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Grid Model-aided Pedestrian Dead Reckoning for Indoor Environments

Abstract: Map filtering can eliminate the accumulative errors of PDR to some extent. However, it only utilizes a limited amount of spatial contexts, and the estimated trajectory may fail frequently when the environment becomes complex or the accumulative error becomes large. This paper proposes GridiLoc, a backtracking grid filter algorithm for indoor pedestrian tracking, which is based on grid model being able to represent accurate and abundant spatial contexts such as geometry, topology and semantics. GridiLoc can effectively reduce the frequency of tracking failure by capturing dead ending and smart spatial search. Evaluation results show the proposed algorithm outperforms map filtering, achieving a better accuracy of 2.5 m with 80% of time in a large multi-floor testing environment.

Keywords. Indoor positioning, Backtracking grid filter, Grid model, Pedestrian Dead Reckoning.

Introduction

Location is the most fundamental and important context in mobile and ubiquitous computing. A number of mobile applications have the requirement on the location knowledge of human or devices. It is estimated that people spend about 87% of their time indoors [1]. Location-based services, such as navigation, and mobile social network are extending to indoor environments. PDR is a self-localization and navigation technique, which can be realized on current mobile devices (e.g., smartphones, tablets) equipped with IMU sensors, without relying on the wireless infrastructure. Compared to these localization techniques needing the support of wireless infrastructure, PDR-based tracking can dramatically reduce the cost of deployment and maintenance.

However, the problem PDR often suffers from is the cumulative error [2]. The location estimation is computed based on the prior result, thus, the error accumulates rapidly over time. Normally, map matching or map filtering [3, 4] is adopted to calibrate the cumulative errors of PDR, which can use the indoor spatial constraints (e.g. obstacles, walls) to rule out some incorrect positioning results. Its implementation is based on Bayes filters by reducing the probability of these locations that violate the spatial constraints, such as walking through walls or obstacles, thereby improving the location estimation. The drawback is that map matching only uses limited spatial contexts, and that the definition of violating spatial constraints is inaccurate. For example, the judgment of crossing walls is that the segment

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between two successive positioning results has crossed the walls, without considering the cases of bypassing the wall between them.

Moreover, map filtering often fails to track the user entirely in some complex indoor environments with many adjacent intersections or passages, because the particles are unable to follow into the correct room, or to enter a wrong passage. Additionally, the floor plan cannot provide further spatial analysis and calculation functions, such as the shortest path distance, the connectivity between two locations, while these contexts can also assist the location estimation.

Compared to simple floor plan, grid model can describe more abundant and refined indoor environment contexts, playing vital roles in indoor LBS such as indoor positioning and navigation. Grid model uses many regular cells to represent the indoor space, and a key advantage is that it can represent arbitrary distributions and describe accurate location [5].

Grid model based positioning methods are mostly used in robotics tracking fields [6, 7], and it is very different from pedestrian positioning. For example, the former considers only a small area in a single floor, while the latter usually involves the multi-floor environments. Also, the former needs the assistance of laser range sensors and ultrasonic rangers, while the latter can only use the IMU sensors embedded in the smartphones. Therefore, positioning approaches in robotics are unable to be directly used for tracking pedestrians. For pedestrian localization, current research works mainly focus on using grid model to improve Wi-Fi and other wireless localization techniques [8, 9]. Thus, without the assistance of any infrastructure and other location hardware (such as the ultrasonic ranger), just utilize grid model to improve the location estimation of PDR on smartphones is a very meaningful and challenging work.

In this paper, we propose a grid model assisted PDR location estimation method-GridiLoc, utilizing grid model to accurately describe the indoor space. PDR will be enhanced with the geometry (e.g., the path distance), topology (e.g., connectivity and adjacency) and semantics (e.g., walls, corridors, elevators) represented in the spatial model. Additionally, a backtracking grid filter is proposed. It uses historical tracking results and smart spatial search to resolve the dead ending issue, thereby effectively mitigating the tracking failures caused by the accumulative errors of PDR and complex indoor environment.

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The Overview of GridiLoc

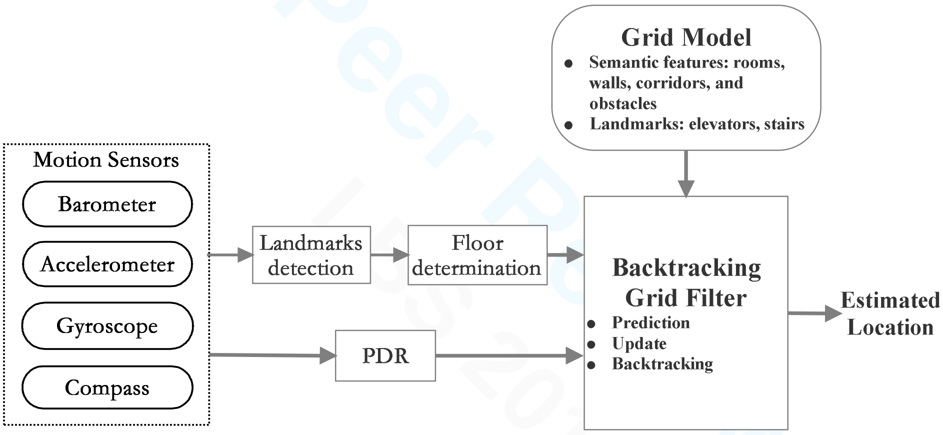

Figure 1. The architecture of GirdiLoc

The architecture of GridiLoc algorithm is shown in Figure 1. It fuses PDR and grid model by using backtracking grid filter. The gird model can limit users' movement and reduce the movement freedom in indoor environment, thus improving the location estimation of PDR. In general, PDR can be divided into three steps: step event capturing, stride length calculation and heading evaluation. Given the initial location of users, PDR can continuously infer the subsequent real-time locations.

In order to implement 2.5-dimension tracking, the event of switching from one floor to another should be captured, and then the changed number of level is determined. We adopt LS-SVM to classify users' states, including walking, going up or down stairs and elevators, where stairs and elevators are treated as seed landmarks [10]. The input data of classification comes from the three-axis accelerometer and the barometers. When capturing a user being at the area of a landmark such as an elevator, we can immediately know his position by finding the elevator nearest to the currently estimated location, and then calibrate his location. The next step is to calculate the number of floors users move in the elevators. In our experimental environments, we can observe a change in barometric pressure at about 0.5hPa when users move from one floor to the next with 3 meters per story. Based on the changed amount in barometric pressure, we can approximately determine how many stories users have moved.

To resolve the dead ending issue, backtracking grid filter is proposed. It utilizes the historical PDR results and smart space search to find a passage from the nearest cells, which can contain the whole trajectory being at the dead ending state.

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Experiments

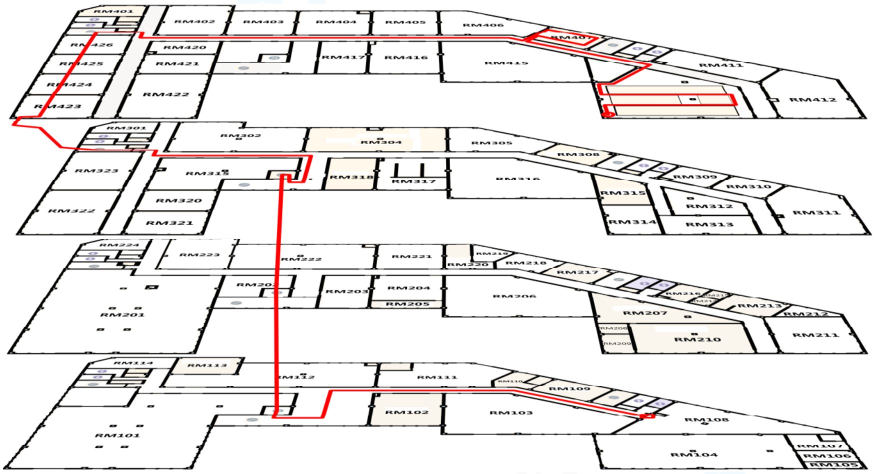

Figure 2. Experimental area

The proposed GridiLoc algorithm was evaluated by a series of experiments conducted in an office building, occupied by the China National Engineering Research Center for Geographic Information System. This office building consists of four floors with an area of 3300 square meters for each floor, which is a typical office environment, including an elevator, staircases, corridors and office rooms. Figure 2 shows the experimental area where the experimental paths are marked in solid lines. The path covers three floors, staring from the first floor to the fourth floor, successively passing the elevator and one staircase. It is 290 meters long, and test users collected 13 trajectories in total. We ran for comparison all our collected data also through map filtering [3,4] and PDR-only, no map base case.

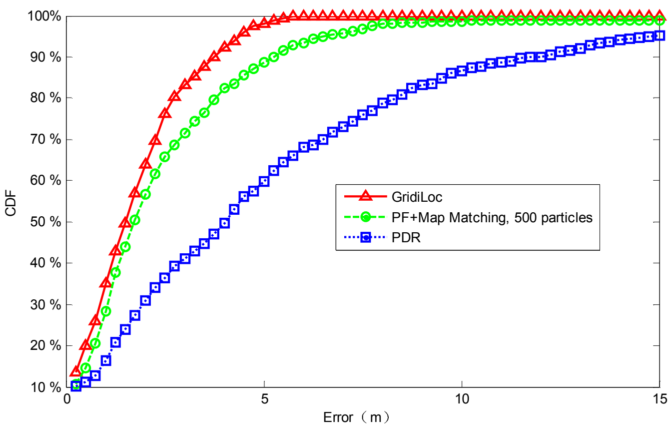

Figure 3. Distribution of positioning error

The localization results of all the three methods are shown in Figure 3. The results indicate that our solution is able to track the user with an accuracy of 2.5 m 80% of the time. Map filtering with 500 particles achieves an accuracy of 3.7 m 80% of the time. PDR has bad estimation results without the assistance of spatial contexts.

Figure 4, 5, and 6 show the estimated trajectories of GridiLoc and map filtering at the first, third and fourth floor respectively. The path in the first and the third is very simple and short, thus, two approaches achieved similar estimated trajectories. However, when it comes to the fourth floor, the experimental environment becomes large and complex with many adjacent passages, especially in the last part of the path, the room. The map filtering is often unable to follow into the correct passages in the room, or fails to track the user entirely due to a large accumulative error after a long-time tracking as well as the existence of several adjacent fork roads. GridiLoc can mitigate the tracking failure by smart space search process, and most of the trajectories can accurately match the ground truth. Although 1-2 trajectories fail in the final part of the path, we believe it is acceptable.

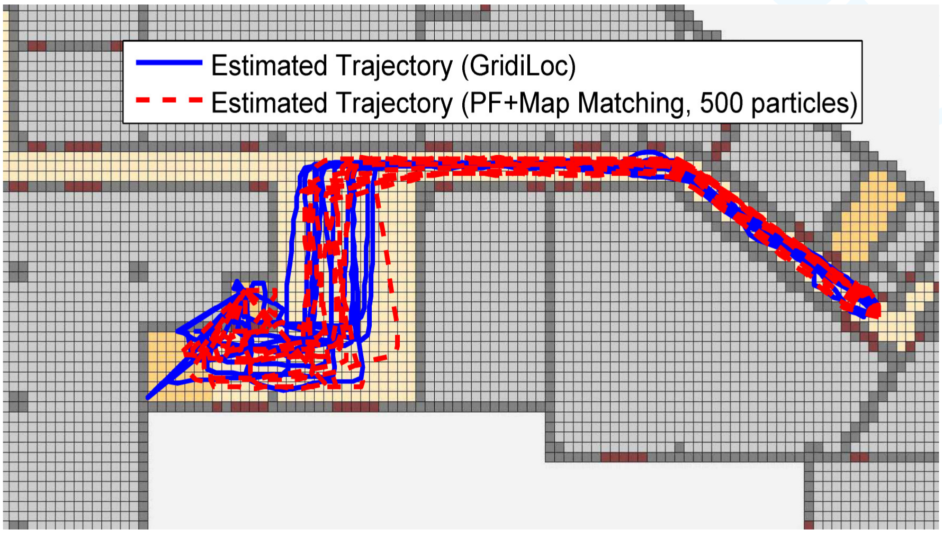

Figure 4. Estimated trajectories in the first floor

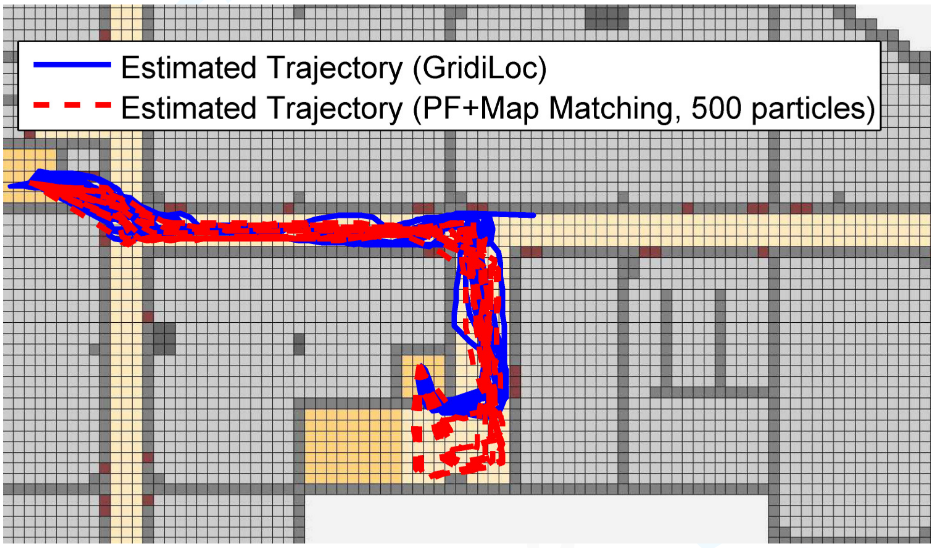

Figure 5. Estimated trajectories in the third floor

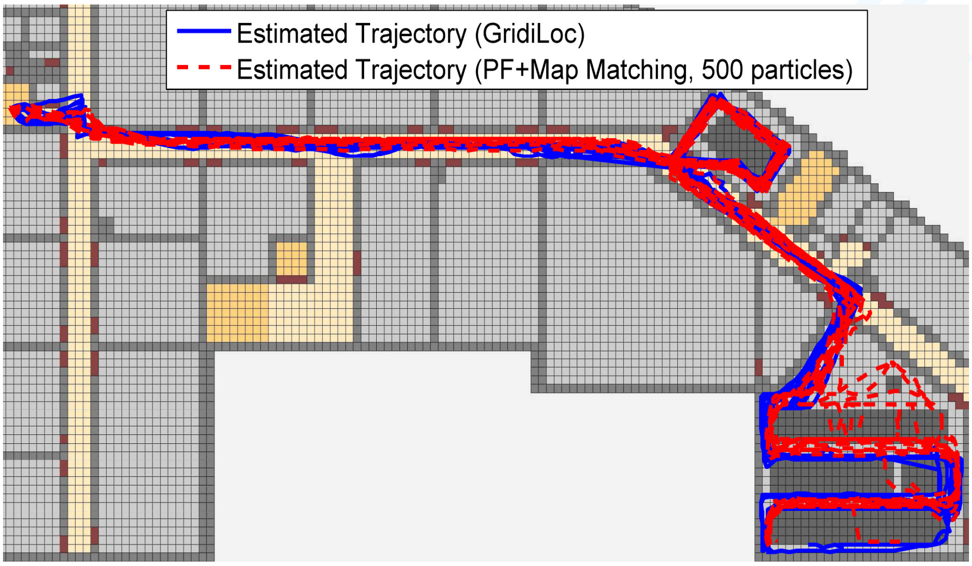

Figure 6. Estimated trajectories in the fourth floor

Conclusion

We presented the GridiLoc indoor tracking algorithm, utilizing grid filter to fuse spatial model and PDR. Based on the grid model, backtracking grid filter is proposed to mitigate the dead ending or tracking failure issue by using historical PDR results and smart spatial search. The experimental results showed compare to the traditional map filtering algorithm with even 500 particles, proposed algorithm can effectively reduce the frequency of tracking failure, achieving a better accuracy with 2.5 m 80% of the time.

We are currently in the process of reducing the complexity of GridiLoc by reducing the number of needed cells which will be utilized to attempt the historical trajectories through interpolating approaches. Moreover, calculate the shortest path distance offline is another solution. Add more semantics such as the functional area which can limit users' movement in grid model is also our future focus.

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