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Fast track article

CSI-MIMO: An efficient Wi-Fi fingerprinting using Channel State Information with MIMO

Yogita Chapre [a,c,*], Aleksandar Ignjatovic [a], Aruna Seneviratne [b,c], Sanjay Jha [a]

[a] School of Computer Science & Engineering, University of New South Wales, Sydney, Australia
[b] School of Electrical Engineering & Telecommunications, University of New South Wales, Australia
[c] Networks Research Group, NICTA, Sydney, Australia

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ABSTRACT

The paper presents a novel Wi-Fi fingerprinting system CSI-MIMO that uses a fine-grained information known as Channel State Information (CSI). The proposed CSI-MIMO exploits the frequency diversity and spatial diversity using Multiple Input Multiple Output (MIMO) system. The proposed CSI-MIMO uses either magnitude or complex CSI based on the mobility in an indoor environment. The experimental performance of CSI-MIMO is compared with Fine-grained Fingerprinting system (FIFS), CSI with Single Input Single Output (SISO) and a simple CSI with MIMO. The experimental result shows a significant improvement with an accuracy of 0.98 m in static environment and 0.31 m in dynamic environment with optimal war-driving over existing systems.

1. Introduction

Localization is playing a vital role in various Location-based Services (LBS) including production, social networking, entertainment, living and public services. Traditionally, LBS is limited to outdoor scenarios and needs further research to implement potential techniques for indoor applications. LBS such as locating an Automated Teller Machine (ATM), tracing a parcel in a post office, location-based mobile adverts and games, and access control demands more accurate indoor localization. The widely used Global Positioning Satellite (GPS) based localization fails indoors due to weak signals, whereas the triangulation technique is less effective due to complex building geometry, mobility of people and multi-path effect. Furthermore, noise and interference due to presence of other radio devices make indoor localization more challenging.

Indoor localization based on wireless signals such as GSM (Global System for Mobile Communications) and Wi-Fi are more popular due to lower cost, ease of access and use of the existing wireless infrastructure. Earlier indoor positioning approaches exploiting infrared, laser and ultrasonic are complex in nature, require higher cost and use bulky devices. Wireless indoor localization uses various signal parameters for location estimation; signal-based Received Signal Strength Indicator (RSSI), time-based Time of Arrival (TOA) and Time Difference of Arrival (TDOA), and angle-based Angle of Arrival (AOA). Among all, RSSI-based Wi-Fi fingerprinting is the most widely used approach. RSSI is a coarse-grained information that represents received signal strength through various paths for a given transmitter–receiver pair. As the distance between the transmitter and receiver increases, RSSI degrades due to attenuation. This phenomenon is utilized in numerous range detection algorithms including deterministic k-Nearest Neighbor in RADAR [1] and probabilistic Bayes rule in Horus [2].

* Corresponding author at: School of Computer Science & Engineering, University of New South Wales, Sydney, Australia.
E-mail addresses: yogitac@cse.unsw.edu.au (Y. Chapre), ignjat@cse.unsw.edu.au (A. Ignjatovic), aruna.seneviratne@nicta.com.au (A. Seneviratne), sanjay@cse.unsw.edu.au (S. Jha).

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However, RSSI is highly sensitive to temporal, hardware and environmental factors [3,4], which affects the localization accuracy significantly. To overcome the volatility of RSSI and improve the accuracy of indoor localization, a more robust fine-grained information is needed.

In 802.11 a/b/n networks, the data is modulated using Orthogonal Frequency Division Multiplexing (OFDM). The modulated data is transmitted and received using multiple data carriers known as sub-carriers. Each sub-carrier has a designated frequency and therefore provides frequency diversity across data sub-carriers. Moreover, data is transmitted and received using multiple antennas using Multiple Input and Multiple Output (MIMO) and offers spatial diversity. The transmitted data travels through the channel using multiple paths. At the receiver side, the received data gets attenuated due to scattering, fading and path loss. The channel quality between a transmitter and a receiver is termed as Channel State Information (CSI) and is extracted from PHY layer. The frequency and spatial diversity offered by CSI can be exploited to justify the multi-path effect.

CSI exhibits various prominent features as compared to RSSI offering more unique location signatures. Traditional RSSI presents an aggregated scalar value at the packet level, whereas CSI indicates the channel information at sub-carrier level. In addition, CSI provides complex channel information that includes magnitude and phase information for each sub-carrier, and for each transmit and receive antenna. Multiple sub-carriers attenuate differently when traveled through various traveling paths, thus resulting in variation of amplitude and phase of each sub-carrier. The fine-granularity of CSI in terms of frequency and spatial diversity makes it suitable metric to represent a location uniquely and to enhance the localization accuracy. Recently, the CSI is extractable using the Linux tool using off-the-shelf Intel 5300 Network Interface Card (NIC) [5].

Current wireless technologies use MIMO antenna systems extensively such as IEEE 802.11n, 3GPP LTE, and mobile WiMAX systems. MIMO enhances data throughput under influence of interference, signal fading and multi-path. Moreover, MIMO systems achieves higher data rates using spatial diverse communication links [6].

The prominent features of the CSI is being explored by researchers for Wi-Fi fingerprinting. FILA [7] and PinLoc [8] uses Single Input and Single Output (SISO) aspect of CSI for localization, whereas FIFS exploits spatial diversity of CSI [9]. FIFS aggregates power of all sub-carriers to represent a location and does not include phase profile of CSI. PinLoc creates a location fingerprint as clusters of amplitude and phase of CSI, however it uses only SISO information. We exploit frequency and spatial diversity offered by CSI to define the location fingerprint distinctly. The resulting high dimensional, complex location signature offers challenges of processing MIMO information for each transmitting and receiving antenna stream.

The paper exploit the fine-grained features offered by CSI to derive the location signatures based on the amplitude and phase of each sub-carrier using MIMO. The main contributions of this paper are as follows.

1. We aggregate the CSI over multiple antennas for each sub-carrier and present a novel location signature CSI-MIMO that consists of magnitude and phase difference between subsequent sub-carriers.
2. We propose a complex CSI-MIMO signature for static environments and an amplitude-based CSI-MIMO signature for dynamic environments. To the best of our knowledge, this is the first system proposing variants of CSI based on the mobility in the indoor environment.
3. We create a radio-map using CSI-MIMO for multiple Access Points (AP) to improve the accuracy and reduce the mean distance error.
4. We investigate the impact on the localization accuracy of CSI-MIMO due to the various factors such as size and type of CSI-MIMO fingerprint used, number of APs, and number of training and test samples.
5. We evaluate the performance of CSI-MIMO using the accuracy as a performance metric with other CSI-based localization systems such as FIFS 2×2, a CSI signature with SISO and a CSI signature with MIMO system.
6. We analyze the effectiveness of the proposed location signature using deterministic k-nearest neighbor (kNN) and probabilistic Bayes Rule algorithms.

The rest of the paper is organized as follows. In Section 2 we briefly present the related work on Wi-Fi fingerprinting using various location signatures. Section 3 introduces preliminaries including RSSI, OFDM, Channel Impulse Response and CSI. Section 4 explains our proposed CSI-MIMO system and the methodology in detail. It includes the system architecture, experiment setup and the CSI-MIMO fingerprint generation. In Section 5, we evaluate the effectiveness of the proposed CSI-MIMO signature for static and dynamic environments. We also evaluate our experimental results for various impact factors including number of APs, war-driving samples and type of localization algorithms. Further, we compare our proposed CSI-MIMO system with other CSI-based fingerprinting systems. Conclusions and directions for the future research are presented in Section 6.

2. Related work

Conventionally, Wi-Fi fingerprinting consists of two phases: Training/Off-line phase and Testing/Localization phase. In the training phase, data at various distinct locations called as Reference Points (RPs) is collected over a duration. The collected N data samples are used to derive a location signature, which is then stored in a database called as radio-map along with the coordinates of the location. In the testing phase, data is collected at an unknown location called as a Test Point (TP), a location fingerprint is created in similar way as in the training phase and is matched against the radio-map to infer the location.

The indoor localization exploits various wireless signals: traditional RSSI, Channel Impulse Response (CIR) and the most recent CSI. We categorize various Wi-Fi fingerprinting methods based on the used signal.