A Pedestrian-Level Strategy to Minimize Outdoor Sunlight Exposure

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1 Introduction

Too much sunlight exposure is thermally uncomfortable and potentially dangerous for people (Brash et al. 1991; Hodder and Parsons 2007; Kurazumi et al. 2013; Richards and Edwards 2017; Young 2009), although the minimum amount of sunlight is required for humans. Sunlight exposure is a major factor of human heat stress, which is a comprehensive parameter influenced by humidity and temperature (Gaffen and Ross 1998; NOAA 2009). Heat stress in summer poses a daily health threat to urban residents and causes morbidity and mortality (Stone et al. 2010). Other than heat stress, unprotected exposure to ultraviolet (UV) radiation in the sunlight is one of the major risk factors for skin cancers (Brash et al. 1991; Armstrong and Kricker 2001). Preventing too much sunlight exposure would help people to decrease the potential dangers caused by sunlight.

Urban streets that carry most of the human outdoor activities in cities (Li et al. 2017) are the major place for human outdoor sunlight exposure. Understanding the

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spatiotemporal distribution of sunlight in street canyons would help us to develop methods to protect people from too much outdoor sunlight exposure. The solar radiation reaching the street canyons is influenced by the obstruction effects of street trees and buildings (Carrasco-Hernandez et al. 2015; Hwang et al. 2011; Johansson 2006; Lin et al. 2010). Buildings and trees on both sides of streets would obstruct sunlight and then reduce the potential human sunlight exposure in street canyons (Li et al. 2018). The urban form and the orientation of the street canyons would influence the obstruction effects of buildings and tree canopies on the sunlight (Algeciras et al. 2016; Ali-Toudert and Mayer 2006; Johansson 2006). Usually, those streets with larger height-weight ratio have less incoming sunlight reaching the ground. Those east-west orientation streets have more solar radiation reaching the ground because of the same direction with the sun's zenith (Sanusi et al. 2016). In different times of 1 day, the different sun positions and the surrounding obstructions would make sunlight exposure significantly different.

The high-resolution building height models make it possible to simulate the obstruction effects of building blocks on sunlight and estimate the transmission of sunlight within street canyons, which further makes it possible to generate the spatiotemporal distributions of sunlight in the street canyons. However, building height models usually oversimplify the geometries of urban canyons (Carrasco-Hernandez et al. 2015). In addition, building height models only consider the shading effects of buildings and the shading effects of tree canopies and other urban features are usually not considered (Li et al. 2018).

The street-level images provide a new approach to simulate the sunlight within street canyons. Different from the building height models, which usually only include the information about building blocks, the street-level images can represent all types of obstructions along the streets (Li et al., 2018; Gong et al. 2018). Therefore, using street-level images would be more reasonable to simulate the shading effects of obstructions and generate more accurate spatiotemporal distributions of sunlight in street canyons. In addition, street-level images, such as Google Street View (GSV) images and Mapillary images, are globally available. All of these make street-level images suitable for predicting human outdoor sunlight exposure along streets.

In this study, we propose an individual-level strategy for people to minimize the outdoor sunlight exposure based on the simulation of the sunlight in street canyons using the GSV images as a surrogate of the streetscape environment. A pre-trained deep learning model (PSPNet model) was used to segment the street-level images and recognize the obstructions of sunlight within street canyons. We then generated the spatiotemporal distribution of sunlight exposure in street canyons by calculating the sun positions over times and projecting sun positions on the segmented GSV images. Based on the generated spatiotemporal distribution of sunlight exposure in the study area, we further developed a spatiotemporal routing algorithm to provide an individualized routing choice for people to minimize their sunlight exposure. The proposed individual-level strategy would help to reduce the negative effects of sunlight exposure for urban residents.

2 Study Area and Dataset

The study area, Shibuya, is a special ward and a major commercial and business center in Tokyo, Japan. Shibuya is very densely populated with an estimated population of 221,800 and population density of 14,679.09 people per km^2. In order to collect GSV images in the study area, we created sample sites along streets every 10 m (Fig. 1(a)). The street map used in this study was collected from Open Street Map. The coordinates of these sample sites were then used to collect the metadata (Fig. 1(b)). This study focuses on human sunlight exposure in hot summer; therefore, only those images captured in similar seasons were used in this study. Based on the time stamps in the collected metadata of GSV panorama, we only selected the most recently captured images in summer for each sample site and downloaded GSV panoramas (Fig. 1(c)).

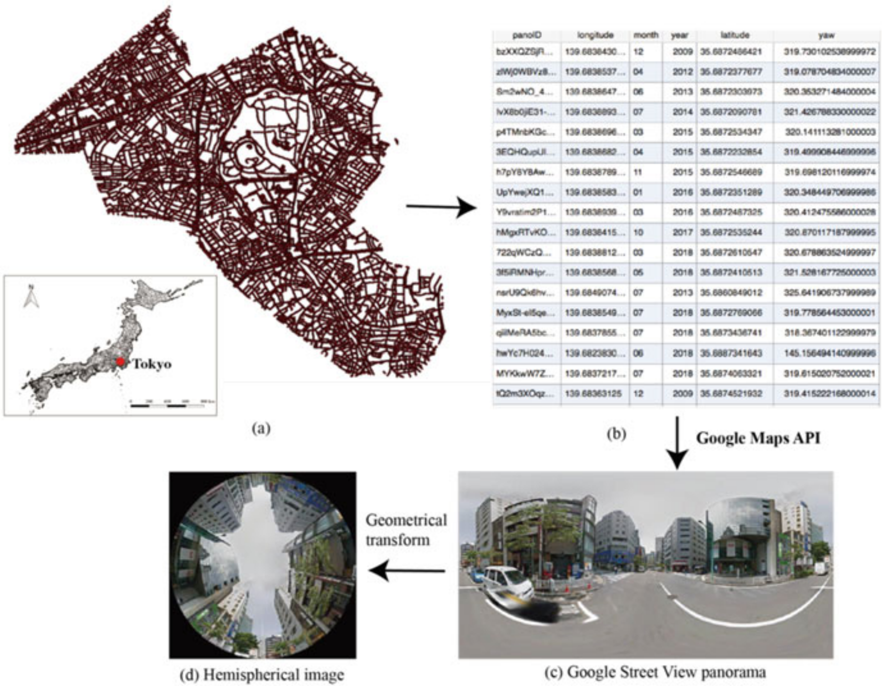

Fig. 1 The workflow for *GSV* google street view panorama collection in Shibuya, Tokyo, Japan, (**a**) the created sample sites in the study area, (**b**) the metadata of GSV panoramas, (**c**) a downloaded GSV panorama, (**d**) a generated hemispherical image based on geometrical transform

3 Methodology

3.1 Hemispherical Image Generation and Segmentation

Hemispherical image-based method is one of the standard methods for estimating solar radiation reaching the ground (Rich 1990; Easter and Spies 1994; Matzarakis et al. 2007, 2010). In this study, hemispherical images were generated from cylindrical GSV panoramas by geometrical transform (Li et al. 2017, 2018). In order to derive the sunlight obstruction information in street canyons, the image segmentation algorithm PSPNet was used to segment GSV panoramas into sky pixels and obstruction pixels (vegetation, buildings, and impervious surface pixels) (Gong et al. 2018; Zhao et al. 2017). The segmented GSV panoramas were further geometrically transformed into hemispherical images, which were used to model the human sunlight exposure within the street canyons. Figure 2 shows the segmentation results (Fig. 2(b)) of PSPNet on three GSV panoramas (Fig. 2(a)) and the segmented hemispherical images based on GSV panorama segmentation results (Fig. 2(c)).

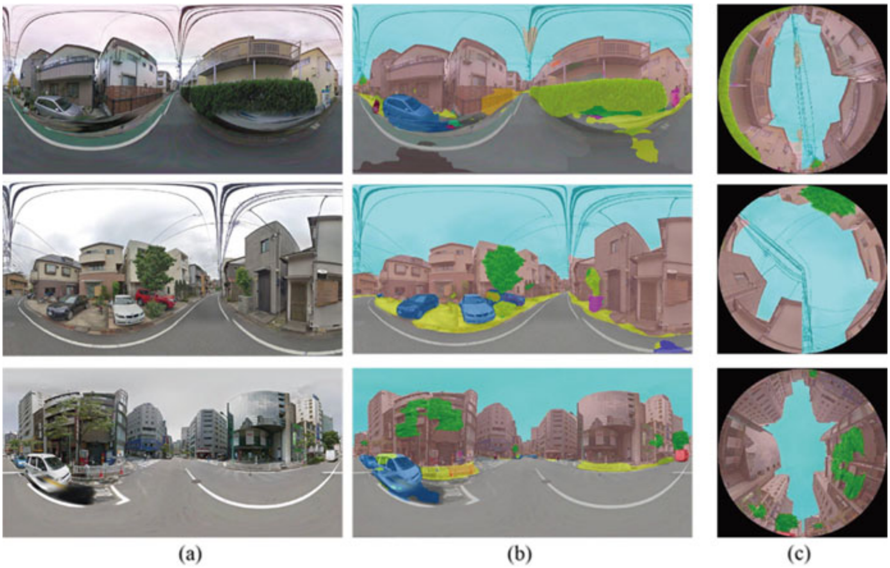

Fig. 2 Image segmentation results using PSPNet, (**a**) original Google Street View (GSV) panoramas, (**b**) the blend of segmentation results on GSV panoramas, (**c**) the hemispheric view of the segmented GSV panoramas

3.2 Human Exposure to Sunlight in Street Canyon

Human outdoor sunlight exposure is influenced by the time, orientation of the streets, buildings, and street tree canopies. Based on the generated segmented hemispherical images, it is possible to estimate whether a pedestrian is exposed to sunlight or not at any time and location by projecting the sun position on the hemispherical images.

In this study, we implemented the sun position estimation algorithm developed by NOAA Earth System Research Laboratory (ESRL, https://www.esrl.noaa.gov/) to estimate the sun position at any specific time. Figure 3 (a) depicts the geometrical model of the sun and a pedestrian. Figure 3 (b) shows the projected sun positions in 1 day on three hemispherical images in the study area. For a person at the location of (*lon*, *lat*), if the sun at one time (t) is projected on sky pixels of the hemispherical images, then the person is exposed to direct sunlight at that time. If the sun position is on non-sky pixels, the person at that time is shaded from sunlight.

The intensity of the sunlight at different times of 1 day varies with the sun elevation angle. In this study, we calculated the weighted sunlight exposure ($E_{w,t}$) at time t as

$$E_{w,t} = B_t \cos \theta_t \tag{1}$$

where θ_t is the sun elevation angle at time t; B_t is the Boolean variable indicating whether the direct sunlight is obstructed or not at time t; if the sunlight is obstructed at time t, B_t equals 0, or B_t is 1. The variations of solar radiation due to cloudiness and other atmospheric conditions are not considered in this study.

3.3 Routing Algorithm for Minimizing Sunlight Exposure

Based on the weighted sunlight exposure, a person's accumulated sunlight exposure E_a from one location at time t_0 to another location at time t_n can be estimated as

$$E_a = \sum_{t=t_0}^{t_n} E_{w,t} = \sum_{t=t_0}^{t_n} B_t \cos \theta_t \tag{2}$$

Figure 4 shows a sequence of hemispherical images with corresponding sun positions overlaid along a street of the study area. The "exposure over distance" parameter α, which indicates the trade-off between sunlight exposure and distance, was used to trade off between distance and sunlight exposure. Therefore, the routing algorithm will find the minimum accumulated sunlight exposure (Min E_a) from several route candidates:

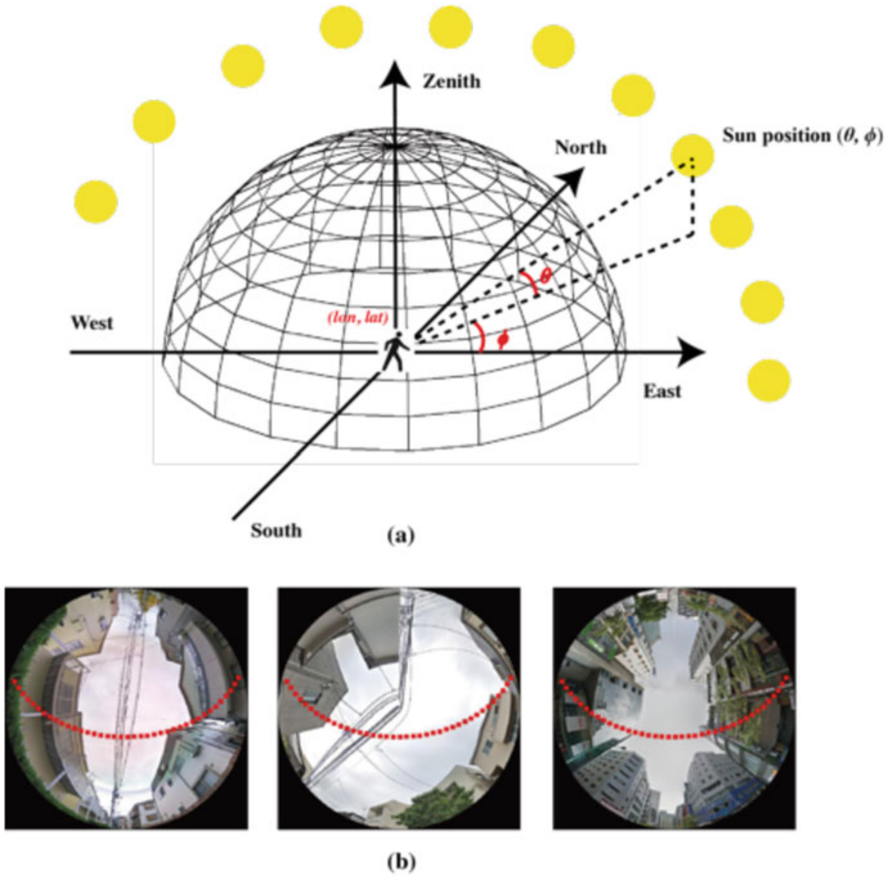

Fig. 3 The geometrical model of the sun (**a**) and the overlay of sun path in 1 day on hemispherical images (**b**)

$$\text{Minimize } E_a = \sum_{t=t_0}^{t_n} \text{dist} \cdot [\alpha B_t \cos\theta_t + (1-\alpha)] \tag{3}$$

where dist is the distance between two nearby stop points along the route. The trade-off parameter α as 0 indicates the shortest geographical distance path from origin to destination. The trade-off parameter α as 1 indicates route with the minimum sunlight exposure. In this study, we set the trade-off parameter α as 0.5.

Routing for the minimum exposure to sunlight is a time-dependent routing issue, in which the weight of the graph changes over time. Therefore, we first generated the sunlight exposure distribution along streets every 5 min. We assume that the sunlight exposure at each street segment is constant in 5 min. We then applied Dijkstra (1959) algorithm with consideration of the temporal change of the sunlight

Fig. 4 Human exposure to sunlight along one route

exposure for different street segments to find the route with minimum accumulated sunlight exposure for any origin and destination in the study area.

4 Results

Based on the metadata of all available GSV panoramas, we only selected the most recent images captured in leaf-on seasons (April, May, June, July, August, September, and October) in this study. Finally, we collected 45,085 GSV panoramas along streets in the study area. Figure 5 shows the spatial distribution of the finally collected GSV panoramas and the time stamps of those downloaded GSV panoramas. Generally, the GSV panoramas cover most streets in the study area. There is a small region in the northern part of the study area, which is the Meiji Shrine, which has no GSV image coverage. Considering the relatively isolated location of the shrine, we think that the unavailability of GSV images in the small portion of the study area will have not much influence on the results of the routing algorithm in the study area.

Based on the segmented hemispherical images and predicted sun positions over time in the study area, we generated the spatiotemporal distribution of the sunlight exposure at the point level for every 5 min. We then aggregated the point-level sunlight exposure map to street segments by assigning each point to the closest street segments. The sunlight exposure attribute for each street segment is the mean

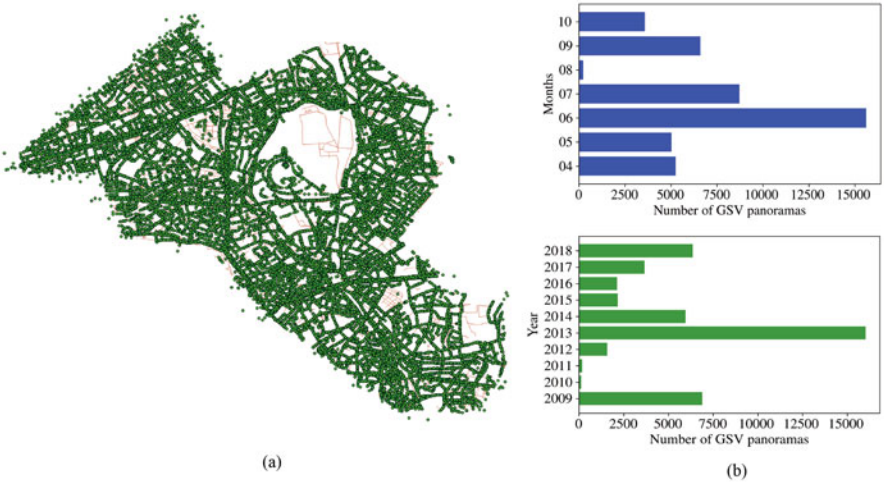

Fig. 5 The spatial distribution of the downloaded Google Street View (GSV) panoramas (**a**) and time stamps (**b**) of those downloaded GSV panoramas

value of all assigned points. Figure 6 shows the spatial distribution of street-level sunlight exposure over time on July 15th, 2018, at 9:00 am, 12:00 pm, 2:00 pm, and 5:00 pm. It can be seen clearly that at 9:00 am and 5:00 pm, those East-West orient streets are exposed to sunlight directly, and streets with other orientations are not directly exposed to sunlight. This is because at sunrise morning and sunset afternoon the sun zenith matches the East-West streets.

In order to compare the results of the shortest geographical distance path and the minimum sunlight exposure path, we randomly created 1000 origin-destination pairs with random starting time from 9 am to 6 pm. Results show that the minimum sunlight exposure paths help to decrease the potential sunlight exposure by 35.23% compared with the shortest geographic distance path. Figure 7 shows 4 of these 1000 paths with the minimum sunlight exposure and trade-off parameter as 0.5 and corresponding paths with the shortest geographic distance from origins to destinations at the starting time of 11 am on July 15th, 2018.

5 Discussion

Too much sunlight exposure would cause human heat stress and unprotected sunlight exposure could cause skin cancers, which is one of the most common cancers. Understanding the spatiotemporal distribution of sunlight exposure would help us to develop strategies to increase human thermal comfort and reduce environmental hazards from the sunlight in cities. Many methods have been developed and applied to protect human beings from too much sunlight exposure, such as planting trees

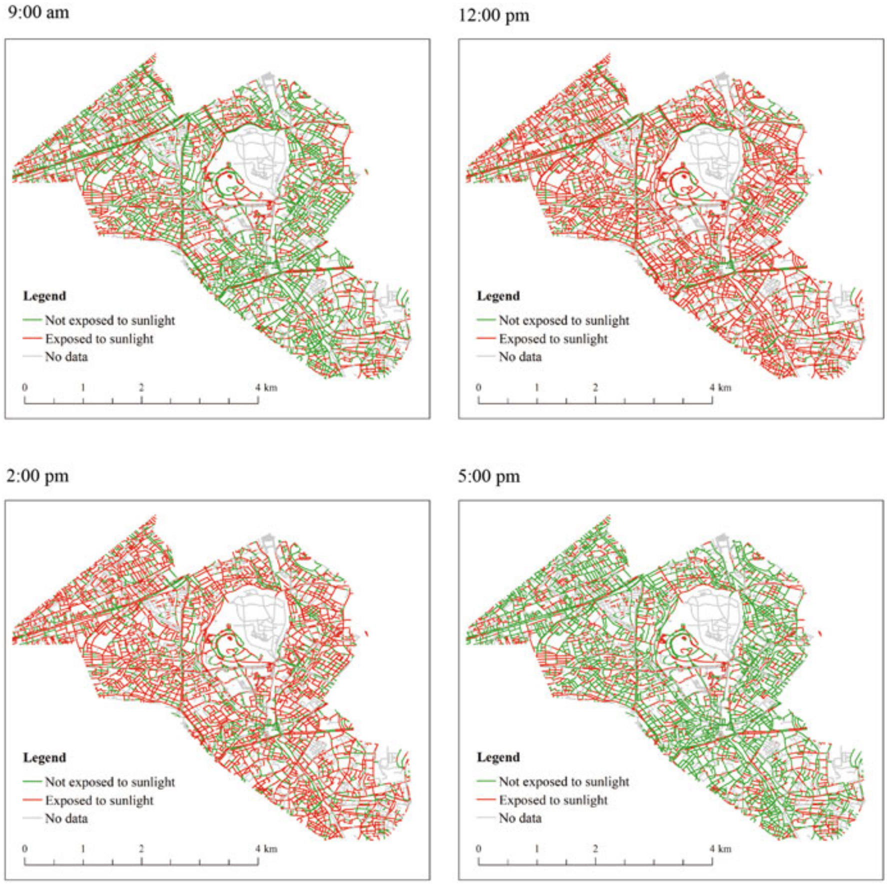

Fig. 6 The spatial distributions of street-level Boolean sunlight exposure variable at 9:00 am, 12:00 pm, 2:00 pm, and 5:00 pm on July 15th, 2018, of the study area

to increase shade, wearing sunscreen, and installing shelters. Different from those plans, this study proposed an individual-level strategy to protect people from too much outdoor sunlight exposure. The Google Street View (GSV) panoramas and deep convolution neural network were used to map the spatiotemporal distribution of the sunlight exposure with consideration of the sun positions and obstruction effects of buildings and tree canopies.

By analyzing the sunlight exposure of 1000 pairs of randomly created origins and destinations in the study area, results show that the proposed routing algorithm can help to reduce the potential sunlight exposure by 35.23% on July 15th, 2018, compared with the shortest geographical distance path. Although the exact number of sunlight exposure reduction would vary for different days and different daily routes of people, this study shows the possibility to significantly reduce the sunlight exposure using the proposed method. This study provides a new way at the

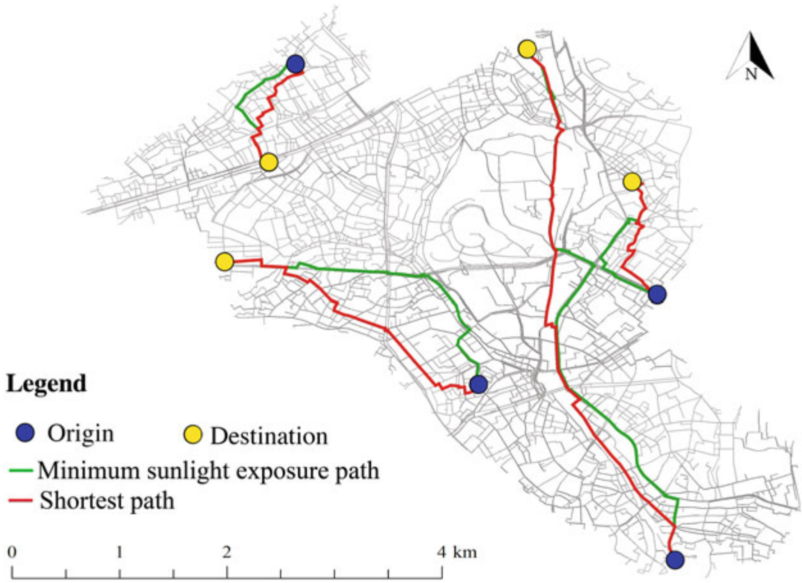

Fig. 7 The paths of minimum sunlight exposure (green line) and the path of shortest geographical distance (red line) of four origin-destination pairs at the randomly starting time from 9 am to 6 pm on July 15th, 2018

individual level to deal with the risks of too much sunlight exposure. Since GSV images are globally available, therefore, the proposed method can be reproduced for other areas to deal with the negative effects of hazards from sunlight. The proposed method provides a bottom-up solution to deal with the human heat stress and unprotected UV exposure caused by outdoor sunlight exposure, because the proposed method would let individuals have the quantitative information about their daily sunlight exposure. With such information available, individuals can change their daily schedule or choose the best route to protect themselves from too much sunlight exposure. This study would also provide an important reference for urban planners and city governments to reduce human sunlight exposure by street designs, such as providing shades and increasing street tree canopies.

The proposed method can generate more accurate sunlight exposure information compared with other digital building height model-based methods since street-level images were used to represent the streetscapes. Using the street-level image-based method is more reasonable to consider the actual human sunlight exposure in street canyons because all kinds of sunlight obstructions are considered using the street-level image-based method.

This study still has some limitations on modeling human sunlight exposure. The street-level image-based method may not be able to perfectly represent pedestrian's sunlight exposure since GSV images were collected in the central part of streets, not sidewalks. Considering the fact that the streets in the study area are very narrow, therefore, it is quite reasonable to use the street-level images to represent pedestrian's exposure to the sunlight. However, the method should be adjusted for other study areas with wide streets and separate sidewalks.

In addition, human thermal stress and UV exposure are influenced by not only the sunlight exposure but also other personal characteristics and meteorological parameters, such as ages, skin types, cloud condition, humidity, wind speed, and air temperature. In this study, only the direct sunlight exposure is considered. The sunlight exposure in street canyons varies spatially and temporally much more than other factors. For one specific site if we assume that other meteorological parameters are constant, therefore, the exposure to the sunlight would be considered as the most important contributing factor of the human thermal comfort and UV exposure. Therefore, it is reasonable to use the sunlight exposure as a surrogate to develop routing algorithm to maximize the thermal comfort and minimize UV exposure for a pedestrian walking from one place to another place. Future studies should also consider more personal characteristics in the sunlight exposure model.

This study used the randomly created sample sites to evaluate the performance of the proposed routing algorithm for reducing the sunlight exposure. In order to better understand the performance of the routing algorithm on local people, future study may also need to use the human actual trajectories. In addition, sunlight exposure is not always a hazard; future studies should also focus on quantitatively managing the sunlight exposure.

6 Conclusions

This study proposed an individual-level and short-term effective strategy to help people get rid of too much sunlight exposure. A time-dependent routing algorithm was developed to minimize human outdoor sunlight exposure based on a bottom-up approach to estimate the spatiotemporal distribution of sunlight exposure along streets using Google Street View. A deep learning-based image segmentation algorithm was used to derive streetscape environment and model the human sunlight exposure within street canyons. Considering the global availability of street-level images around the world, the proposed method would provide us an effective method in dealing with the sunlight exposure protection.

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