FLOOR PLAN RECONSTRUCTION WITH HIGH-PRECISION RF-BASED TRACKING

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ABSTRACT

Indoor maps are essential to indoor location-based services, but are not widely accessible despite considerable efforts from the industry. Existing solutions employ costly hardware to achieve accurate mapping, or resort to laborious crowdsourcing methods, which may suffer from low accuracy due to inaccurate inertial sensing. In this paper, we leverage advanced RF-based inertial tracking and present a high-accuracy and low-cost floor plan reconstruction system. The proposed system combines local information from RF tracking with the global contexts from inertial sensing (e.g., magnetic field strength) for an accurate map. We validate the performance with commodity WiFi in an office building, which shows that the proposed system can efficiently generate faithful maps for a targeted area. With the ubiquitous deployment of WiFi devices, our approach will make a wide range of indoor location-based systems possible.

***Index Terms*—** Map reconstruction, Simultaneous localization and mapping

1. INTRODUCTION

Location-Based Services (LBS), including navigation, item searching and targeted advertising, are becoming more popular nowadays. However, most of the LBS are only available outdoors due to the lack of indoor maps [1]. Despite efforts from projects like Google Indoor Maps, indoor maps are still too scarce to cover the numerous buildings worldwide. In addition, the floor plans are mostly manually generated in these projects, requiring professional technicians and specialized measurement devices, which is time-consuming and costly. When the environment changes, it needs great efforts to update the maps.

Efforts have been made to generate indoor maps automatically. Solutions based on lidar and cameras could achieve moderate accuracy but are very costly and/or privacy-intrusive. Systems based on WiFi fingerprinting require dense Access Points (APs) deployment, which may not always be available, especially in home environments. Map reconstruction based on crowdsourced trajectories is also extensively studied [2–10], which, however, mainly relies on inertial sensors [4, 6, 10–15] with limited accuracy. To eliminate the error, existing approaches resort to various reference anchors (e.g., elevators) [6, 12], and hundreds of trajectories collected by a large number of users over a long time [9, 10], which are either not available or impractical [5]. By revisiting numerous approaches to mitigate the errors, we believe the potential breakthrough lies in replacing erroneous inertial sensing with high-accuracy trajectory tracking.

Recent advances in RF-based tracking enable an opportunity for this breakthrough. Our earlier work RIM [16], an RF-based Inertial Measurement system, allows one to collect high-accuracy trajectories with cost-effective WiFi clients and a single AP for a broad variety of environments. However, leveraging RF-based tracking like RIM for high-precision floor plan construction entails great challenges. First, with only a single AP, it is difficult to obtain global reference information, which is necessary to connect different trajectories and construct a floor plan. Second, since RIM only provides distance estimation, we still need to rely on inaccurate sensors for the direction information.

In this paper, we tackle the above challenges and propose a novel system to boost the automatic construction of indoor floor plans in three distinct procedures. We first break down the crowdsourced trajectories of arbitrary lengths into *atomic segments*, which circumvent the potential accumulative orientation errors and underpin trajectory matching. Second, we propose a robust hierarchical matching scheme to group the atomic segments. The atomic segments are first sorted by their intrinsic *geometric constrains* and then further clustered by examining the Received Signal Strength Indicator (RSSI) and magnetic field strength (MFS) information. Third, we present a trajectory bundling and fusion technique to robustly embed the clustered segments, i.e., determining their positions and thus reconstructing the floor plan.

Leveraging a relatively small number of crowdsourcing trajectories, the proposed system is shown to be able to generate detailed maps with high accuracy when implemented in an office building. We believe, as the foundation of further applications, the proposed system makes a wide range of indoor location-based systems possible.

The rest of this paper is organized as follows. Section 2 elaborates on the system design and detailed solutions. Section 3 shows the implementation, experiments, and evaluation results. In Section 4, we conclude this study.

2. SYSTEM DESIGN

In this part, we present an overview about the design of our map reconstruction system as Fig. 1 illustrates.

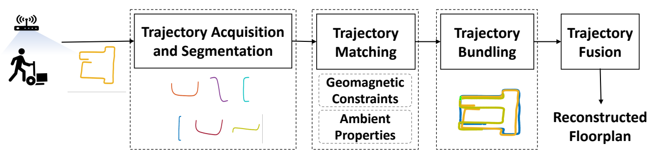


Fig. 1: System overview.

2.1. Trajectory Acquisition and Segmentation

We collect trajectories using a wheeled platform with a tracking device equipped with a commodity WiFi chipset and Inertial Measurement Unit (IMU). The traces contain the distance information obtained by RIM [16] and direction information derived from inertial sensors. The RSSI of the AP and the MFS are also recorded.

Since we rely on inertial sensors for orientation estimation, long trajectories suffer from significant accumulative errors. We propose to decompose all collected trajectories into short pieces in a novel form of *atomic segments*. The atomic segment consists of a path section with two turns on the two ends. This structure divides the original trajectories at each turn, where orientation errors easily accumulate, and preserves each path's accurate geometric shape information. Fig. 2 illustrates the structure of the atomic segment with two atomic segments collected at the same path.

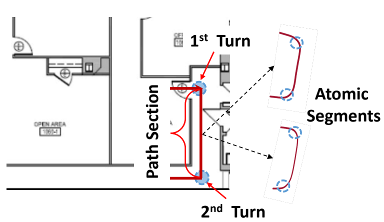
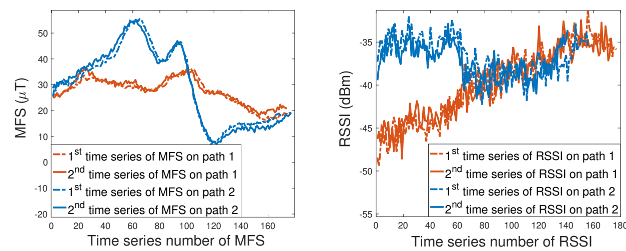


Fig. 2: Example of atomic segments.

2.2. Segment Matching

In this part we present the principles of trajectory matching to recognize the segments belonging to the same location by their geometric shapes and time series of RSSI and MFS.



(a) Time series of MFS. (b) Time series of RSSI.

Fig. 3: Time series of MFS and RSSI on two paths.

2.2.1. *Geometric Constraints*

Atomic segments belonging to the same path show similar geometric shapes, and thus can be sorted by certain geometric constraints, including the distance constraint and the angle constraint. As for the distance constraint, based on experimental observations and the distance tracking accuracy of the tracking client, we limit the distance difference between segments on the same path to 3 m. As for the angle constraint, considering angle errors, the angle difference is limited to 30 degrees.

2.2.2. *Ambient Properties*

Since geometric constraints cannot separate the segments from different paths but with similar geometric shapes, we utilize the time series of MFS and RSSI along the segment, denoted as *ambient properties* for global reference information and propose a robust algorithm to fuse them.

As described in CrowdMap [8], the magnetic field anomalies caused by ferromagnetic construction materials (e.g., reinforcing steel bars) on an indoor path generally maintain steady and unique. As shown in Fig. 3(a), the time series of MFS data along the same indoor path is similar. In contrast, those along different indoor paths differ considerably. The same characteristics also apply to RSSI, as shown in Fig. 3(b). Although the RSSI values at a single location suffer from very limited spatial resolution, a series of RSSI along a path provides more distinctive information.

A cluster can be generated when the similarity value of two atomic segments based on the time series of MFS and RSSI is below a threshold. The similarity vector can be calculated for an atomic segment, measuring the similarity between it and each existing cluster of atomic segments. For an atomic segment j, dynamic time warping (DTW) [17] can be applied to calculate its RSSI similarity vector $D_{j,R}$ and MFS similarity vector $D_{j,M}$, respectively. $D_{j,R}$ and $D_{j,M}$ are normalized and summed together to obtain the similarity vector by

$$D_j = \overline{D_{j,R}} + \overline{D_{j,M}} = [d_{j,1}, d_{j,2}, ..., d_{j,i}, ..., d_{j,N}], \quad (1)$$

where $d_{j,i}$ denotes the similarity value between atomic segment j to the i^{th} cluster, and N denotes the total number of clusters. If $d_{j,i}$ is below a pre-defined threshold (e.g., 0.2), this atomic segment is clustered to the i^{th} cluster and can be matched with other segments from the i^{th} cluster. If an atomic segment cannot be matched with any existing cluster, we generate a new cluster for it. Based on our experimental observations, two segments with a similarity value below 0.2 can be considered matched. As we have normalized the RSSI vector and MFS vector during fusion, the threshold can be generalized to various environments.

2.3. Trajectory Bundling

In this part, we present a trajectory bundling algorithm to determine the position of atomic segments. For every two trajectories that have matched segments, they are bundled in the following two steps: 1) The first turning points of two matched segments are stitched together, and 2) The trajectories are rotated so that the direction of the path section of the two matched segments is consistent. Every trajectory is bundled to others via aligning their matched segments. After the trajectories are bundled, we can determine the coordinates of the atomic segments by utilizing their spatial relationship on their original trajectories.

An example of trajectory bundling is shown in Fig. 4, where two trajectories are bundled by aligning their matched segments.

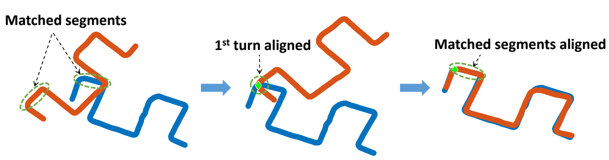


Fig. 4: Bundling process.

2.4. Trajectory Fusion

Although the rough position of an atomic segment can be inferred by bundling the trajectories, atomic segments belonging to the same path still have coordinate deviation, as shown in Fig. 5, which is undesirable. Hence, we propose a trajectory fusion algorithm to generate a more accurate and well-shaped map next.

First, we update the locations of the endpoints for each atomic segment. For atomic segments in the same cluster, we calculate the medium coordinate of their endpoints at the same turn and update the coordinate of each endpoint by

$$New\ coordinate = (1-b)^{*} cluster\ medium\ coordinate + b^{*} original\ coordinate \quad (2)$$

where b is a parameter between 0 and 1.

Then, with new coordinates of two endpoints, each atomic segment is transformed to its new position by Helmert transformation [18], which is a similarity transformation that preserves the shape and 2D information of the original atomic segments. Fig. 5 illustrates the trajectory fusion process, where four trajectories are fused together.

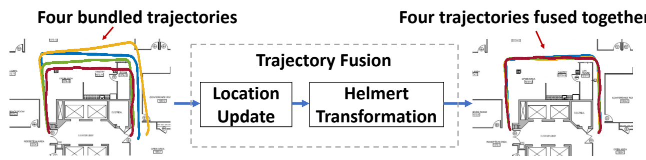


Fig. 5: Trajectory fusion process.

Finally, the alpha-shape method [19] is utilized to extract a well-shaped hallway plan.

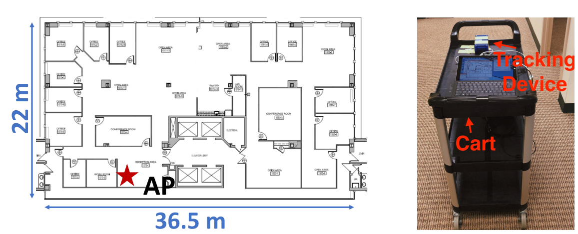
3. EXPERIMENT

3.1. Experimental Setup and Data Collection

RF tracking data is collected in an office building with an area of 22 m×36.5 m, which consists of corridors, rooms, doors, and elevators as shown in Fig. 6(a). The goal is to reconstruct the detailed floor plan using the proposed system. The tracking device is installed on a cart pushed by humans, as shown in Fig. 6(b). Traces are collected on 12 different days in 5 months. There are a total of 64 trajectories collected.

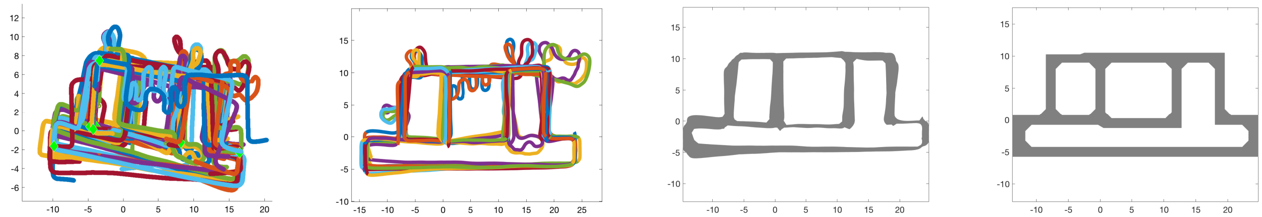
3.2. Reconstructed Floor Plans

The results are presented in Fig. 7. Fig. 7(a) shows the bundled trajectories with color lines. The reconstructed floor plan is shown in Fig. 7(b), where we can see the accessible area of rooms and open space are also well reconstructed. The reconstructed hallway plan is shown in Fig. 7(c), while the ground-truth hallway plan is shown in Fig. 7(d). The result shows that the proposed system can accurately reconstruct the floor plan for a large area with only a single AP.



(a) (b)

Fig. 6: Ground-truth floor plan and device setup. (a) Ground-truth floor plan. (b) Data collection device setup.



(a) (b) (c) (d)

Fig. 7: Reconstruction result an office building. (a) Trajectories bundling result. (b) Reconstructed floor plan. (c) Reconstructed hallway plan extracted by alpha-shape. (d) Ground-truth hallway plan.

3.3. Performance Evaluation

The matching performance and hallway shape of the reconstructed maps using the proposed system are evaluated, where the latter is compared with the best claimed performance of SenseWit [6] and CorwdInside [10].

3.3.1. Matching performance

The matching performance is evaluated by purity measure and Normalized Mutual Information (NMI) score [20]. The purity score s_c is defined as $s_c = \frac{1}{N_{seg}} \sum_{i=1}^{c} C_i$, where C_i is the number of atomic segments in the largest class inside each cluster, c is the number of clusters, and N_{seg} is the total number of atomic segments.

The NMI is defined as $NMI(Y,C) = \frac{2 \times I(Y;C)}{[H(Y)+H(C)]}$, where Y denotes class labels, C denotes cluster labels, $H(.)$ is Entropy, and $I(Y;C)$ is Mutual Information between Y and C.

In this experiment, we collected 206 atomic segments belonging to 18 true clusters, which are clustered into 20 clusters as our algorithm mistakenly separates one of the clusters into three. All the atomic segments belong to the largest class inside the cluster, except for one, resulting in a purity score of 99.51% and a normalized mutual information score of 95.05%. Furthermore, the matching performance is also evaluated without adopting the geometric constraints, where the purity score is 87.38%, and the NMI score is 81.80 %, showing that geometric constraints improve matching performance significantly.

3.3.2. Hallway shape

We evaluate the hallway shape with the same metrics as SenseWit [6]

$$\begin{aligned}
\mathcal{P} &= \frac{|S_{gen} \cap S_{true}|}{|S_{gen}|}, \\
\mathcal{R} &= \frac{|S_{gen} \cap S_{true}|}{|S_{true}|}, \\
\mathcal{F} &= 2 * \frac{\mathcal{P} * \mathcal{R}}{\mathcal{P} + \mathcal{R}},
\end{aligned} \tag{3}$$

where $\mathcal{P}$ is the precision of the hallway shape, $\mathcal{R}$ is the recall, and $\mathcal{F}$ is the harmonic mean of precision and recall. $\mathcal{P}$ is defined as the overlapped area divided by the reconstructed hallway area. $\mathcal{R}$ is defined as the overlapped area divided by ground-truth hallway area.

The evaluation result is shown in Table 1. From the table, we can find that the $\mathcal{P}$, $\mathcal{R}$ and $\mathcal{F}$ of our system are better than CrowdInside and comparable with SenseWit. The precision of our system is higher than SenseWit, while the recall rate is lower than SenseWit, which is because we do trajectory fusion so that the hallway widths are less than the ground-truths. Note that SenseWit needs various anchors and around 300 trajectories to achieve comparable performance with the proposed system using only 64 trajectories, showing that the proposed system can generate accurate hallway plans more efficiently with much a lower cost.

Table 1: Evaluation Results of Hallway Shape

	Presented system	***SenseWit***	***CrowdInside***
$\mathcal{P}$	78.18%	75.3%	59.5%
$\mathcal{R}$	75.10%	82.4%	47.1%
$\mathcal{F}$	76.61%	78.69%	52.0%

4. CONCLUSION

In this paper, we present a universal automatic floor plan reconstruction system that processes crowdsourced trajectories with a novel pipeline and reconstructs a floor plan with not only skeletal layouts but also detailed information of corridors, open spaces, and rooms. The results demonstrate that our system can generate detailed floor plans accurately and efficiently, outperforming the state-of-the-art approaches.

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