Pedestrian Path Choice in Crowded Indoor Environments

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Abstract

Indoor crowds can be regarded as dynamic obstacles and they could impede the movement of pedestrians. For instance, the scope of crowds could significantly impact accurate path choices. There are few discussions from an individual's perspective to reveal the decision-making process of reasonable path choices. In this paper, we aim to address how an indoor pedestrian would walk in a crowded indoor environment. We propose a method to simulate a pedestrian's path choices during wayfinding process. It is wrapped in a workflow that can capture near-real-time crowd uncertainty. First, the measurement errors of crowds are alleviated with a Bayesian filter. According to crowd locations at each moment, the method of Kernel Density Estimation (KDE) is applied to a grid model of the building to obtain the uncertainty map of the crowds. Based on a two-level spatial model, the logical path represented by a room sequence can be derived from a 'room-door' network, while detailed path choices on the 'operational' level are refined in each room. By considering both crowd uncertainty and time cost, path choices for a user are determined by using the A* algorithm at each time slot. By iterating the optimal path to the next door/the target in the current room, the user location of the next moment can be inferred. Our test initially validated the feasibility of the method on the path choices of a pedestrian. In the future, we plan to further conduct field tests with different users in crowded indoor environments.

1. Introduction

Indoor navigation services have been significantly developed, and corresponding technologies lay the foundation for indoor location-based services. Path planning is one of the core tasks. For pedestrian navigation in daily scenarios, indoor networks are abstracted to represent the space where users are located and are used for path planning. Commonly indoor access networks are pre-generated based on indoor maps. However, a fixed network could not fit a dynamic scenario where indoor crowds can block the pre-generated paths (Boguslawski et al., 2022).

Crowds are mobile obstacles and their boundaries may change over time (Wang et al., 2017a, Wang et al., 2017b). Different from indoor static obstacles (Liu and Zlatanova, 2015), mobile obstacles are hardly reflected in navigation networks, yet their density can be regarded as a variable for path planning. The traffic of indoor crowds can obviously affect a user's path choice. A wayfinding study in a virtual shopping mall shows indoor pedestrians may follow crowds and slowly walk (Li et al., 2019). Some researchers (Tan et al., 2019) used a support vector machine (SVM) and designed VR experiments to calibrate route selection parameters influenced by crowdedness. Other indoor pathfinding studies (Liu et al., 2021) considered such dynamic changes in building as well. Nevertheless, with the development of indoor positioning and localization technology, crowd locations could be obtained in a near-real-time way. Accordingly, it is possible to distinguish path selections within the spaces of finer granularity (Zlatanova et al., 2020) in such cases.

The key factor for path selection is to identify the influence range of crowds. Uncertainty is common in dynamic environments, and path planning and individual behavior simulations need to take it into account. Correspondingly, location uncertainty would essentially impact path choices. For example, indoor traffic could lead a user to follow people ahead, shortly stay in congested regions, or avert them using an alternative path. However, related research seldom brings real-time path choices into discussions, especially from an individual's perspective. In this sense, it is helpful to check the decision-making process of a pedestrian's path choice along with environmental changes.

Therefore, we aim to simulate the decision-making process of wayfinding of a single pedestrian in this paper, especially for those in the presence of crowds. We plan to investigate the reaction on path options and related movements along with different room traffic. The simulation method is proposed and wrapped in a workflow to capture real-time crowd changes and their influence on path options of a pedestrian user. First, the errors in the raw measurements of crowd locations are alleviated with a Bayesian filter. According to crowd distribution at each moment, the method of Kernel Density Estimation (KDE) (Gramacki, 2018, Georgievska et al., 2019) is applied to a grid model of the building. The kernel density map represents the uncertainty caused by these filtered crowd locations. We also create a 'room-door' network to depict the connections between different rooms and their transition openings. After assigning the start and target locations, all accessible logical paths (Liu et al., 2019) can be computed in the 'room-door' network. These doors in logical paths are supposed the anchors of wayfinding of the user in the relevant rooms. For each time slot, we search paths in the current room for the user with the A* algorithm on the uncertainty map in a stepwise manner. In this way, the current path choice is defined and calculated with the Heuristic function $h(n)$ of the A* search.

We conducted an initial test on a floor plan of a campus building. 120 samples of pedestrians are simulated to represent indoor crowds. By searching with time cost, we simulated the wayfinding process of a single pedestrian in terms of different walking speeds. The test results demonstrate the path choices of a pedestrian user can be addressed in each time step of crowd location measurements. In this way, the user's path choices can reflect the wayfinding process in the presence of crowds. In addition, several key factors could influence wayfinding simulation results, such as the bandwidth of KDE and correspondence between crowd density and walking speed.

The remainder of this paper is organized as follows. Section 2 introduces the background of this work. Section 3 introduces the proposed method for simulating user path selection in crowded rooms. Section 4 presents the initial test and its results. Section 5 concludes this paper with some future work.

2. Background

For the topics of indoor pathfinding and wayfinding, researchers have considered crowd density for indoor route planning (Tan et al., 2019). Some other researchers aim to introduce crowd objects into BIM (Li et al., 2022), and try to infer user spatial experiences including mobility.

Crowds are mobile obstacles, and their boundaries may change over time and impede the movements of a pedestrian. For instance, Tan et al. (Tan et al., 2019) employed support vector machines (SVM) and VR experiments to model how crowdedness impacts route selection. Li et al. (Li et al., 2019) observed that though crowdedness did not affect initial route choices, it influenced locomotion. Pedestrians could avoid crowds by moving to the boundaries of the indoor environment. In addition, some studies (Fang et al., 2021, Kinateder and Warren, 2021, Zhang et al., 2023) have demonstrated that indoor crowds significantly influence path choices in evacuation. Another group of studies (Xie et al., 2022, Xie et al., 2023) suggested that pedestrians may adjust their local path choices under emergencies via 3D motions (*e.g.*, bent-over walking, low crawling, jumping) leading to motions above/below indoor objects.

Recently, some researchers have started to consider such dynamic changes in path choices influenced by indoor crowds in indoor navigation. For instance, Ibrahim et al. (Ibrahim et al., 2023) introduced a simulation model that performs Monte Carlo simulations to forecast possible crowds/congestion areas and then dynamically guide pedestrians away from congestion areas. Aleksandrov et al. (Aleksandrov et al., 2023) employed a connectivity graph between building entities to model hazard flow and its interaction with indoor pedestrians. Liu et al. (Liu et al., 2021) predict time-dependent flows and indoor populations and conduct Indoor Crowd-Aware Fastest Path Query and Indoor Least Crowded Path Query among subdivided regions. The cost of time and the density of areal crowds have been incorporated into the pathfinding process. However, related research seldom brings detailed path choices into discussions and mainly represents indoor crowds in simplified spatial models of simulation/prediction. These representations of indoor crowds may be not reliable enough to confirm the precise path choices of a pedestrian user.

With the fast development of indoor localization technology, it is possible to investigate precise path choices inside rooms. Some studies (Jung et al., 2016, Xu et al., 2018, Chen et al., 2020, Liu et al., 2020, Chen and Liu, 2021, Liu et al., 2021, Alamri et al., 2022) used Internet of Things (IoT) technologies to locate indoor pedestrians' positions and performed pathfinding for each pedestrian. For example, Chen and Liu (Chen and Liu, 2021) proposed a framework where the real-time position of each user is detected by her/his smartphone. Under normal situations, the framework can estimate the density of mobile users in each area and the moving speeds to pass through different areas. Then an indoor navigation path is planned to provide the shortest moving time for a mobile user. Alamri et al. (Alamri et al., 2022) established an indoor multi-user routing approach designed for social distancing, without causing congestion on the same route. However, previous research seldom reveals the decision-making process from an individual's perspective, which may not justify a realistic and precise movement of a pedestrian.

Shortest paths are not always the best option for users (Vanhaeren et al., 2020). Researchers point out that shortest path calculation has limitations in capturing the impact of building structures on wayfinding (Gath-Morad et al., 2022). Autonomous wayfinding (Kalakou and Moura, 2014) has been studied for many years and visual perception has been introduced into wayfinding (Gath-Morad et al., 2020). In this way, one can attempt to optimize the indoor layout and plan by simulating wayfinding behavior. However, in this paper we focus more on how to quickly and precisely make choices for pedestrians based on the sensing of environmental information. In other words, we investigate a user's possible detailed movement on the so-called 'operational' level, *i.e.,* calculating the next steps with consideration of obstacle-avoidance (Vizzari et al., 2020).

Therefore, we plan to analyze path choices in a crowded microscopic environment from a pedestrian user's perspective. There could be different path characteristics for distinct individuals. Here we aim to answer an important question regarding indoor pedestrian walking, that is, how would a specific user walk in measurable crowd-impacted regions? This user may have different path preferences, *e.g.*, the shortest, the fastest or the least crowded choice for the next path segment. We can provide the estimate of the time cost of the given user with a near-real-time localization of crowds. So in this paper we use trajectory (with errors) to represent indoor crowds, instead of predicting their areal density change.

3. Method

We propose a simulation method to investigate the stepwise path choices of a human user during a wayfinding process. First, we adopt a two-level spatial model (Liu and Zlatanova, 2022, Liu and Zlatanova, 2023) for the simulation. This first level is about the connectivity of rooms and doors (*i.e.,* a logical network), while the second level relies on grid models of indoor environments. After deriving a room sequence RS between a given start and destination, the path selection of a user can be calculated in every room of the RS. Meanwhile, all the transition doors are affiliated with the related rooms of the RS. In addition, crowd locations are determined at short time slots (*e.g.*, with WiFi passive localization). The crowd trajectories consist of their locations at equally-divided time slots (*e.g.*, 5s). A Bayesian filter, such as the Kalman filter (Kalman, 1960), can be applied to alleviate the errors of crowd locations. Furthermore, Kernel Density Estimation (KDE) (Georgievska et al., 2019) is used to merge the location distribution and its uncertainty, which results in an uncertainty map for the grid model in the related rooms. The above steps are included in the workflow in Figure 1.

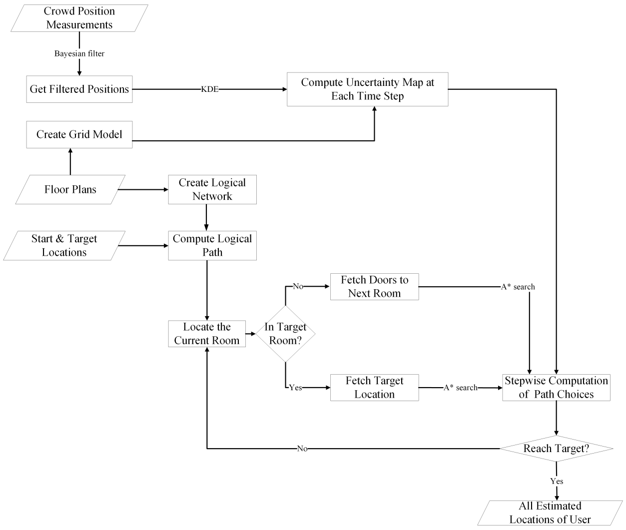


Figure 1. Workflow of the proposed method.

At each time slot, path choices for a user are determined via the A* algorithm (Hart et al., 1968). In its Heuristic function *h(n)*, we combine the uncertainty of crowds and walking time cost to consider the comfort of paths. In the first place, we calculate the optimal path P_0 to next door candidates in the current room, and select the location of the next time step in P_0 as the next start point S_i. The new optimal path P_i from S_i to next door candidates on the *RS* is continually calculated at each time step from room to room, until entering the room of the target location.

In each room, the optimal path is calculated to the next door or the target and the user location of the next moment can be inferred in this path. The stepwise computation of path choices continues until the target location (see the workflow in Figure 1). As a result, time-dependent path choices at different moments are aggregated after this step-by-step calculation, which also reflects the influence of crowds at each time step.

More specifically, we adopt time cost to reflect the weights for the A* search when computing stepwise path options inside rooms. In this paper we focus on the walking time of a user and try to balance the impact of crowdedness and time cost. Accordingly, we define the Heuristic function *h(n)* of the A* algorithm as follows:

$$h(n) = u(n) * md_n / v_n \tag{1}$$

In Equation 1, *u(n)* is the uncertainty of location *n*, and v_n is the speed of the user at *n*; while md_n represents the Manhattan distance from *n* to the next door or the target location (see Figure 1). In a word, Equation 1 implies that *h(n)* positively correlates to grid location uncertainty and the time cost.

To reflect the realistic influence of crowds on a user's movement, some rules are added to adjust the walking speed of the user. This measure is employed to simulate user actions of ’fast walk’, ’slow walk’, and ’stop’. In this paper, a user's walking speed is subject to location uncertainty on the grid model. Two thresholds T_1 and T_2 ($T_1 > T_2$) related to crowd density are defined. Comparing T_1 with location uncertainty *u(n)*, if *u(n)* $> T_1$, then the corresponding speed is 0 and the user would stop at this grid *n* until the next time step. If *u(n)* $<= T_1$ and *u(n)* $> T_2$, then the walking speed of the user is set to 0.4 m/s (one to third of the initial speed). In other cases, we assume the user will keep the initial speed of 1.2 m/s.

As mentioned above, after searching a possible path to the next door or the target with *h(n)* (Equation 1), the time cost to each grid of the path can be derived via cumulative calculation (Figure 1). Accordingly, we select the following location at the next time step by comparing the time cost with the given time slot (*e.g.,* 5s). The selected location represents the user's probable option in terms of time and accessibility.

4. Experiment

In this section, we introduce our implementation of the proposed method. An initial test is conducted to verify the feasibility of the method on a building floor (Figure 2). To compare with ground truth, we decided to simulate crowd trajectories on the floor. The crowd trajectories are separated into equal time slots (5s). Random errors were added to their locations to simulate the realistic measurement errors, *e.g.*, using a normal distribution with a mean of 0 and a standard error of 3 meters (m). For instance, the random errors can represent the fluctuated accuracy of WiFi localization. In this way, we obtained near-real-time crowd data at each time slot.

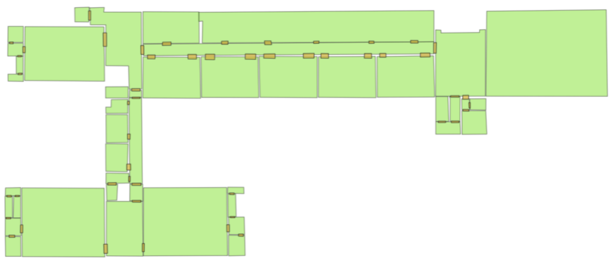


Figure 2. Rooms and doors of test floor.

On the detailed level, a grid model is created for each room and it can be used to support the path selection inside the rooms (see Figure 3). The red dots are grid centers for path selection. For simplicity, we adopted 4-neighborhood (left, right, up, and down) for path computation in this test.

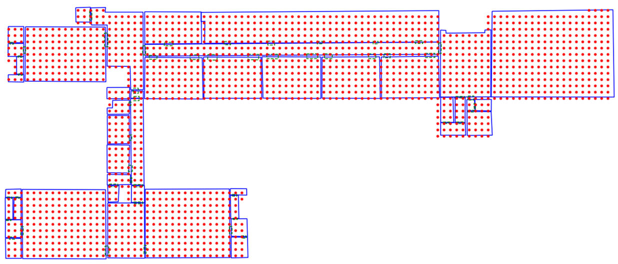


Figure 3. Grid model of test floor.

Moreover, a Kalman filter (Kalman, 1960) was applied to these crowd trajectories, which curbs their location errors. Figure 4 shows the raw data with noise (the simulated crowd locations) at a moment. Figure 4 presents the location RMSE of crowd samples (individuals). The RMSE of filtered data (in red) indicates the Kalman filter effectively curbs noise and improves the location accuracy of samples.

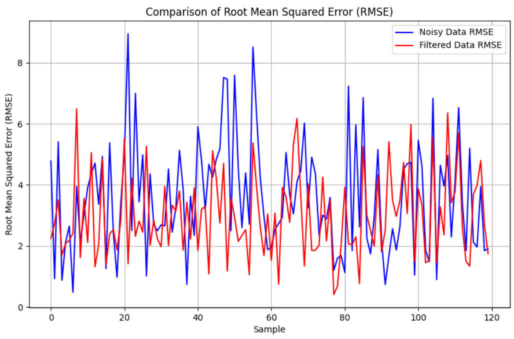


Figure 4. Example of RMSE of raw data and filtered results at a moment.

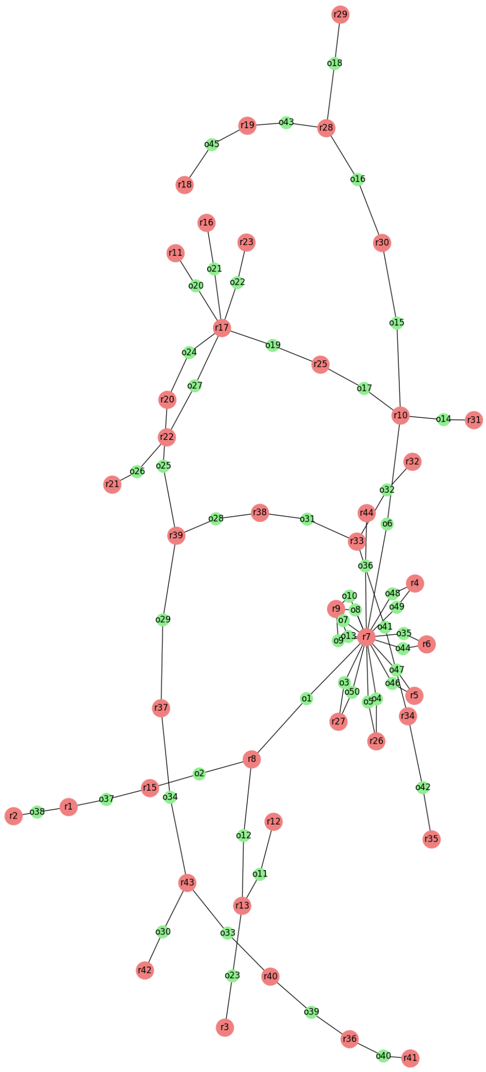
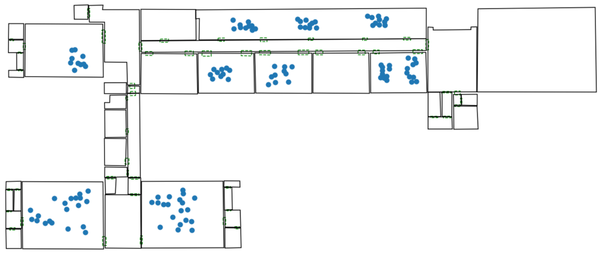
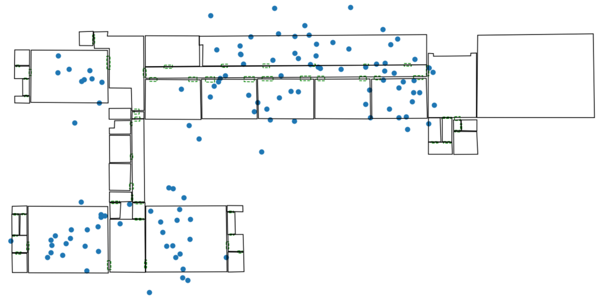


Figure 5. Logical network of rooms and doors.

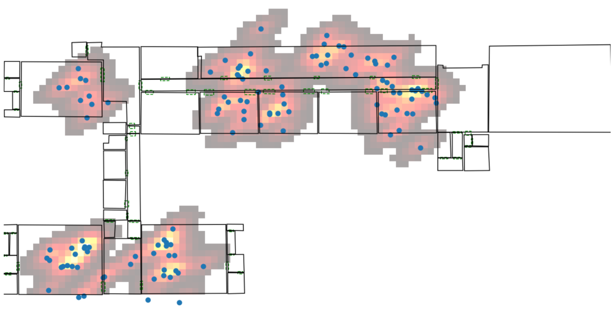
For a pair of start and destination, we first computed the shortest room sequence *RS* and extracted relevant doors. Figure 5 presents the logical network of rooms and doors. Given a start and a target location, their rooms are located and accessible routes between both rooms are computed, including their transition doors. In the following example, we randomly picked two locations in two rooms ’r37’ and ’r44’. Then we calculated the logical path via doors and packed them into a sequence: [’r37’, ’o29’, ’r39’, ’o25’, ’r20’, ’o24’, ’r17’, ’o19’, ’r25’, ’o17’, ’r10’, ’o6’, ’r7’, ’o36’, ’r44’]. In this sequence, the first character ’r’ or ’d’ indicates the type of node, *i.e.,* ’r’ and ’d’ represent rooms and doors, respectively.



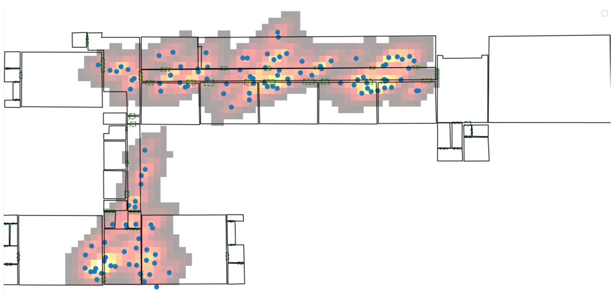
(a)



(b)



(c)



(d)

Figure 6. Crowd initial locations and uncertainty maps derived with filtered crowd locations. (**a**) genuine initial locations (t=0); (**b**) initial locations with noise (t=0); (**c**) uncertainty map (t=1); (**d**) uncertainty map (t=5).

120 samples of pedestrians are simulated as crowds and set to several groups in this test. Figure 6a presents the ground truth of their initial locations (t=0) and Figure 6b shows the initial locations with noise (representing measurements). Starting from time step 0 (t=0), they head to different destinations via these corridors (Figure 6c and d). We checked the influence of varied crowds on a user’s path choices. Based on the filtered trajectories, KDE is employed to generate an uncertainty map of crowd locations at each time slot. Figure 6c gives an example of uncertainty map at time step 1 (t=1), while Figure 6d presents that at time step 5 (t=5). We set a small bandwidth of KDE and the impacted region is relatively limited (Figure 6c and d). By comparing Figure 6c with d, one can find the uncertainty maps are inevitably shaped by location errors of the crowds, such as the parts outside these rooms. Nevertheless, the uncertainty maps still provide relatively precise trends of crowdedness and they are supportive in the following computation of path choices.

In each room, the user starts from the current location and she/he needs to approach a door to the next room. According to the criteria of obstacle-avoidance and fast walking, we applied the A* algorithm to search appropriate path choices in a stepwise way. If the user has to cross the areas influenced by crowds, those with low uncertainty are preferred for path choices.

Moreover, if the current path to the next door/ the target is longer than the previous one, it indicates a detour impacted by the current crowd distribution. According to the speed setting rules in Section 3, we update the grids where the user would stop and those regarding the slower speed. Consequently, path choices at each moment were obtained for the given start and target locations, *i.e.*, a complete wayfinding process of the user.

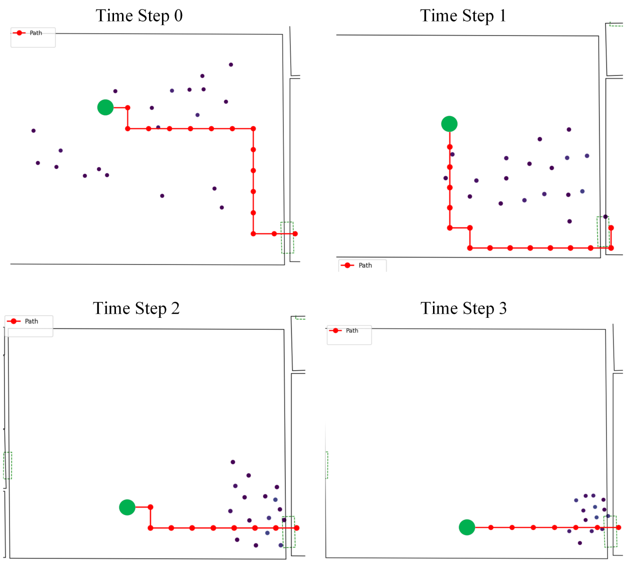


Figure 7. Example of wayfinding process in a room at different time steps.

In Figure 7, the groups of dots represent the genuine locations of the crowds, and the green one stands for the current location of the user at each time step. According to the test result in Figure 7, the proposed method can deal with the potential collisions during the user’s movement. At the time steps in Figure 7, we employed the A* algorithm to yield the optimal path to the door of the next room.

Figure 8 presents the complete path choices of the user, which reflects the wayfinding movement. As mentioned before, we have incorporated the actions of ’fast walk’, ’slow walk’, and ’stop’ into the wayfinding weights. In each room, the wayfinding process is ’door-oriented’ and the walking speed is subject to the current distribution of crowds and their uncertainty. Obviously the movement is not the shortest-distance route and it takes obstacle-avoidance into account.

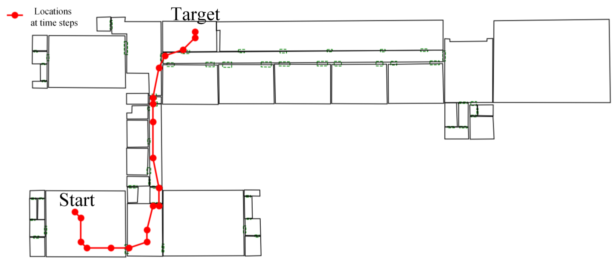


Figure 8. Test example of simulating user wayfinding process between two locations.

By comparing all these path choices with the ground truth of crowds at each time slot, we initially validated the feasibility of the proposed method on path selection in the preliminary result. The selection process shows the user follows the crowds while keeping a certain distance from them, which achieves our goal of wayfinding simulation to some extent.

To sum up, the proposed method can simulate the path choices of a user. Although the test result is promising, the rules regarding walking speed are relatively simple in this phase. For instance, the ’slow walk’ and ’stop’ conditions are triggered by two thresholds defined with crowd uncertainty. So far we have not discussed the appropriate values of these thresholds, their selection method needs to be further confirmed in future work.

5. Conclusions

Aiming to simulate path choices of human users within a crowded indoor environment, we proposed a feasible method to support path selection of pedestrian wayfinding. This method incorporates crowd location measurements and adopts their filtered locations to generate the uncertainty map at each time step. Based on a two-level spatial model, a logical path can be computed and presented as the sequence of rooms and transition doors. Specifically, this method focuses on stepwise path choices inside rooms of the logical path. We defined the rules to reflect the influence of crowds on walking time costs, and applied the A* algorithm to obtain the current path choice. The test has initially validated the feasibility of the proposed method.

At present, this work is still in development and several aspects need to be further investigated. Path selection results would vary with several factors, including KDE bandwidth selection and the correlation between crowd uncertainty and walking speed. Their distinct combinations could shape different path choices of a user, which will be investigated in the next phase.

Moreover, the proposed method can support distinguishing path preferences between different users by adjusting the Heuristic function *h(n)*. In the future, we plan to test the method in different indoor environments and conduct field tests with individuals, which could facilitate investigating and revealing the decision-making process of different pedestrians.

Acknowledgements

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