Machine Learning for Location and Orientation Fingerprinting in MIMO WLANs

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***Abstract*—To detect the position and the orientation of a mobile device within a Wireless Local Area Network (WLAN) covered by multiple access points (APs), the intrinsic properties of multiple-input multiple-output (MIMO) channels are used linking the received signal strength indicators (RSSIs) to the distance and exploiting the received signal correlation structures. Location and orientation fingerprinting is a map based positioning solution that stores for a given orientation past measurements of RSSIs at known reference/grid points in a database that is later used to localize a mobile device at an unknown location and with unknown orientation to the closest reference point. This paper focuses on processing the RSSI data vectors from multiple receiving antennas on a downlink by applying the core tools of Machine Learning (ML) classification methods to evaluate the effects of MIMO RSSI meta-data when capturing 802.11n/ac packets using commodity hardware. Specifically, the paper provides insights into the design of the overall location fingerprinting system operating with new WiFi physical link layer protocols. To verify the operation of the proposed system, experimental results are presented to investigate the impact of different factors, like the number of receive antennas, affecting the estimation accuracy for the location and the orientation of mobile user.**

***Index Terms*—RSSI, indoor localization, fingerprinting, machine learning**

I. Introduction

The viability of precise indoor localization using physical layer information in 802.11 networks is an important problem as location information has many potential applications from context aware services through efficient radio frequency (RF) resource allocation and management [1], [2]. The state of the art in indoor localization is quite sophisticated. Researchers have explored different techniques such as those based on RSSI, Angle of Arrival (AoA), Time Difference of Arrival (TDoA), and Channel State Information (CSI) principles [3], [4]. The RSSI-based approach using conventional neural networks is the simplest and most cost effective but it has its limits in terms of location accuracy to one meter when one antenna transceivers are deployed [5]. Over time, the frontier of indoor localization technology has advanced by deploying more sophisticated classification methods such as those using machine or deep learning and channel state information (CSI) achieving decimeter accuracy [6]. With the proliferation of WiFi APs supporting MIMO communications, indoor positioning and localization techniques which use multiple antennas are becoming ever-more challenging, and ML has the potential to contribute in this area as ML performs nonlinear approximations and is intrinsically data-driven [2].

The challenge when designing an indoor localization system using WiFi infrastructure is that for this system to be a ubiquitous service, it has to be installed on already deployed WiFi infrastructure or commodity hardware without requiring any major firmware changes in APs or network interface cards (NICs). When capturing wireless frames, the 802.11 overhead in a frame is pre-pended by the device driver with a metadata header, offering information about how the frame was captured. Some of the most common parameters include channel (frequency) and data rate (based on Modulation and Coding Scheme (MCS) index value). The physical layer information particularly important in this paper is the power level in dBm at which the sniffing adapter antenna received the packet, i.e., RSSI. In 802.11g, the receiver was using only one antenna and the device driver was reporting only one RSSI value for a given frame. In 802.11n and ac physical link layer standards when the data is received using multiple spatial streams, the RSSI should be reported by the device driver as a vector of dimensionality determined by the number of receive antennas as shown in Fig. 1. At this point, different wireless sniffers and device drivers use different metadata header formats to encode the wireless physical layer and not always report the vector representation for RSSI but rather its average value. In

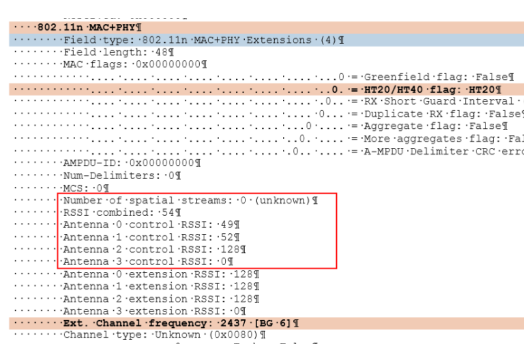

Fig. 1. Per Packet Information 802.11n header from AirPcap NIC.

this paper, in the experimental part, we use Atheros wireless 802.11n/ac chipsets and corresponding drivers that provide us with more than one RSSI value when receiving data on multiple spatial streams. Specifically, Atheros QCA9558, a 802.11n chipset, presents four different RSSIs per received packet if it uses three receive antennas: one is a combined

RSSI for all antennas, the other three represent three individual antennas' RSSI values.

The main contribution of this paper is a localization system that works on commodity off-the shelf WiFi hardware that provides (i) decimeter localization accuracy and (ii) reliable orientation estimation for four directions: North-South (N-S), East-West (E-W), W-E and S-N with possible extension to eight directions. This system uses location fingerprinting (i) to leverage existing RSSI information from multiple receive antennas as part of the IEEE 802.11 n and ac protocols when receiving data from different APs on multiple spatial streams and (ii) to capture details unique to the environment. The fingerprinting deployed in this paper is an extension of our previous work when working with one antenna as in [5], where location fingerprinting was presented mathematically as a statistical classification problem. In this paper, since we work with both location and orientation fingerprinting, the classification space is expanded by the factor given through the number of orientations we attempt to differentiate. The feature space for our classification algorithms is also expanded by the number of RSSI values we obtain on one packet from one AP.

II. Fingerprinting Indoor Localization

A. Background

The proposed location and orientation fingerprinting has two phases: a training and an operational/test phase. During the training phase, it collects different RSSI measurements related to the position and orientation reference points as its fingerprints (or features) database. In the operational phase, mobile device reads its RSSI values and use the fingerprints database to find the closest reference points to determine its location and orientation. ML classification method like k-nearest-neighbor (kNN), Decision Tree (DT) are used to extract the core features and reduce the computational complexity for localization [7], [8].

RSSI is the signal strength received at the receiver measured in decibel-milliwatts (dBm) or milliWatts (mW), which can be used to approximate the distance d between transmitter and receiver by [9]:

$$RSSI = -10n\log_{10}(d) + A \tag{1}$$

where n is the path loss exponent (which varies from 2 in free space to 4 in indoor environments) and A is the RSSI value at a reference distance from the receiver. RSSI-based fingerprinting localization is simple and cost effective since we can have the RSSI values from off-the-shelf WiFi NICs easily, but this approach suffers from performance degradation in some propagation environments where RSSI values exhibit large variations due to multi-path fading, shadowing effect and measurement noise. As an alternative to RSSI environment characterization, some WiFi NICs, like Atheros-based, report the receive signal strengths called in this context Channel State Information (CSI) for individual subcarriers in OFDM frames, i.e., 56 subcarriers for 20MHz channel and 114 subcarriers for a 40MHz channel. This is in contrast to RSSI which represent received power in the whole signal bandwidth [9]. CSI amplitude values are believed to be more stable over time than RSSI values. However, while CSI-based fingerprinting may improve positioning accuracy, it also brings up computational complexity because of the data scale of CSI amplitude values. In this paper, with the focus on reduced computational complexity localization algorithms suitable for mobile device, the proposed localization method is only using the RSSI values, though our experimental setup is capable to work with both RSSI and CSI MIMO channel characterization.

Since introduction of MIMO in 802.11n, multiple antennas are used (i) to form more spatial streams to increase data rates (multiplexing gain) or (ii) to increase the reliability by working with space-time block coding (diversity gain). Atheros WiFi chips used in our experimental WiFi setup provide more than one RSSI values on 802.11n or ac data frames. Specifically, Atheros QCA8558, a 802.11n WiFi chip used in our experiment, can offer 4 RSSI values when it utilizes two or three spatial streams for MIMO with three receive antennas. By analyzing these four values for RSSI, we found that the vector values for RSSIs offer better characterization of the network environment for the purpose of localizing mobile device than working with independent RSSIs from individual antennas when the correlation structure between the received signals on different antennas is lost and this motivated the work in this paper

From the perspective of machine learning (ML), fingerprinting-based localization approach can be treated as multi-label classification problem. Hence, many ML methods, such as kNN, DT and support vector machine, are applied to reduce the computational complexity and dig out the core features for better localization performance. We use kNN and DT algorithms in our experiments to show how the vector representations for RSSI values improve localization accuracy if they are included in the fingerprints (features) database. kNN algorithm compares its real-time RSSI values with k nearest weighted RSSI values of known locations to find the matched location. Decision Tree can learn decision rules from the off-line fingerprints database and then uses these rules for classification (localization) to determine which location the real-time RSSI belongs to.

B. Experimental Setup

Our experiment setup include three location-fixed APs and one Mobile Device (MD) as showed in Fig. 2. The MD works in a monitoring model which can receive data packets from three APs simultaneously. During the training phase, MD records the RSSI values as fingerprints in the off-line database for ML classification training. In the test phase, MD uses its real-time RSSI values and the trained model to predict (search) the matched location. In our experiment the separation into APs and MD is only at the logical level, as we actually deploy four TP-Link AC1750 Archer C7 wireless routers to emulate our testing scheme. Three of the TP-Link devices are used as fixed APs and one simulates MD where the differentiation is through the CSI-Tools software run on these devices. TP-Link

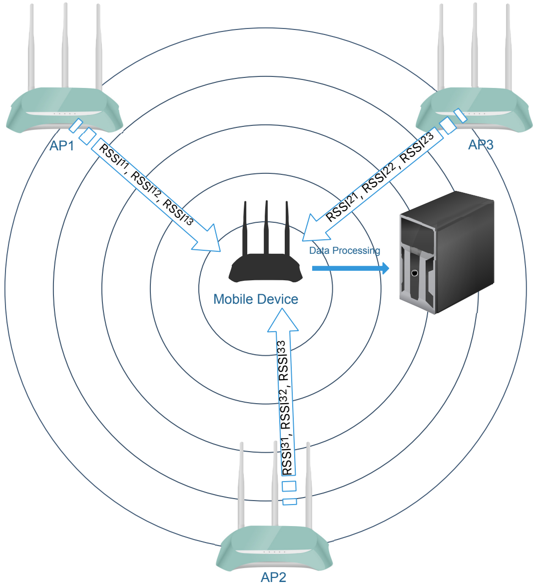

Fig. 2. WiFi equipment configuration.

AC1750 C7 802.11n/ac wireless router is 2.4G/5G Hz dual band Wi-Fi router with 6 antennas (3 for 2.4GHz and 3 for 5GHz) installed. Its powered by Atheros QCA9558 Scorpio system-on-chip, a 720-MHz processor, and 128MB of RAM. In order to fully control these APs and MD, we refreshed them with open source firmware developed by OpenWrt community and installed Atheros-CSI-Tools program [10]. Thanks to the powerful CSI tools developed by Li and Xie, not only can we extract CSI info but also we can retrieve RSSI values we need in our experiment.

III. ML Location and Orientation Fingerprinting

A. *Fingerprinting Localization Flow Chart*

With the help of Atheros-CSI-Tools, MD can obtain CSI data packets from APs, from which we can extract many useful features for indoor localization including RSSI, CSI, timestamps, number of transmitting antennas, transmit-rate, number of receiving antennas, number of spatial streams etc. As the name implies, timestamps create the time line when the CSI data packet is received. Other features' meaning can be also inferred from the names themselves. To reduce the computational complexity and evaluate the performance improvements with the introduction of multiple RSSI values from multiple receive antennas, we exclude CSI and other features. We only work in this paper with RSSI values as our localization features.

Fingerprinting localization approach used in this paper is visualized with the flow chart in Fig. 3. MD receives three groups of RSSI values from three APs simultaneously, $RSSI1, RSSI2, RSSI3$, and each group of RSSI is consist of 3 RSSI values related to 3 antennas of MD, respectively. We use $RSSI_{ij}, (i$=1-3, j=1-3$)$ to denote the RSSI value received at antenna j from AP(i) for a given orientation as shown in Fig. 3. $(COMRSSI_i, i$=1-3$)$ is the combined RSSI values corresponding to three APs. In total our fingerprints dataset is denoted as follows:

$$\begin{aligned} RSSI =& [RSSI, RSSI2, RSSI3, COMRSSI] \\ =& [RSSI_{11}, RSSI_{21}, RSSI_{31}, COMRSSI_1, \\ & RSSI_{12}, RSSI_{22}, RSSI_{32}, COMRSSI_2, \\ & RSSI_{13}, RSSI_{23}, RSSI_{33}, COMRSSI_3] \end{aligned} \tag{2}$$

After collecting RSSI values/vectors as in (2), we establish an off-line features database including the reference points (physical location) where these RSSI values are collected. ML builds up a prediction model based on this database in a training phase. Then in the test phase, MD reads its new RSSI values and uses the database and corresponding statistical classification algorithms to predict (search) its most likely location/orientation. We treat this as a multiple classifications (locations/orientations) problem and solve it using two ML classification methods: kNN and DT. This is with the objective to determine which methods offers the performance improvement if RSSI values from multiple antennas are considered.

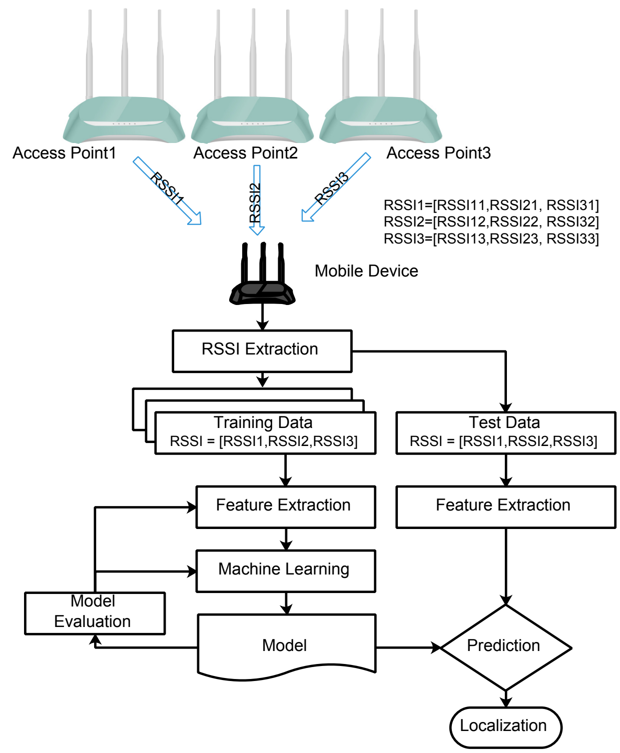

Fig. 3. RSSI-based fingerprinting localization.

1) Indoor Environment Fingerprints Survey: The first step to performing the experiments was to place the APs in certain known locations and select their frequency channels. Grid points were placed in an even pattern, roughly 30cm apart from each other. In addition to each grid point, a test point was placed near each reference point to be used during the operational/test phase. Once the environment had been marked and measured, MD in the monitoring mode was placed at each grid point in turn. Data was captured for eight orientations. All experiments were conducted in our laboratory which is

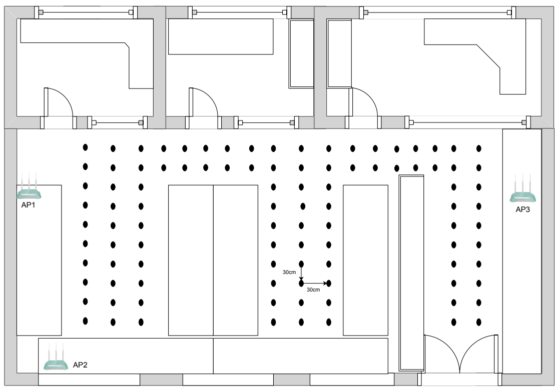

Fig. 4. Lab layout.

composed of three small rooms and one big room with the floor layout in Fig. 4. There are lots of tables, bookshelves, and PCs crowed in the big room, which block most of light of sight (LOS) paths. Three APs are placed in corners with different heights from the floor. We separate laboratory spare space into many 30cm X 30cm grids and collect the RSSI values from each location marked in red. To obtain fine-tuned fingerprints, we collect 500 groups of RSSI values for eight orientations at every location. Each group contains three small groups of RSSI as presented in (2). In practice, we use a alternative but more practical way to check the performance of localization method. We collect the fingerprints database once and separate the database into two parts by random, 70% of data are used for training to build , the rest 30% are used to test the localization accuracy to see the performance improvement along with the number of RSSI (antennas).

IV. Results Analysis

This section provides a performance summary of two localization methods based on kNN and DT methods as presented in the previous sections when we collected 500 RSSI vectors from each APs with packets arriving at the average rate of 500 packets per second. Figure 5 shows the relationship between localization accuracy and the number of antennas (or number of RSSI values) when deploying kNN and DT based localization. The actual number of antennas varies from 1 to 3, though in all performance graphs we add the forth group of RSSI values that represents the average reading from the metadata overhead which actually does not gives any new information and does not affect the performance. The number 1 means that only one RSSI (either the combined RSSI used in most RSSI-based localization approaches, or one of three individual RSSIs). The results in Fig. 5 represent the mean of all possible combinations of antenna for a given number. Specifically, the number of 2 along the x-axis means any two of the three individual antennas' RSSI, but not include the combined RSSI. We use all three individual antennas' RSSI if the number is 3. Number 4 includes all antennas' RSSI together with the combined RSSI.

A. Localization Accuracy Improvements

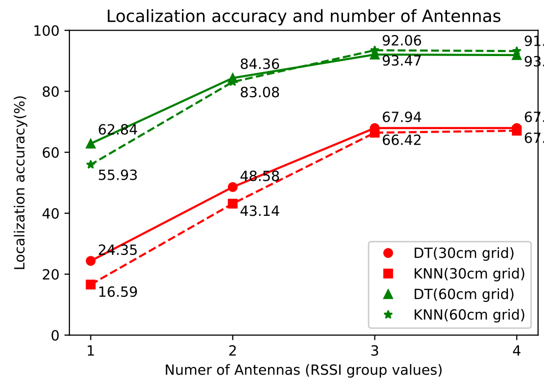

Fig. 5. Localization accuracy with number of antennas.

From Fig. 5, we have 16.59% and 24.35% accuracy using kNN and DT when working with single RSSI values on a 30cm grid, respectively. Detection accuracy reaches 48.58% and 43.14% if we use 2 antennas, which is a big performance improvement of about 24% (double). If we include all three antennas, we can see another about 23% enhancement. We also dropped out some locations to form a new database whose locations have 60cm distance between each other, figure shows us the overall localization accuracies are increased due to the localization requirement decreased from 30cm to 60cm. In this situation, we also see one more antenna brings up about 20% improvement. We see about 92% positioning accuracy in case of 60cm distance, which is a much better result compared with our past work, which can only have about 1.8m or worse location accuracy. However, both situations do not see improvement comparing if we include the combined RSSI. Adding up the combined RSSI does not bring new features for ML classification.

B. Orientation Detection of Mobile Device

In the process of executing initial experiment in Section IV-A, we noticed that the orientation/direction of MD has an influence on the RSSI values. Therefore, we always keep the MD in predetermined direction with the purpose to get improved localization accuracy. In other words, in order to reach about 92% accuracy on 60cm grid, we arranged that MD had the same orientation when collecting data in offline features database. Since the RSSI values reflect the directions of the MD, we can use it to detect its direction reversely if we can read its RSSI values. Therefore, in this part of our experiment, we collected the RSSI values on one location but in eight directions as shown in Fig. 6 to see if we can detect the orientation change of MD. It also can be looked as an ML classification problem. Figure 7 shows that results for detecting the orientations of MD in eight possibilities. With one antenna RSSI values, the accuracy to determine the orientation is only about 53% to 59%. One more antenna RSSI values will enhance the detection accuracy to about 85%. It

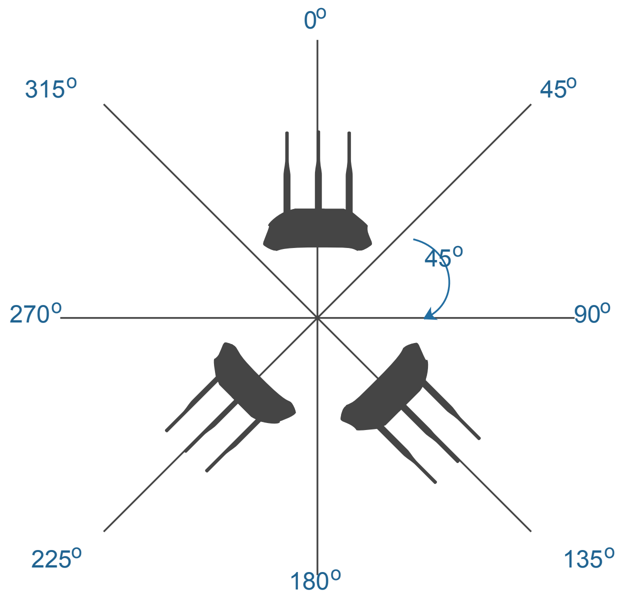

Fig. 6. Antenna orientation detection.

gets a very respectable result of about 93% or 94% when three antennas RSSI values are used. Similarly, introducing the combined RSSI as the fourth RSSI value does not improve the accuracy. Since the orientation of MD will impact the

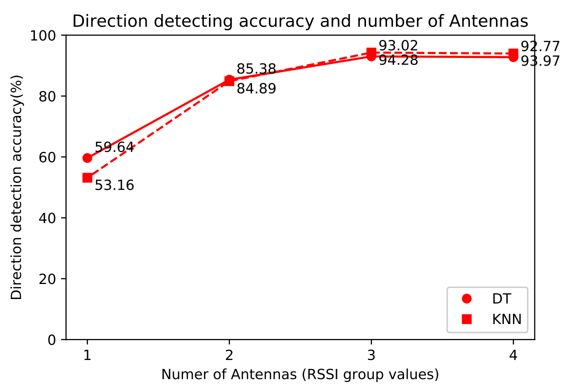

Fig. 7. Orientation detection accuracy vs number of antennas.

accuracy of localization, we collect more RSSI values in eight directions at each grid point and use ML classification to check the influence. Each orientation per location has 500 groups of RSSI from three APs as the same before, so we have eight times data scale (4,000 groups of RSSI) comparing our last features database. The categories of classification also increase up to eight times of former experiment. To show the impact of orientation change of MD on the localization accuracy, we redraw one direction accuracy together with eight directions localization accuracy for comparison, which means that we not only want to locate where MD is and want to know which direction MD is. From Fig. 8, it is obvious that localization accuracy in case of detecting eight orientations at certain location are much lower than detection location (one orientation only) case in 60cm grids situation. But we still can see the accuracy is enhanced with the increment of antennas. Similarly, adding up combined RSSI values does not improve much the accuracy. To attain comparable localization accuracy, more antennas need to be equipped in case of localizing both eight possible orientation and location. The experiment results also show that the potential reason for poor RSSI-based localization accuracy in our past work, that is, we did not take the influence of orientation of antennas into consideration.

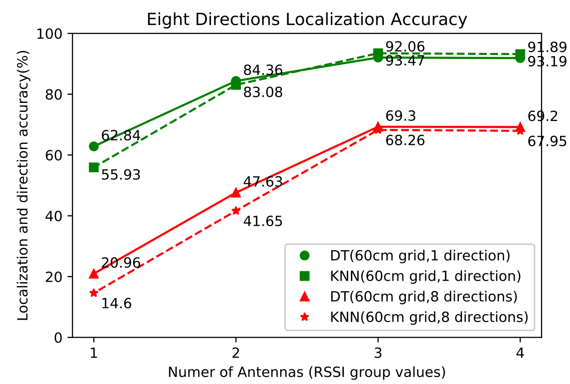

Fig. 8. Eight directions detection accuracy vs number of antennas.

V. Conclusion

The contributions of this paper are twofold: (i) the development of new algorithms for localization and orientation prediction in WLANs with MIMO links; and (ii) the performance evaluation of these algorithms in a real world test environment on commodity hardware. RSSI values not only represent the distance between transmitter and receiver, but they also potentially contain core features which can be used by machine learning method to attain more accurate localization and orientation detection. The most interesting observations in our work are that (i) increasing the number of receive antennas and working with vector representations of RSSIs can improve the performance of the localization system more than working with individual readings from the same antennas; and (ii) we could differentiate the device orientation, e.g., N-S vs S-N, which seems counter intuitive when one considers the symmetry of the receiving antenna array in different cases. Disregarding orientation impact on RSSI values in training phase will deteriorate machine learning location accuracy subsequently.

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