (Lu, Yang, Sun, & Gou, 2019; Vanwolleghem et al., 2014).

The majority of recent studies have demonstrated that virtual audits undertaken with SVIs have acceptable levels of concurrent validity and inter-rater reliability, and that these audits eliminate the geographic constraints imposed by travel costs and field logistics (Badland et al., 2010; Clarke et al., 2010; Curtis, Curtis, Mapes, Szell, & Cinderich, 2013; Odgers, Caspi, Bates, Sampson, & Moffitt, 2012; Rundle et al., 2011; Wilson et al., 2012). For example, audits based on Google SVIs can save time and have acceptable agreement levels with in-person audits (Badland et al., 2010; Rundle et al., 2011).

In general, data on walking activity are more difficult to collect than data on the built environment, especially at the large geographic scale. In the past, data on walking behaviors were often collected in two conventional ways: responses to surveys and field audits (Brownson, Hoehner, Day, Forsyth, & Sallis, 2009). Both methods are time-consuming, labor-intensive, and inefficient.

In recent years, image-based pedestrian detection techniques have undergone impressive transformations. Video-based and image-based human detection systems have found a wide range of applications in robotics and intelligent transportation (Prioletti et al., 2013). The classic pedestrian detection methods include the Support Vector Machine (SVM) and the Decision Tree. These methods classify environmental features by assessing relationships between Histogram of Oriented Gradient (HOG) readings at different scales in the image pyramid (Benenson, Omran, Hosang, & Schiele, 2015; Dollár, Appel, Belongie, & Perona, 2014).

Researchers in the public health and urban planning fields have made some initial applications of manual or automated pedestrian detection systems based on Google SVIs. For example, Ewing and Clemente (2013) used desk-based audits of Google SVIs to count pedestrians as one aspect of their street-level urban quality assessments. Similarly, Goel and colleagues used manual methods to audit seven types of street users and then applied the data from their audit to predict city-level travel patterns (Goel et al., 2018). Yin and colleagues developed an improved method for automatically extracting pedestrian count data with Google SVIs and machine learning techniques (Yin et al., 2015). However, the automated methods have not been rigorously tested for validity.

2.4. Current gaps and our study

Pedestrian volume is an important indicator that can reflect physical activity levels, walkability, and urban vitality. Therefore, monitoring pedestrian volume is important to create healthy neighborhoods and pedestrian-oriented cities. Pedestrian volume data have been traditionally collected through field counting or self-reported surveys, which have significant limitations. For instance, self-reported data on walking may introduce recall bias and social desirability issues (Adams et al., 2005; Prince et al., 2008). In addition, the data reported are often not linked with specific geographic locations (Saelens & Handy, 2008). Measuring pedestrian volume by field audits can also be challenging; the time required for observation, the number of observers and the financial costs are often substantial (S. Lee & Talen, 2014). Both the field counting and self-reported methods are unfeasible for assessments of large, spatially dispersed study areas (Purciel et al., 2009; Rundle et al., 2011).

Measuring pedestrian volume from SVIs with machine learning techniques can overcome these problems because this approach offers large geographic reach, consistent image acquisition, and inherent geographic information (Bader et al., 2015). This promising method may stimulate more extensive walkability studies. As mentioned above, several studies have explored the possibility of using Google SVIs with machine learning techniques for automated pedestrian detection (Yin et al., 2015). However, the accuracy of this new method has not yet been rigorously tested. It is unclear whether SVI characteristics (such as service providers, collecting times, and levels of image quality) or street segment features may affect the level of accuracy. In this study, we conducted a large-scale validation test, by comparing pedestrian volumes extracted from SVIs with those from field observation for 701 street segments. We hypothesized that different SVIs parameters and street features could affect the levels of agreement with the field observation data.

3. Method

3.1. Study area

This study was conducted in Tianjin, China, one of four municipalities directly administered by the central government. It is a large city in northern China, with a population of 15.5 million in 2015 (Liu, Gao, & Wang, 2018). Tianjin remains a monocentric city, and this study focused on several parts of the downtown area (Fig. 1). The “street segment” was used as the unit of analysis, which was defined as the portion of street between two adjacent street intersections. The lengths of these street segments were relatively short, ranging from 30 to 400 m (M = 138 m, SD = 72 m), and a total of 701 street segments were selected for this study. The sampling streets were located in several established neighborhoods within city center, featuring iron-grid street pattern, high walkable urban environment, and mainly business and residential land uses. The neighborhoods were selected due to their high pedestrian activities.

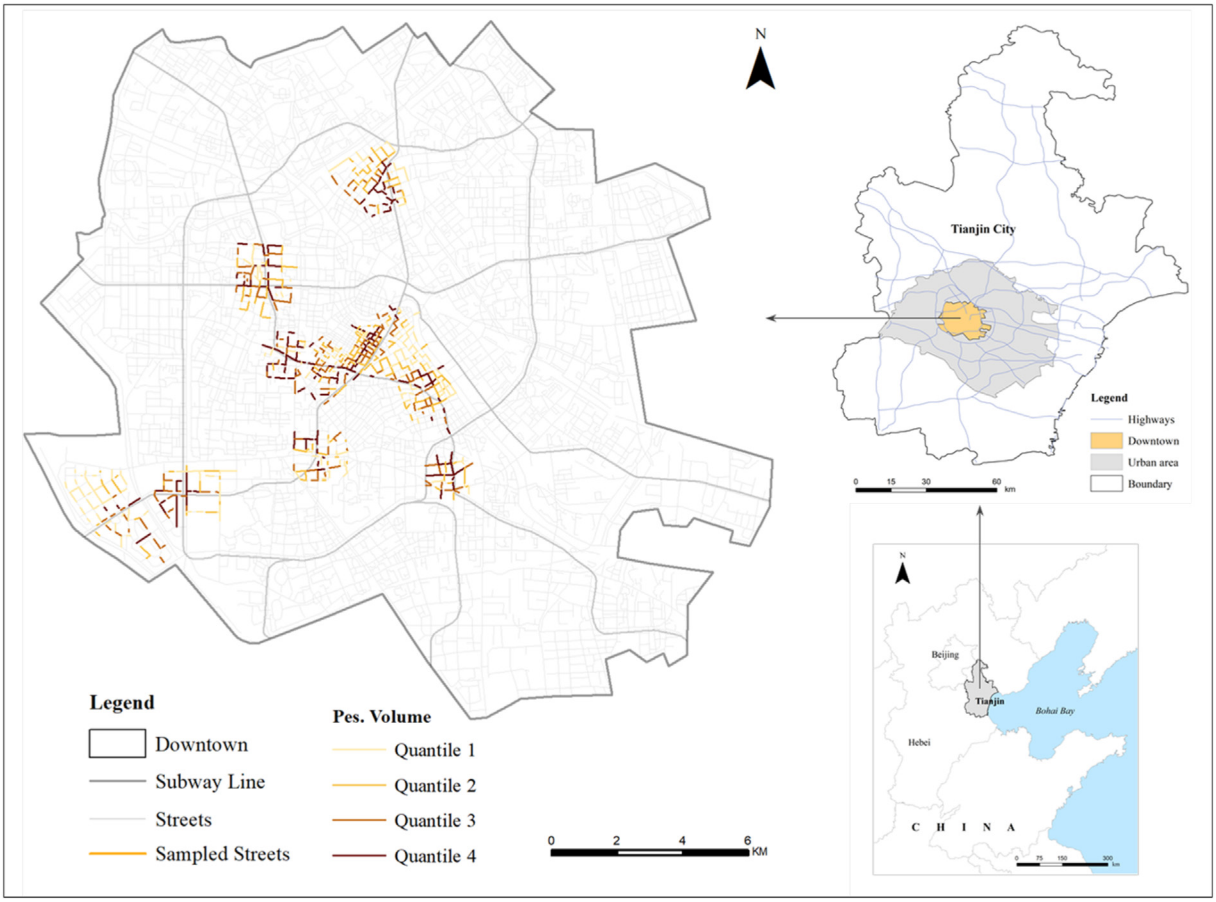

Fig. 1. Study areas and streets. The pedestrian volume of the 701 street segments in Tianjin, China, were obtained by field observation.

3.2. Pedestrian volume data from field observation

To test the accuracy of automated pedestrian counts from SVIs, field observation counts of pedestrian volume were collected in March 2015, by a group of university students from a major public university in Tianjin. For each street segment, the students recorded a 20-min video, which represented four recordings of five minutes each, taken at different times during one day, at a fixed location, covering both sides of the street segment. Then, the number of pedestrians passing an imaginary fixed-location were counted in the videos. The weather on the days of the recordings was mild and conducive to walking activities.

3.3. Assessing pedestrian volumes from SVIs

The overall workflow of extracting pedestrian volumes from SVIs contained three steps (Fig. 2): retrieval of SVIs, pedestrian detection with LDCF algorithm, and data aggregation. The data on the SVIs were retrieved from two service providers of SVIs in China: Tencent and Baidu Maps. As Google SVIs are unavailable in China, this provider was excluded. A Python web crawler technique was developed to download SVIs via API.

The process of retrieving SVIs images were described below (Fig. 3). SVIs sampling points were generated along the streets at intervals of 20 m in the ArcGIS mapping platform, and the direction of each street was calculated. The use of 20-m sampling intervals avoids the problems of excessive or incomplete coverage along the street. For each sampling point, SVIs were retrieved with the following parameters. For Baidu Street View panoramas, the horizontal directions of 0°, 90°, 180°, and 270° (as heading parameters in the Baidu API) represented the front, right, back, and left directions, based on the camera car's direction of movement, parallel to the corresponding streets. Two images were obtained for the left and right directions of each panorama. Hence, those two images were perpendicular to the street centerline. The vertical direction (pitch parameter in the Baidu API) was set at 0°, which meant that the images were retrieved at the horizontal view angle. The field of view (FOV parameter in the Baidu API) was set at 90°. The maximum image pixel-size was set at 1024*1024 pixels, and the highest image quality selected was 100 out of 100 in API.

For the Tencent Street View panoramas, a total of 24 image tiles (512*512 pixels for each tile) for each sampling point were directly downloaded from the Tencent API, and the 24 image tiles were stitched together to create a panoramic image with three tiles (1536 pixels) in the vertical direction, and eight tiles (4096 pixels) in the horizontal direction. We first constructed a panoramic image and then cut out two images perpendicular to the street with a vertical extent from 284 to 684 out of 1536 pixels, and a horizontal extent of two tiles (1024 pixels) from each image.

To improve the accuracy of the pedestrian extraction, the Baidu and Tencent images were cropped at their vertical axes to a size of 1024*400 pixels. The cropped images usually covered the sidewalk range of the street. The Baidu images were cropped from 312 to 712 pixels at the vertical axis, using the retrieved images at maximum pixel-size. The Tencent images were directly cropped at 1024*400 pixels from the stitched panoramic images. The cropped images excluded redundant visual information at the tops and bottoms of images containing no pedestrians. In a pilot test, we compared manual counts from 50 randomly selected images and found that cropped images outperformed the original images in automated pedestrian extraction (Pearson $r = 0.75$ vs. $r = 0.69$).

Furthermore, in another pilot test with 50 randomly selected Baidu

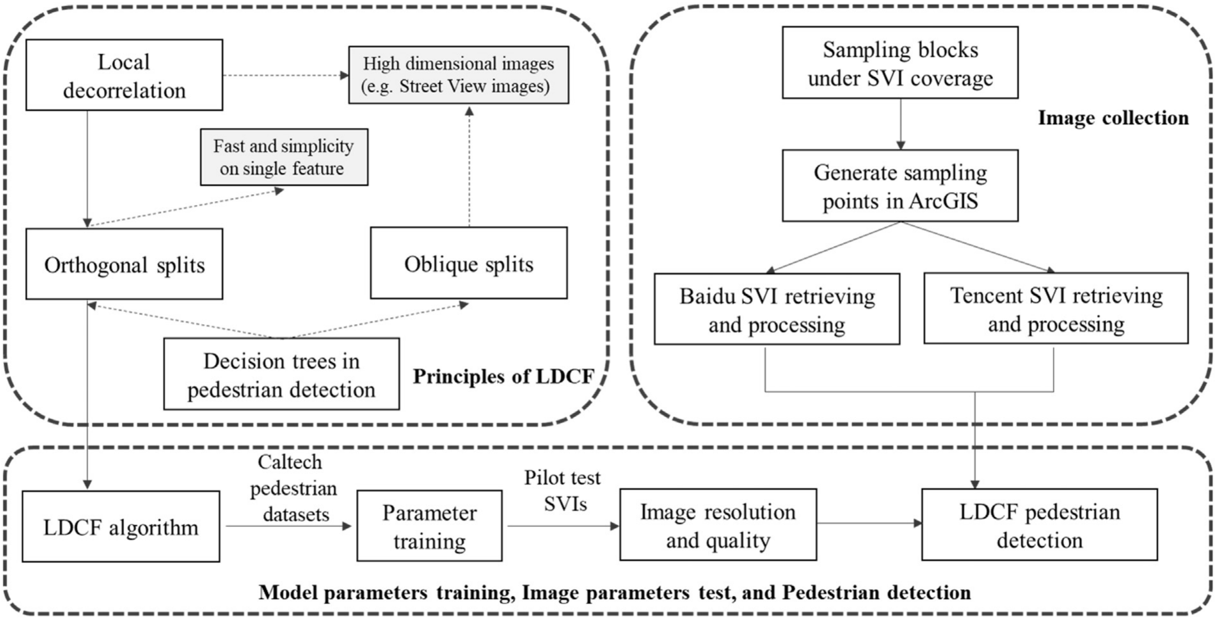

Fig. 2. The overall workflow of this study.

images, we found that larger-size images (1024*1024 pixels for each image; 0.55 MB file size for each image, averaged by 1000 images) outperformed medium-sized images (800*800 pixels; 0.37 MB file size) or small-sized images (512*512 pixels; 0.16 MB file size) in terms of accuracy in automated pedestrian extraction. We determined image performance by comparing the automated counts with the manual counts from those images (Pearson r = 0.75, 0.66, and 0.19 for the large-, medium-, and small-size images, respectively). Hence, all of the Baidu SVIs were retrieved at the maximum image size. The quality of the Baidu images ranged from 0 to 100 in the API. Images with high quality (100 in quality, 0.55 MB file size) outperformed low-quality images (60 in quality, 0.49 MB file size) in our third pilot test (Pearson r = 0.75 vs. r = 0.71). The results demonstrated that both the pixel-size and the quality parameter could influence the resolution of Baidu SVIs. The pixel sizes of Tencent images were equivalent to those of the retrieved Baidu images and covered roughly the same areas. However,

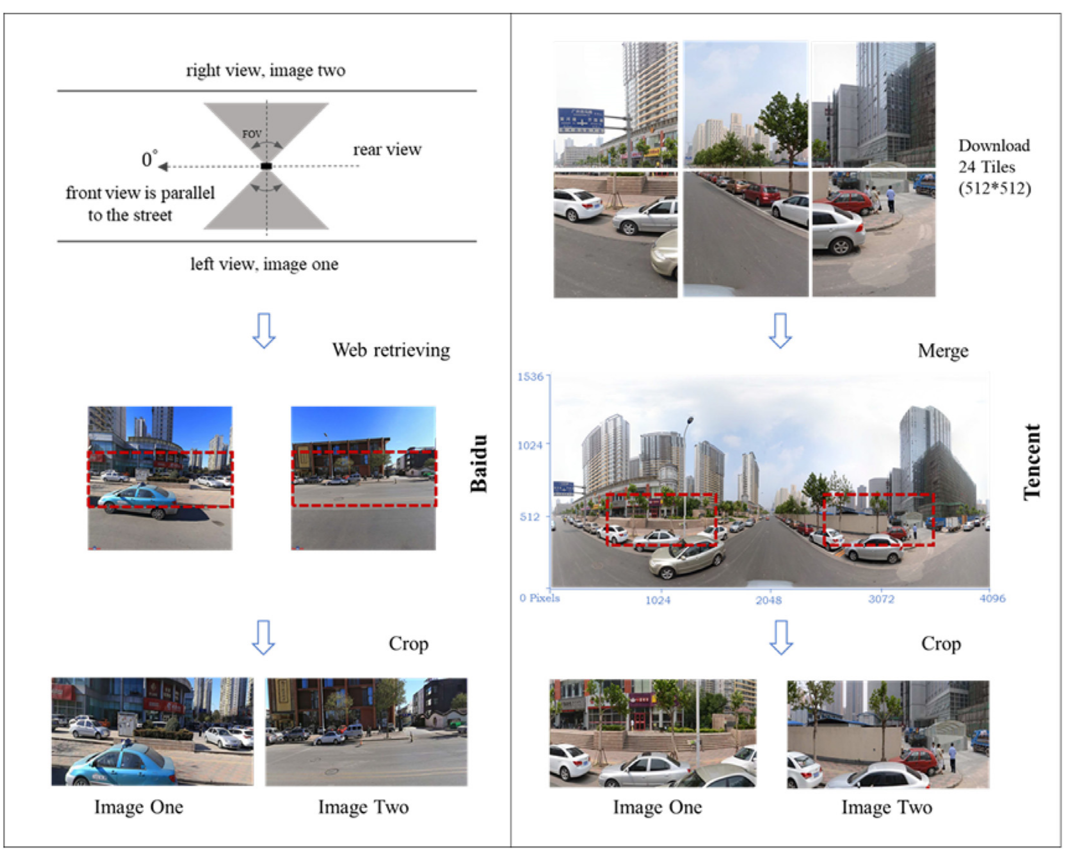

Fig. 3. Retrieving and transforming Tencent or Baidu SVIs.

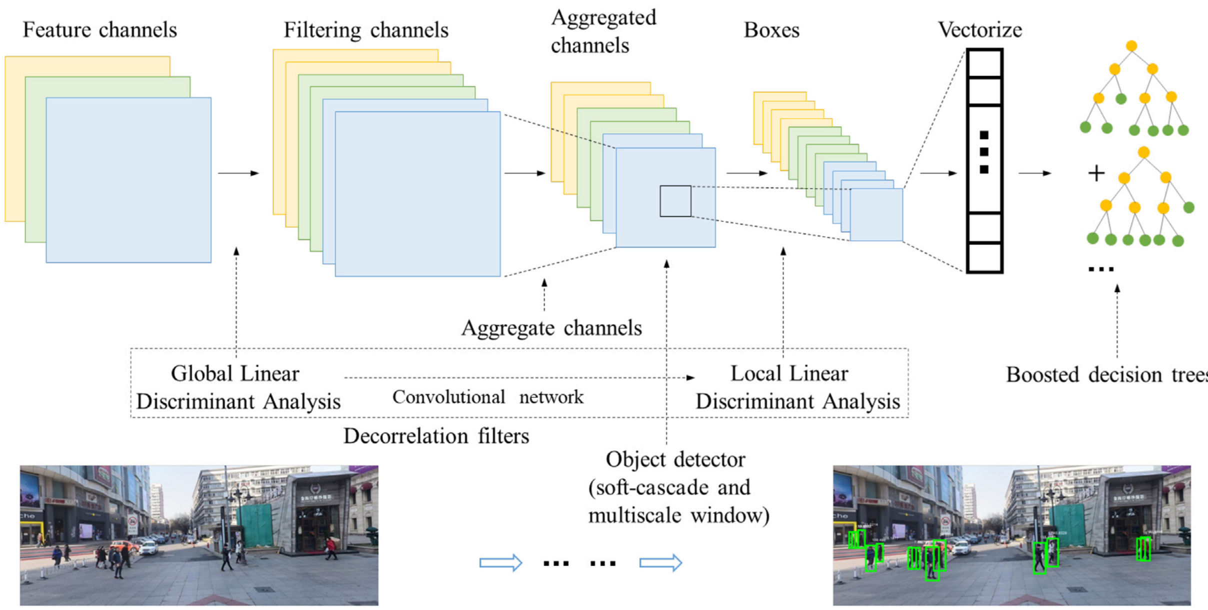

Fig. 4. Illustrating the process of pedestrian detection with the LDCF algorithm.

the quality of the Tencent images (Pearson $r = 0.80$, 0.61 MB file size) was better than the Baidu images.

Baidu Street View API provides a feature that enabled us to retrieve not only the most recent images but also previously collected images. Hence, we retrieved Baidu SVIs from 2013, 2015, 2016, and 2017, and we retrieved Tencent images from 2014.

Images facing both sides of the streets as retrieved from the Baidu and Tencent panoramas were used for automated pedestrian detection, with the application of an advanced machine learning technique involving the Locally Decorrelated Channel Features (LDCF) algorithm (Fig. 4). The LDCF algorithm is capable of counting pedestrians from any images without involving the image segmentation process. In the pedestrian detection field, decision trees with orthogonal splits have remained popular. Orthogonal splits are more efficient and have lower computational costs during training and detection than the oblique splits, although oblique splits may have considerable advantages when processing high-dimensional data with heavily correlated features (Nam, Dollár, & Han, 2014). Based on a scheme proposed by Hariharan, Malik, and Ramanan (2012) for estimating covariances between Histogram of Oriented Gradients (HOG) features using Linear Discriminant Analysis (LDA) for fast training, Nam and colleagues proposed LDCF algorithm which can introduce an efficient feature transformation that removes correlations in images of local neighborhoods (Nam et al., 2014). In this way, Nam's research finds that orthogonal trees with locally decorrelated HOG features are more applicable to pedestrian detection than oblique trees (e.g., ACF detector with oblique splits).

In addition, the LDCF algorithm was trained with Caltech pedestrian dataset (Dollar, Wojek, Schiele, & Perona, 2009). The dataset was collected by a camera in a car driving through regular traffic in an urban environment. The images usually have low resolution and frequently occluded people which are similar with Baidu and Tencent SVIs. In the Caltech dataset, approximately 250,000 images with a total of 350,000 bounding boxes and 2300 unique pedestrians were annotated. Roughly half of the images were used in LDCF training, while the remaining were used in test. As shown in Nam's research, the trained LDCF algorithm achieved a performance with a higher successful rate about 80% to detect pedestrian compared with previous algorithms (Nam et al., 2014). A pilot test was conducted with 50 Baidu SVIs and 50 Tencent SVIs. The number of pedestrians detected by LDCF algorithm strongly correlates with manual pedestrian counts in these images (Pearson $r = 0.75$, $p < .01$ for Baidu SVIs, and $r = 0.80$, $p < .01$ for Tencent SVIs).

Finally, we aggregated the count data from sampling points at the street level. The count data from the 20-min videos were used to measure pedestrian volumes, i.e., pedestrian counts over a fixed duration of time. However, each SVI is only able to capture pedestrians at a certain point in time. A street segment can have multiple SVI sampling points and hence multiple SVIs. These multiple SVIs represent pedestrian activities at multiple points of time. Therefore, the average number of pedestrians per image (rather than the total number of pedestrians for all sampling points) should be used to represent the automated pedestrian volume of each street segment in this study. For instance, there are two street segments (A & B) with same pedestrian volume, but with different length (20m and 200m respectively). Segment A has one SVI sampling point, while Segment B has ten. Let's assume the number of pedestrians in each SVI is similar, because these two street segments have same pedestrian volume. The pedestrian volume for Segment B will be tenfold inflated, if it is calculated as the total number of pedestrians in all SVIs.

Pedestrian volume data were separately calculated for Baidu images from 2013, 2015, 2016, 2017, and Tencent images from 2014. In addition, we calculated the multi-year or multi-source averages with two additional combinations: collection times of SVIs close to the field audits (Baidu from 2015 and Tencent from 2014), and all data sources of SVIs (Baidu for 2013, 2015, 2016, and 2017, and Tencent for 2014). It should also be noted that the proportions of Street View coverage for the 701 street segments varied for different years and different sources, ranging from 73.6% to 99.7% (Table 1).

3.4. Statistics

Descriptive statistics were compiled to describe the pedestrian volume data collected from both the field audits and the SVIs. Those statistics included minimums, maximums, means, standard deviations (SDs), the number of street segments, street segment coverage, and data collection years.

Cronbach's alpha was used to test the data reliability and compare the pedestrian volumes collected by field audits to the volumes extracted from various SVIs (Ewing & Clemente, 2013; Yin et al., 2015). Cronbach's alpha is a widely accepted reliability indicator used to measure the degree to which two variables hold the same construct. As a rule of thumb in social science studies, an alpha value ≥ 0.70 is

Table 1
Pedestrian volumes derived from different data sources.

Street view	Min. ped. volume	Max.ped. volume	Mean ped. volume	SD. ped. volume	Num. of street segments	Coverage (%)	Collection Year
Field audit	2	4356	432.32	508.08	701	100%	2015
Baidu_13	0	10	1.70	1.21	580	82.7%	2013
Baidu_15	0	12.10	1.30	1.29	516	73.6%	2015
Baidu_16	0	10.75	1.56	1.50	557	79.5%	2016
Baidu_17	0	12	2.58	1.98	610	87.0%	2017
Tencent_14	0	13.5	2.52	1.68	699	99.7%	2014
B5T4	0	9.90	2.09	1.44	699	99.7%	Multiple
B3567T4	0.20	9.14	2.07	1.24	699	99.7%	Multiple

B5T4 is the combination of Baidu 2015 and Tencent 2014 image data; B3467T4 is the combination of all SVIs data sources, including Baidu 2013, 2015, 2016, 2017, and Tencent 2014.

regarded as acceptable reliability, and an alpha value ≥0.80 is regarded as good.

To identify which street segment characteristics may affect the reliability of SVIs pedestrian detection, we further classified the street segments according to three factors: segment length, pedestrian volumes (as assessed by field audit), and the walkable catchment. The walkable catchment (Duany, Plater-Zyberk, & Speck, 2000) of each segment was calculated as the total length of all streets within a 500-m street network buffer, and it is typically used to compare levels of walkability and street connectivity for different locations Fig. 5. Each factor was split into quartiles, and separate Cronbach's alpha tests were conducted for each subset of street segments.

4. Results

The descriptive statistics are presented in Table 1. Most of the sampling street segments were covered by Tencent service in 2014. However, the coverage of Baidu Street View was more inconsistent in different years. A total of 4507 sampling points from 701 streets were used in this study. As a result of SVIs availability, 4840, 3440, 4134, and 7376 images were collected from Baidu 2013, 2015, 2016, 2017 datasets respectively. A total of 9012 images were collected from Tencent 2014 dataset. Automated pedestrian counts illustrated different statistical results from different years or sources. The average number of detected pedestrians in each image within each segment ranged from 1.30 to 2.58 in all SVIs datasets (Table 1). The proportion of street segments covered in SVIs also vary by SVIs providers and collection years.

It is worth noting that the automated pedestrian count method is more efficient than field observation. The whole process only took about 1.5 s per image to automatically obtain pedestrian count (the time may vary by computer configurations), including the tasks of image retrieving, image processing, and pedestrian detecting. As a comparison, field observation usually took two hours per street segment, including the tasks of transportation, video recording, manual pedestrian counting with video.

Table 2
Levels of agreement between automated pedestrian detection from different Street View (SV) sources and the results of field audits.

SV source	Cronbach's alpha (vs. field audit)	Level of agreement
Tencent_14	0.80	Good
Baidu_13	0.46	Unacceptable
Baidu_15	0.60	Questionable
Baidu_16	0.35	Unacceptable
Baidu_17	0.47	Unacceptable
B5T4	0.81	Good
B3567T4	0.71	Acceptable

B5T4 is the combination of Baidu 2015 and Tencent 2014 data; B3467T4 is the combination of all SVIs data sources, including Baidu 2013, 2015, 2016, 2017, and Tencent 2014.

Table 2 illustrates the level of agreement between the automated pedestrian detection results and the field audit results. As an individual data source, Tencent SVIs in 2014 achieved good agreement (Cronbach's alpha = 0.80). Baidu SVIs in 2015 had questionable agreement, and Baidu SVIs in 2013, 2016, and 2017 had unacceptable agreement. For combinations of multiple data sources, the averaged results of Baidu 2015 and Tencent 2014 had a good agreement (Cronbach's alpha = 0.81), and the averaged results of all data sources (B3567T4) had an acceptable agreement (Cronbach's alpha = 0.71).

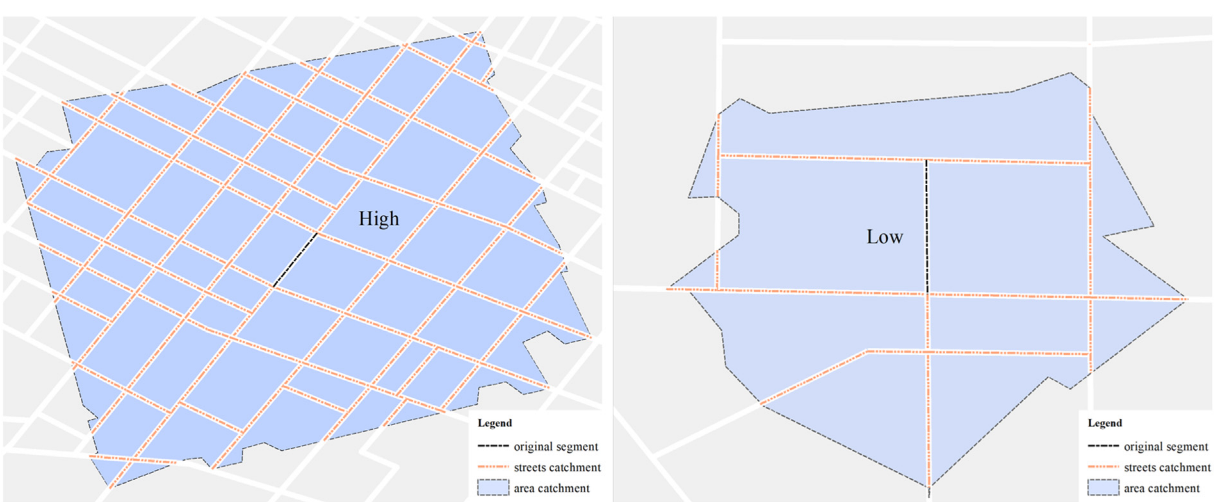

Fig. 5. High and low walkable streets catchment, as defined by the total length of streets within a 500-m street network buffer, i.e., the total length of all streets that can be reached by walking 500 m from one street segment.

Table 3
Level of agreement for street segments grouped by three factors: segment length, pedestrian volume, and walkable catchment.

Variables used to group street segments	Quartiles	Cronbach's alpha (SV count vs. Field count)		
		T4	B5T4	B3567T4
Segment length	Q1-short	0.79	0.79	0.72
	Q2	0.79	0.85	0.77
	Q3	0.86	0.87	0.70
	Q4-long	0.70	0.70	0.61
Pedestrian volume	Q1-low	0.46	0.41	0.47
	Q2	0.46	0.48	0.57
	Q3	0.56	0.58	0.58
	Q4-high	0.80	0.86	0.72
Walkable catchment	Q1-low	0.60	0.65	0.65
	Q2	0.68	0.67	0.70
	Q3	0.69	0.67	0.62
	Q4-high	0.86	0.87	0.74

Table 3 illustrates the agreement test for street segments grouped by three factors: segment length, pedestrian volumes (as measured by field audits), and walkable catchment. The Cronbach's alphas of each quartile demonstrated several interesting patterns. Segment length was not a significant factor affecting the agreement test, and pedestrian volume affected the level of agreement. Those segments with the highest volumes (Quartile 4) had significantly higher Cronbach's alphas than the other quartile groups for all three SVIs data sources. Similarly, segments with the highest street connectivity (Quartile 4) had significantly higher Cronbach's alphas than the other quartile groups.

5. Discussion

Previous studies have verified the feasibility of using SVIs to conduct environmental audits, such as audits of general neighborhood environments (Charreire et al., 2014; Rundle et al., 2011), street greenery (Lu, 2018), and open skies (Yin & Wang, 2016). However, most of these studies have focused on static environment features, rather than dynamic information such as pedestrian volumes, which constantly fluctuate over time and space. In this study, we sampled 701 street segments in Tianjin and compared the automated detection results with pedestrian volumes collected by field observation. The results demonstrated that using Tencent and Baidu SVIs with machine learning techniques is a promising method for estimating pedestrian volumes on a large geographic scale. We concluded that with appropriate processing and parameters, automated pedestrian volume detection could achieve reasonable levels of accuracy. More specifically, we found that variable factors of SVIs and street segments may influence the accuracy of automated assessment of pedestrian volume.

5.1. Image quality and processing

Image quality is important in the process of automated pedestrian detection. The resolution of the images should be selected carefully to avoid omissions and misrecognition in the process of machine-based pedestrian recognition. In this study, we found that both image size (in pixels) and image quality (1–100 scale) influenced the accuracy of counts from Baidu SVIs. As our pilot test with Baidu SVIs demonstrated, large-sized images (1024*1024 pixels) had higher levels of accuracy than medium-sized (800*800 pixels) or small-sized images (512*512 pixels). Similarly, Baidu images with high image quality (100 out of 100) outperformed those with low image quality (60 out of 100) in the pilot accuracy tests. The API parameters provided by Tencent differed from those provided by Baidu, and the Tencent panoramic images were composed of 24 image tiles. However, Tencent outperformed Baidu in the pilot accuracy test, which may be attributed to its relatively large file size. Hence, Tencent is more suitable for automated pedestrian detection than Baidu, when other conditions are equal. In addition, SVIs can be cropped to remove the tops and bottoms of those images, because those areas contain no pedestrians. In summary, appropriate image parameters and processing should be tested and implemented to increase the accuracy of automated pedestrian detection.

5.2. Image collection time

Matching the collection times of SVIs with those of field observations may also affect the accuracy of automated pedestrian detection. In our study, pedestrian volume data were collected from field observations conducted in 2015. The Baidu images from 2015 demonstrated questionable agreement with the field observations, but the Baidu images from other years (2013, 2016, and 2017) had unacceptable agreement. Tencent images from 2014 had the highest levels of agreement of any single data source, and the combination of Baidu images from 2015 and Tencent images from 2014 also achieved acceptable agreement, which indirectly confirmed our assumption. In contrast, images collected at times further away from the targeted period demonstrated reduced accuracy. The fluctuations of pedestrian volumes across different SVI collection times might be explained by the rapid urban development of China in recent years. The walking-influencing factors, such as population density, commercial activity, and major transport modes have recently undergone major changes in Tianjin.

5.3. Street segment characteristics

Regarding street segment characteristics, street segments having higher pedestrian volumes, better walkability, and greater street connectivity (as measured by walkable catchment) had greater accuracy. It is worth noting that pedestrian volume and street connectivity are highly correlated (Hajrasouliha & Yin, 2015; Hillier & Iida, 2005; Lerman, Rofè, & Omer, 2014; Ozbil, Peponis, & Stone, 2011). Hence, street connectivity may affect accuracy via the mediation effect of pedestrian volume. Furthermore, the street segment length does not affect the accuracy of automated pedestrian detection. We tentatively suggest that automated pedestrian detection may work well in streets with higher pedestrian volumes, and researchers should be cautious in using this method in streets with low pedestrian volumes.

The findings of this study can advance multidisciplinary research that aims to promote walking behaviors and create healthy cities. Researchers can use SVIs and machine learning techniques to assess pedestrian volumes at any location having Street View coverage. Hence, the automated pedestrian detection method can help urban planners and policymakers to identify areas with low pedestrian activity, and generate tailored urban design strategies to improve urban environment. Researchers who focus on the associations between the built environment and walking can also use this method to identify critical built environment characteristics that may promote walking behaviors on a citywide or even nationwide scale.

We also found that the parameters of SVIs are important in machine learning. Image size and quality should be increased to detect fine-grained street elements. In our study, Tencent SVIs had higher quality and better accuracy than Baidu SVIs. Furthermore, our findings suggest that Tencent and Baidu should provide more API parameters, such as image collection times, weather conditions, and temperatures, as these factors may also affect pedestrian activities.

Several limitations of this study should be noted and hopefully overcome in the future. First, we used a fixed distance of 20 m between sampling points along each street. The street front coverage varied by street width. For example, there could be gaps in the SVIs for narrow streets and overlaps for wide streets. Hence, in future studies the distance between sampling points may be adjusted by street width. Second, some cities or some parts of a city are not currently covered by any Street View service. The proposed method cannot be applied to those areas. Third, automated pedestrian detection has unacceptably low accuracy in locations with low pedestrian volumes. Researchers should be cautious in interpreting data from these areas. Fourth, pedestrians in SVIs obscured by other objects, e.g., vehicles or trees, cannot be detected, hence pedestrian volumes were underestimated. Last, some factors of SVIs were not considered, e.g., weather, daylight, month, or season of the image collection time. These factors should be considered in subsequent studies.

6. Conclusion

The traditional method of assessing pedestrian volume with field observations is often time-consuming, labor-intensive, and with limited study areas. In this study, we have investigated the accuracy of an automated method for assessing pedestrian volume. This method uses Tencent and Baidu SVIs with machine learning techniques, to overcome the limitations of field observations. Our results demonstrated that overall, the new method provided acceptable or good levels of agreement with field observation data. It is worth noting both SVI and street segment characteristics can affect the accuracy. SV images of high quality, large size, and times of collection close to the targeted periods proved better able to produce accurate counts. The proposed automated method also worked better in areas with high pedestrian volume and high street connectivity. Future researchers should be cautious in using this method for areas with low pedestrian volumes.

Declaration of Competing Interest

None.

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