Indoor Localization Using Commodity Wi-Fi APs: Techniques and Challenges

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***Abstract*—Over the past decade, many research studies have contributed to making indoor localization of Wi-Fi devices accurate and practically useful for emerging applications wherein GPS becomes incompetent. Significant interest is shown and efforts have been put by the research community on using Wi-Fi technology such as 802.11n standard for indoor localization because of its minimal deployment complexity and cost. Also, the Wi-Fi capability in almost every electronic device makes it a promising technology for indoor localization. The main aim of this survey is to review the most recent works on Wi-Fi based localization systems that use commodity hardware highlighting their strengths and limitations, investigating major technical challenges, and outlining opportunities for future research. Commodity Wi-Fi equipments have fewer number of physical antennas, suffer from non-trivial phase noises due to imperfect signal processing hardware and operates in narrow bandwidth range. We elaborate state-of-the-art methods used by a number of research papers to overcome above-mentioned hurdles in order to achieve decimeter level accuracy which will benefit a plethora of applications. We also intend to make the interested readers aware of possible improvements that can be done to make the existing work even better.**

***Keywords*—**Indoor Localization, Channel State Information (CSI), OFDM (Orthogonal Frequency Division Multiplexing), MIMO (Multiple Input Multiple Output)

I. Introduction

Adoption of MIMO-OFDM techniques in 802.11n Wi-Fi standard have revolutionized wireless communications. These techniques together offer increased data rates (upto 600Mbps), improved reception and reliability, better spectral efficiency and larger range [1], [2]. About 40% of data rate improvement comes from OFDM which is a special case of multi-carrier communication system. It uses multiple orthogonal sub-channels called subcarriers for modulating and transmitting information in parallel. Another major factor for this superior performance comes from the use of multiple antennas (MIMO) at transmitting and receiving nodes [2]. In addition to higher data rates, MIMO also brought with it the new possibility of location tracking capability for commodity hardware by making phased array signal processing possible. Off-the-shelf Wi-Fi chip families such as Intel [3] and Atheros [4] expose PHY layer information called Received Signal Strength (RSS) and Channel State Information (CSI). CSI is a complex matrix that represents signal attenuation and phase distortion for each wireless MIMO link between TX-RX pair. CSI matrix is usually used for beamforming at the TX and for cancelling the effect of end-to-end phase distortion in the equalization process at RX [2], [5]. Recently, CSI phase difference [6]–[9] across MIMO antennas is used extensively to estimate the direction of the signl arrival. Classical direction finding algorithms like Multiple Signal Classification (MUSIC) [10] produces Angle of Arrival (AoA) pseudo-spectrum by AoA estimation techniques or by Time of Flight (ToF) ranging or produces joint estimation of AoA and ToF [6]–[8], [11], [12]. MUSIC uses the principle of orthogonality between noise and signal space to find AoA. Many location-aware applications for indoor navigation demand sub-centimeter accuracy. Few meters of errors are not acceptable because of smaller indoor space; a meter error may direct you to a different office room than intended. To achieve decimeter level accuracy using commodity hardware is challenging [4], [6], [7], [11] because of random hardware noises and dynamic multipath reflection in indoor environments. The reported CSI includes phase distortion due to channel along with non-trivial phase noises owing to the lack of fine-grained synchronization between oscillator clocks at TX-RX nodes [13]–[15]. In order to exploit the phase information provided by the Network Interface Cards (NICs), one must first eliminate the noises from CSI measurements before applying MUSIC or other direction finding algorithms. Triangulation and trilateration are the two underlying methods commenly used by the current localization systems.

We have structured rest of the paper as follows. In section II, we classify existing research methods along with their pros and cons. In section III, we list all the sources of phase errors that plague the CSI data obtained from commodity hardware. In section IV, we bring together all the data sanitization/cleaning techniques employed so far by researchers that report high accuracy. Section V talks about future research direction and in section VI, we render our conclusion.

II. Classification of Indoor Localization Systems

We broadly classify Wi-Fi based indoor localization systems into four categories: RSS based, fingerprinting based, CSI based and machine learning based. Each of these approaches have its own advantages and limitations.

A. RSS Based Localization Systems

RSS is a PHY layer information that could be easily obtained in current APs. This value depends on the distance of the target relative to the RX along with the dynamics of multipath components. RSS readings from multiple APs are acquired and combined with the propagation model to triangulate and locate the target [16]–[18]. The main advantage

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of such system is that they are simple, do not need transmitter cooperation and are easy to deploy. However, the median error in location estimation is reported to be around 2-4 m [16] which is too coarse for many indoor applications that demand finer precision.

B. Fingerprinting Based Localization Systems

The idea of fingerprinting is to create a database by collecting extensive signatures such as vector of RSS readings for a specific location with respect to all the RXs in range of TX. Later, when the TX is at the same location, it would exhibit the same signature in the database and by finding the associated map to the location, the device can be localized. A heat-map based fingerprinting system named HMF [19] and another system [20] that utilize the similarity of access points are able to achieve improved localization accuracy. Several other methods that use fingerprinting are [21]–[26]. Fingerprinting methods can give high accuracy of up to 60 cm. However, these methods are labor-intensive, time-consuming and recursive. Furthermore, they are highly sensitive to minor environmental changes, for example, moving or adding a furniture would completely change the fingerprints, making the database unusable.

C. CSI Based Localization Systems

CSI based systems work by resolving all the Multipath Components (MPCs). It is necessary to disentangle MPCs because only Line of Sight (LoS) signal parameters like AoA and ToF is required for ranging. CUPID [27] is a CSI based localization design that estimates the angle of direct path signal. It produces a localization error of 5 m. SAIL [28] combined CSI and human motion to compute propagation delay of direct path and achieves accuracy of 2.5 m. System called Ubicarse [29] has high accuracy of 39cm, but requires that the human holding the device performs a specific circular motion in order to emulate multiple antennas. Such a technique is not suitable when locating a misplaced or lost objects. SpotFi [7] uses both CSI and RSS measurements to obtain an accurate estimate of AoA and ToF. It can localize the target with an accuracy of 40 cm using commodity NICs and avoids the need for expensive dedicated hardware or tedious fingerprinting scheme. They use Intel IWL 5300 card for CSI measurements. This card has only three physical antennas and thus at most two multipaths can be separated. They contribute by overcoming the limitation of few antennas in commodity cards by using OFDM subcarriers as virtual antennas and thus extending antenna array to 30. The idea is that the ToF will cause phase offset across subcarriers and for this reason they form a virtual antenna array. Cronos [11] is the first decimeter level indoor localization system that can obtain accurate absolute ToF from CSI readings. It hops all available (i.e. 35) Wi-Fi frequency bands within the channel coherence time, emulating a wideband CSI and beating the narrow bandwidth limitation. It has great localization accuracy of 65 cm using only one AP. The only limitation is that its algorithm need to scan multiple frequency bands and could result in high latency and large power usage. ArrayTrack [8] has a highest accuracy of 23 cm but uses a specialized Rice WARP FPGA radio boards and needs relatively more antennas, i.e., 8 as compared to SpotFi or Cronos that have 3 receiver antennas. Phaser [6], an extension of ArrayTrack, solves the problem of fewer antennas by using two NICs at the same time. It loses one antenna for synchronization and has total of 5 antennas. The accuracy obtained is 1-2 m. ToneTrack [30] has higher accuracy of 90 cm, but uses WARP radios.

D. Machine Learning based Localization Systems

Machine learning (ML) is another category, recently adopted for Wi-Fi sensing and localization because of its powerful prediction and data analytics functions [31]–[35]. Most of the current machine-learning methods use RSS or fingerprinting methodology. Requirement of large training data set is one big disadvantage of ML based methods.

III. Sources of Errors in CSI Measurements

Aforementioned research works using AoA and ToF, aim to achieve a high accuracy for indoor localization that is practical and deployable on commercial off-the-shelf (COTS) hardware. Different from specialized wireless modules, COTS wireless devices usually introduce various errors due to imperfect and/or uncalibrated signals. Consequently, CSI reported by commodity Wi-Fi NICs are mixed with phase rotations due to rich hardware error (delays). The raw CSI cannot derive accurate localization results. In this section we identify, list and explain major sources of phase rotations in 802.11n PHY layer digital processing pipeline. We also discuss and present state-of-the-art methods employed by current studies for compensating each of these errors.

A. Random Initial RF Oscillator Phase Offset

Upon starting up a wireless card, RF chains at TX and RX are locked at random different initial phase offsets $\psi 1$ and $\psi 2$ respectively. This will incur a constant phase value $\psi = \psi 2 - \psi 1$ added to each CSI measurement for a given TX-RX pair till the next recalibration or reset and such a constant phase offset need to be corrected only once before the next hardware reset. This offset is constant for all three dimensions i.e. time, frequency and space (MIMO antennas).

B. Carrier Frequency Offset (CFO)

CFO occurs when the transmitting oscillator carrier frequency f_c and the receiver$\tilde{f}_c$ are not synchronized. When passband signal is downconverter to baseband, this mismatch in central frequency will cause frequency offset of $\Delta f_c = \tilde{f}_c - f_c$ and phase rotation of $e^{-j2\pi\Delta f_c t}$. This offset is constant for all the subcarriers and across all the antennas or receiver chains. It is a function of time and thus, will vary across packets. This offset appears as y intercept in the phase response plot [6]. If this error is large, orthogonality of subcarrier frequencies would be destroyed causing Inter Carrier Interference (ICI). CFO corrector module is added to handle this problem. However, it cannot fully compensate and some residual frequency offset remains. For accurate location estimation, one must eradicate them completely.

C. Sampling Frequency Offset (SFO)

The DAC at the TX and ADC at the RX sample the signal at different times causing an offset of δt.This offset is constant for all subcarriers and antennas. It is relatively stable across packets [4]. SFO adds a phase rotation of $e^{-j2\pi kdf\delta t}$, where df= 312.5kHz is the subcarrier spacing and k is the subcarrier index. SFO is linear across subcarrier index. Please note that this linearity across subcarriers is not visible in the phase response plot until the phase wrapping is removed.

D. Packet Boundary Detection Delay (PBD)

Each 802.11n packet contains preamble, data fields and a transmission vector information [2]. Using this field information, the receiver prepares its PHY demodulation modules for successfully decoding the received packet. Preamble contains long and short training symbols for estimating the effect of channel. PBD is the task of finding the start of preamble for an incoming data packet. The simplest algorithm for packet detection detects the incoming packet by finding the correlation with already known preamble patterns. The number of samples needed to cross its energy detection threshold varies based on power of received signal and the noise floor. This error will be constant for one antenna but may vary across antennas and packets as the signal energy varies over time and space. The difference in noise floors for individual antennas also contribute to the randomness for PBD.

E. Symbol Timing Offset (STO)

STO is also referred to as packet detection delay (PDD). IFFT and FFT are the digital modulation and demodulation techniques for TX and RX for OFDM systems. To detect the starting point of OFDM symbol which facilitates obtaining the exact samples, symbol-timing synchronization must be performed [36], [37]. STO of δt_d samples in time domain causes frequency domain phase rotation of $e^{-j2\pi k\delta t_d/N}$. This offset is linearly proportional to the subcarrier index k as well as detection delay of δt_d. STO is thus variable across packets.

F. Power Control Uncertainty

The received RF signal will vary as square of distance between the receiver and transmitter (path loss). AGC is a closed-loop feedback circuit for maintaining a suitable signal amplitude. AGC (Automatic Gain Control) cannot perfectly compensate the signal attenuation. Paper [4], [38] compensates power uncertainty by averaging. The drawback of compensating error by averaging is that it requires large number of measurements. The more the sample measurements, the better is it in terms of error sanitization. But, large number of measurements may not always be possible especially when hopping multiple bands due to the coherence time limitation.

G. Antenna Coupling Errors

Angle of arrival is computed by comparing the signal phase across array of antennas. The model [10] considers the receiver antennas as independent. This assumption may be rough for Wi-Fi systems. The receiver antennas are usually separated by half-wavelength and for Wi-Fi which operates in 2.4GHz or 5GHz, this distance is in cms. Small distances between antennas influence each other causing antenna coupling and violating the statistically independent MIMO channel property requirement. An error of 5-10 degrees was reported in paper [39]. It would be difficult to achieve decimeter level accuracy without minimizing such large errors.

IV. CSI data Cleansing Techniques

A. Spatial Smoothing

If two multipath signals arrive at the antenna with the same phase i.e. they are coherent, then the most commonly used direction finding algorithm [10] sees the two signals as one superimposed signal resulting in an unresolvable situation and highly distorted AoA spectra. Spatial smoothing [40] is employed by [7], [8] as it decreases the correlation by averaging incoming signals over group of antennas. The disadvantage of this approach, however, is the number of physical antennas is reduced, a quantity already scarse in 802.11n radio. The Kalman filter [41] could be a better method for smoothing noisy data by taking a sequence of noisy values and reliably estimating the values of the underlying true variables.

B. Using Channel Reciprocity

Cronos [11] which uses only one AP and yet achieves very high accuracy uses the property of channel reciprocity to correct the errors. It uses the novel idea that zero subcarrier does not suffer from packet detection delay. They hop 35 frequency bands within coherence time and interpolate the CSI measurement for zero subcarrier for each band. They then use Chinese Remainder Theorem (CRT) over zero subcarrier readings to calculate the propagation delay. Slope of phase response for different packets across subcarriers for a single frequency band is observed. This slope is a mixture of propagation delay, packet detection delay and symbol time offset delay. Propagation delay obtained from zero subcarriers is subtracted from the total delay to separate the packet detection delay. They report that in their experiments, the median packet detection delay was 173 ns which is way too large as compared to propagation delay of less than 100 ns in indoor environment. Clearly, these errors if left uncorrected will hamper the location accuracy tremendously.

C. Using Wired Communication to Cancel the Errors

Another technique to eliminate error was introduced in the ArrayTrack [8] paper. In this paper, the error was measured by connecting the RF port of the transmitter with the RF ports on the receiver using a wired circuit i.e. via a RF splitter [8]. By switching the cables to the RF ports on the receiver that they are connected to, one can obtain the relative phase between the transceiver chains. at RX. The phase then can be calibrated out by subtracting the appropriate phase from the CSI measurements obtained through actual on-air experiments. This method is not very convenient for real world implementation since it requires offline calibration which will interrupt the ongoing Wi-Fi communication.

D. Removing Antenna Coupling with Larger Distances

Larger the distance between the antennas, lower the correlation between the spatial paths [5]. This means, larger distance between the receiver antennas would yield independent measurements across the antennas [11]. Usually, the AP is fixed in a place and has more room for far-spaced antennas as compared to TX which is mostly a client device (e.g. a mobile phone) and does not have this freedom of space for larger antenna spacing. However, in most cases it is the AP that will do the location estimation for the client. Considering and eliminating mutual coupling can reduce the angle estimation errors and as a consequence increase the accuracy.

E. Using the Property of Constant Power Delay Profile

Power Delay Profile (PDP) is an intrinsic time domain property of the channel. It can be obtained by taking the IFFT of the CSI matrix. For stationary environments and nodes, different frequency bands within channel coherence time should result in same PDP even though the CSI matrices are different. This idea was noticed and implemented by paper [4]. In their system called Splicer, multiple packets are averaged to reduce power uncertainty and PBD errors. Then they use constant multipath characteristic property across bands to remove SFO. They rotate the CSI measurements from two bands until two bands produce the same PDP.

F. Complex Conjugate Method

Studies in [13]–[15] use the property that the phase noises caused by the STO and SFO vary only in time and frequency and not space. This implies that all the three RF chains in the receiver experience the same unknown phase noises during the same time interval. So, taking one antenna as reference and multiplying the other antenna readings with complex conjugate of this reference antenna data, will cancel the errors. We summaries the error-correction methods and the accuracy obtained by various systems in Table I below.

TABLE I
SUMMERY OF EXISTING SYSTEMS THAT USE COMMODITY INFRASTRUCTURE

System	Accuracy	Error-correction techniques
Cronos [11]	65cm (LOS), 98cm (NLOS)	averaging, channel reciprocity,zero subcarrier, larger antenna distance
SpotFi [7]	40cm (LOS), 160cm (NLOS)	manual calibration, linearity removal, spatial smoothing
Ubicarse [29]	22,28,18 cm (x,y,z LOS), 32,46,20 cm (x,y,z NLOS)	robust to CFO and SFO
Splicer [4]	95cm(LOS)	averaging, uses property of same power delay profile for multiple bands
Indotrack [14]	48cm (passive tracking)	complex conjugate
Wiradar2.0 [13]	75cm (passive tracking)	complex conjugate

V. Discussion and Future Research Direction

Indoor localization has found a broad range of applications including marketing, museums, airports, health services, disaster management, drone navigation, Internet of Things (IoT) devices, heterogeneous sensor networks [42] and many other applications. Accurate location information could benefit other standards like LTE-Advance particularly in spectrum management and interference mitigation in femtocells [43], [44]. Most of the current works using off-the-shelf hardware do not remove all the errors and/or rely on some assumptions or prior calibration. The 2017 Microsoft Indoor Localization Competition [45] offered uniform and realistic settings to participants to implement their localization techniques. The results show that many groups from academia and industry could not achieve their reported accuracy. We believe that this inconsistency stems from the difference in implementation environment; researchers report high accuracy obtained in ideal settings and thus are not able to get the same results in an unfamiliar environment. We strongly believe that eliminating all the errors we listed could produce accurate and reproducible results in any environmental setting. The intentional focus of this survey is to expose and better understand the non-trivial phase noises that plague the raw CSI measurements obtained from the commodity hardware. With this clear understanding, we aspire that the community can come up with efficient error compensation mechanisms either using signal processing techniques or machine learning algorithms; turning the vision of precise and inexpensive indoor localization system into a reality.

Wi-Fi standards are continuously evolving. Newer standards like 802.11ah, 802.11af and 802.11ad (60 GHz) will enable development of entire new class of localization algorithms. For example, 802.11ad standard created for gigabit data rates will support tiny antennas as they operate in very high frequency. As a result, large number of antennas can be stuffed into small devices like smart phones and smart watches that typically have one antenna; making phased-array antenna signal processing feasible on small devices. Also, at these high frequencies the communication would be highly directional leading to fewer multipaths and increased accuracy.

VI. Conclusion

In this paper, we presented key techniques and challenges of indoor localization using commodity Wi-Fi equipment supporting 802.11n protocol. The major problem with using COTS Wi-Fi cards are the phase noises. In practice, it is challenging to meet the millimeter accuracy requirement using the commodity hardware without eliminating phase noises. We enumerated all the possible error sources, clarified how each varies across time, frequency and space, so that they can be removed more efficiently making Wi-Fi commodity hardware a mainstream indoor localization solution.

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