A Hybrid Wi-Fi/PDR Smartphone Indoor Localization for Low Wi-Fi Access Point Density

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Abstract
This paper proposes a hybrid Wi-Fi/PDR indoor localization scheme for smartphones to overcome low Wi-Fi access point density issue in emergency situations. This approach not only takes a benefit of smartphone based-inertial sensing to continuously track its position via pedestrian dead reckoning without Wi-Fi signals, but also has capability to adapt transient signal strengths based on current environment condition.

I. Introduction
Recently, Wi-Fi based indoor localization has been used widely since it does not require extra infrastructure and specialized hardware. Wi-Fi access points (APs) become more prevalent not only in indoor buildings but also in public common places (e.g., airports, city hall). On the other hand, smartphones have been already equipped with Wi-Fi antennas which can receive wireless signals for localization purpose. Current studies [1]-[3] showed that received signal strength (RSS) based ranging is erroneous, while RSS fingerprint-based positioning requires labour effort and maintenance costs. In order to achieve better accuracy, multiple techniques are integrated into one system. For instance, combining pedestrian dead reckoning (PDR) and Wi-Fi can provide meter-level tracking for users, while bringing the benefits from smartphones enabled inertial sensors. Inspired by the approach in [3], in this paper we adopt a hybrid Wi-Fi/PDR scheme to perform self-localization and tracking on smartphones (e.g., iPhones), when AP density in the environment is low as illustrated in Fig. 1. We improve the localization accuracy of [2] by (i) working with a radio map adaptation with reference APs; (ii) assisting user mobility information with RSS vectors during moving to provide a precise location.

![Fig. 1. An example of low Wi-Fi AP density scenario.](image)

II. Proposed Hybrid Wi-Fi/PDR Indoor Localization
Our proposed system is divided into three components: Wi-Fi AP radio map generation, smartphone inertial sensors and a localization engine. During the training phase, a smartphone carried by the user collects Wi-Fi RSS characteristics at all AP locations and stores the RSS radio profile as well as its mapping to real locations. Then, when the user gets into online, the PDR utilizes inertial sensor readings to construct a moving trajectory, while extracting the Wi-Fi RSS profile to fix accumulated drifts in the trace.

1. Wi-Fi AP Radio Map Generation
In order to obtain a reachable range of a Wi-Fi AP, during the offline phase we collect a series of fingerprints from several reference locations and identify the maximum coverage that a smartphone can get acceptable RSS for localization. For each Wi-Fi AP, this procedure is repeated over a set of distinct locations, which results in a set of dissimilarity RSS values. Mathematically, a radio map \( \psi = < \text{AP}_i, R_i > \) contains \( n \) APs with coordinates \( \text{AP}_i = (x_i, y_i) \) and the corresponding coverage \( R_i \) obtained from the offline phase, where \( 1 \leq i \leq n \). Thus, the distance from \( \text{AP}_i \) to the smartphone is derived as

\[
d_i = 10^{(\text{RSS}_i - \text{RSS}_0)/10},
\]

Here, \( \text{RSS}_i \) and \( \text{RSS}_0 \) are the RSS values measured in the distance \( d_i \) and the reference distance \( d_0 \), respectively, and \( \gamma \) is the path loss exponent (e.g., \( \gamma = 4 \) in practice). Specially, we denote \( C_i \) as the circle centered at \( \text{AP}_i \) with radius \( R_i \). To support the low APs density (LAPD) cases, we also estimate the intersection between \( C_i \) and each path way, which are illustrated as yellow points in Fig. 1. For each \( \text{AP}_j \), all intersection points form a set \( S_j = \{ s_1, \ldots, s_{K_j} \} \) corresponding to the \( \text{AP}_j \), where \( K_j = \text{numel}(S_j) \), \( s_{ij} = (s_x, s_y) \) and \( 1 \leq j \leq K_i \).

2. Smartphone Inertial Sensors and Pedestrian Dead Reckoning
Modern smartphones have been usually equipped with inertial measurement units (IMUs), which are primarily designed to collect ability information such as velocity, orientation and gravity[1]-[3]. Human activity measured by smartphone-enabled inertial sensors are the inputs to the PDR. Denoting the initial position \((x_0, y_0)\), the PDR updates the user position \( P_k = (x_k, y_k) \) at time \( t_k \) as

\[
\begin{align*}
x_k &= x_0 + \sum_{m=1}^{K} \lambda_m \cos(\alpha_m) \\
y_k &= y_0 + \sum_{m=1}^{K} \lambda_m \sin(\alpha_m)
\end{align*}
\]

Here, \( \lambda_m \) and \( \alpha_m \) are the corresponding estimated step length and the orientation angle obtained from the IMUs, respectively.
3. Localization Engine

The overall workflow of the proposed localization algorithm on the smartphone is given in Fig. 2. First, the smartphone scans a detectable list of nearby APs \( \{ A_{P_1}, \ldots, A_{P_n} \} \), identifies the AP with the strongest RSS signal. It also calculates the corresponding distances \( \{ d_1, \ldots, d_k \} \) between the smartphone and the APs on the list according to (1), and retrieves the set of circles \( \{ C_1, \ldots, C_k \} \) formed by the APs and their coverage radii \( R_{1}, \ldots, R_{K} \). If \( C_1 \cap \cdots \cap C_k = \emptyset \), it is considered as an LAPD, otherwise it is considered as a normal case. Then, the smartphone position is estimated according to the following cases.

(1) **Normal case** The smartphone position at time \( t_i \) is calculated by applying the weighted centroid localization (WCL) as

\[
P_i(x, y) = \sum_{i=1}^{K} w_i(x, y) \left( \sum_{i=1}^{K} w_i(x, y) \right),
\]

where \( w_i = (\text{RSS}_i^k - \text{RSS}_{\text{min}}^k) / (\text{RSS}_{\text{max}}^k - \text{RSS}_{\text{min}}^k) \).

(2) **LAPD case** At the current step, if there is no Wi-Fi signal detected, only PDR will be used, i.e., the smartphone position is updated according to (2). In the next step, if the smartphone recognizes a number of available nearby APs again, its locations are selected as the closest intersection point to the smartphone previous position \( P_i(x, y) \) as

\[
P_{k+1}(x, y) = \min_{s_i \in \mathbb{S}} \| s_i - P_k \|_2.
\]

IV. Conclusion

Observations from real indoor environments have inspired us to design a practical, flexible and rapid localization scheme for the smartphones, especially for LAPD scenarios. Experiment results show that our scheme is effective under certain conditions of the moving paths.

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References

