TOWARDS PEDESTRIAN ACCESSIBILITY ANALYSIS IN INDOOR ENVIRONMENTS WITH CROWDS

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ABSTRACT:

Except in emergency cases, indoor crowds could also decrease the walking speed of pedestrians in daily life. To investigate daily-based accessibility of locations to a pedestrian in the presence of crowds, this paper proposes a method of indoor accessibility analysis. We adopt a hierarchical spatial model to represent indoor environments and evaluate the varied accessibility to a user. The first level refers to a door network representing door connectivity. On the second level, spaces are gridified so that crowd density can be readily measured, and its obstruction to pedestrians can be quantified at different time slots. Instead of generating specific obstacle-avoidance paths in a short period, we depict accessibility variation with two types of paths, *i.e.,* central and periphery paths inside rooms. Based on the hierarchical model, pathways are pre-computed between doors for a user and indexed in the grid model. In a path query, a sequence of doors is derived from the door network, and the pre-computed pathways are readily retrieved to form the two types of paths. Accordingly, walking time can be estimated with crowd density in these grids at each time slot. We conducted an initial test on a building floor to demonstrate the use of the proposed method. We sampled the locations of simulated crowds (50 persons) every 10 seconds, and the time cost between given doors in both paths are compared. A slowdown occurred in the central path, and the periphery path involves the minimum time in the test scenario. In the future, the relationship between crowd density and the possibility of blockage to pedestrians will be further investigated.

1. INTRODUCTION

Path planning is an important measure for indoor navigation. At present, most applications for pedestrians prioritize path selections where static obstructions are considered (*e.g.,* walls and furniture). However, indoor environments contain other varied barriers, *e.g.,* crowds (Boguslawski et al., 2022). Although sparse crowds may not greatly impede a person's movement, they need to be taken into account when the density grows and the pace of a pedestrian user obviously decreases.

Previous studies have defined indoor objects in different data models, and obstacle-avoidance is considered in some scenarios (Li et al., 2018). There has been relevant research for evacuation pathfinding in emergency scenarios (Xie et al., 2022). Generally, they are based on a fixed indoor network, and the main objective is to evacuate all crowds to safe exits in the minimum time (Wang et al., 2015, Li et al., 2020). But these works seldom aim for indoor scenarios of moving barriers in normal circumstances.

Crowds may lead to slight congestion and decrease the walking paces of users under some conditions. Its effect evaluation is restricted to monitoring techniques, suitable spatial models and analysis methods. Now it is able to detect crowd distribution with a given accuracy (*e.g.*, 2-5m) with wireless sensing technologies. Crowds can be regarded as movable and dynamic obstacles to an individual (Diakité and Zlatanova, 2018). To handle the replanning of obstacle-avoidance paths, hierarchical spatial models for indoor navigation can sustain efficient pathfinding approaches that search available paths from a coarse scale to a refined one (Liu and Zlatanova, 2013, Liu and Zlatanova, 2022). Researchers have proposed grid-based models for indoor emergency evacuation and considered spaces, sensors, fire extension and human behaviours (Xiong et al., 2017, Gorte et al., 2019a, Gorte et al., 2019b, Aleksandrov et al., 2021, Xie et al., 2022). Recent studies started to depict and model dynamic barriers for indoor pathfinding (Schmalfuß-Schwarz et al., 2020, Liu et al., 2021b). They basically focus on dynamic path planning in the presence of obstacles.

However, it is not economical to recalculate obstacle-avoidance paths at a high frequency. A field study in buildings shows pedestrians tend to avoid or move slowly by following crowds (Li et al., 2019). In a shopping mall, crowdedness may not impact the route choices of wayfinding users, yet their walking paces can be impeded (Yan et al., 2021). In this case, wayfinding users are more possible to approach boundary areas so as to avoid central crowd areas. Thus, it may not be a priority to find the shortest route and it may not be feasible to find alternative obstacle-free paths in some cases. For such cases, we need to assess the impact of crowds on the movement of a user, which can provide indicators to evaluate the indoor accessibility to this user.

In this paper, we aim to devise a model to assess the accessibility of indoor locations in the presence of crowds. We apply a hierarchical spatial model to represent indoor environments and evaluate the varied accessibility to pedestrian. Instead of an emergency evacuation, we focus on daily-based pedestrian movements in a building with respect to crowds. A logical network consists of nodes representing doors (*i.e.,* door network), and indoor crowds are incorporated into a grid-based model to reflect their impact on pedestrian accessibility. For a pedestrian, we pre-computed two types of geometric pathways and defined an indicator regarding walking time to differentiate accessibility in these paths. According to a given pair of doors for a pedestrian, the door sequence between the start and destination are computed in the door network and geometric pathways

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are retrieved and concatenated with grids (Liu and Zlatanova, 2022). The pedestrian's walking state can be estimated with crowd density in these grids at each time frame.

We conducted an initial test to verify the use of the proposed method. A building floor is employed to consider horizontal movement, and we created a door network with a 1m*1m grid model. We sampled the locations of simulated crowds (50 persons) in each 10 seconds, and visualized them in the grid model. Central and periphery paths are concatenated for the given doors and represented in grids. The time cost of a user in the both paths was computed for each time slot in terms of crowd density. Test results show a pedestrian on the both paths may not need to stop, while slower walking speed can occur in the test scenario of directional crowd movements.

2. RELATED WORK

Pathfinding algorithms for emergency dynamics have been widely developed and employed, such as different heuristic algorithms for evaluational routes (Wang et al., 2015, Li et al., 2020, Gorte et al., 2019a, Xie et al., 2022). Many applications of crowd evacuation and pathfinding adopted Ant Colony Algorithm (ACA) for emergency scenarios (Wang et al., 2023). There are a bunch of studies on evaluation speed and crowd density of emergency scenarios (Wang et al., 2019), and human motions on micro-levels (Best et al., 2015).

Researchers proposed different indoor spatial models to delineate indoor dynamics including crowds and hazardous factors (Xiong et al., 2017, Zhao et al., 2022). In general, both vector and discrete data models are adopted, and a group of hierarchical data models are designed to process possible changes. Although they involve various hierarchies or combinational spatial forms, studies of data models have to address its related path planning. For instance, a time-dependent route map was proposed for evacuation (Wang et al., 2015), and a user could decide whether to wait, avoid, or cross obstacle area (Wang et al., 2017, Wang and Zlatanova, 2020). Dynamic risk models of sensor network can be used to measure different risks, and time-expanded routes and the capacity of evacuees are considered.

For normal circumstances, a study defined time-critical barriers (Schmalfuß-Schwarz et al., 2020) for motion-impaired people, including varied crowds, temporarily unavailable elevators, and scheduled maintenance work. Thus, continuous collection of indoor mobility data is important to accessibility evaluation for pedestrians.

However, there is still lack of discussions about indoor dynamic path planning considering daily crowds. Indoor crowds may lead to a slight congestion and decrease walking paces in some cases. In this case, accurate pathfinding relies on IoT localization techniques, suitable spatial models and proper path planning methods. Nowadays, it is able to detect crowd distribution in a given accuracy (*e.g.,* several meters) with wireless sensing technologies (Khelifi et al., 2019). A previous research has shown Wi-Fi sensing can be used to track indoor users in grid-based models with certain localization errors (Xu et al., 2018).

Thus, a proper spatial model and corresponding routing method are motivated for flexible path planning regarding indoor crowds. BIM IFC is an important data source to support the creation of navigation models (Liu et al., 2021a). Hierarchical spatial models for indoor navigation can support efficient pathfinding that can be solved from a coarse scale to a refined scale (Liu and Zlatanova, 2013, Liu and Zlatanova, 2022). Computational models for different levels have demonstrated their use for frequent changes.

There are studies have considered indoor accessibility in terms of building circulation (Dao and Thill, 2018, Shin and Lee, 2019), while on the micro-level indoor accessibility of user transit is less discussed. A recent study has investigated indoor accessibility restrictions (Alattas et al., 2020). Some indoor obstacles are usually not included in a building dataset because they are temporary and with no fixed location. Relevant studies started to depict and model dynamic barriers for indoor pathfinding (Schmalfuß-Schwarz et al., 2020, Liu et al., 2021b). A crowd-aware pathfinding algorithm has been proposed to approach accurate crowd-avoiding paths (Liu et al., 2021b).

Nevertheless, it is inevitable to encounter crowds for a user in some cases. Researchers have pointed out the interactions between different pedestrians can impact their movement (Alhawsawi et al., 2020). A tricky problem is how to characterize the walking behaviour (stop, avoid, or keep going) of a pedestrian when she/he continuously runs into other people.

In the next section, we will introduce the method to investigate the accessibility of paths to a pedestrian in the presence of crowds.

3. ACCESSIBILITY WITH CROWDS

This section introduces our method of accessibility estimation in the presence of crowds. We apply a hierarchical spatial model to represent indoor environments and evaluate the varied accessibility of pedestrian in paths. The devised method aims to capture and quantify the accessibility of queried paths, when crowd locations are reflected in a grid model in a time frame. This study focuses on capturing accessibility change with crowds in a period of time. By estimating accessibility in selected paths, we can reveal the possible walking time the user will need.

3.1 SPATIAL MODEL

Figure 1 present the workflow of the proposed method. Basically, we generate two models from a building model on separate levels. The separate levels can support prompt query by limiting search scope. The first level is the 'door' network (Liu and Zlatanova, 2022). More specifically, it is a graph to represent the connectivity between doors of the same room (see Figure 2). A room can relate to several doors, and the edge of two doors contains accessibility crossing the room's interior.

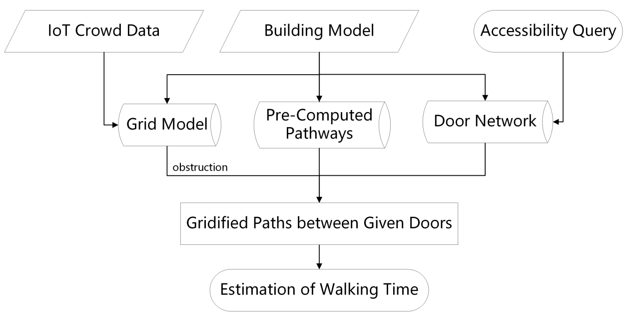

Figure 1. Workflow of the proposed method.

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On the second level, each room is gridified so that the density of crowds can be measured (see Figure 2). Crowds of indoor spaces are reflected in the grid model, and the variation of its density can be represented at different time slots. In addition, the obstruction on pedestrian paths can be quantified as well. According to the crowd state at each time slot (*i.e.,* 'IoT Crowd Data' in Figure 1), we can also update the edge weights of the door network.

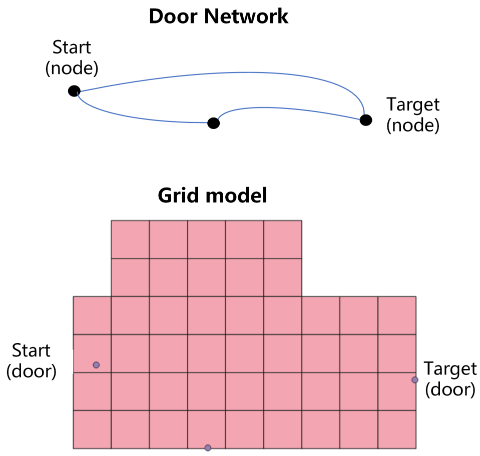


Figure 2. Two adopted spatial models.

Based on the hierarchical model of building, we can pre-compute pathways between different doors for a walking user. We can compute available paths in the door network *i.e.,* the sequence of doors, while these paths would be transformed into grids in the grid model. Then the impact of crowds on accessibility is assessed in these paths. Instead of depicting specific obstacle-avoidance paths in a short period, we aim to observe the changes in accessibility on the pre-computed pathways, which can provide an estimation of walking time between the doors.

We employ two types of pre-computed pathways in this paper (Figure 3). One is based on medial axis networks, while the other one is along with walls. They represent the central and periphery paths in a room, respectively. As distinct indoor navigation networks would result in different shapes of routes, the both types of paths reflect the main regions of a walking user, *i.e.,* to walk in the central area or to avoid other people via the periphery region close to walls. In this way, we can track the changes in the both paths according to their obstruction level that relates to crowd density at a certain time.

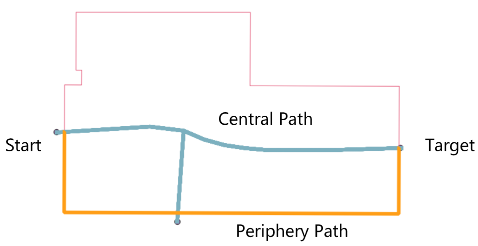


Figure 3. Two types of pre-computed pathways.

3.2 ACCESSIBILITY ESTIMATION

As mentioned before, we assess the obstruction level of the pre-computed pathways according to the crowd density at separate time slots. Based on the number and locations of people collected by IoT device at each time slot, we can pinpoint the related cells in the grid model.

Afterwards, all the pathways are pre-computed between doors in the two types. When a query is set for two specific doors, we can concatenate connected pathways via relevant doors (*i.e.,* door sequence derived by routing in the door network) . These pathways are used to estimate the influence of crowds and they refer to transit time in separate time slots.

Specifically, we employ a list of grid id to depict the concatenated paths.That is, we index these paths in the grid model. In this manner, transit time relates to the number of grids of a path and that of occupied grids. In addition, we adopt an indicator to reflect the influence on a pedestrian's behaviour, *i.e.,* the density of people (D) in a short range of a user. Then we set rules to reflect such influence. For horizontal movement, a user would halve her/his walking pace when the density is larger than a threshold of 1 person $/m^2$; while the user would stop for a while when the crowd density reaches 2 persons/m^2. For vertical movement, the user halve the speed when D is larger than 1 person $/2m^2$, and could stop when D is larger than 1 person $/m^2$.

To quantify the transit time between two doors (including waiting), we define four cases as follows:

1. The both paths include no obstruction.
2. Only periphery path is blocked.
3. Only central path is blocked.
4. Both central and periphery paths are blocked.

Case 1 and 2 has no obvious influence on the transit of a given pedestrian user, which means the user does not need to lower the speed. While a user in case 3 can switch the option to the periphery path to avoid people in the central region. In case 4, we have to examine the potential blockage during the transit between the doors since the user often inevitably encounter other people in the both paths. Case 4 is the main scenario considered in this paper.

4. TESTS AND DISCUSSIONS

We conducted an initial test in a building floor to verify the concepts and demonstrate the use of the proposed method of accessibility analysis. To reflect the variation in crowd density, we simulated several groups of people and their movements on a floor. We extracted the floor surface from a BIM model and selected the resolution of 1m*1m to create a grid model (see Figure 4). As the test floor contains narrow corridors, we selected a high spatial resolution of 1m*1m to distinguish the central and periphery regions of a room. To consider path accessibility for a pedestrian, we set a user's walking pace to 1.2m/s (*i.e.,* average walking speed).

Here we adopt temporal resolution of crowds movement in a relative short span, *i.e.,* 10s. It caters for the processing time of IoT device, and the span could support a prompt update of crowd locations. For simplicity, this paper employed agent-based simulation data to represent crowds. 50 people of several groups are simulated, and the walking speed of each person is set to 1.19m/s. They are in different rooms and directed

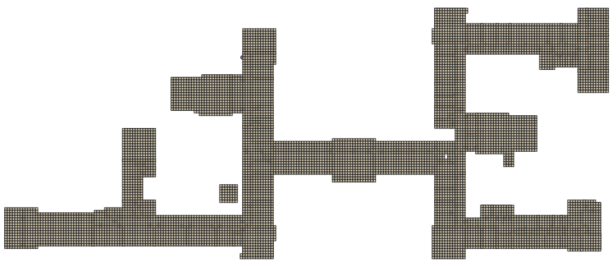


Figure 4. Grid model of test floor.

to two different destinations (see Figure 5). The groups moved in opposite directions and they met in the middle corridor at a certain point, which caused a short slowdown. The test period lasts 171.5 seconds(s). The movements are split into different time frames. We sampled the crowds state in each 10s, and we obtained their distribution data in 17 time slots.

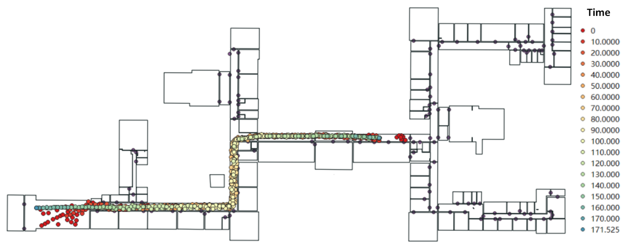


Figure 5. Simulation of crowds movement.

Density of people are continuously calculated in the grid model along with time. In this case, the density values of different time correlate to the obstruction degree to a user. We adopted density of people (D) and the rules in Section 3.2 to define a user's interaction. Crowd/people density can influence the waiting duration of a pedestrian, and available space ahead of the user is an important sign (Best et al., 2015). Based on empirical data, we set speed thresholds based on the crowd density in front of a user. Specifically, we search the grids of the next 5s on a pre-computed pathway and check the number of occupants.

In the floor we selected two doors o_130 and o_261 as start and destination for path query. Figure 6 shows the logical network of doors of the test floor. Large green nodes represent the routing result on the door network. We obtained the logical path in a door sequence of o_130, o_144, o_213, o_462, o_600, o_601, o_261.

Based on the door sequence, we promptly fetched the pre-computed pathways via these doors. Figure 7 shows both the central and periphery paths in grid forms. Then we started to analyse the user's speed in the both paths at each time slot.

As a result, we compared the estimated time cost of the both paths between o_130 and o_261. We found the user's possible slowdown action in the central path at the time of 70s (see Figure 8). Before the point, the periphery path involves a little longer walking. As the estimated walking speed does not decrease in the periphery path after 70s, the walking progress is slightly ahead of that in the central path.

Specially, Figure 9 shows the scenario of the user's slowdown in the central path from o_130 to o_261. The highlighted cell represents the estimated location at the time 70s. According to

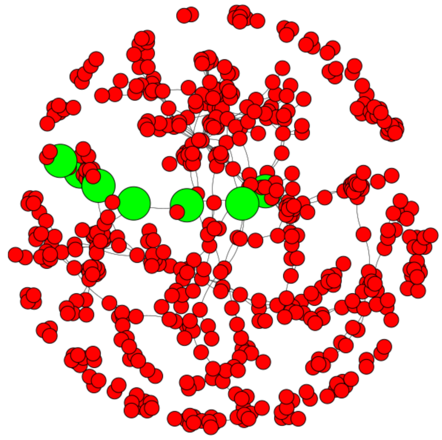
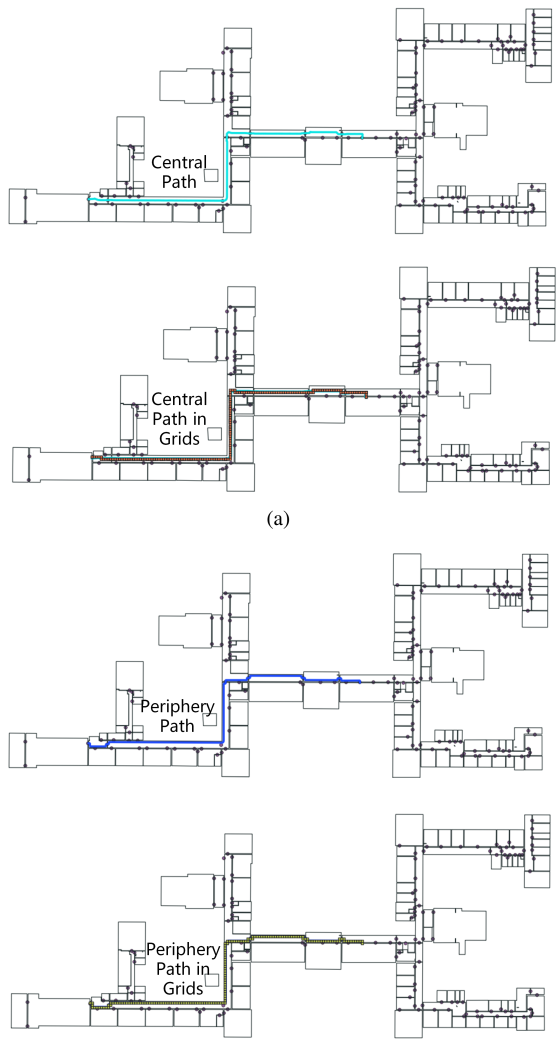


Figure 6. Logical network of doors of the floor (door network).



(a)

(b)

Figure 7. Two types of paths between given doors. (a) Central path; (b) Periphery path.

Section 3.2, here we halved the user's walking speed (0.6m/s) since the density of the assigned region (*i.e.,* the next 6 grids) reached 1 person/m^2. It is impacted by a short and slight congestion when other people were getting through the door.

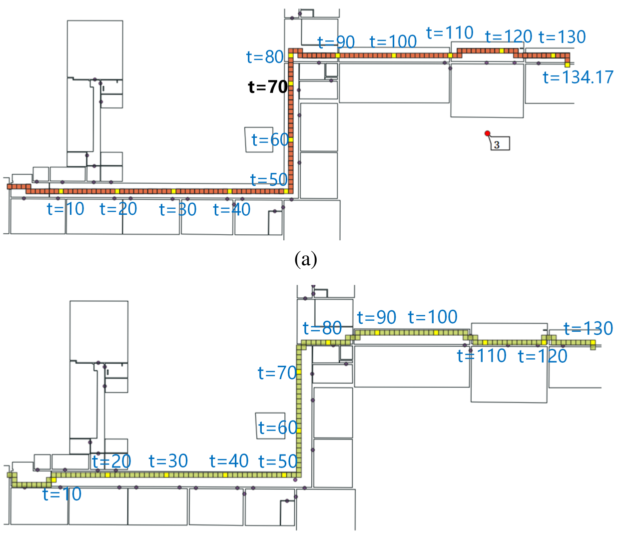


Figure 8. User location at each time slot. (a) In central path; (b) In periphery path.

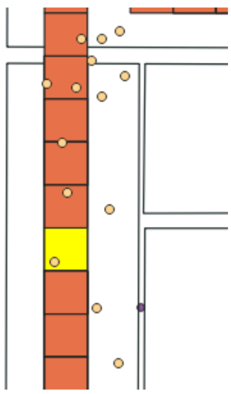


Figure 9. Scenario of slowdown (t=70) in central path from o_130 to o_261.

Table 1 and 2 provide more details of the estimated motion. The length of central and periphery paths are almost the same (155 and 157m), while the estimated motion in the central path is a little longer (134.17s). Except the slowdown in the central path, a pedestrian user does not need to stop in the both paths (see 'Wait' column). Also, it results from a fact that simulated crowds did not form congestion in any door. After the time 100s, the motion in the periphery path involves less density.

According to the density at separate time slots, the relevant edges weights of the door network are updated. For the central path from o_130 to o_261, the updated edge weights implies the movement of crowds (see Figure 10). The weights represent the people density (person/m^2) in the area of pathway grids between two doors in the same room. The weights provide a straightforward description of accessibility on crowd flow change, which can support path selection of users. For instance, the edge weight between o_213 and o_462 increase to 0.31 from 10s to 100s. This trend indicates the the behavior of crossing the central region of the related room is growing.

Although this work is in its first stage, it shows the potential use for monitoring real-time accessibility of paths in building. Several important issues need to be investigated in the next steps.

Time	Count	Density	Speed	Distance	Wait
10	3	0.50	1.2	12	0
20	3	0.50	1.2	24	0
30	3	0.50	1.2	36	0
40	0	0.00	1.2	48	0
50	0	0.00	1.2	60	0
60	2	0.33	1.2	72	0
70	6	**1.00**	**0.6**	78	0
80	2	0.33	1.2	90	0
90	1	0.17	1.2	102	0
100	2	0.33	1.2	114	0
110	3	0.50	1.2	126	0
120	3	0.50	1.2	138	0
130	3	0.50	1.2	150	0
134.17				155	

Table 1. Statistics of user motion in central path.

Time	Count	Density	Speed	Distance	Wait
10	0	0.00	1.2	12	0
20	0	0.00	1.2	24	0
30	0	0.00	1.2	36	0
40	3	0.50	1.2	48	0
50	4	0.67	1.2	60	0
60	3	0.50	1.2	72	0
70	2	0.33	1.2	84	0
80	1	0.17	1.2	96	0
90	4	0.67	1.2	108	0
100	4	0.67	1.2	120	0
110	0	0.00	1.2	132	0
120	1	0.17	1.2	144	0
130	0	0.00	1.2	156	0
130.83				157	

Table 2. Statistics of user motion in periphery path.

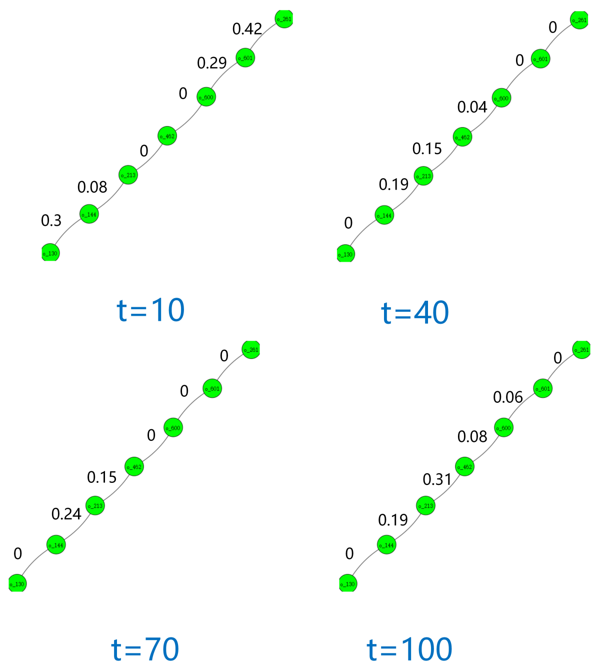


Figure 10. Update edge weights of door network according to crowd density at 4 time slots.

First, the current test is about the horizontal movement only. It is necessary to incorporate vertical movements of crowds and their influence on accessibility. Second, the crowd data are simulated without location accuracy issue. However, indoor localization results can reflect the real-time crowds yet include uncertainty. Its relationship with the genuine obstruction of crowds needs to be further formulated. And last but not least, more cases of human reaction to crowds on a micro-level need to be tested and calibrated. As shown in our test, a pedestrian user may not reduce the walking speed even in front of a group of people.

5. CONCLUSIONS

To investigate indoor accessibility among doors in the presence of crowds, this paper proposes a method of indoor accessibility analysis. This method employs two spatial models, *i.e.,* door network (logical model) and grid models (geometric model). Geometric pathways are pre-computed between doors and indexed in the grid model. In a path query one can compute a sequence of doors in the door network, and readily retrieve the pre-computed pathways to form geometric paths. The obstruction of crowds on these paths are converted to estimated transit time in each time frame. Thus, one can visualize and compare the walking time in these paths. Meanwhile, the values of crowd density are also used to update the edge weights of door network dynamically.

This is an initial work towards real-time pedestrian accessibility analysis. We tested the proposed method in a building floor with simulated crowds, and showed the feasibility of the proposed method in estimating time cost in queried paths regarding crowds. The simulated crowds can also be replaced with monitored locations of IoT sensors. The initial test shows a pedestrian user barely need to stop in the simulated scenario. In the future, more tests are required for vertical movements (*e.g.,* stairs). In addition, the resolution of grid models shall adapt to the accuracy of localization. In this sense, 'unidentified' occupied regions caused by low location accuracy need to be regarded as constrained area for a pedestrian user. Also, the relationship between crowd density and the possibility of blockage to pedestrians will be further investigated.

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REFERENCES

Alattas, A., van Oosterom, P., Zlatanova, S., Hoeneveld, D., Verbree, E., 2020. LADM-IndoorGML for exploring user movements in evacuation exercise. *Land Use Policy*, 98, 104219. https://doi.org/10.1016/j.landusepol.2019.104219.

Aleksandrov, M., Heslop, D. J., Zlatanova, S., 2021. 3D Indoor Environment Abstraction for Crowd Simulations in Complex Buildings. *Buildings*, 11(10). https://doi.org/10.3390/buildings11100445.

Alhawsawi, A., Sarvi, M., Haghani, M., Rajabifard, A., 2020. Investigating pedestrians' obstacle avoidance behaviour. *Collective Dynamics*, 5, 413–422. 10.17815/CD.2020.77.

Best, A., Narang, S., Curtis, S., Manocha, D., 2015. Densesense: Interactive crowd simulation using density-dependent filters. *Proceedings of the ACM SIGGRAPH/Eurographics Symposium on Computer Animation*, SCA '14, Eurographics Association, Goslar, DEU, 97–102.

Boguslawski, P., Zlatanova, S., Gotlib, D., Wyszomirski, M., Gnat, M., Grzempowski, P., 2022. 3D building interior modelling for navigation in emergency response applications. *International Journal of Applied Earth Observation and Geoinformation*, 114, 103066. https://doi.org/10.1016/j.jag.2022.103066.

Dao, T. H. D., Thill, J.-C., 2018. Three-dimensional indoor network accessibility auditing for floor plan design. *Transactions in GIS*, 22(1), 288-310. https://doi.org/10.1111/tgis.12310.

Diakité, A. A., Zlatanova, S., 2018. Spatial subdivision of complex indoor environments for 3D indoor navigation. *International Journal of Geographical Information Science*, 32(2), 213-235. https://doi.org/10.1080/13658816.2017.1376066.

Gorte, B., Aleksandrov, M., Zlatanova, S., 2019a. TOWARDS EGRESS MODELLING IN VOXEL BUILDING MODELS. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, IV-4/W9, 43–47. https://isprs-annals.copernicus.org/articles/IV-4-W9/43/2019/.

Gorte, B., Zlatanova, S., Fadli, F., 2019b. NAVIGATION IN INDOOR VOXEL MODELS. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, IV-2/W5, 279–283. https://isprs-annals.copernicus.org/articles/IV-2-W5/279/2019/.

Khelifi, F., Bradai, A., Benslimane, A., Rawat, P., Atri, M., 2019. A Survey of Localization Systems in Internet of Things. *Mobile Networks and Applications*, 24(3), 761-785. https://doi.org/10.1007/s11036-018-1090-3.

Li, F., Zlatanova, S., Koopman, M., Bai, X., Diakité, A., 2018. Universal path planning for an indoor drone. *Automation in Construction*, 95, 275-283. https://doi.org/10.1016/j.autcon.2018.07.025.

Li, H., Thrash, T., Hölscher, C., Schinazi, V. R., 2019. The effect of crowdedness on human wayfinding and locomotion in a multi-level virtual shopping mall. *Journal of Environmental Psychology*, 65, 101320. https://doi.org/10.1016/j.jenvp.2019.101320.

Li, Z., Huang, H., Li, N., Chu(Zan), M. L., Law, K., 2020. An agent-based simulator for indoor crowd evacuation considering fire impacts. *Automation in Construction*, 120, 103395. https://doi.org/10.1016/j.autcon.2020.103395.

Liu, L., Li, B., Zlatanova, S., van Oosterom, P., 2021a. Indoor navigation supported by the Industry Foundation Classes (IFC): A survey. *Automation in Construction*, 121, 103436. https://doi.org/10.1016/j.autcon.2020.103436.

Liu, L., Zlatanova, S., 2013. *A Two-level Path-finding Strategy for Indoor Navigation*. Springer Berlin Heidelberg, Berlin, Heidelberg, 31–42.

Liu, L., Zlatanova, S., 2022. A spatial data model for accessibility with indoor temporal changes. *Transactions in GIS*, 26(8), 3277-3294. https://doi.org/10.1111/tgis.13002.

Liu, T., Li, H., Lu, H., Cheema, M. A., Shou, L., 2021b. Towards Crowd-Aware Indoor Path Planning. 14(8), 1365–1377. https://doi.org/10.14778/3457390.3457401.

Schmalfuß-Schwarz, J., Loitsch, C., Weber, G., 2020. Considering time-critical barriers in indoor routing for people with disabilities. K. Miesenberger, R. Manduchi, M. Covarrubias Rodriguez, P. Peňáz (eds), *Computers Helping People with Special Needs*, Springer International Publishing, Cham, 315–322.

Shin, J., Lee, J.-K., 2019. Indoor Walkability Index: BIM-enabled approach to Quantifying building circulation. *Automation in Construction*, 106, 102845. https://doi.org/10.1016/j.autcon.2019.102845.

Wang, J., Zhao, H., Winter, S., 2015. Integrating sensing, routing and timing for indoor evacuation. *Fire Safety Journal*, 78, 111-121. https://doi.org/10.1016/j.firesaf.2015.08.009.

Wang, K., Yuan, W., Yao, Y., 2023. Path optimization for mass emergency evacuation based on an integrated model. *Journal of Building Engineering*, 68, 106112. https://doi.org/10.1016/j.jobe.2023.106112.

Wang, Z., Liu, R., Wu, X., Liu, Z., 2019. Estimation models for the safety level of indoor space pedestrian flows. X. Qu, L. Zhen, R. J. Howlett, L. C. Jain (eds), *Smart Transportation Systems 2019*, Springer Singapore, Singapore, 9–18.

Wang, Z., Zlatanova, S., 2020. Safe Route Determination for First Responders in the Presence of Moving Obstacles. *IEEE Transactions on Intelligent Transportation Systems*, 21(3), 1044-1053.

Wang, Z., Zlatanova, S., van Oosterom, P., 2017. Path Planning for First Responders in the Presence of Moving Obstacles With Uncertain Boundaries. *IEEE Transactions on Intelligent Transportation Systems*, 18(8), 2163-2173.

Xie, R., Zlatanova, S., Lee, J. B., 2022. 3D indoor environments in pedestrian evacuation simulations. *Automation in Construction*, 144, 104593. https://doi.org/10.1016/j.autcon.2022.104593.

Xiong, Q., Zhu, Q., Du, Z., Zhu, X., Zhang, Y., Niu, L., Li, Y., Zhou, Y., 2017. A Dynamic Indoor Field Model for Emergency Evacuation Simulation. *ISPRS International Journal of Geo-Information*, 6(4). https://www.mdpi.com/2220-9964/6/4/104.

Xu, W., Liu, L., Zlatanova, S., Penard, W., Xiong, Q., 2018. A pedestrian tracking algorithm using grid-based indoor model. *Automation in Construction*, 92, 173-187. https://doi.org/10.1016/j.autcon.2018.03.031.

Yan, J., Zlatanova, S., Lee, J. B., Liu, Q., 2021. Indoor Traveling Salesman Problem (ITSP) Path Planning. *ISPRS International Journal of Geo-Information*, 10(9). https://doi.org/10.3390/ijgi10090616.

Zhao, J., Xu, Q., Zlatanova, S., Liu, L., Ye, C., Feng, T., 2022. Weighted octree-based 3D indoor pathfinding for multiple locomotion types. *International Journal of Applied Earth Observation and Geoinformation*, 112, 102900. https://doi.org/10.1016/j.jag.2022.102900.