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Measuring visual enclosure for street walkability: Using machine learning algorithms and Google Street View imagery

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ABSTRACT

One major limitation currently with studying street level urban design qualities for walkability is the often inconsistent and unreliable measures of streetscape features across different field surveyors even with costly training due to lack of more objective processes, which also make large scale study difficult. The recent advances in sensor technologies and digitization have produced a wealth of data to help research activities by facilitating improved measurements and conducting large scale analysis. This paper explores the potential of big data and big data analytics in the light of current approaches to measuring streetscape features. By applying machine learning algorithms on Google Street View imagery, we generated objectively three measures on visual enclosure. The results showed that sky areas were identified fairly well for the calculation of proportion of sky. The three visual enclosure measures were found to be correlated with pedestrian volume and Walk Score. This method allows large scale and consistent objective measures of visual enclosure that can be done reproducibly and universally applicable with readily available Google Street View imagery in many countries around the world to help test their association with walking behaviors.

1. Introduction

The recent advances in sensor technologies and digitization have produced a large amount of data at fine resolution. These new data can help research activities by facilitating improved measurements or new variables of interest (Ruppert, 2013), and conducting large scale study at micro level. Big data such as Google Street View imagery that documents most North American cities in high resolution and is available and accessible online to everyone provides new opportunities to measure characteristics of physical cities at fine spatial scales. These data and big data analytics make it increasingly possible to better measure the physical city and study behaviors that may be influenced by the urban built environment (Yin, Cheng, Wang, & Shao, 2015). This paper aims to explore the potential of big data and big data analytics in the light of current approaches to measuring street level urban design qualities for walkability. Emphasis is placed here on how Google Street View imagery and machine learning techniques can help us approach conventional questions on evaluating streetscape features with objective measurement of visual enclosure or possibility of better identification.

How people use the built environment depends on what the spatial structure that designers and planners created offers. Multidisciplinary researchers and practitioners have been exploring ways to improve physical activity outcomes through modifying the built environment. “Urban design may influence people's choices and behavior in the use of the built environment. This influence, however, remains assumption and unclear until urban design qualities can be defined, quantified, measured, and tested empirically” (Yin, 2014, p. 273). Ewing and Handy (2009) developed quantitative but subjective measurement protocols of five categories of urban design qualities on their contribution to street walkability through field survey, including visual enclosure, imageability, human scale, transparency, and complexity. They demonstrated in detail how to quantify and rate street level urban design features by surveys to develop street design metrics for walkability. As Ewing and Clemente (2013) suggested, the challenge is to move from subjective definitions and measures to operational objective ones that can be done reliably and consistently across raters to capture the essence of each category of street level urban design quality. Purciel, Neckerman, and et al (2009) translated some of the variables in these five categories using GIS.

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However, there are still two major limitations with developing such street design metrics: 1) the unfeasible or inefficient large scale field observation in terms of time and cost; and 2) the often inconsistent and unreliable measures of street design qualities across different raters even with costly training due to lack of more objective processes. Moreover, there is no established standard procedure to handle the error margin involved to ensure the comparability and reliability from different raters.

In this paper, we explore and discuss how applying machine learning algorithms to Google Street View imagery can help study the morphology of the built environment, in particular, by generating objectively some street level urban design measures related to walkability. We use visual recognition techniques and visual images of the streetscape to create variables on visual enclosure for over 300 sampled street blocks across Buffalo, New York. Big data sources such as Google Street View imagery and big data analytics like machine learning technology together can help fill the gaps on current approaches to measuring street level urban design qualities that have been traditionally subjective and limited based on small samples. The results can provide new insight into the pedestrian friendly design and urban planning.

2. Assessing street level urban design qualities for walkability

Recent studies have shown that obesity and obesity-related diseases are associated with lack of physical activity and unhealthy diet (Papas et al., 2007). A promising approach to addressing this problem is through various interventions on the modification of the built environment to create streetscapes and neighborhoods that are walkable and livable. Planners and urban designers who are concerned with designing and planning the built and landscape elements in space and how people interact with these elements play an important role in shaping the built environment to encourage walking (Ewing & Handy, 2009).

Many studies have characterized and measured the built environment using the D variables – *density, design, diversity, destination accessibility*, and *distance to transit*, and explained travel mode choice and walking frequency in terms of these variables (Saelens, Sallis, & Frank, 2003; Ewing & Cervero, 2010; Frank et al., 2006; 2007; Sallis and Glanz, 2006; 2009; Smith et al., 2008; Marshall & Garrick, 2010; Boer, Zheng, Overton, Ridgeway, & Cohen, 2007). One of the Ds, *design*, has usually been represented by street network characteristics of the studied area and measured by street network density or block size. However, pedestrian activities can vary significantly from street block to street block even within a small geographic area with similar street network density (Desyllas & Duxbury, 2001). The currently widely used *design* variables are not sufficient to reflect the micro and street level environment and its impact on pedestrian experience, as discussed in classic urban design readings like Lynch (1960) and Hedman (1984). Hajrasouliha and Yin (2015) argued that the current street network connectivity measures only captured physical connectivity and suggested the important role of visual connectivity on its impact of pedestrian volumes. Other *design* variables have been occasionally used including street width, sidewalk coverage, number of trees, building setbacks, etc. The findings are mixed, however, with regard to their impact on physical activity or pedestrian activity (Desyllas & Duxbury, 2001).

A set of indicators and matrixes can help systematically quantify the impact of components of the street environment on the level of walkability to compare street and neighborhood design. Clemente et al. (2005) and Purciel and Marrone (2006) developed a field manual with detailed measurement protocols for coding the street physical features contributing to the five urban design qualities and provided detailed guidance for the field work and survey that are focusing on the street level experience.

One of the five qualities is visual enclosure (Ewing & Handy, 2009; Purciel et al., 2009). Two variables used to measure visual enclosure are proportion of sky ahead the street and across the street. These two variables were used to measure the amount of sky visible from a standing point on a street, with trees, buildings, street lights, and other street furniture and man-made objects as visual obstruction. Designers and literature suggested that this information on enclosure measure how the built environment encapsulated the pedestrian and related it to people's perceived confinement of space and sense of intimacy, and a place's livability and sense of security (Ewing & Handy, 2009; Porta and Renne, 2005; Zhang et al., 2012). These two sky visibility variables can be influenced by many factors that have been used to characterize the built environment linked to physical activity in health-related research such as street width, building height, and presence of trees. Section height to width ratio has been used to measure the degree of sense of visual enclosure (Carmona & Tiesdell, 2007). Tree canopy can help to reach some level of intimacy on streets. Streets that are wide, with lower buildings, small building setback, and without trees have relatively high level of sky exposure and low level of visual enclosure.

To estimate the proportion of sky for measuring visual enclosure, Purciel et al. (2009; p15) suggested to form a frame of vision box using the thumb and pointer fingers of both hands "that is visible when you look ahead with your line of sight parallel to the ground" and "hold it up to your face", then "move it away until you can see all four sides" (See Fig. 1). This method is subjective to field surveyors' heights and individual definitions and interpretations of how far away is the right distance to see all four sides. Different field surveyors may get dissimilar proportion of sky numbers for the same location even with systematical training. This raises the problem of reliability. The current literature suggested moving to operational objective street design measures for street walkability studies. However, little has been done on objectively measured sky related visual enclosure variables because of the limitation on both data and method.

3. Big data and big data analytics for planning and designing walkable streets

Big data is defined by high volume, velocity, variety, and variability of information. Big data analytics can analyze information with high volume, velocity, variety, and variability better than conventional tools and helps to uncover patterns, correlations, and other useful information. The internet and a wide range of programs online are important sources of big data. Google Street View provides street level imagery along most streets in the U.S. and many countries around the world, and is available over the Internet and through Google Earth software. The total road length covered is more than 5 million kilometers. It allows users to view streetscape and experience walking down streets in the virtual street environment.

Photographs and sections have been used by designers and planners for many years for graphic representations of spaces for analysis and design. Google Street View imagery provides more information and flexibility than these traditional representations for analyzing street morphology and its impact on pedestrian volume or movement. It also covers much larger area than traditional small sampled areas limited by time and budget. Google Street View has been used in several studies for streetscape audits. Rundle, Bader, Richards, Neckerman, and Teitler (2011) suggested Google Street View effective for auditing walkable street environments. They found high levels of agreement between measurements based on audits from field work and from Google Street

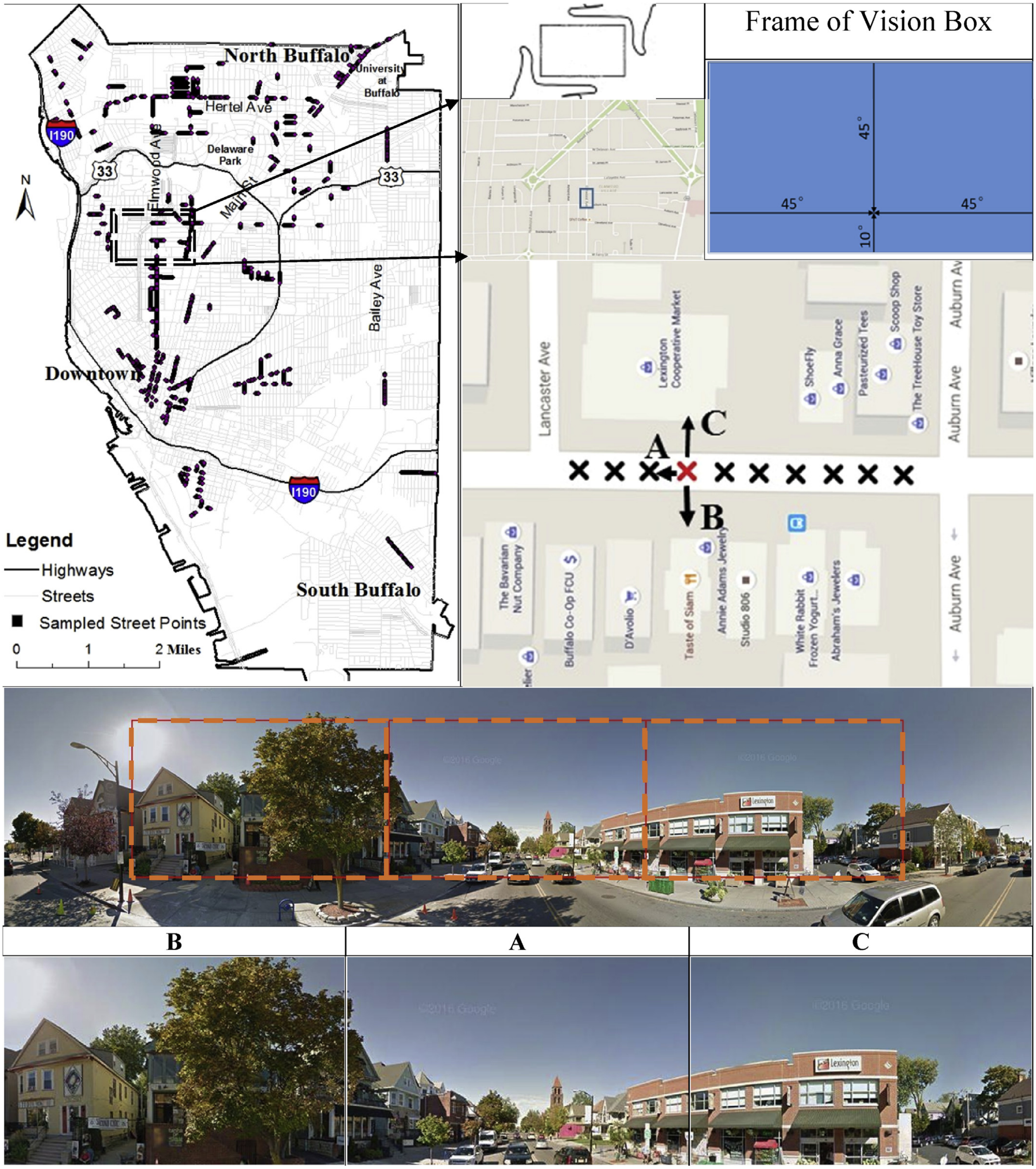

Fig. 1. Sampled streets and vision frame.

View. Other studies also suggested the effectiveness of Google Street View as an audit instrument for street level environment (Badland, Opit, Witten, Kearns, & Mavoa, 2010; Clarke, Ailshire, Melendez, Bader, & Morenoff, 2010). However, as Yin et al. (2015, P2) suggested that current studies “are still limited and subjective with regard to the use of Google Street View for environment audits … because of the manual information extraction and compilation, especially for large areas”.

Machine learning evolved from artificial intelligence on computational learning and pattern recognition. It is a method to learn and make predications on data. One machine learning method is Artificial Neural Network (ANN). They are models used to estimate based on a large amount of input data. The neural nets formed by interconnected neurons are adaptive to input data and capable of learning. ANN has been used for computer vision and speech recognition (LeCun, Bengio, & Hinton, 2015). Support Vector Machine (SVM) is another machine learning method with supervised learning models for classification. This method has been used for the classification of images (Press, Teukolsky, Vetterling, & Flannery, 2007). These data-driven prediction methods can help us to learn and analyze for planning and designing urban built environment based on big data like Google Street View images. Yin et al. (2015) found that applying machine learning technology on Google Street View imagery can help to determine the presence of pedestrian with a reasonable level of accuracy to help get an objective estimate of pedestrian volume.

4. Method

4.1. Data collection and preparation

We collected 3592 panoramic images for 311 street blocks sampled in the City of Buffalo, following the method and suggestions by Yin et al. (2015). These sampled street blocks were scattered in the city, but focusing more in the main part of the city (See Fig. 1). Every black dot represents one sampled street point with panoramic images. Fig. 1 illustrates that there are multiple sites with panoramic images provided by Google Street View for each street block as marked by the "X"s in the second row of the figure on the right side. The resolution of each image is 1664 × 832 pixels. Because each side of the street was represented by half of the panoramic circle with perspective views, these images gave people an impression of street intersections.

Using one image downloaded from one site on Elmwood Avenue as an example, Fig. 1 shows how we formed the frame of vision boxes for this one location. We drew three boxes on each panoramic image to show the view areas reflecting eyelevel equivalent pedestrian experience to calculate proportion of sky for three directions: front (A), left (B), and right (C). The one in the middle represents the front view (A). Every box was drawn according to the view angles illustrated in the top right corner, which were decided based on the vision frame box used by Purciel et al. (2009). The vertical view ranges from 10° down to 45° up, and 45° left and right angles for the horizontal view range. After this step, three images were created for each site on the sampled street blocks to be processed by machine learning technique for the proportion of sky calculation.

4.2. Applying machine learning technique

We applied machine learning techniques, specifically Artificial Neural Network and Support Vector Machine, to develop an algorithm to identify sky areas for measuring the proportion of sky on our sampled street blocks. Our method followed the conventional machine vision and pattern recognition methods, which first extracted design features from the original images, and then classified the input feature vector using learning subsystem. We went through the process in three steps as illustrated in Fig. 2. The first step was analyzing texture and color on images using ANN. Second step combined detection and segmentation with feature extraction to analyze image structure and extract features such as adjacent regions and their areas and locations, possibility of these regions being sky, and the likelihood of shared borders being straight lines. These extracted features were used as input for the third step on classification using SVM.

For every pixel on the input image (416 × 254 pixels in each vision frame box), a neural network with 5 pixel by 5 pixel patch centered at each input pixel was used to estimate whether it is a point representing sky. There are four features used: shape, area, location, and region. Since SVM was used, no weight was applied to each feature. The pixels with similar possibility of being sky are connected to each other to form regions. According to the shape, area, and location of their adjacent areas, SVM classified and labeled images sky or non-sky. During training, we labeled each pixel sky or non-sky on 100 street view images. Seventy of them were used for training and thirty for testing. The precision is 90% and recall is 98%.

The processing time of each image ranged from 20 s to 2 min depending on the complexity of the image. It took about 2–4 s for the ANN calculation for each image. The rest of time was for further identification of the regions by their locations in the vision frame, area, shape of adjacent areas, and classification. This automatic image process took two days to finish the sampled street blocks in Buffalo. Using the results from the classification with sky or non-sky identified, we calculated the proportion of sky in our vision frames for three directions: front, left, and right, for each site.

4.3. Correlation tests: Objectively measured visual enclosure and walkability

After objectively generating the proportion of sky variables for three directions on the sites of our sampled streets, we ran a few tests to see whether and how these representations of visual

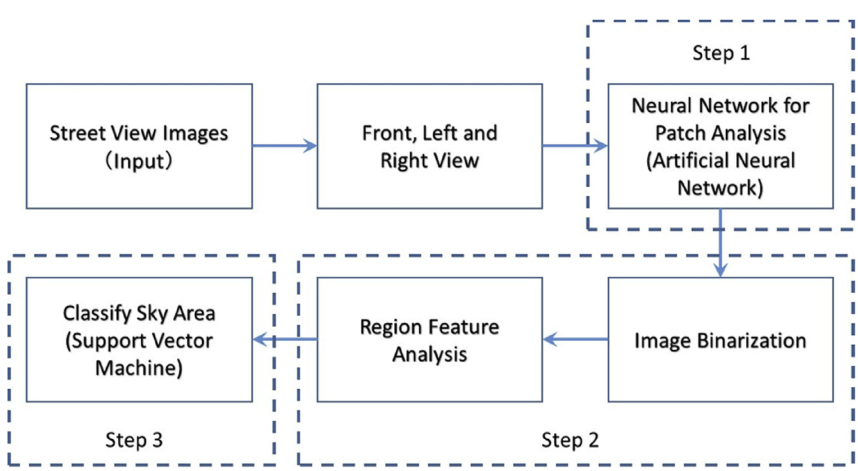

Fig. 2. Machine learning process to identify sky areas.

enclosure are associated with pedestrian activity and walkability. Two quantitative measures that have been used to help evaluate pedestrian activity and walkability were observation pedestrian counts and Walk Score (Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011; Hajrasouliha & Yin, 2015; Talen, 2014). Walk Score data were developed by a private company called Walk Score and have been used in researches as a proxy of walkability in recent years (Rauterkus and Miller, 2011; Talen, 2014). We also ran some tests to see whether and how proportion of sky is associated with some other *design* variables, in particular, presence of trees and building heights along the streets.

The number of passing pedestrians was sampled for 10 min periods during peak and off peak hours on weekdays at each sampled street block in spring and fall for two years. Since these two sets of data showed similar patterns of pedestrian activity, we used only one for this study, off peak hour pedestrian counts. Likewise, because data collected from 2013 to 2014 showed similar patterns, we used the mean pedestrian counts from these two years. Walk Score data were collected for each of the sampled street blocks using an API provided by Walk Score. Tree data were collected from City of Buffalo with information on street side tree locations and tree DBH (tree diameter measured at 4.5 feet above the ground). Kennel density was used to get tree density, weighted by DBH, assuming trees with higher DBH have more leaves to obstruct the sky. Building height data were compiled from several datasets collected from the city and from University at Buffalo, The State University of New York.

The widely used correlation test *Pearson r* correlation was applied to measure the strengths of association between several pairs of variables. We used the proportion of sky in different directions as measures of visual enclosure to correlate against observed pedestrian volume and Walk Score numbers. We also tested how proportion of sky and tree density and building heights are related to each other. In addition, correlation tests were done between each pair of the proportion of sky in different directions.

5. Findings

5.1. The proportion of sky by machine learning techniques

Fig. 3 illustrates the results after applying machine learning techniques on Google Street View images with skies classified and identified as white colored areas for selected sites from three different street blocks. All these three street blocks are commercial. The upper one shows the same street location as the one in Fig. 1 on Elmwood Avenue. This is a two-lane street with trees and different building shapes. There is also a tower in distance as shown in the vision box A. Buildings, trees and other objects were distinguished from the sky as indicted by the black color areas. The middle part of Fig. 1 shows a street with barely any trees and a large front setback for a parking lot of a chain grocery store. The lower part shows a site on a street in downtown Buffalo with trees and higher buildings.

As shown in Fig. 3, the skies were identified fairly well on all three different types of street blocks with different street level urban design qualities in terms of visual enclosure. With the clear and reasonably accurate sky identification using machine learning technology, the proportion of sky can be calculated. As we can see, the first and third location have lower proportion of sky ratios for all three directions than the second location.

5.2. Visual enclosure and street walkability

The *Pearson r* correlation coefficient varies between −1 and 1. A value around 1 or -1 indicates a perfect degree of positive or negative association between the two variables. As the coefficient values get closer to 0, the association between the two variables gets weaker. We followed Cohen, Cohen, West, and Aiken (2003) standard to evaluate the coefficients on their strength of the association. Coefficients between 0.10 and 0.29 represent a small association, between 0.30 and 0.49 for a moderate association, and above 0.50 for a strong relationship.

Table 1 shows that all coefficients are significant at the 0.01 level (2-tailed). The proportion of sky (front) has 1) a strong positive association with proportion of sky (left) and proportion of sky (right); 2) a moderate negative association with pedestrian volume, Walk Score, and tree density; and 3) a close to moderate negative association with building heights. These findings suggest that the sky area that people can see ahead a street is influenced by what is on both sides of the street, such as trees and buildings, and it also has influence on street walkability. Number and size of trees along streets and heights of buildings both have impacts on visual enclosure. These two variables were used at times as the *design* variables in research on physical activity and the built environment. It is not surprising to see that this sky proportion measure (front) is only moderately correlated with observed pedestrian volume and Walk Score. Previous literature suggested five categories of urban design qualities and proportion of sky ahead the street is only one of over 20 variables in these five categories.

There is a small association between proportion of sky across the street, both left and right, and pedestrian counts and Walk Scores, which is less strong comparing with the front sky ratio. This suggests that when a person looks ahead, visual enclosure ahead has more impact on walkability than that of the left and right side. Both left and right are strongly correlated to the front, but with less association between them. This suggests that some streets may have different built elements on different sides of streets. Previous studies used both variables of proportion of sky ahead the street and across the street. These results suggest that even though proportion of sky across the street is strongly correlated with that of ahead the street, including across the street variable may still be needed when built elements are different on different sides of a street.

6. Conclusion and discussion

We illustrated in this paper that image processing on Google Street View imagery provides a way to objectively measuring some key street level urban design features related to walkability that were previously measured inconsistently and subjectively using field surveys. By applying machine learning algorithms on Google Street View imagery, we generated objectively three urban design measures: the proportion of sky in three directions measuring visual enclosure. The results showed that machine learning algorithms that we developed were able to classify and identify sky areas fairly well to allow the calculation of proportion of sky. This method allows large scale and consistent objective measures of visual enclosure that can be done reproducibly and universally applicable with readily available Google Street View imagery in many countries around the world.

This method arms researchers with objective measures of some key features of the street environment to test for their association with walking behaviors. The results from the correlation tests showed that the proportion of sky ahead the street is strongly associated with the sky proportions across the street on both left and right hand sides. These visual enclosure variables are significantly associated with pedestrian counts and Walk Score negatively, the two quantitative measures used to help evaluate pedestrian activity and walkability. They are also negatively correlated with tree density and building heights, the two variables used to represent *design* factor in research on physical activity and

Fig. 3. Estimating proportion sky.

Table 1
Results of correlation tests: Visual enclosure and street walkability.

	Sky (front)	Sky (left)	Sky (right)	Pedestrian counts	Walk score	Tree density	Building heights
Sky (Front)	1	0.63**	0.66**	−0.30**	−0.33**	−0.43**	−0.28**
Sky (Left)	0.63**	1	0.42**	−0.20**	−0.30**	−0.43**	−0.15**
Sky (Right)	0.66**	0.42**	1	−0.23**	−0.29**	−0.40**	−0.16**

**Correlation is significant at the 0.01 level (2-tailed).

the built environment. While building heights might be related to walkability through spatial enclosure, other streetscape features such as tree density are more likely to change with advocacy efforts. In addition, building height may be related to another D variable: *density*. Future work might be done to explore the correlation.

As more development on artificial intelligence, more computational resources, and more and better big data like Google Street View imagery are expected in the near future, more objective and reproducible measures of street level urban design qualities such as window areas and building shapes for transparency and imageability can be done. The possibilities for improvement with objective variables and including other design aspects can be endless with the big data and big data analytics to better study the morphology of the built environment that have been traditionally subjective in small sampled areas.

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