Using Street View Imagery and Computer Vision Method for Visual Walkability Measurement in London

Jiaming Lu*[1], James Haworth†[1] and Meihui Wang[1]

[1]Department of Civil, Environmental Geomatic Engineering, University College London

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Summary

Walking, as a friendly mode of transport, also contributes to physical and psychological well-being. However, since the 20th century, the rapid development of modern road networks and urban architecture has led to degradation in the quality of walking environments in major cities such as London. This research aims to evaluate the Integrated Visual Walkability (IVW) index in Inner London, reflecting pedestrians' walking experiences, and analyze the outcomes in consideration of the physical environment. The results contribute to develop strategies for London walkability optimization and improve upon the urban planning, and subsequently encourage people to walk more.

KEYWORDS: Street View Imagery, Computer Vision, Integrated Visual Walkability, Urban Planning

1. Introduction

Walking is an environmentally friendly mode of transport, and a healthy, low-cost physical activity. Thus, increasing city streets' walkability is a key policy goal for many cities. Historically, London has always been a walking city and walking is currently at the forefront of the Mayor's plans for transport in London, illustrating an ambitious vision to transform London into the most walkable city in the world (Mayor's Transport Strategy 2018, 2020).

Walkability is defined as "the extent to which the built environment supports and encourages walking by providing for pedestrian comfort and safety, connecting people with varied destinations within a reasonable time and effort, and offering visual interest in journeys throughout the network" (Michael Southworth, 2005, p. 247-248). Constituent components to describe walkability can include various factors corresponding to different research scenarios. These include street connectivity, destination accessibility, traffic and crowdedness, mixed land use, green spaces, et al. (McCormack and Shiell, 2011).

However, roads also act as public leisure areas besides a part of transportation network. As central London's streets became clogged with cars and other modern facilities, the quality of London as a walking environment declined (Walking action plan, 2018). Therefore, psychological and subjective comfort of pedestrians are referred as key factors for walkability.

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* j.lu.19@ucl.ac.uk

† j.haworth@ucl.ac.uk

Previous studies into walkability are mainly associated with physical environmental attributes. A walkability index for London at neighbourhood level has been constructed from residential dwelling density, street connectivity and land use mix (Stockton et al., 2016). Then, in the Walking Action Plan, walkability was investigated at street level in the context of pedestrians walking frequency and found that people living in areas with dense, mixed-use, integrated buildings and with good access to public transport are more likely to walk (Walking Action Plan, 2018). However, walkability assessments in terms of pedestrian psychology are still missing. Besides, researches are often performed by audit methods and participatory research techniques like field surveys and questionnaires (Schlossberg et al., 2015), which are deficient in time and physical costs.

In this study, we employ the IVW framework built by Zhou et al., (2019), using street view imagery combined with computer vision to assess the IVW across Inner London. The outcomes help improve walking experiences in London and facilitate London's urban planning process.

2. Study Area and Data

This paper chooses Inner London as the study area. The road network data is obtained from Ordnance Survey. There are 63,565 links in this dataset in total.

Figure 1 Road network within Inner London

Street view images are accessed using the Google Street View Static API. Three images can entirely cover the physical environment at one site. After removing all ineligible data, 54,529 images can be used for the walkability evaluation. Moreover, the CamVid dataset is used in the SegNet construction.

Figure 2 Three viewports collectively cover the panorama at one site

3. Method

3.1 SegNet-based image segmentation and modification

SegNet is a deep convolutional encoder-decoder architecture for semantic pixel-wise labelling. It comprises a set of non-linear processing layers (encoder) and their corresponding group of decoders with a pixelwise classifiers following (Badrinarayanan et al., 2017).

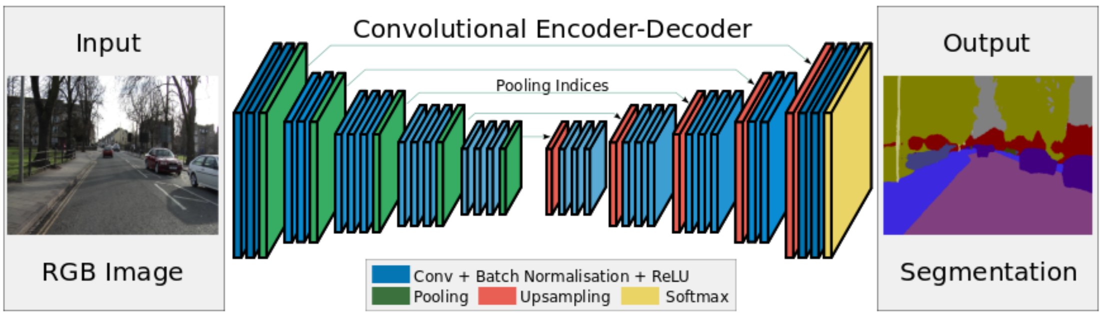

Figure 3 SegNet network (SegNet, 2020)

The CamVid dataset is used to develop a usable SegNet. The trained SegNet model is used to realize segmentation of the street view imagery and all pixels of the input images are labelled with the corresponding category. To apply initial outcomes for walkability calculation, pixels are reclassified as shown in figure 4. Then, after the noise removal process, well-labeled images are ready for visual walkability evaluation.

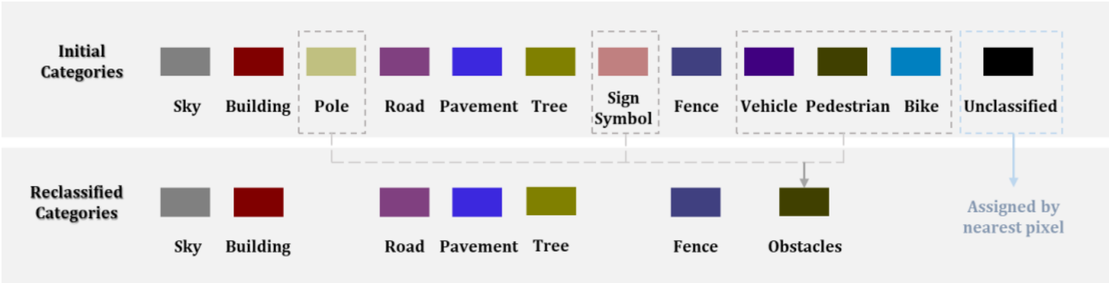

Figure 4 Reclassification process

3.2 IVW Framework

The IVW framework can be used in measure of psychological and subjective comfort for pedestrians. Four sub-indicators are involved: greenery, crowdedness, outdoor enclosure and visual pavement.

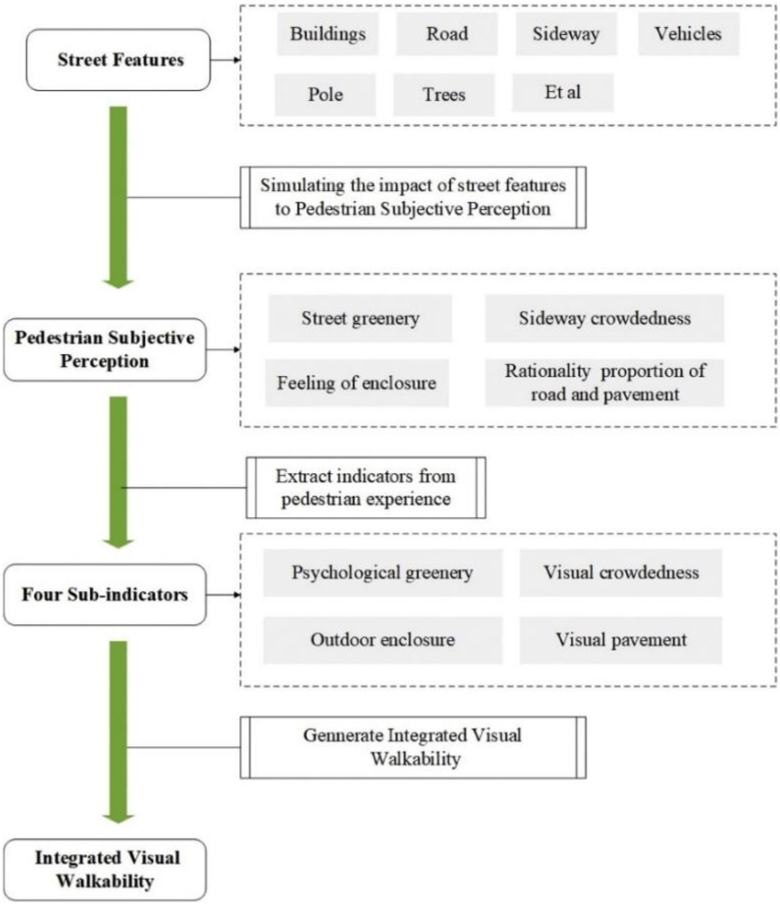

Figure 5 IVW framework model (Zhou, 2019)

3.3 IVW Calculation

The calculation formulas are shown in Table 1. The sub-indicators (Gi, Ci, Si, Di) for one location are calculated using three images collectively.

Table 1 Four sub-indicators calculation

Indicator	Formula
Greenery	$G_i = \frac{\sum_1^3 T_n}{3 \times Sum}$
Crowdedness	$C_i = \frac{\sum_1^3 C_n}{3 \times Sum}$
Outdoor Enclosure	$S_i = \frac{\sum_1^3 B_n + \sum_1^3 T_n}{\sum_1^3 P_n + \sum_1^3 R_n + \sum_1^3 F_n}$
Visual Pavement	$D_i = \frac{\sum_1^3 P_n + \sum_1^3 F_n}{\sum_1^3 R_n}$

* *Explanation:* T_n is the total tree pixel number; Sum is the total pixel number; C_n is the total obstacle pixel number; B_n is the total building pixel number; P_n is the total pavement pixel number; R_n is the

total road pixel number; F_n is the total fence pixel number.

Considering the impact of the central visual field and the accuracy of segmentation, four sub-indicators' values are reclassified into five levels (Table 2).

Table 2 Sample images and classification of four sub-indicators

	Level 1	*Level 2*	*Level 3*	*Level 4*	*Level 5*
G_i	< 0.070	$0.070 - 0.127$	$0.127 - 0.175$	$0.175 - 0.228$	≥ 0.228
Sample					
C_i	≥ 0.574	$0.413 - 0.574$	$0.286 - 0.413$	$0.169 - 0.286$	< 0.169
Sample					
S_i	$D_i < 0.800 \cup D_i \geq 2.864$	$1.063 < D_i \leq 0.800 \cup 2.210 \leq D_i < 2.864$	$1.213 < D_i \leq 1.063 \cup 1.884 \leq D_i < 2.210$	$1.213 < D_i \leq 1.350 \cup 1.656 \leq D_i < 1.884$	$1.350 - 1.656$
Sample					
D_i	$D_i < 0.480 \cup D_i \geq 4.000$	$0.480 \leq D_i < 0.650 \cup 3.007 \leq D_i < 4.000$	$0.650 \leq D_i < 0.806 \cup 2.137 \leq D_i < 3.007$	$0.806 \leq D_i < 0.953 \cup 1.707 \leq D_i < 2.137$	$0.953 - 1.707$
Sample					

The IVW of each road can be calculated by:

$$IVW = 5 \times (\mathrm{G}_{\mathrm{level}} + C_{level} + S_{level} + D_{level}) \qquad (1)$$

Calculated IVW ranges from 20 to 100. Higher IVW corresponds to a higher quality walking environment from the perspective of visual psychology.

4. Results and Discussions

4.1 Spatial patterns of IVW

The spatial patterns of IVW at street level are shown in Figure 6, illustrating great variation across the study area. Few clusters can be found, which means roads at different IVW levels have a mixed distribution. To comprehensively analyze the distribution pattern and provide improvement measures for city designers, the distribution of four sub-indicators is shown in Figure 7.

Figure 6 IVW indices of each street within Inner London

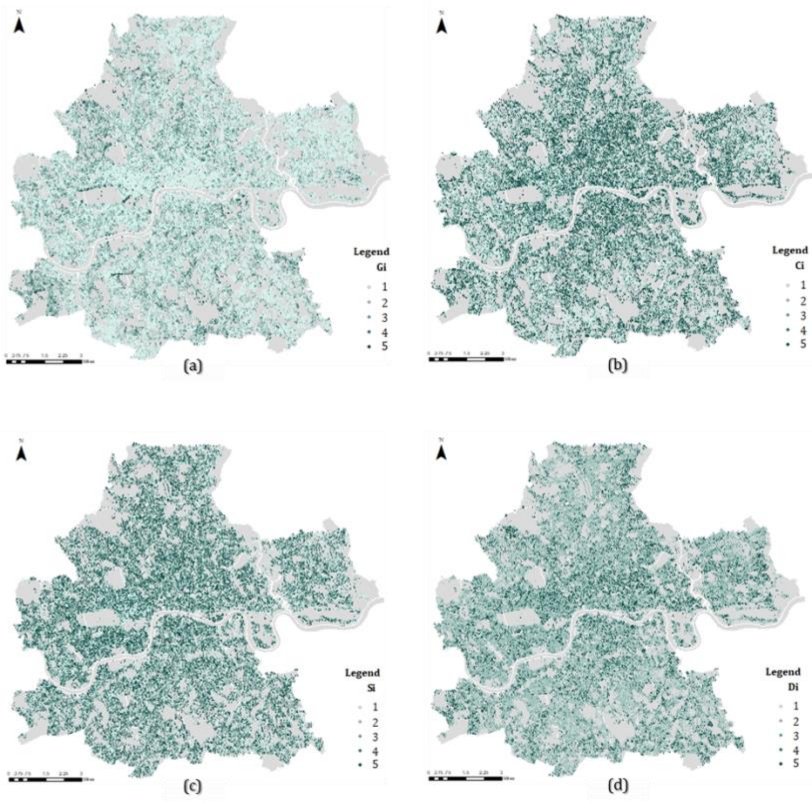

Figure 7 Distribution of four sub-indicators: (a) greenery, (b) crowdedness, (c) visual enclosure and (d) visual pavement.

It can be found that high-level streets of greenery appear around the green land, like Hyde Park (Figure 7(a)). Mixed distribution can be found at large scales in the other three domains. But some local features existed. For example, higher density of low IVW streets appears in Marylebone, Soho, Oxford Circus etc. (Figure 8), which are busy areas of London. Low IVW in these areas results from lack of greenery, too many vehicles and pedestrians, and unbalanced design of buildings and roads, collectively (Figure 9).

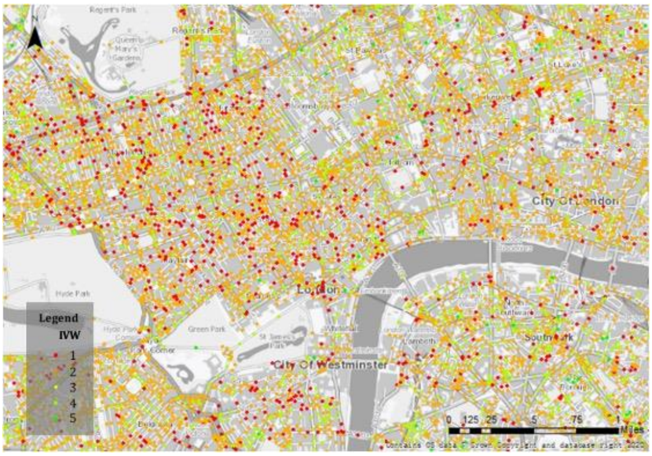

Figure 8 An area with high proportion of low IVW streets

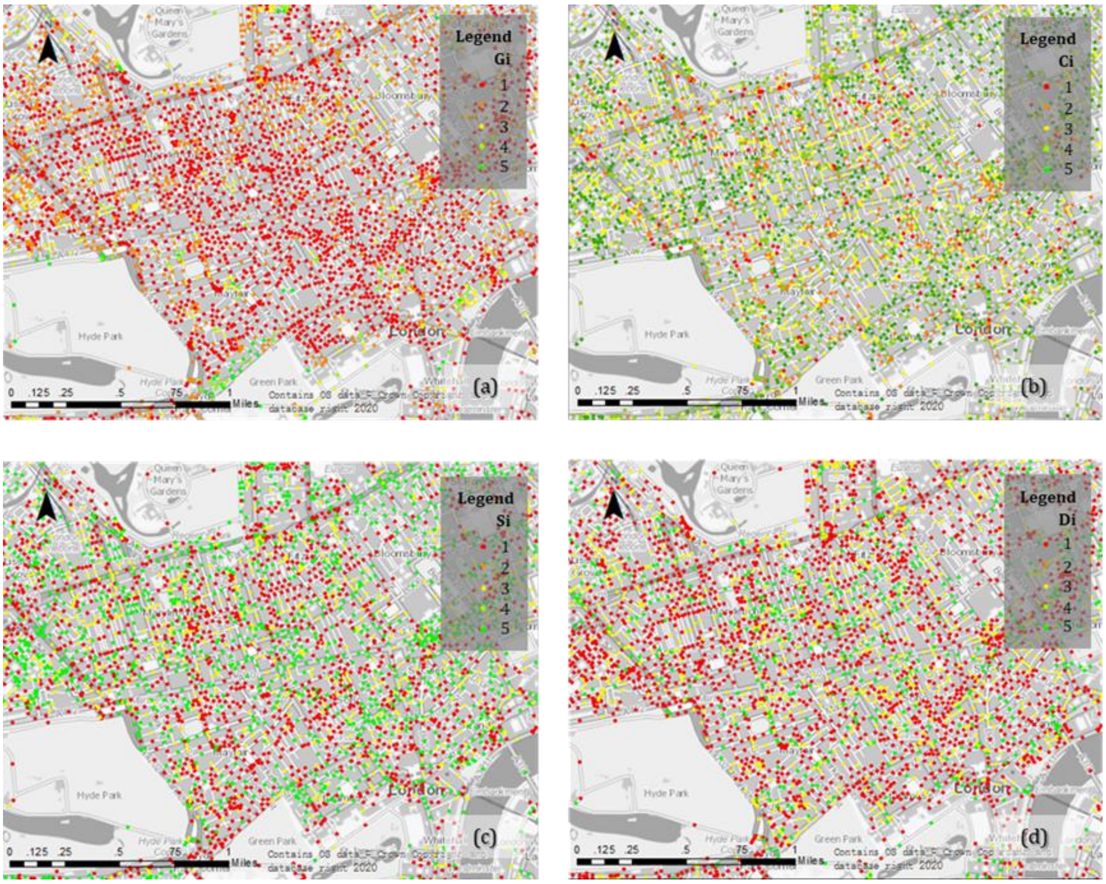

Figure 9 Distribution of four sub-indicators

4.2 Performance of the IVW Framework

To examine the model's performance, images are extracted to test the concordance between IVW and subjective feeling results (Figure 10). Streets with a higher IVW level indicate a more comfortable feeling, which reveals the framework's usability.

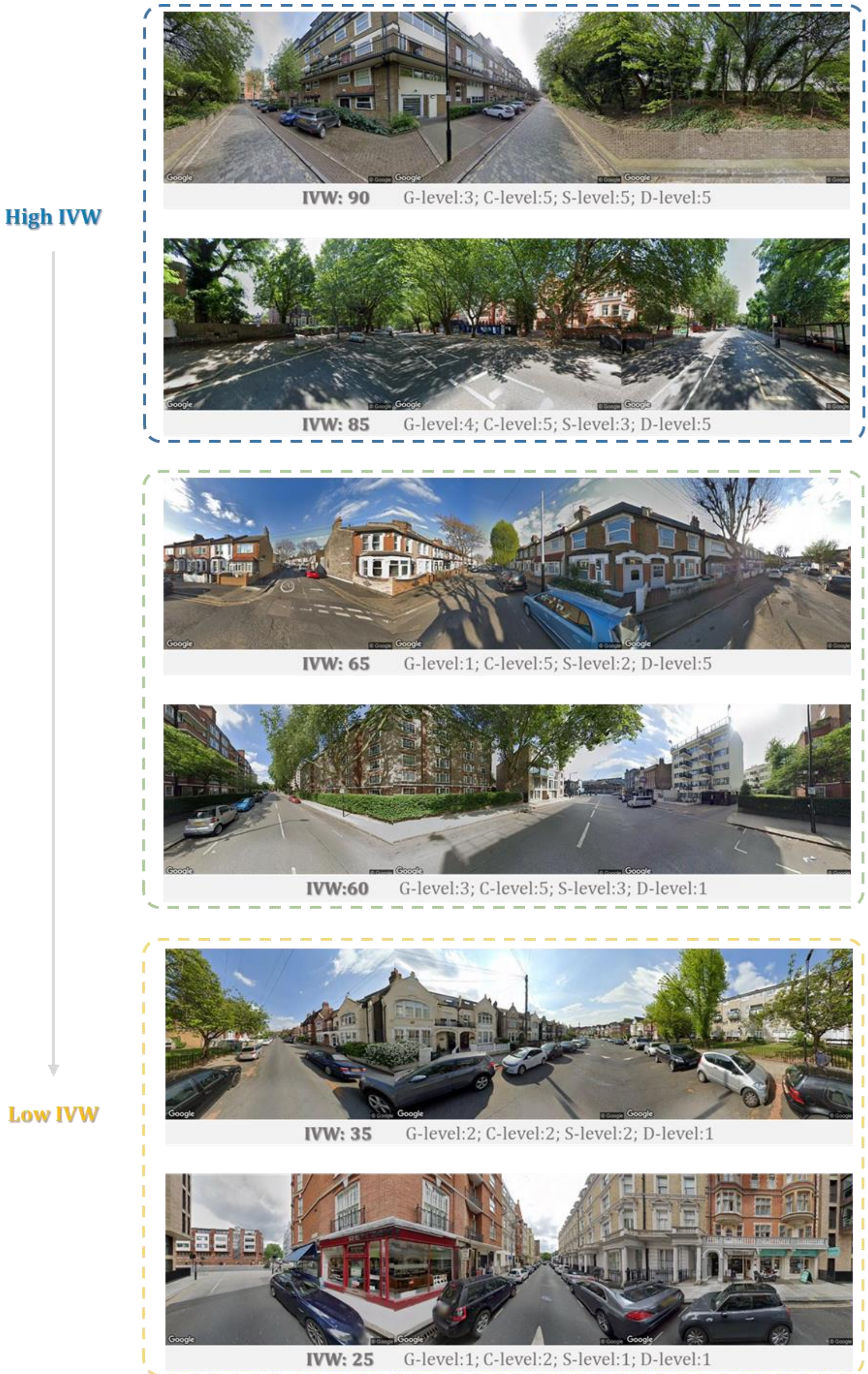

Figure 10 Street View Imagery at differing IVW levels

4.3 Discussion and Limitations

Limitations are as follows. Firstly, CamVid dataset only provides images with similar weather, traffic condition, and urban landscape, making it difficult to interpret complex cityscapes.

Secondly, the transplant of IVW framework lacks consideration of London's specific characteristics. The framework performs well in Shenzhen, a modern city, with numerous newly built skyscrapers and broad streets lined with trees. However, London is an ancient city with a long history and buildings were built in different ages. This does not mean London is not walkable. Thus, the sub-indicators can be considered as incomplete for lacking in nuanced factors capture varied by location.
Furthermore, urban vibrancy and safety should also be considered according to the definition of walkability. In this way, a more generalizable and comprehensive framework for walkability can be established.

5. Conclusions

This study evaluated walkability in Inner London from pedestrians' psychology based on IVW framework. It contributes to urban designers developing strategies to help with the pedestrian experience optimization and further facilitate more trips by walking.

Several future directions are: to further enhance the segmentation accuracy; to validate results through questionnaires and interviews.

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Biography

Jiaming Lu is a recent graduate of the Geospatial Sciences (GIS and Computing) MSc at UCL. She has background in spatial analysis, programming and cartography.

James Haworth is a Lecturer in Spatio-temporal Analytics at UCL, with research interests in spatio-temporal modeling and analytics, in particular applications of machine learning, deep learning and computer vision to the geoinformation sciences.

Meihui Wang is a PhD candidate in the Department of Civil, Environmental and Geomatic Engineering at UCL. Her research interest includes spatio-temporal data mining, deep learning and urban planning.