Personalized Walkability Assessment for Pedestrian Paths: An As-built BIM Approach Using Ubiquitous Augmented Reality (AR) Smartphone and Deep Transfer Learning

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Abstract: The walkability of pedestrian paths serves as an urban semantic infrastructure for the global smart city development. However, traditional methods cannot fulfill the task of personalized walkability assessment on (i) automation of assessment, (ii) the level of details, and (iii) meeting the personalized demands of pedestrians (e.g., with a wheelchair). This paper presents a novel as-built building information model (BIM) approach based on ubiquitous augmented reality (AR) smartphone and deep transfer learning. First, an 'as-is' 3D point cloud is scanned by AR smartphone. Then, an as-built BIM containing semantic objects such as paved footway, guardrail, and obstacles can be created with pre-trained 3D point classification models. Finally, calculation of walking characteristics of the semantic as-built BIM leads to personalized walkability assessment. A pilot study involving five walking characteristics was conducted on a real case near the University of Hong Kong for the personalized requirements of five types of pedestrians: (1) people in wheelchair, (2) leisure traveler with a baby stroller, (3) business traveler with a rolling luggage, (4) senior people, and (5) exerciser (joggers). The results of the pilot study showed that the personalized walkability was correctly assessed using the proposed as-built BIM approach. With advanced ubiquitous computing devices, the proposed approach is expected to apply to everyday AR smartphones to enable crowd-sourcing and real-time assessment of the personalized walkability for pedestrian paths. The semantic as-built BIM, as an intermediate solution in this approach, can also open new avenues for many innovative smart city applications to foster a smart, sustainable, and resilient future.

Keywords: Personalized walkability; As-built BIM (building information model); Augmented reality (AR) smartphone; 3D point cloud; Deep transfer learning; Urban semantics; Ubiquitous computing; Data-driven modeling; Smart city.

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1 Introduction

This paper focus on *personalized walkability assessment* (PWA) for pedestrian paths (or sidewalks). *Walkability* is conceptualized as the extent to which the characteristics of the built environment may or may not be conducive to residents in the area walking for leisure (e.g., with a baby stroller), traveling (e.g., in a wheelchair), or exercise (e.g., jogging)[1]. Beyond walking, walkability impacts many aspects of urban living[2] such as health[3], residential housing value, and neighborhood crime[4]. In view of the fact that 65% world's population will be urban residents by 2050[5], walkability is not only an essential concept for semantically-rich information retrieval but also an important analytical concept in infrastructure for human-centered smart, sustainable, and resilient city development [6].

Researchers have developed many indices and approaches for assessing walkability at the macroscale (city)[7], neighborhood scale[4], and microscale[2,8-9]. However, it is costly and time-consuming to apply the traditional methods (e.g., audit tools) to the citywide pedestrian paths due to the vast amount, heterogeneous conditions, and frequent changes. The task becomes even more challenging for *personalized* assessment, e.g., walkability for people in a power wheelchair means something different to that for a jogging person. Hardware that enables PWA is readily available in the market, e.g., ubiquitous smartphones are evolving to *augmented reality* (AR) devices that can scan the as-is conditions with a centimeter accuracy. Computer vision software libraries such as deep learning models have also been developed to understand the results of AR scanning. So far, these advanced technologies have not been integrated into an automatic and inexpensive approach to PWA, as far as we are aware.

This paper presents a novel as-built *building information model* (BIM) approach to PWA for pedestrian paths using the up-to-date ubiquitous AR smartphone, deep transfer learning, and as-built BIM creation and analytics. The remainder of this paper is organized into the following sections: related work, a framework of the approach, a pilot case study, discussion, and conclusion.

2 Related Work

Many conventional walkability assessment methods rely on observational audit tools. For example, Sun *et al.* employed 67 characteristics to measure the walking environments of access routes to urban metro stations in China in an urban planning viewpoint[2]; Griew et al. employed *Google street view* for facilitating their audit tool[9]. Although audit conducted by surveyors can, with care and attention to validation, be reliable and accurate, it is too laborious and costly to apply to PWA for the complex network of dynamic pedestrian paths. Using *geographic information systems* (GIS) technologies, such as GPS records[10] and imagery analysis of aerial photos[11] to collect real-world walking data, is also investigated in the literature, to supplement audits. Yet, the methods based on GIS suffer from inaccuracy (*i.e.*, the unsatisfactory error level of GPS signal or path details in aerial photos for the built environment) and incomplete data (*e.g.*, the paths are mostly a centerline in most GIS platforms)[12]. In summary, for PWA, especially in the contemporary settings for smart city applications, traditional assessment methods fail in at least one of three aspects: (i) automation of assessment, (ii) the level of details, and (iii) meeting the personalized demands of pedestrians (e.g., different physical impairments)[13].

A *building information model* (BIM) involves physical as well as functional characteristics of a facility and serves as an information hub to facilitate construction management along the whole life-cycle[14]. An as-built BIM focuses more on the as-is conditions[15] such as *actual* building geometries, *current* functions, and *real* topology to enable various smart city applications such as construction automation, energy consumption, and facility management [15]. Approaches to as-built BIM creation can be broadly categorized as *data-driven* (*i.e.*, based on the *input data*'s features, shapes, materials, and statistics)[15-16] and *model-driven* (*i.e.*, based on the *BIM components and knowledge* fitted into the input)[17-18]. Due to the variety of objects on uncontrolled real-world pedestrian paths, data-driven methods such as those exploiting architectural regularity and *random sample consensus* (RANSAC)[16] are more competitive in creating as-built BIMs for PWA[18]. It should be noted that the generated as-built BIMs can also be exported to GIS platforms to enable advanced spatial-temporal analyses as well as many existing GIS-based walkability assessment methods, once the as-built BIMs are geo-referenced[19].

These challenges motivate the as-built BIM approach to PWA presented in this paper. The as-built BIM is the information hub about various walking characteristics that facilitate the PWA for different pedestrians. In contrast to conventional assessment methods, the proposed approach is automatic and ubiquitous, rich in details and urban semantics, and compatible with multiple types of pedestrians.

3 An As-built BIM Approach to Personalized Walkability Assessment

The approach presented in this paper, as shown in Figure 1, is a straightforward technological pipeline that integrates the state-of-the-art data standards and processing methods in AR scanning from remote sensing and robotics, deep transfer learning from artificial intelligent and computer vision, and as-built BIM creation from civil engineering and construction management. In the proposed approach, the as-built BIM is the semantic information hub about walkability. The input to the approach, as shown in Figure 1, is the actual 3D geometry of the built environment, *i.e.*, pedestrian paths. In the pipeline, there are three main steps of automatic data processing: (1) 3D scanning, (2) as-built BIM creation, and (3) assessment. The intermediates in the approach include the as-is 3D point cloud of the geometry of a path scene and an as-built BIM. The outputs of the proposed approach include PWA and recommendations from simulations. The proposed approach is thus classified as a data-driven as-built BIM approach.

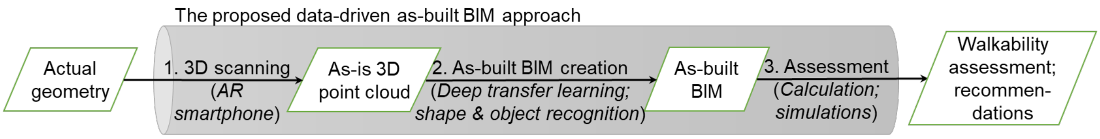


Figure 1. The technological pipeline of the proposed as-built BIM approach

Given a target pedestrian path, *the first step* is 3D AR scanning of the actual geometry to form an as-is 3D point cloud. Accuracy and density of the point cloud are crucial for the whole approach. Thus, advanced AR mobile devices which incorporate depth sensing 3D cameras, motion tracking, and area learning, such as Google Project Tango, are preferred over other AR devices such as Google ARCore and Apple ARKit. Because of the limited computational capacity for running deep learning models on current AR smartphones, the sensed as-is 3D point cloud can be uploaded to a GPU (graphics processing unit) powered workstation for post- processing.

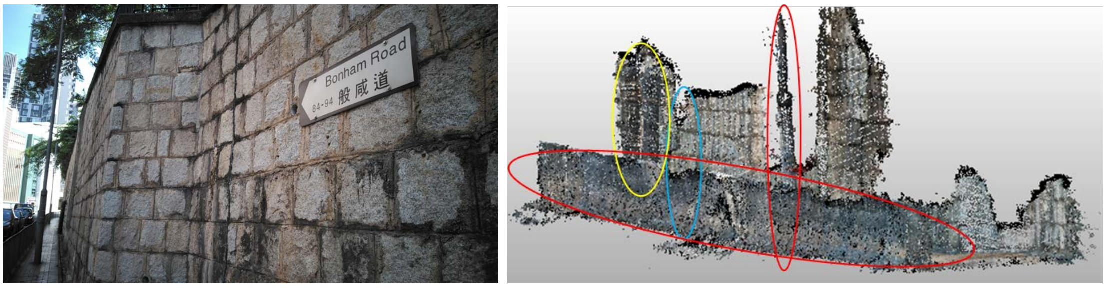
The second step is as-built BIM creation from the as-is 3D point cloud, by taking advantage of deep transfer learning, shape extraction and object recognition. In computer science, *transfer learning* aims at reducing the recollection of training data by transferring knowledge from related domains (models), and can thus save a significant amount of labeling effort[20]. As a subset, *deep transfer learning* focuses on reusing pre-trained deep learning models such as *convolutional neural networks* (CNNs), usually accelerated by modern GPUs. For example, *Semantic-8*[21] is an open dataset about street scenes, scanned in Germany, and annotated with 8 semantic labels (e.g., “man-made terrain,” “natural terrain,” and “buildings”). Deep transfer learning can reuse a *PointNet*[22] (or other CNN) model pre-trained on *Semantic-8* to segment any 3D point cloud of street scene captured from anywhere. Based on the segmented labels (*e.g.*, “man-made terrain” and “buildings”), shape extraction methods and object recognition methods such as *a priori* rules can recognize and rectify[16] the semantic components to create a data-driven as-built BIM. This step can be automatic or semi-automatic, depending on the as-built BIM creation methods.

The final step of the proposed approach is PWA by calculation and simulations. Quantitative walking characteristics (e.g., slope grade and the number of steps) of the as-built BIM can be calculated and compared to the pre-defined requirements of a specific type of pedestrians (e.g., people in a hand-powered wheelchair or joggers). The walkability of the input pedestrian path can thereafter be assessed as “*OK*,” “*Limited*,” or “*Failed*” though a *floor* function (*i.e.*, the worst) on all the characteristics individually for each type of pedestrians. For example, an “OK” in slope grade and a “Failed” in the number of steps result in a “Failed” in PWA. In addition, obstacles and walkability recommendations can also be inferred from a series of ‘what-if’ simulations on the as-built BIM. For example, a *major obstacle* implies that its removal improves the walkability from “Failed” to “OK,” while a *minor obstacle* means removal refines the walkability from “Failed” to “Limited” (or from “Limited” to “OK”).

4 A Pilot Study

4.1 As-is 3D scanning using AR smartphone

To validate the proposed approach, we selected a scene of a pedestrian path on Bonham Road next to the University of Hong Kong, as shown in Figure 2 (a). The scanned area was 56.2 m². We collected a dense cloud of 569,344 colorful points (over 10,000 points per m²) using an in-house developed Android app on a Google Tango AR smartphone (model: Lenovo PB2-690Y). The as-is 3D point cloud, though somehow noisy, was adequately registered, stitched, and uniformly sampled in the *Stanford polygon* (.ply) format. It was observed in Figure 2 (b) that there existed two obstacles (*i.e.*, a light pole in the red oval and a meter pole in the blue oval) on the pavement, two drainage pipes (in the yellow oval) on the wall, and a guardrail (in the flat oval) between the pavement and the roadway. The time spent on the 3D scanning was about four minutes. At the end of scanning, the app uploaded the as-is point cloud, as shown in Figure 2 (b), to a GPU powered BIM workstation in a few seconds via a local 4G mobile network.

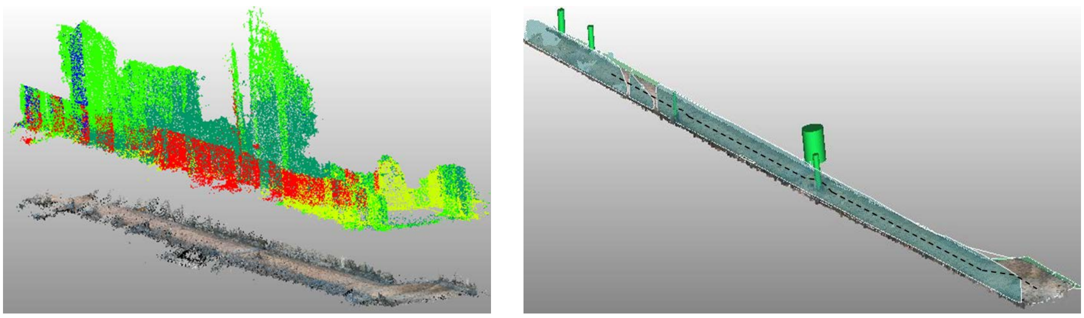


(a) A scene of Bonham Road, Hong Kong (b) As-is cloud of 569,344 points through AR scanning

Figure 2. A pilot case of a pedestrian path near the University of Hong Kong

4.2 As-built BIM creation using deep transfer learning

An as-built BIM was then created on the BIM workstation. The workstation has two Intel XEON E5-2690 v4 CPUs (2.6GHz, 28 cores), 64 GB memory, an Nvidia Quadro P5000 GPU, and Windows 10 Enterprise 64-bit operating system. Before the as-built BIM creation, a *PointNet*[22] model was already trained on the *Semantic-8* dataset[21] on *Google TensorFlow* (version 1.4, with GPU support) in Python (version 3.6) to enable the deep transfer learning. First, the uploaded point cloud was converted from the Stanford polygon (.ply) format to a *Numpy* (version 1.12) data file. The pre-trained *PointNet* model spent 4 seconds on the segmentation of the scanned 569,344 points. Figure 3 (a) shows the result of segmenting the 3D points in Hong Kong with training data from Germany, which was surprisingly satisfactory. For instance, it can be observed in Figure 3 (a) that the points labeled as “man-made terrain” were very close to the actual geometry of the pavement. Next, the excessive 3D points above the height of 1.5 m were removed, as shown in Figure 3 (b), for focusing on the major space for pedestrians.



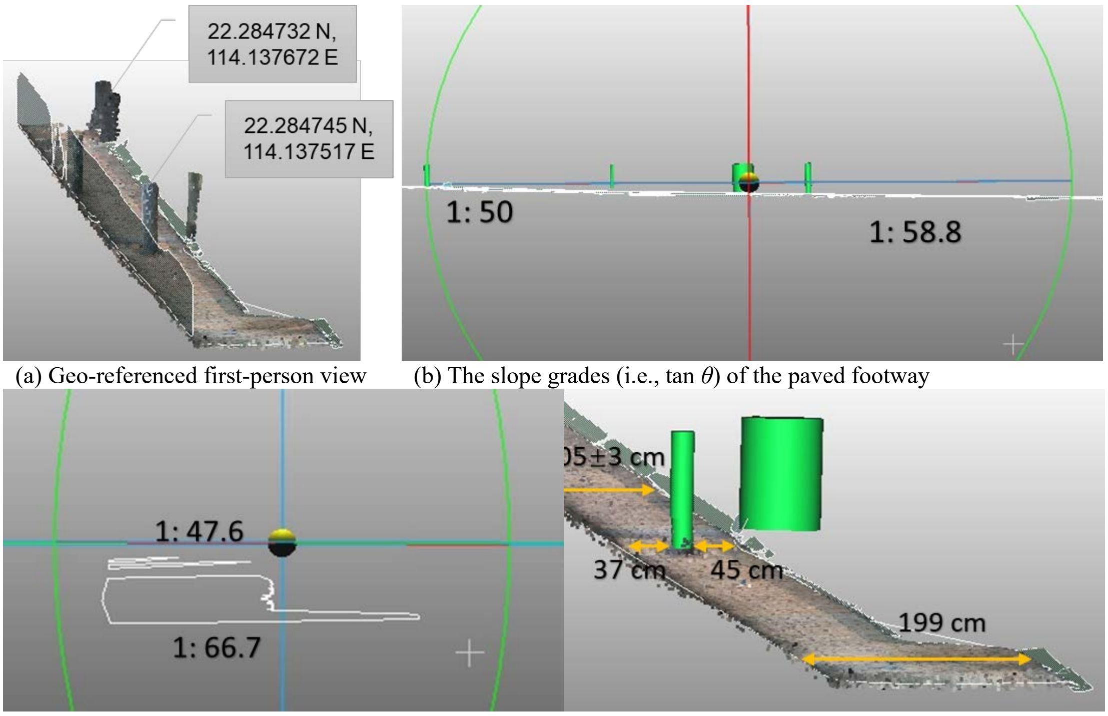
(a) 3D point classification (*e.g.*, the points labeled as “manmade terrain” were detached as the pavement) (b) As-built BIM consisting of semantic objects (walls omitted in this view)

Figure 3. The results of 3D point classification and the as-built 3D model of the pilot case

Planes and cylinders were detected from the segmented and filtered point cloud using an up-to-date as-built BIM creation algorithm[16] in less than 1 second. The detected geometric primitives were further screened by the proximity of their normal direction to the *z*-axis for focusing on the vertical and horizontal objects. Furthermore, the boundaries of planar objects were refined by the 2D *concave hull* algorithm provided by the *point cloud library* (PCL, version 1.8.1). The resulting objects were associated with semantic labels to form semantic BIM components through *a priori* rules. Examples of rules are “vertical planes along the pavement are guardrails or walls,” and “vertical cylinders connected to the pavement are possible obstacles.” Finally, an as-built BIM was formed as shown in Figure 3 (b). The as-built BIM included the reconstructed guardrail (i.e., the transparent flat polygon) and the pipes and poles (i.e., the four narrow cylinders). It was interesting that an unexpected object, which was actually a concrete trace of a former construction work left on the wall, was also recognized as shown as the wide cylinder in Figure 3 (b). Although the as-built BIM in this pilot case was preliminary (*i.e.*, not volumetric and in popular BIM formats), the semantic information (*i.e.*, the geometry and labels) was capable of reasoning and calculating many detailed walking characteristics and problems.

4.3 Personalized walkability assessment based on the as-built BIM

To demonstrate the PWA of the proposed approach, this paper employs five walking characteristics: (1) the number of steps, (2) slop grade of the footway, (3) tile grade of the footway, (4) footway width, and (5) pavement surface clearance (*i.e.*, non-existence of gaps and pebbles). The as-built BIM was geo-referenced first, as shown in Figure 4 (a), for visualization and compatibility with GIS platforms. The number of steps was identified as zero by analyzing the variation in altitude of the paved footway. The pave footway in the as-built BIM had two sections, as shown in Figure 4 (b). the left section had a slope grade of 1:50 (or 1.1°) while the right one had a grade of 1:58.8 (or 1.0°). The title grades of the two sections of the footway, as shown in Figure 4 (c), were 1:47.6 (or 1.2°) and 1:66.7 (or 0.9°), respectively. The width of the paved footway varied in different sections, as shown in Figure 3 (d). The maximum width was 199 cm in the beginning and minimum width (*i.e.*, the bottleneck) was only 45 cm, where the average width was around 105 cm for the remaining parts of the paved footway. The green cylinders in Figures 3 (b) and 4 (d) stand for the possible obstacles. The surface clearance of the paved footway was good, because no considerable gap was found, e.g., the gap shown in Figure 4 (c) was about 2 cm, neglectable as an error of planarization of a curved surface footway.



(a) Geo-referenced first-person view (b) The slope grades (i.e., tan θ) of the paved footway

(c) The tilt grades of the paved footway (d) The actual widths of the pavement with obstacles

Figure 4. The results of point cloud classification and as-built 3D model of the pedestrian path

Based on the calculated values of the five characteristics, the walkability can be accurately assessed for different pedestrians regarding their individual requirements. In this pilot study, we defined five types of pedestrians: (1) people in a wheelchair, (2) leisure travelers with a baby stroller, (3) business travelers with rolling luggage, (4) senior people, and (5) exerciser (joggers). Table 1 shows the walkability assessment matrix between the five walking characteristics and the five types of pedestrians. The bottom row indicates the results of PWA as the worst (floor function) evaluations in each column. The results in Table 1 indicated that the pilot scene was unwalkable for any people in wheelchair, and only walkable for travelers with a limited walkability for baby strollers and rolling luggage.

Table 1. Assessing the walkability of the pilot case for five types of pedestrians

Walking characteristic	Calculated value	Type of pedestrians				
		Wheelchair ♿	Stroller	Luggage	Senior	Exercise
No. of steps	0	OK	OK	OK	OK	OK
Slope grade*	1:50.0~58.8	OK	OK	OK	OK	OK
Tilt grade†	1:47.6~66.7	OK	OK	OK	OK	OK
Footway width‡	45~199 cm	**Failed**	Limited	Limited	OK	OK
Clearance	Good	OK	OK	OK	OK	OK
Overall walkability (the worst)		**Failed**	Limited	Limited	OK	OK

*: Reference maximum slope grade: 1:8~12 (wheelchairs);

†: Reference maximum tilt grade of pavement: 1:15 (wheelchairs);

‡: Reference minimum width: 70~90 cm (wheelchairs), 40~70 cm (strollers), and 30~60 cm (baggage).

In addition, obstacles to the walkability can be identified by a series of simulations. In each simulation, a 'what-if' analysis of PWA (*i.e.*, repeating Table 1) was carried out by removing one possible obstacle. Table 2 lists the identified obstacles in three categories: major obstacles, minor obstacles, and inoffensive obstacles. It can be found that the light pole in the middle of the paved footway was identified as the only major obstacle. As a result, alternative recommendations can be made, for example, moving the light pole to the guardrail, which can be subject to subsequent cost-benefit analysis as well as public consultation, leading to a schedule of improvement works to upgrade a PWA.

Table 2. A list of identified obstacles to walkability

Major obstacles	Minor obstacles	Inoffensive obstacles
Light pole	(None)	Meter pole, drainage pipe #1, #2, and concrete trace on the wall

4.4 Discussion

This pilot study preliminarily confirms the technological feasibility of the proposed approach. Nevertheless, some minor details such as volumetric BIM components and commercial BIM platforms (e.g., Autodesk Revit) were not tested in the study. In terms of the computational time cost, the 3D scanning accounted for the significant portion, while other automatic processes like network transmission, execution of deep transfer learning, object recognition, and as-built BIM creation only cost a few seconds on the workstation. The flexible settings of the walking requirements in the proposed as-built BIM approach lead to a personalized walkability assessment. The high efficiency (fast processing speed) indicates that it is now possible to crowdsource the PWA to ubiquitous AR smartphones. When ubiquitous AR smartphones become more and more potent in computational power (*e.g.*, with powerful GPUs) in future, the proposed approach can also be fully embedded in everyday AR smartphones for real-time PWA and obstacle detection.

In comparison to the conventional walkability assessment methods, the proposed approach has several advantages. First, the automation level of walkability assessment is elevated, so that the traditional reliance on human surveyors by audit tools and inaccurate data by GIS-based methods is now relieved. The proposed approach leverages state-of-the-art technologies in remote sensing, deep transfer learning, and as-built BIM creation and achieves an accurate, consistent and inexpensive assessment. Consistency is very important for the use of a walkability rating system. Furthermore, the details of pedestrian paths are modeled and assessed, thanks to the centimeter accurate, dense as-is 3D point cloud scanned by the AR smartphone. Last but not least, the proposed approach measures personalized walkability for each individual pedestrian like a person in a power wheelchair or a traveler with a large-model (e.g., 70 cm) baby stroller. To sum up, the proposed approach yielded a novel, automatic, semantically rich PWA, which is expected to be very competitive with manual surveying in smart city scenarios.

Disadvantages, nevertheless, can also be identified. In the first step of 3D scanning, noise is problematic because the capacity of the embedded AR sensors and the related software libraries are not perfect. Another limitation is the requirement of an additional BIM workstation and network transmission apart from the AR smartphone, due to the reliance on powerful GPUs. The GPUs and memory in state-of-the-art smartphone models are not powerful enough to execute large-scale CNN models. Additionally, the as-built BIM, though successful in the pilot case, was neither volumetric nor in popular commercial BIM formats. Errors, though not significant, can be found in the results of *PoinNet* and as-built BIM creation as shown in Figures 3 (a) and (b). However, with the promised technological advancement in AR smartphone and continuous research, all these drawbacks are likely to be resolved in the near future.

5 Conclusion

This study presented an as-built BIM approach to PWA for pedestrian paths. The as-built BIM of a target pedestrian path represents the actual geometry, semantic components (*e.g.*, potential obstacles), as well as the real topology, and serves as an information hub for assessing walkability. In our approach, the everyday AR smartphone becomes a potent walkability assessment tool, and pre-trained CNN models serve as a part of the automatic as-built BIM generator. The PWA created, is automatic, highly detailed, and capable of assessing walkability for various types of pedestrians. A pilot case of a real-world pedestrian path scene gave initial validation of the proposed approach.

This study is expected to enrich research of PWA, as well as as-built BIM study, for pedestrian paths with a novel ubiquitous computing enabled framework for near-instant automated modelling of a walking environment. Although the findings are preliminary, the technological feasibility of crowdsourcing walkability assessment has been demonstrated by our prototyping pilot study. Further research will aim to reduce noise in the 3D scanning stage, embed the approach to AR smartphones without assistance from a BIM workstation, integrate with popular BIM/GIS software and standards, and refine the deep learning models.

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References

[1] Leslie, E., Coffee, N., Frank, L., Owen, N., Bauman, A., and Hugo, G. (2007). Walkability of local communities: Using geographic information systems to objectively assess relevant environmental attributes. Health & place, 13(1): 111-122.

[2] Sun, G., Webster, C., and Chiaradia, A. (2017). Objective assessment of station approach routes: Development and reliability of an audit for walking environments around metro stations in China. Journal of Transport & Health, 4: 191-207.

[3] Althoff, T., Hicks, J. L., King, A. C., Delp, S. L., and Leskovec, J. (2017). Large-scale physical activity data reveal worldwide activity inequality. Nature, 547(7663), 336.

[4] Gilderbloom, J. I., Riggs, W. W., and Meares, W. L. (2015). Does walkability matter? An examination of walkability's impact on housing values, foreclosures and crime. Cities, 42: 13-24.

[5] World Health Organization. (2015). Global Report on Urban Health—Executive Summary. http://www.who.int/kobe_centre/measuring/urban-global-report/en/ <accessed 29/04/2018>

[6] Birkmann, J., Welle, T., Solecki, W., Lwasa, S., and Garschagen, M. (2016). Boost resilience of small and mid-sized cities. Nature, 537(7622): 605-608.

[7] Frank, L. D., Sallis, J. F., Saelens, B. E., Leary, L., Cain, K., Conway, T. L., and Hess, P. M.

(2010). The development of a walkability index: application to the Neighborhood Quality of Life Study. British journal of sports medicine, 44(13): 924-933.
[8] Clifton, K. J., Smith, A. D. L., and Rodriguez, D. (2007). The development and testing of an audit for the pedestrian environment. Landscape and Urban Planning, 80(1-2): 95-110.
[9] Griew, P., Hillsdon, M., Foster, C., Coombes, E., Jones, A., and Wilkinson, P. (2013). Developing and testing a street audit tool using Google Street View to measure environmental supportiveness for physical activity. International Journal of Behavioral Nutrition and Physical Activity, 10(1): 103.
[10] Carlson, J. A., Saelens, B. E., Kerr, J., Schipperijn, J., Conway, T. L., Frank, L. D., Chapman, J. E., Glanz, K., Cain, K. L., and Sallis, J. F. (2015). Association between neighborhood walkability and GPS-measured walking, bicycling and vehicle time in adolescents. Health & Place, 32: 1-7.
[11] Kasemsuppakorn, P., and Karimi, H. A. (2013). Pedestrian network extraction from fused aerial imagery (orthoimages) and laser imagery (lidar). Photogrammetric Engineering & Remote Sensing, 79(4): 369-379.
[12] Brownson, R. C., Hoehner, C. M., Day, K., Forsyth, A., and Sallis, J. F. (2009). Measuring the built environment for physical activity: state of the science. American journal of preventive medicine, 36(4): S99-S123.
[13] Aghaabbasi, M., Moeinaddini, M., Shah, M. Z., Shekari, Z. A., and Kermani, M. A. (2018). Evaluating the capability of walkability audit tools for assessing sidewalks. Sustainable Cities and Society, 37: 475-484.
[14] National Institute of Building Sciences. (2015). National Building Information Modeling Standard. Version 3, Retrieved from https://www.nationalbimstandard.org/ <accessed 29/04/2018>
[15] Tang, P., Huber, D., Akinci, B., Lipman, R. and Lytle, A. (2010), Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Automation in Construction, 19(7): 829-843.
[16] Chen, K., Lu, W., Xue, F., Tang, P., and Li, L. H. (2018). Automatic building information model reconstruction in high-density urban areas: Augmenting multi-source data with architectural knowledge. Automation in Construction, 93: 22-34.
[17] Xue, F., Chen, K., Liu, D., Niu, Y., and Lu, W. S. (2018). An optimization-based semantic building model generation method with a pilot case of a demolished construction. In Proceedings of the 21st International Symposium on Advancement of Construction Management and Real Estate: 231-241.
[18] Xue, F., Lu, W., and Chen, K. (2018). Automatic generation of semantically rich as-built building information models using 2D images: A derivative-free optimization approach. Computer-Aided Civil and Infrastructure Engineering, in press, doi:10.1111/mice.12378.
[19] Lu, W., Peng, Y., Xue, F., Chen, K., Niu, Y., and Chen, X. (2018). The fusion of GIS and Building Information Modeling for big data analytics in managing development sites, in Comprehensive Geographic Information Systems: 345-359.
[20] Pan, S. J., and Yang, Q. (2010). A survey on transfer learning. IEEE Transactions on knowledge and data engineering, 22(10): 1345-1359.
[21] Qi, C. R., Su, H., Mo, K., and Guibas, L. J. (2017). Pointnet: Deep learning on point sets for 3D classification and segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition: 652-660. doi:10.1109/CVPR.2017.16
[22] Hackel, T., Savinov, N., Ladicky, L., Wegner, J. D., Schindler, K., and Pollefeys, M. (2017). Semantic3D.Net: A new large-scale point cloud classification benchmark. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2017(IV-1-W1): 91-98.