LEVERAGING HUMAN MOBILITY AND PERVASIVE SMARTPHONE MEASUREMENTS-BASED CROWDSOURCING FOR DEVELOPING SELF-DEPLOYABLE AND UBIQUITOUS INDOOR POSITIONING SYSTEMS

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ABSTRACT:

Nowadays, it's hard to imagine life without smartphones. These devices surround us and have become an inseparable part of our daily lives, since they provide end-users with unlimited access to information, services, and communication through their multitude of sensors and computational capabilities. Through sensor-rich smartphones, it is possible to collect pervasive crowdsourced signatures. Manual training approaches to localize these signatures and construct offline radio and magnetic maps required for fingerprinting-based positioning techniques are time-consuming, labour-exhausted, and restrict the scalability of ubiquitous signals, such as Wi-Fi and magnetic field. As an alternative, autonomous localization of pervasive signatures can eliminate human supervision and scalability barriers, prompting to development of self-deployable systems. The development of these systems offers unparalleled potential for extending the ubiquity of indoor positioning systems (IPS) and makes realizing ubiquitous IPSs one step closer. This study proposes a scheme to leverage pervasive crowdsourced data to develop a ubiquitous IPS without the need for external resources.

1. INTRODUCTION

As human life evolves rapidly due to technological advancements, the demand for context-awareness services to support and ease daily life is increasing to keep up with this pace (Mostafa, 2023). Location-based services (LBS) are essential context-awareness services with diverse applications, serving both life-saving and commercial purposes. Undoubtedly, nowadays, LBSs are required at any time and in all environments, including indoor and outdoor settings. In clear skies outdoors, the maturity of global navigation satellite systems (GNSS), which rely on precise timing from multiple satellites, has greatly improved outdoor LBSs. In contrast, building walls tend to disrupt or block GNSS signals in indoor environments, resulting in significant localization errors or complete unavailability. However, accurate indoor LBS is essential for many reasons, given that most people spend most of their time indoors, where IoT scenarios and LBSs are used. Also, because of urbanization, indoor spaces have become larger and more complex, which has created navigation challenges and a need for precise positioning inside. GNSS signals have therefore been replaced or augmented by alternative positioning technologies, such as inertial sensors, Wi-Fi, and Bluetooth.

Since sensors are embedded in smartphones today, different localization methods are no longer limited by the cost of end-user devices. For example, off-the-shelf inertial sensors embedded in smartphones enable motion tracking and navigation through either Inertial Navigation (INS) or Dead Reckoning (DR) systems. These systems can be used as an infrastructure-free solution to fill the outage of wireless localization systems. However, both inertial solutions can only provide short-term accuracy and are highly prone to accuracy degradation over time owing to low-grade sensors' bias and thermal drift. Pervasive wireless indoor signals can be exploited to provide absolute position and update inertial solution. As Wi-Fi chips become ubiquitous, wireless localization with pervasive Wi-Fi infrastructures in current buildings becomes more feasible. Leveraging pervasive Wi-Fi RSSI using fingerprinting-based localization approaches is more precise than multi-trilateration because the former alleviates multipath effects. Additionally, fingerprinting approaches can provide position without prior knowledge of the locations of Wi-Fi APs or propagation models, thereby have gained substantial attention. However, most existing training methods of offline radio and magnetic maps required for fingerprinting approaches are human-supervised.

In brief, fingerprinting-based IPSs are ubiquity limited by human-supervised offline Radio Map (RM) database training methods. Despite performance enhancements that could be achieved by multi-sensor integration, the involvement of wireless localization techniques in these systems requires considering the offline requirements of wireless positioning methods, such as training offline databases, as the case for fingerprinting methods, or identifying the location and propagation parameters (PP) of the anchor nodes (AN), as the case for multi-trilateration methods.

The autonomous generation of offline requirements from pervasive resources enables the development of a self-deployable system. The dependency on pervasive resources to generate these offline requirements can lead to achieving a ubiquitous system. Collecting pervasive crowdsourced signatures to generate these requirements is more feasible now with the proliferation use of smartphones in our life that enables almost unlimited coverage of human mobility. IPSs involving crowdsourcing take advantage of the historical data of the users, even if they only contribute

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their data without any participation. As shown in Figure 1, IPSs can generally be divided into two types based on users' roles, interactions, and participation: those that are based on a single user and those that include multiple users. Crowdsourcing-based IPSs, or the systems that leverage the power of multiple users' data to generate offline RMs.

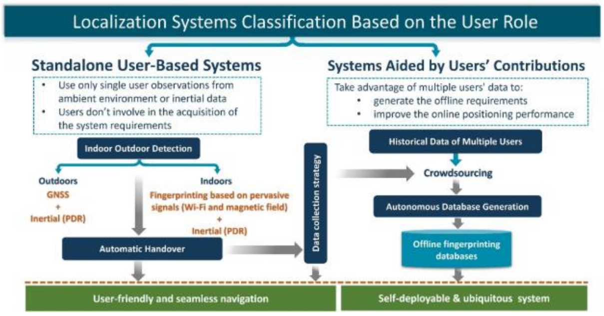

Figure 1. Classification of IPSs based on the user role or interaction

This work proposes a novel scheme to leverage pervasive crowdsourced data to develop a ubiquitous IPS. The key contributions of this scheme are as follows:

1. Proposing a crowdsourced data collection strategy to manage the real-time data collection and reduce data collection impact on the user smartphones, encourage consumers to participate in, and ensure widespread adoption of crowdsourcing-based IPSs.
2. Without the dependency on external resources, this work introduces criteria to qualify and select inertial measurements that relied principally on the features of the off-the-shelf measurements to maintain ubiquity.
3. Toward reducing the significant errors anticipated while using GNSS data to localize crowdsourced fingerprints in multistorey buildings and buildings enclosed by GNSS-denied areas, this study proposes an intelligent location to deploy low-cost AN. This location is inside the building elevators. deploying one anchor node per elevator is a cost-effective solution to maintain high localization accuracy for all floors in a building. This approach minimizes costs and effort by a factor of N:1, where N represents the number of floors in the building.
4. This study takes advantage of the accumulation of crowdsourced traces over time to infer the information of internal and pervasive anchor nodes, such as fixed Wi-Fi Access Points (APs), and obviate to install auxiliary anchors at each floor. This helps to reduce the heading drift of long traces and widen the spatial coverage of the offline fingerprint maps.

Throughout the rest of this paper, we follow the following organization. Section 1 reviews related works. Section 2 discusses the proposed method, the experiments, and the achieved results, followed by the conclusion in Section 3.

2. CHALLENGES OF CROWDSOURCSING-BASED INDOOR POSITIONING SYSTEMS

Table 1 presents a summary of the challenges associated with the development of IPSs based on crowdsourced data, including the data collection process, the selection of qualified data to contribute, and the localization adjustment and calibration method. It also outlines the proposed methods in related literature to overcome these challenges, as well as their limitations.

Crowdsourcing-based systems face various challenges, including the data collection process, selection of inertial data, and calibration and adjustment of selected traces for localization. However, existing studies in crowdsourcing often overlook the costs incurred by user devices during voluntary data collection, despite the crucial role users play in these systems. Previous research on indoor positioning-based crowdsourcing fails to fully consider the overarching goal of harnessing crowdsourcing.

Existing methods encounter limitations that impede the achievement of system ubiquity. Firstly, the criteria used to select data for autonomous tracing and localization improvement are often insufficient. While a few studies, such as (Zhang et al., 2018), have established factors to judge data quality based on the availability of external resources, the general practice has been to consider all collected data eligible for contribution. This approach may negatively impact the quality of database generation. Secondly, the sources used to adjust trace localizations can hinder the implementation of a truly ubiquitous system. These challenges necessitate further exploration and innovative solutions to ensure the effectiveness and ubiquity of crowdsourcing-based systems. Specific studies (Lee et al., 2020; Lohan et al., 2017; Santos et al., 2021) have considered active and experienced user participation. Some systems ((Gu et al., 2020; Rai et al., 2012; Santos et al., 2021) assume the availability of floor plans to facilitate the correction of collected traces. In contrast, other systems (Zhang et al., 2018) heavily rely on internal anchor nodes (IANs) placed densely within each floor, rather than leveraging pervasive resources. Additionally, certain systems (Li et al., 2019) solely depend on accurate Global Navigation Satellite System (GNSS) data, which may result in significant localization errors, particularly in areas where GNSS signals are unreliable or blocked (LUO et al., 2021).

Challenge	The methods of the existing studies	Limitation
Data collection	Collected **all** user data **continuously**	User-**un**friendly
Inertial data selection	Considered **all** collected data	Quality degradation
	Installed **BLE anchor nodes** inside each floor	Costly labor intensive
localization calibration & adjustment	Depended on the **floor plans.**	Not always available
	Asked Feedback from the **users**	User-**un**friendly
	Used **GNSS data** as outer ANs	Suitable for open-sky areas only

Table 1. Crowdsourcing-IPSs challenges, the methods of the existing studies to address these challenges, and their limitations.

3. METHODOLOGY, EXPERIMENTS, AND RESULTS

This section presents the research methodology proposed to develop self-deployable and ubiquitous IPS based on crowdsourced data.

3.1 Overview

Figure 2 summarizes the process of the proposed scheme to autonomously generate offline RMs from crowdsourced data collected by free-moving users and heterogenous smartphones. It started by introducing a strategy to manage the real-time data collection by confining it to indoor areas only. This was conducted by introducing an automatic indoor-outdoor detection approach. The strategy also observed the user static and walking intervals and the database availability of the occupied area to control the collection sampling rate. The collected data were then qualified using the proposed inertial data selection criteria. The traces that satisfied these criteria only contributed where a DR method was used to generate these traces. After that, the traces bounded by OANs (refer to Figure 6) were only included in the initial generation stage. These traces were combined after aligning their locations and the RMs grids were obtained. The consistency of the signatures included in each grid was checked and grids with consistent signatures were only converted to fingerprints and included in the initial RM. This RM was used to infer IAN (i.e., the fixed Wi-Fi APs with fingerprints with highly consistent signatures). The inferred IANs and OANs (refer to Figure 6) were used to align the qualified traces in the subsequent generation stages to improve the fingerprints' location estimation and widen the spatial coverage of the initial RM.

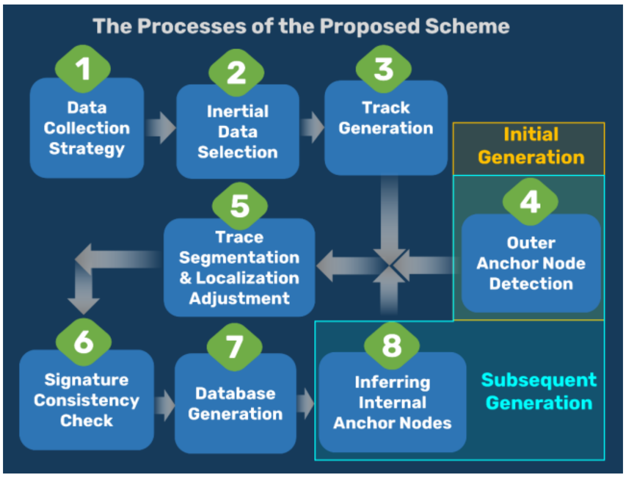

Figure 2. The processes of the proposed scheme for autonomous RM generation from crowdsourced data

3.2 Data Collection Strategy

A crowdsourcing-based indoor positioning system should be easily adopted by the public through the user-friendly data collection. As a result, universal indoor positioning solutions can be promoted. In the proposed system, the collection of crowdsourced data was managed by the following factors, see Figure 3:

1. Indoor-Outdoor Detection (I/O): With GNSS available outdoors, collection of crowdsourced signatures is not necessary. On the other hand, crowdsourced signatures are required for fingerprint database training in indoor areas or when travelling from indoors to outdoors. With low power consumption and accurate identification of ambient environments, crowdsourced data was restricted to areas that needed it to prevent battery drain. This was conducted by utilizing the proposed user-friendly I/O detection in (Mansour & Chen, 2022).
2. Initial database generation or updating: Interior environments often undergo changes in furniture layouts, Wi-Fi AP settings, and network updates. To make the database updated, data collection for a specific area should not be discontinued, even though the database has already been created for that area. It is not necessary to collect unnecessary data if the database for a particular area has already been created. To update and evaluate the existing database, a small amount of data is only needed. Thus, sampling rates were lower for the subsequent collection.
3. Static and walking mode: The identification of static and walking modes can be helpful in managing data collection and reducing excessive collections in a static mode. Dynamic collection extends access to spatial databases by covering different locations. In static intervals, when a user remains in a fixed point, continuously collecting signatures for that location does not expand the spatial database coverage. As a result, there is no requirement for extensive data collection, and a lower collection rate suffices.

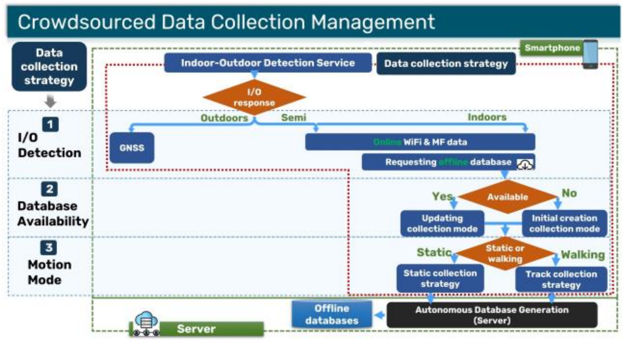

Figure 3. Crowdsourced data collection management

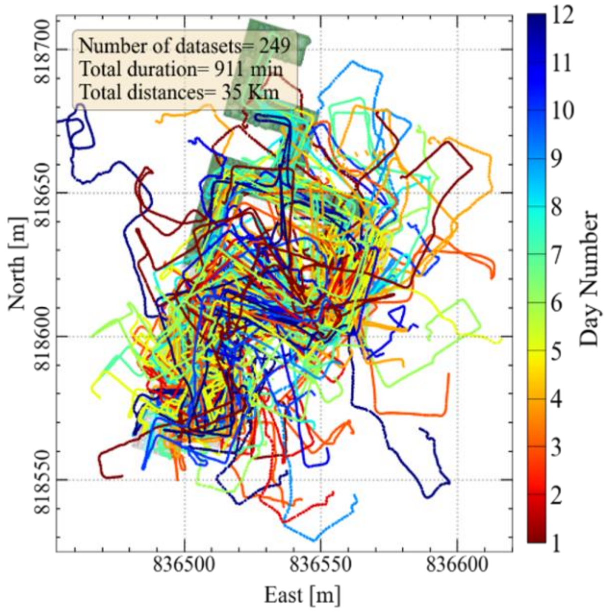

Figure 4. All collected crowdsourced data before filtering.

Based on the data collection strategy described above, an Android application was developed to gather user data. Volunteers participated in crowdsourcing data collection, which took place over a span of twelve days on a large campus floor measuring approximately 7200 m2. The collected data encompassed various components and included raw measurements from inertial sensors, information from Wi-Fi scans (such as APs' BSSIDs and RSSI), data from BLE scans, GNSS data, magnetic readings, and the measurement timestamp. Figure 4 displays the generated tracks of all collected traces before handling.

3.3 Inertial Data Selection and Track Generation

When aiming for a ubiquitous system, pervasive resources should only be used. Thus, the selection of data should also depend only on pervasive resources. The proposed scheme operates under the following concept: PDR-based methods rely on measuring horizontal attitude angles assuming that there is no external acceleration, except for the walking acceleration affecting the device. However, when gathering inertial data from users in unrestricted motion, external acceleration becomes prominent. As a consequence, the attitude angles are susceptible to notable distortions, leading to generated traces that deviate from the actual ones. To maintain ubiquity, selection criteria that are independent of external resources are necessary.

To ascertain the data that can best represent traces with higher geometric similarity (GS), an examination was conducted to understand the relationship between GS and the characteristics of inertial data. An empirical test was conducted, involving approximately 65 tracks between two OANs. The test encompassed different users, walking velocities, and smartphone postures (holding, calling, swinging, and pocket). By comparing the results with a reference track as the ground truth, both GS and RMSE were calculated. For further details on the empirical test procedures, results, and the inferred selection criteria, refer to (Mansour et al., 2022). Table 2 summarizes the selection criteria. Figure **5** shows the tracks satisfied the selection criteria. After applying the selection criteria to the inertial data, the collected traces that met the criteria were deemed qualified for further steps. The Pedestrian Dead Reckoning (PDR) method was employed to estimate the position of the steps taken and signatures collected within the selected traces. For further details, please refer to (Mansour et al., 2022).

Criteria	Threshold
Max differences between the successive steps extremes (peaks/valleys)	< 3.0 m/s^2
Max acceleration variances of sliding windows	< 7 m^2/s^4
Max angular velocity variances of sliding windows	< 0.25 deg^2/s^2

Table 2. Inertial selection criteria

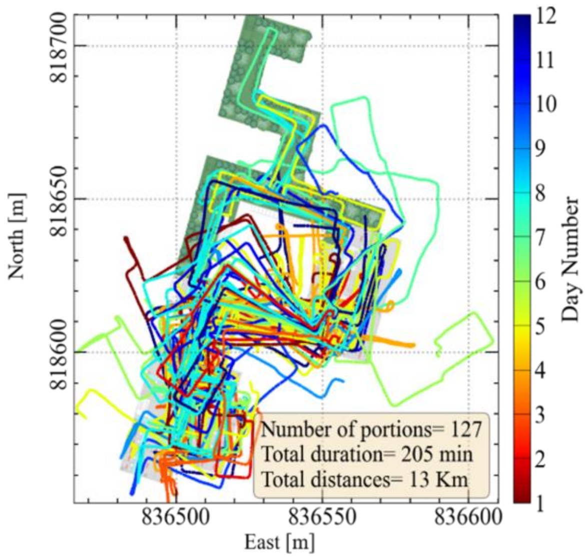

Figure 5. Tracks collected with qualified inertial data.

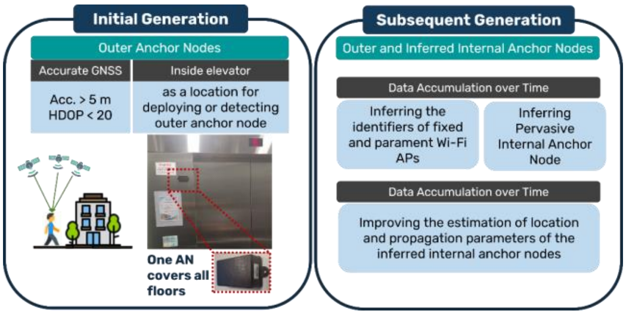

Figure 6. The stages of RM generation and the localization adjustment resources used for each stage.

3.4 Initial Radio Map Generation

3.4.1 Outer Anchor Node (OAN) Detection: During the initial stage of database generation, we identified GNSS data that met the criteria of having a position accuracy higher than 5.0 m and HDOP less than 20 to serve as qualified OANs for aligning the collected traces. In the case of elevator OANs, BLE RSSI measurements often display significant fluctuations. To address this, we applied an average filter to smoothen the raw RSSI data and utilized a sliding window technique to detect the peak RSSI when the user entered the coverage area of the beacon. Once the RSSI peak exceeded a specific threshold, it indicated the user's proximity to the identified OAN, enabling us to update the position of the BLE OAN (i.e., elevator location) to align with the user's location. Figure 6 (left) visually depicts the utilization of outer nodes to correct and calibrate the selected traces during the initial stage.

3.4.2 Trace Aligning and Combining: Once the number and positions of the detected OANs within segments containing qualified inertial data were determined, the segments were categorized accordingly to closed (with two or more ANs) and opened (with less than two ANs). To align the measured locations within each closed segment, the reference locations of the detected ANs bounding the segment were employed. This alignment process involved estimating translation, rotation, and scaling parameters that minimized the root mean square error (RMSE) between two sets of pairs: the measured locations and the reference locations of the ANs. Figure 7 presents two examples of closed traces aligned by OANs. The aligned closed traces were merged and divided into small square grids, measuring 1.0×1.0 m² for RMs. It's worth mentioning that grids with a low number of steps (less than 10% compared to the grid with the highest step count) were excluded. This filtering process aimed to retain only the grids with dense signatures, ensuring higher quality and accuracy.

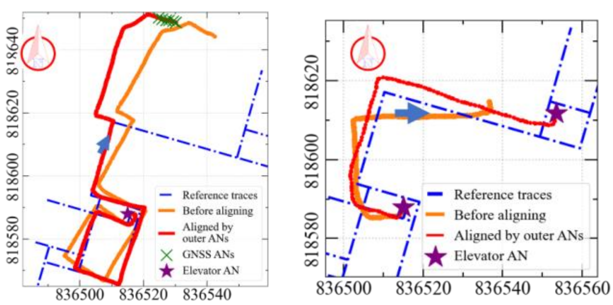

Figure 7. Samples of traces aligned by OANs.

3.4.3 Signature Data Selection and Consistency Check: The following checks were conducted to ensure consistent signature at each grid to convert it to RP:

a. Wi-Fi access points (APs) with weak received signal strength (RSSI), such as values below -90 dBm, were excluded from consideration.
b. Within each grid, APs with sparse signatures were discarded.
c. Grids containing fewer than five unique APs were also discarded.
d. Outlier filtering was applied to grids with data exceeding a specific threshold. The RSSI values for AP higher than $Q_3 + 1.5\,IQR$ or lower than $Q_1 - 1.5\,IQR$ were filtered out.

Figure 8 (left) depicts the closed traces that have been aligned using OANs. Figure 8 (right) showcases the grids generated from the aligned traces shown in Figure 8 (left). These grids are utilized to create the RM during the initial generation stage. Each grid represents a specific area and contains the relevant radio frequency (RF) data collected from the aligned traces. Together, Figure 8 (left) and (right) demonstrate that there are certain limitations when relying solely on OANs to achieve ubiquitous systems. These limitations include:

1. Long traces are prone to experiencing significant heading drift.
2. Many traces with qualified inertial data were opened without enough number of OANs.
3. The generated databases may not provide complete coverage of the entire floor area.

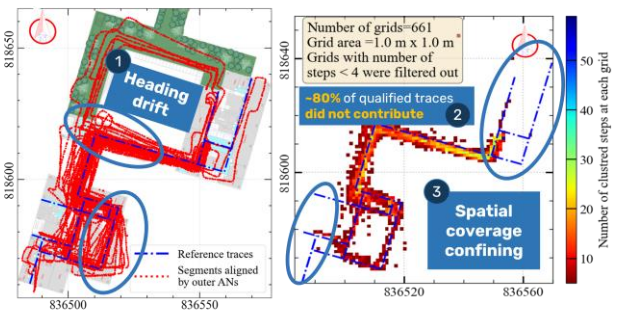

Figure 8. Initial database generation: (left) combining of traces aligned by OANs, and (right) initial RM grids.

3.5 Subsequent Radio Map Generation

3.5.1 Inferring Internal Wi-Fi Anchor Nodes: To overcome the limitations of the initial database generation, we sought to determine the locations of anchor Wi-Fi APs that could serve as IANs within the floor. Figure 6 (right) summarizes the concept of IANs inference. It was crucial to accurately estimate the positions of these fixed APs. We leveraged the RM created from the closed segments aligned by the outer ANs to infer the qualified reference points (RPs).
For each fixed AP, we assessed the signatures of its associated RPs using the following criteria:

1. An RP was considered suitable for estimating the AP's location if it contained dense signatures for that AP from different traces, along with minimal signature variation.
2. Only APs with more than fifty qualified RPs.
3. There is presence of strong RSSI than -50 dBm.

If the qualified RPs for a fixed AP satisfied the aforementioned conditions, we deemed it qualified to serve as an anchor node (AN). The location and propagation information of this AP were estimated using the least-squares estimation method based on the path-loss propagation model, as described in (Munoz et al., 2009). Figure 9 shows an example of inferring the location of fixed Wi-Fi AP that satisfied the signature consistency criteria for acting as AN.

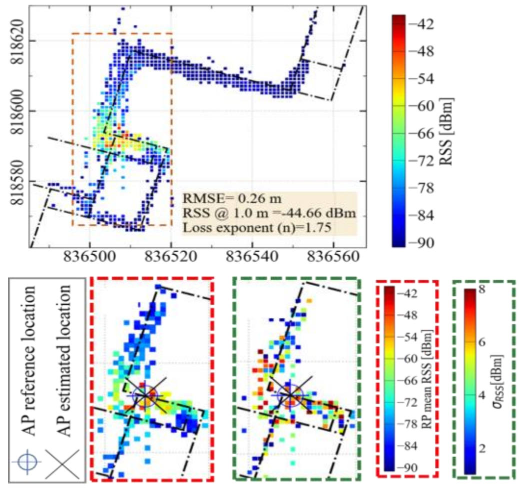

Figure 9. Inferring the location of fixed Wi-Fi AP that satisfied the signature consistency criteria for acting as AN

3.5.2 Aligning Traces Using Outer and Internal ANs: In order to align the collected traces using the inferred Wi-Fi IANs, a smoothing process was applied to the Wi-Fi RSSI data. This involved using an average filter for each detected Wi-Fi AN within the trace data, allowing for the identification of RSSI peaks. If the RSSI value of a peak was equal to or higher than the estimated RSSI at a distance of 1 meter for that particular AP, the location of that peak was considered the measured AN location. It was then added to a vector containing the measured locations of the detected ANs. A vector containing the reference locations of identified ANs was updated with the estimated reference location for that AN. Using these two vectors, the transformation parameters were determined to align the trace with the inferred ANs. Figure 10 showcases examples of traces aligned by OANs and Wi-Fi IANs

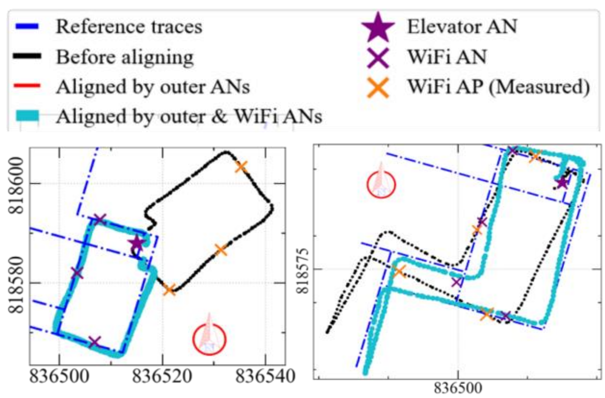

Figure 10. Traces aligned by OANs and Wi-Fi IANs.

Figure 11 (left) showcases the grids generated during the subsequent generation, which exhibit extended spatial coverage compared to the initial generation. Moreover, compared to the

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initial generation, the grids in Figure 11 (left) demonstrate a decrease in heading drift, resulting in improved alignment and accuracy of the collected data. Figure 11 (right) depicts a RM generated for Wi-Fi AP from the subsequent generation.

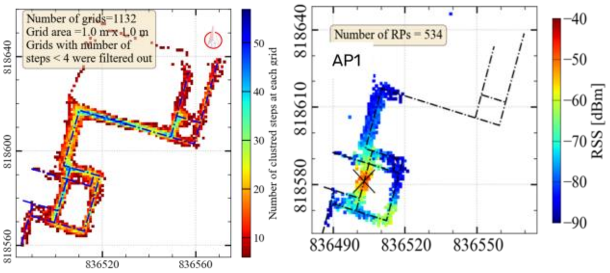

Figure 11. Subsequent database generation: (left) the generated grids from the subsequent generation; and (right) a RM generated for Wi-Fi AP from the subsequent generation.

3.6 Online Positioning Results

To evaluate the performance of the generated database, a long track was utilized. Figure 12 shows the positioning performance of the different techniques. The fingerprinting solution demonstrated excellent performance, achieving an average error of approximately 2.30 m. Furthermore, the 90% error was consistently below 4.00 m. In comparison, the PDR solution yielded a mean error of around 3.6 m, with a 90% error reaching approximately 5.1 m. By fusing both solutions using the Extended Kalman Filter (EKF), refer to (Mansour & Chen, 2022), remarkable results were obtained. The mean error was reduced to 2.10 m, with 90% errors below 2.90 m.

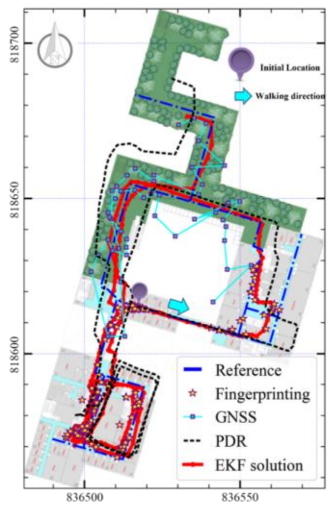

Figure 12. The positioning results of the fingerprinting, GNSS, PDR, and EKF.

4. CONCLUSIONS

Crowdsourced signatures are becoming increasingly prevalent due to smartphones' extensive coverage of human mobility. As a result, pervasive signatures can be leveraged to create a self-deployable and ubiquitous Indoor Positioning System (IPS). To achieve that, firstly we proposed user-friendly data collection strategy to encourage users to participate and ensure widespread adoption. Moreover, we proposed inertial data selection criteria that depended only on the collected data characteristic and have proven to be valuable in achieving better trace localization and consistent signatures per fingerprint. The proposed approach involves proposing to deploy a single Outer Anchor Node (OAN) in a strategic location (inside the elevators). This has been shown to maintain high localization accuracy, while minimizing the deployment cost and effort. Meanwhile, exploiting the data increasing over time helps to infer internal and IAN. The mean and maximum root mean square errors (RMSEs) of the estimated positions of the inferred Wi-Fi IAN were about 1.1 and 1.9 m, respectively. The online fingerprinting solution achieved an average accuracy of 2.10 m. In conclusion, the proposed scheme has the promise to foster the development of ubiquitous indoor positioning systems for buildings, regardless of whether they are located in areas with an unobstructed sky view or GNSS-denied regions.

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