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 received 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 environments is low as illustrated in Fig. 1. We improve the localization accuracy of [3] 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.

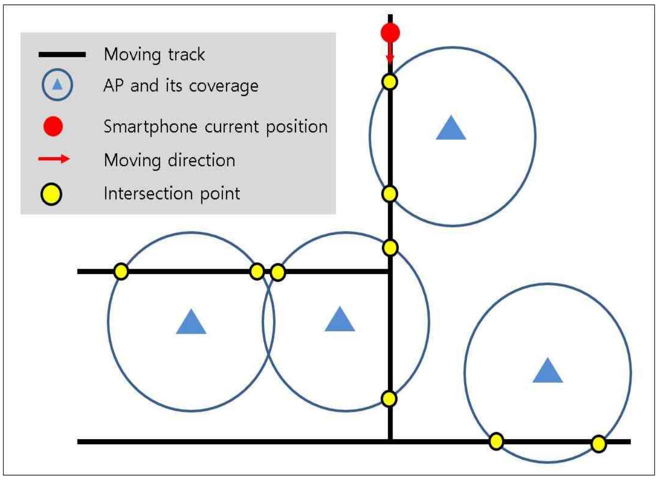

Fig. 1. An example of low Wi-Fi AP density scenario.

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 $\Psi = < AP_i, R_i >_{1 \le i \le n}$ contains n APs with coordinates $AP_i = (x_i, y_i)$ and the corresponding coverage R_i obtained from the offline phase, where $1 \le i \le n$. Thus, the distance from AP_i to the smartphone is derived as

$$d_i = 10^{(RSS_i - RSS_0)/10\gamma}. \quad (1)$$

Here, RSS_i and RSS_0 are the RSS values measured in the distance d_i and the reference distance d_0, respectively, and γ is the path loss exponent (e.g., $\gamma = 4$ in practice). Specially, we denote C_i as the circle centered at 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 AP_i, all intersection points form a set $S_i = \{\boldsymbol{s}, \cdots, \boldsymbol{s}_{iK_i}\}$ corresponding to the AP_i, where $K_i = \mathrm{numel}(S_i)$, $\boldsymbol{s}_{ij} = (sx_{ij}, sy_{ij})$ and $1 \le j \le K_i$.

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

$$\begin{cases} x_k = x_0 + \sum_{m=1}^{k} \lambda_m \cos(\alpha_m) \\ y_k = y_0 + \sum_{m=1}^{k} \lambda_m \sin(\alpha_m) \end{cases}. \quad (2)$$

Here, λ_m and α_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 $\{AP_1,\cdots,AP_K\}$, identifies the AP with the strongest RSS signal. It also calculates the corresponding distances $\{d_1,\cdots,d_K\}$ between the smartphone and the APs on the list according to (1), and retrieves the set of circles $\{C_1,\cdots,C_K\}$ formed by the APs and their coverage radii $R_1,\cdots,R_K$. If $C_1 \cap \cdots \cap C_K = \varnothing$, it is considered as an LAPD, otherwise it is considered as a normal case. Then, the smartphone position is estimated regarding to the following cases.

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

$$P_k(x,y) = \left(\sum_{i=1}^{K} w_i^k AP_i^k\right) \Big/ \left(\sum_{i=1}^{K} w_i^k\right), \tag{3}$$

where $w_i^k = (RSS_i^k - RSS_{\min}^k)/(RSS_{\max}^k - RSS_{\min}^k)$.

(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 is selected as the closest intersection point to the smartphone previous position $P_k(x,y)$ as

$$P_{k+1}(x,y) = \min_{s_{ij} \in S} \|s_{ij} - P_k\|_2. \tag{4}$$

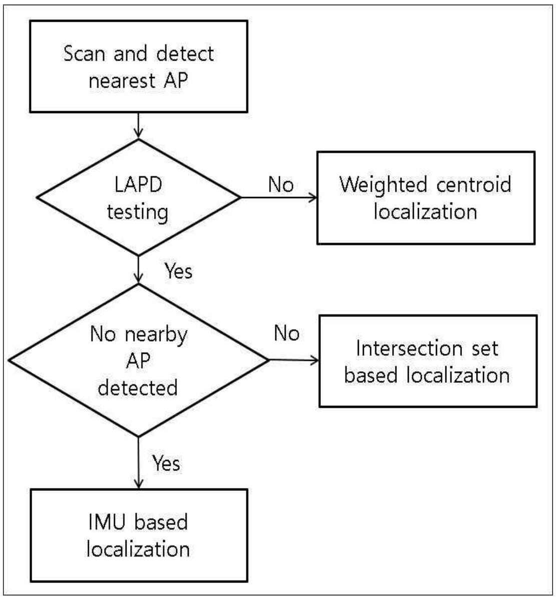

Fig. 2. Workflow of the proposed localization algorithm running on the smartphone.

III. Experiment Results

In order to validate the localization performance of the proposed scheme, we conducted several experiments at the 12th floor of Huyngnam Engineering Building in Soongsil University. The floor plan of our experiments is shown in Fig. 3.

For a given error bound ϵ and number of steps N_{sum} that the user took to finish a predefined path, we evaluate the localization accuracy by calculating the outlier rate as follows.

$$F = \frac{\text{Number of points}: \{\text{RMSE} > \epsilon\}}{N_{\text{num}}}, \tag{5}$$

where root mean square error (RMSE) of $\hat{x}$ respect to parameter $\hat{x}$ is defined by $\text{RMSE}(\hat{x}) = \|x - \hat{x}\|_2$. Table 1 shows the localization tracking results respect to ϵ with different approaches. We observe that with the same ϵ, the proposed scheme guarantees lower outlier rate compared to the other conventional ones.

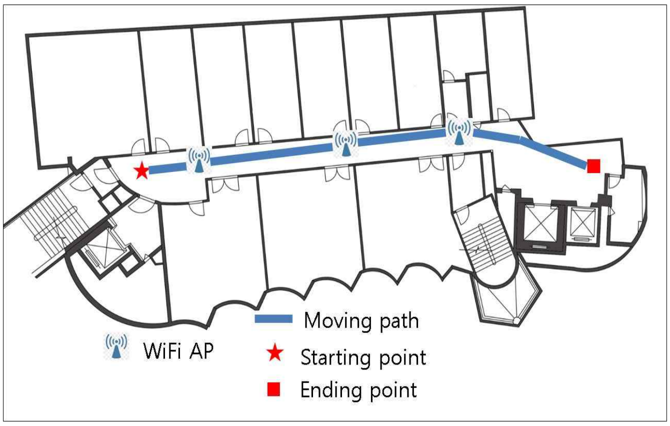

Fig. 3. Floor plan for the experiments.

Table 1. Outlier rate comparison with other localization methods

Method	Error bound ϵ		
	0.5m	1.0m	1.5m
WCL only	< 81%	< 76%	< 67%
IMU only	< 77%	< 76%	< 74%
Proposed algorithm	< 50%	< 47%	< 40%

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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