Wi-Fi

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Indoor positioning poses a number of challenges as several effects, such as signal attenuation, signal fluctuations, interference, and multipath occur in signal propagation. The severity depends on the method and technology adopted to perform user localization. Wi-Fi is a popular method because of its ubiquity with already available public and private infrastructure in many environments and the ability for mobile clients, such as smartphones, to receive these signals.

Keywords: received signal strength RSS ; round trip time RTT measurements ; location fingerprinting ; lateration ; combination and fusion of techniques ; positioning algorithms ; indoor smartphone user localization

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1. Introduction

Wi-Fi is one of the most widely used signal-of-opportunity for positioning and tracking mobile users, as it is commonly adopted for smartphone-based indoor positioning systems due to the availability of already deployed infrastructure for communications and the ability for mobile devices to receive these signals. Nowadays, a high number of Access Points (APs) of public and private networks can be sensed providing a high signal ubiquity.

The vast majority of current IPS are designed for sub-meter accuracy in position estimation, which is unnecessary for certain indoor navigation applications, such as most LBS as well as pedestrian navigation (see e.g., [1]). Then, a room-level or region-level granularity of location is sufficient [2][3][4][5]. The use of Wi-Fi is predestinated and capable of achieving such a level of precision with high performance. Therefore, Wi-Fi signals have a high potential to employ them for numerous applications for localization and guidance. Thus, Wi-Fi advances in wireless communication and the consequent ubiquity of Wi-Fi infrastructure provide the ability to extract human-related information, such as location, movement, and other activity by analyzing wireless connectivity between mobile clients and the APs [6].

Localization using Wi-Fi is either based on direct measurements of the Received Signal Strengths (RSS) of the surrounding Wi-Fi APs or on the measurement of the two-way travel time, i.e., the Round Trip Time (RTT), between the mobile device and several APs. Therefore, localization methods include lateration and fingerprinting algorithms. Thereby, the RSS-based fingerprinting approach has the advantage that no direct line-of-sight (LoS) is required and it does not need any prior knowledge of the APs deployment and their location [7]. It works also well in environments with high multipath. Fingerprinting is a so-called feature-based technology as a spatial variable feature, the RSS, is measured and georeferenced. Thereby, the measured RSS are used directly for a matching process where the current RSS measurements in the positioning phase are matched to previously measured RSS in a preceding system training phase. Fingerprinting is not so severely affected by signal fluctuations and interference than RSS-based lateration methods. This is why Wi-Fi fingerprinting is currently the most popular technology for an IPS. On the other hand, new developments for lateration-based approaches lead to further possibilities in Wi-Fi positioning. By measuring the RTT [8][9], the double distance between the AP and the mobile client can be obtained, which usually can provide higher accuracies for the ranges than with RSS-based methods. In RSS-based ranging [10], complex signal propagation models have to be derived and employed for the estimation of the signal path loss. The way to go in the future is a combination of different techniques to be able to use the advantages of all individual localization approaches.

2. Assessment of Major Localization Technologies

The two most commonly employed techniques in Wi-Fi positioning are the location fingerprinting and lateration-based approaches. For fingerprinting, deterministic and probabilistic approaches, and for lateration, methods based on the measurement of the RSSI and Time-of-Flight referred to as Round Trip Time (RTT) measurements are possible.

Fingerprinting can be referred to as a feature-based positioning method, which locates a mobile device through the geographical dependency between positions and signal observables. Thus, a spatially varying feature, such as the Received Signal Strength Indicator (RSSI), is measured and used directly for position estimation. In contrast to lateration, fingerprinting uses signal attenuation and the multipath effect to determine the position. The fingerprints are in general significantly different in different environments, facilitating localization. In Wi-Fi fingerprinting, the user's location is determined by measuring the Wi-Fi RSSI of the surrounding APs whose locations must not be known. In a first step, the off-line training phase, either signal propagation models for the specific environment are used or the RSS are measured at known reference locations to estimate and build up a fingerprinting database. In the second step, which is referred to as the on-line positioning phase, the current RSS measurements are used and matched with the RSS values in the database to estimate the users' location. Deterministic and probabilistic matching approaches are commonly used. Thereby, nearest neighbor (NN), *K*-nearest neighbor (KNN), and *K*-weighted nearest neighbor (KWNN) approaches for matching of the fingerprints from the off-line training to the on-line positioning phase are employed. Case studies have shown that probabilistic methods based on Bayes' theorem usually deliver higher positioning accuracies. In probabilistic fingerprinting, especially, the calculation of the Mahalanobis vector distance d^M is a promising approach. It is given by the form:

$$d^M\left(f^i_{map}, f_{obs}\right) = \left(f_{obs} - f^i_{map}\right)^T C^{-1}_{ff_{map,i}}\left(f_{obs} - f^i_{map}\right). \tag{1}$$

where f_obs are the current on-line RSSI measurement at the position f_map^i and $C_{([\![ff]\!] _{(map,i)})^{(} -1)}$ is the covariance matrix. If the covariance matrix is the unit matrix, the Mahalanobis distance corresponds to the Euclidean vector distance, which is most commonly used in the deterministic fingerprinting approach. As the inverse of the covariance matrix is the weight matrix, the weighted square sum of the RSSI differences (between off-line training and on-line positioning phase), whereby the weights are inversely proportional to the variances of the corresponding fingerprints, is calculated for the Mahalanobis distance.

As a conventional algorithm employed is surveying, lateration can be employed in Wi-Fi positioning as well. In RSSI-based techniques, lateration is based on the signal propagation of the RSS, which varies with changes of the range to the AP. Theoretically, the RSSI decreases with the transmitted energy propagating into space. A number of models, termed path loss models, have been developed to establish the RSS to range relationship. Their principle is that the trend can be mathematically modeled. One of the simplest models that describes the decreasing trend without the effects from reflections and obstructions is presented as the log-distance path loss model *PL*(*d*) as given in:

$$PL(d) = PL(d_0) + 10 * \gamma * \log\left(\frac{d_0}{d}\right) \text{ with } d \geq d_0 \geq d_f \tag{2}$$

where *d* is the distance between the transmitter and receiver, *PL*(*d*) the path loss at *d*, d_0 is the reference distance, d_f is the Fraunhofer distance, and γ is the path loss exponent. Thereby, the Fraunhofer distance defines the boundary of the region.

With the latest generation of Wi-Fi hardware, the two-way Time-of-Flight between the APs and the mobile client can be measured. It is referred to as Round Trip Time (RTT). One advantage of this method is that the mobile device is both a transmitter and receiver at the same time, which means that there is no need for exact time synchronization between the smartphone and the AP. However, the exact time delay caused by the responder must be known, which is difficult to determine. This problem was solved with introducing the IEEE 802.11mc standard, which makes it possible to determine the turnaround time with sufficient precision [13,14,68,69]. The operational principle is as follows: the smartphone scans the APs in the surroundings and recognizes which of them are RTT-capable. Then, a request is made to the APs, and the AP responds with a so-called ping-pong protocol. First, a so-called FTM (Fine Timing Measurement) protocol is sent to the smartphone (ping). Then, the smartphone sends an acknowledgement back (pong). The transmitted and receiving time on each device is added to the protocol. In order for the smartphone to calculate the complete turnaround time, it needs four time stamps. For this reason, the AP sends out a package containing all four time stamps. Then, the smartphone calculates the travel time by subtracting the time stamps of the AP and the smartphone. Then, the difference between these two time stamps is the travel time it took to send the package from the AP to the smartphone and back again. Then, the travel time is multiplied by the propagation speed and divided by two to obtain the range between the AP and mobile device. Equation (3) describes the relationship if four measurements are carried out and the mean is calculated:

$$t_{RTT} = \frac{1}{N}\left(\sum\nolimits_{i=1}^{N} t_{4_i} - \sum\nolimits_{i=1}^{N} t_{1_i}\right) - \frac{1}{N}\left(\sum\nolimits_{i=1}^{N} t_{3_i} - \sum\nolimits_{i=1}^{N} t_{2_i}\right) \tag{3}$$

where $t_{(1_i)}$ is the timestamp when the FTM framework is first sent by a Wi-Fi AP, $t_{(2_i)}$ is the timestamp when the FTM signal arrives at the smartphone, $t_{(3_i)}$ is the timestamp when the smartphone returns the acknowledgment (ACK) signal to the AP, $t_{(4_i)}$ is the timestamp when the ACK signal is finally received by the AP, *N* is the successful burst number (where $N > 0$, $N < B$) and B is the total burst number (i.e., burst size, B=8 by selected default).

Generally, the protocol excludes the processing time on the smartphone terminal by subtracting $t_(3_i) - t_(2_i)$ from the total Round Trip Time $t_(4_i) - t_(1_i)$, which represents the time from the instant the FTM message is sent $t_(1_i)$ to the instant that the ACK is received ($t_(4_i)$). This calculation is repeated for each FTM-ACK exchange, and the final RTT is the average over the successful number of FTM-ACK bursts. The estimated range D_est can be obtained through Equation (4):

$$D_{est} = \frac{1}{2} * t_{RTT} * c. \tag{4}$$

If the ranges to at least 3 APs are measured, then the location of the user can be determined by means of lateration. Wi-Fi RTT is a promising method enabling to determine the ranges even on the sub-meter level, and for the position, the achievable accuracy lies in the meter range [14]. However, this method is currently only available with a few smartphones on the market with Android version 9 or higher. RSSI-based approaches will still be needed since the coverage with new hardware cannot always be guaranteed. Therefore, a combination and integration of technologies as a hybrid solution will be appropriate.

As a novel approach that benefits from all advantages of the different techniques, the fusion of location fingerprinting and lateration was proposed by the author [71]. This development was termed Differential Wi-Fi (DWi-Fi) in analogy to Differential GPS (DGPS) satellite positioning. As in DGPS, reference stations are now deployed transmitting and scanning Wi-Fi signals. The approach aims at a significant reduction of the effects caused by signal fluctuations on the positioning result. The principle of operation in more detail is as follows: The user applies the corrections derived from the continuous observations of the RSs in real-time to improve his current localization accuracy. In an RS network, so-called FKPs (Flächenkorrekturparameters) are estimated, representing a spatial and temporal model of the range corrections. Thus, the influence of Wi-Fi signal fluctuations can be reduced if the corrections are applied in real time at the user side in the case of the RSS-based approach. The RS were realized by low-cost computers, i.e., Raspberry Pi units, which serve at the same time as AP and RS. Equations (5) and (6) are used for the calculation in the case if four APs (APs: 1, 4, 5 and 6) are sensed:

$$P_{received} = P_{transmitted} + +20 \log(\frac{\lambda}{4\pi d}) \tag{5}$$

$$dR = w_2 \times dR_2 + w_4 \times dR_4 + w_5 \times dR_5 + w_6 \times dR_6 \tag{6}$$

where w are the weights for the different APs.

RSSI observations are continuously carried out at the RSs; they can be used to derive dynamically changing and updated radio maps in real-time to encounter for large temporal and spatial variations of the radio channel. From the radio maps arrays, correction parameters are derived to estimate the ranges between the RSs (serving at APs at the same time) and the user. Then, the location of the user is calculated via lateration. An assessment of the benefits and results yielded a significant performance improvement.

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