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# Wi-Fi fingerprinting based on collaborative confidence level training

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ABSTRACT

Wi-Fi fingerprinting has been a popular indoor positioning technique with the advantage that infrastructures are readily available in most urban areas. However wireless signals are prone to fluctuation and noise, introducing errors in the final positioning result. This paper proposes a new fingerprint training method where a number of users train collaboratively and a confidence factor is generated for each fingerprint. Fingerprinting is carried out where potential fingerprints are extracted based on the confidence factor. Positioning accuracy improves by 40% when the new fingerprinting method is implemented and maximum error is reduced by 35%.



## 1. Introduction

With the advancement in positioning as well as mobile technologies, location based services (LBS) are no longer just trendy fantasies. LBS applications are expanding from military and government sectors rapidly into commercial and civil applications. Therefore, the fundamental requirement for positioning and navigation is becoming more demanding as solutions are required in more complicated environments, where traditional positioning methods such as Global Navigation Satellite Systems (GNSS) fails. This is known as the indoor positioning problem and numerous methods have been explored over the years to improve positioning performance in such environments [1,2]. Wireless network signal based positioning, such as Wi-Fi fingerprinting, have become widely applied in indoor positioning due to high availability of Wi-Fi signals in urban environments [3,4].

Yet Wi-Fi positioning is far from the perfect solution. Wi-Fi networks are not positioning dedicated systems thus signals can be unstable, and sometimes unsuitable for positioning. Hence accuracy and robustness cannot be guaranteed [5]. The complete process of Wi-Fi fingerprinting is achieved in two phases, the training phase which must be carried out first to collect received signal strength (RSS) measurements and the positioning phase to obtain positions based on the fingerprints [6,7]. The positioning performance of fingerprinting relies on the applied positioning algorithm as well as the accuracy and details of the fingerprint database. Therefore, in order to achieve accurate positioning, a detailed database is required. This relies on carefully chosen training points across the building as well as sufficient access points (AP) that covers the area of interest, as more APs will give more information on the variation of signals when in different locations. Although training can be very time consuming, databases must be retrained and updated whenever the internal building structure

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or AP locations change [8,9]. Furthermore, while some buildings have been setup with dedicated dense wireless network enabling high accuracy positioning, most indoor environment still lack such coverage.

To reduce the time and human labour required for database training, Wi-Fi simultaneous localisation and mapping (SLAM) had been applied to enable a quicker way of learning the signal pattern around a new environment and allows the system to navigate in a new environment. However inertial measurements and building information is required, and building information may not always be accessible [10–12].

A basic requirement in fingerprinting is that the positions of the fingerprints must be accurate and their RSS measurement should be up-to-date. Studies have looked into the possibility of reducing training effort by reducing training points and training time [13]. Authors in [14,15] look into autonomous crowdsourcing method for training and updating the Wi-Fi database. For crowd-sourced database, the accuracy of estimated positions of the training data is essential. Collaborative positioning improves positioning accuracy and reliability by applying network constraints on user's positioning measurements. Nearby users may form local networks where relative constraints can be applied to adjust and share each other's measurements [16,17]. Authors in [18,19] improve fingerprinting performance by allowing the user to interact with the system to label locations and changes. However this requires active collaboration with the user who may not be willing or could potentially make mistakes.

This paper looks into reducing the training effort by introducing a collaborative Wi-Fi fingerprint database training (cFPDB) approach, which achieves quicker and more reliable training. Gaussian Process (GP) regression is applied to generate fingerprints for the entire database from a small amount of training data and a confidence factor is produced for each fingerprint indicating how reliable it is. On the other hand, this solution especially addresses Wi-Fi positioning problems in locations where dedicated network is unavailable and are covered only by very sparse APs. With very few APs, users may not be able to observe enough signal variation patterns for accurate positioning. An adaptive collaborative fingerprinting algorithm (WARCP) based on the concept of collaborative positioning is also introduced which provides the location reference for fingerprints as well as knowledge on the expected relationship between Wi-Fi measurements collected by nearby users. Positioning flexibility is also improved as users have the option of performing inertial navigation alone, with collaborative ranging aiding or Wi-Fi fingerprint aiding based on available sensors and number of users.

This paper firstly introduces the collaborative Wi-Fi fingerprint training method and an analysis on training data is presented to understand how much data is required for generating a reliable database. WARCP is then discussed to achieve positioning based on the collaboratively trained database and ranging constraint between users. Simulations are carried out based on the proposed algorithms and discussed in Section 4. Both training and positioning results are analysed for efficient and reliable Wi-Fi fingerprint training and positioning.

## 2. Collaborative Wi-Fi database training

### 2.1. Wi-Fi fingerprinting

Wireless network based positioning relies on measuring the signal strength of the received signals. Wireless signal strength will attenuate as it travels from the transmitter (i.e. Wi-Fi APs) to the receiver based on the signal path loss model [3],

$$P_{RX}(d) = P_{d0} - 10n\log_{10} d + a \cdot WAF + \varepsilon \tag{1}$$

where $P_{d0}$ is the RSS in dB at a reference distance, usually 1 m, away from the AP, $n$ is the space loss factor which varies in different environments, $WAF$ is the wall attenuation factor and $a$ is the number of obstructions in between the receiver and AP, $\varepsilon$ is a zero mean Gaussian distributed noise. Positions can be obtained based on computing the change of signal strength from each AP to the receiver. However, wireless signals are quite noisy due to interference and obstructions inside buildings. Therefore the actual observation $\tilde{P}$ and the expected $P_{RX}(d)$ from Eq. (1) can differ up to 20 dB. Wi-Fi fingerprinting overcomes this problem by taking advantage of signal disruptions in complicated environments. Although signals are easily disturbed and measurement error $\varepsilon$ is hard to predict, but as long as the building structure remains unchanged, the disturbance reflected in the signal strength will remain alike in the same location. Therefore, the RSS measurements from each AP form a pattern that reflects a specific location, known as fingerprints.

The first step of fingerprinting is the training phase, where a number of locations, known as training points (TPs), are selected within the area of interest and the RSS from all APs are measured at each TP. These are stored into a database as one fingerprint. If the RSS are carefully measured, APs are well spread out and the structure of the building is complicated enough, each fingerprint should be unique referring to one specific location in the building. During the positioning phase, the user measures the current RSS and compares it to the fingerprints in the database. Usually, the mean location of $k$ fingerprints with the smallest difference to the current RSS, known as the $k$-nearest neighbours ($k$NN), is returned as the estimated position [20].

The biggest problem with fingerprinting is that the training process requires a huge amount of human labour, especially in large complex buildings. This increases the possibility of human error and time cost. Moreover, the database needs to be retrained and updated each time the infrastructure changes to maintain an up-to-date database for accurate positioning.