WLAN Indoor Localization Using Angle of Arrival

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Abstract. With the development of information technology and the rising of demanding for location-based services, indoor localization has obtained great attentions. Accurate estimation of Angle of Arrival (AoA) of signals make it possible to achieve a high precision location. So as to resolve multipath signals effectively and then extract AoA of the direct path, in this paper we first use the existing three-antenna commercial Wi-Fi Network Interface Card (NIC) to collect radio Channel Frequency Response (CFR) measurements and then jointly estimate AoA and Time of Arrival (ToA). Second, we propose a sensing algorithm to distinguish Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) propagation and therefore obtain finer localization. Our experiments in a rich multipath indoor environment show that the AoA-based the proposed localization system can achieve a median accuracy of 0.8 m and 1.3 m in LoS environment and NLoS environment, respectively.

Keywords: Indoor localization · Wi-Fi · CFR · AoA

1 Introduction

Recent years have witnessed a great interest in developing indoor localization system that can enable clients to navigate indoor spaces. Location-based service has become more and more important with the rapid development of Internet of Thing (IoT) and smart home. Outdoors, users can share a robust and accurate localization from Global Positioning System (GPS) and BeiDou Navigation Satellite System (BDS) while indoor localization is unavailable since signals of satellite are faded severely due to obstacle. Thus, providing a high accuracy indoor location is significant important.

Many high accuracy indoor localization systems have been developed recently, such as radio frequency identification (RFID) [1], RSSI based, and AoA based. RFID is limited by power and can only be used for short-range localization. Fingerprint based localization system in WLAN is labor and time consuming. At the same time, this system is difficult to deploy since they require

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an expensive and recurring fingerprinting operation when there are changes in the environment. AoA of multipath computation with conventional MUSIC algorithm [2] requires that the antenna number must greater than multipath components. But typically in an indoor environment there are around 6–8 significant reflectors [3], so it is impossible for current commodity Wi-Fi device. Indoor localization using AoA based on WiFi signal is a well studied problem and there are many prior works in AoA. Niculescu and Nath [4] emulate AoA-based localization in an ad hoc mesh network. AoA has been proposed in CDMA mobile cellular systems, especially as a hybrid approach between AoA and TDoA [5], and also in concert with interference cancellation and ToA estimation [6]. Patwari and Kasera [7] propose a system that uses the channel impulse response and channel estimates of probe tones to detect when a device has moved, but it does not address localization problem. Geo-fencing [8] utilizes directional antennas and a frame coding approach to control APs indoor coverage boundary. SpotFi have been proposed in [16] to obtain centimeter-level localization, but the coherent signals are not considered.

In this paper we propose a novel indoor localization system that can be deployed on commodity Wi-Fi infrastructure. The system incorporates spatial smoothing algorithm that can accurately estimate AoA of multipath components even when the access point (AP) has only three antennas. Then, we use clustering algorithm to classify multipath components in indoor multipath environment. After that, we use weighting factor to identify the direct path among multiple paths, moreover we can discern identify LoS and NLoS propagation. Finally, the target can be localized by least squares (LS) algorithm with several direct path AoA.

The organization of this paper as follows: the system design is presented in Sect. 2. Our experimental evaluation is presented in Sect. 3. Then, we conclude this paper in Sect. 4.

2 System Design

In this section, we detail three techniques: super-resolution AoA estimation algorithm, direct path identification and propagation recognition algorithm. The super-resolution AoA estimation algorithm mainly solves the problem of limitation of the number of physical antennas by using a spatial smoothing technique, and then we can realize precise AoA estimation of indoor multipath signals with commodity AP equipped with only three antennas. The direct path recognition algorithm uses the AoA and ToA computed by the super-resolution algorithm to classify the path with clustering algorithm and then selects the direct path by means of weighting analysis method.

2.1 Channel Model Description

The Wi-Fi signal in 802.11n standard use orthogonal frequency division multiplexing (OFDM) modulation. OFDM is an encoding method using multiple carriers and widely used in wireless communication. It divides the channel into many orthogonal sub-channels in the frequency domain and then transmit data with subcarriers in parallel. For OFDM modulation signal, channel frequency response (CFR) can be used to describe the channel parameters including attenuation and delay of multipaths. It can be denoted as

$$Y\left(e^{jw}\right) = H\left(e^{jw}\right) X\left(e^{jw}\right) + \mathbf{N} \tag{1}$$

where $Y\left(e^{jw}\right)$ and $X\left(e^{jw}\right)$ are the received and transmitted signal in frequency domain, respectively. $H\left(e^{jw}\right)$ denotes CFR, $\mathbf{N}$ denotes white Gaussian noise. At the transmitter, the original data is converted into symbol sequence and inverse fast Fourier transform (IFFT) algorithm is used to realize the orthogonal subcarrier modulation and the cyclic prefix is added to the radio frequency (RF) emission. At the receiver, the frequency conversion of the RF signal is carried out first, after removes cyclic prefix fast Fourier transform (FFT) algorithm is used to demodulation the orthogonal sub-carrier. Next, system carries on channel estimation according to the incoming leading signal (Pilot), the obtained value is the CFR measured value for each sub-carrier. According to the IEEE 802.11n standard, the 40 MHz bandwidth uses 114 subcarriers, and the corresponding subcarrier measurements are outputted during signal processing.

2.2 Super-Resolution AoA Estimation Algorithm

MUSIC algorithm [9] requires that the number of array antennas is greater than the number of multipath components or the signal and noise subspace cannot be separated. Moreover, the performance of MUSIC algorithm degraded severely in indoor environment because of the signal subspace diffusing into the noise subspace when the source is coherent.

Super-resolution AoA estimation algorithm uses spatial smoothing technology to create a virtual antenna array. The CFR in different subcarrier is written as

$$\mathrm{CFR}\left[f_n\right] = \sum_{k=1}^{K} \alpha_k e^{-j2\pi(f_0+n\Delta f)\tau_k} \tag{2}$$

where K is the number of propagation paths, α_k is the complex attenuation of the k^{th} path, τ_k is the time delay of the k^{th} path, and $f_n = f_0 + n\Delta f$ is carrier frequency of subcarrier, Δf is the subcarrier spacing. We implemented our system on Intel 5300 commodity Wi-Fi card, which can measure CFR at 30 of the subcarriers while data is sent on 114 subcarriers for 40 MHz bandwidth.

We assume there are K paths arriving at receiver, so CFR measurement matrix of 30 subcarriers on three antennas can be expressed as follows:

$$\mathbf{H} = \left[h_{1,1}, \ldots, h_{1,N}, h_{2,1}, \ldots, h_{2,N}, \ldots, h_{M,1}, \ldots, h_{M,N}\right]^{\mathrm{T}} \tag{3}$$

where $h_{m,n}$ is the CFR of n^{th} subcarrier at m^{th}antenna. And then, $\mathbf{H}$ is given by

$$\mathbf{H} = \mathbf{AX} + \mathbf{N} \tag{4}$$

where matrix $\mathbf{N}$ is additive white Gaussian noise of zero mean and covariance $\sigma^2\mathbf{I}_{MN}$ can be write as $\mathbf{N} = [n_{1,1},\dots n_{1,30}, n_{2,1},\dots n_{2,30}, n_{3,1},\dots n_{3,30}]^{\mathrm{T}}$, and attenuation coefficient vector X is given by

$$\mathbf{X} = [\alpha_1, \alpha_2, \dots \alpha_K]^{\mathrm{T}} \tag{5}$$

The matrix $\mathbf{A}$ is a steering matrix which can be written as:

$$\mathbf{A} = [\mathbf{a}(\theta_1, \tau_1), \mathbf{a}(\theta_2, \tau_2), \dots, \mathbf{a}(\theta_k, \tau_k)] \tag{6}$$

where $\mathbf{a}(\theta, \tau)$ expressed as:

$$\mathbf{a}(\theta, \tau) = [\alpha_1(\theta, \tau), \alpha_2(\theta, \tau), \dots, \alpha_m(\theta, \tau)]^{\mathrm{T}} \tag{7}$$

where $\alpha_m(\theta_k, \tau_k) = [\alpha_{m,1}(\theta_k, \tau_k), \dots, \alpha_{m,n}(\theta_k, \tau_k)]^{\mathrm{T}}$ is the steering vector of the k^{th} subcarrier at m^{th} antenna, $a_{m,n}(\theta_k, \tau_k) = e^{-j2\pi[(n-1)\Delta f \tau_k + d(m-1)\sin\theta_k/\lambda]}$ and Δf is subcarrier frequency spacing, τ_k and θ_k are the TOA and AOA of the k^{th} path, respectively, d is antenna spacing.

The covariance matrix of measured CFR is given by

$$R = E\left\{H \times H^{\dagger}\right\} \tag{8}$$

where $(.)^{\dagger}$ represent the transpose-conjugate operator. A prior work [17] has noted that the minimal eigenvectors are orthogonal to the steering matrix $\mathbf{A}$. So, the spatial spectrum of multipath components, which respect to AoA and ToA is written as:

$$P_{\text{music}} = \frac{1}{\alpha^{\mathrm{H}}(\theta, \tau)\, E_N {E_N}^{\mathrm{H}} \alpha(\theta, \tau)} \tag{9}$$

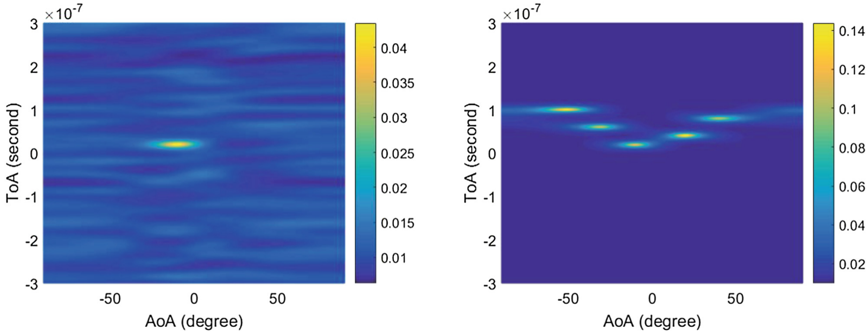
where E_N is the noise subspace eigenvector of covariance matrix R.

MUSIC algorithm can determine AoA only when the received signals are incoherent with each other. But the received signals include many coherent signals that can degrade the performance of MUSIC in indoor environment. Prior work [16] propose a novel method to get several dependent snapshots by reconstructing CFR measurements, but the coherent signals are not be considered. In order to decorrelate the coherent signals, we propose a two-dimensional spatial smoothing algorithm.

Indeed, one could check that the total number of overlapping subarrays is equal to $L_1 \times L_2$, where $L_1 = M - M_{sub} + 1$ and $L_2 = N - N_{\text{sub}} + 1$. The CFR measurement $N_{\text{sub1}} = 2$ and $N_{\text{sub2}} = 15$, and therefore a total of $L_1 \times L_2 = 32$ subarrays. The 2D spatial smoothed covariance matrix is given by

$$\overline{R} = \frac{1}{L_1 \times L_2} \sum_{m=1}^{L_1} \sum_{n=1}^{L_2} R_{m,n} \tag{10}$$

where $R_{m,n}$ is the CFR covariance matrix of subarray $\{(i,j)\}_{j=n\dots N_{sub}+n-1}^{i=m\dots M_{sub}+m-1}$. Plug Eq. (9) into MUSIC algorithm to estimate each path AoA and ToA.



(a) with no decorrelate. (b) with decorrelate.

Fig. 1. (a) Plots the AoA and ToA of five coherent signals in typical algorithm and (b) plots the AoA and ToA of five coherent signals in spatial smoothing.

Simulation results are presented to show the validity of 2D spatial smoothing. Simulations have been done with $M = 3$ antennas and $N = 30$ subcarriers. The antenna spacing d is half a wavelength. The subcarrier spacing is chosen 1.25 MHz and carrier frequency is 5.2 GHz.

We have fixed $s = 5$ coherent signals, where there corresponding angles and times of arrival are $(\theta_1, \tau_1) = (-10^\circ, 20\,\text{ns})$, $(\theta_2, \tau_2) = (20^\circ, 40\,\text{ns})$, $(\theta_3, \tau_3) = (40^\circ, 80\,\text{ns})$, $(\theta_4, \tau_4) = (-50^\circ, 100\,\text{ns})$, $(\theta_5, \tau_5) = (-30^\circ, 60\,\text{ns})$. Figure 1 shows the determine result of no spatial smoothing and spatial smoothing. It is shown that the 2D spatial smoothing technology can accurately estimate AoA and ToA.

2.3 Identifying Direct Path AoA

Phase Correction: In multipath propagation indoor environment, the spatial spectral function calculated by the MUSIC algorithm has more than one peak which stands for the existence of the multipath signal. According to triangulation principle, it is necessary to determine the direct path for each LoS AP. To the best of knowledge, there are some conventional direct path identification using the shortest ToA or biggest spectral peak to determine the direct path. The signal with shortest ToA is treated as the direct path in [11,12] since the sender and receiver are time synchronization and the accuracy of ToA estimation is nanosecond level. But for the current Wi-Fi network cannot achieve so high accuracy. Moreover, in Wi-Fi networks each received packet introduces a random packet detection delay (PDD) which introduces an additional delay for all multipath components.

The PDD is different for each received data packets and the additional phase shift at subcarrier caused by PDD is $-2\pi \Delta f\,(n-1)\,\tau$ presented in [13]. Usually, τ is the additional delay with 3 to 6 sample times. For 20 MHz bandwidth Wi-Fi signal, the signal is sampled once every 50 ns. Thus, τ is 75 to 150 ns which is much larger than the normal ToA of WiFi signal in indoor environment. Consequently, the CSI phases between subcarriers are approximately linear. However, all the RF channels in the same Wi-Fi chip are fully synchronized, so the phase shift at a particular subcarrier is same across all antennas. We use least squares linear fit algorithm to estimate and then eliminate the effect of PDD on CFR phase for each subcarrier. Assuming $\Phi_i(m,n)$ is the n^{th} subcarrier CFR phase in the i^{th} packet received at m^{th} antenna. The least squares fit using CFR phases of 30 subcarriers at 3 antennas is given by

$$\hat{\tau}_i = \underset{\tau_i}{\arg\min} \sum_{n=1}^{30} \sum_{m=1}^{3} \left(\Phi_i(m,n) + 2\pi \Delta f (n-1)\tau_i + \beta\right)^2 \tag{11}$$

Then, we correct the CFR phase as following:

$$\overset{\wedge}{\underset{i}{\Phi}}(m,n) = \Phi_i(m,n) + 2\pi \Delta f (n-1) \overset{\wedge}{\underset{i}{\tau}} \tag{12}$$

Identifying Direct Path and NLoS/LoS Environment: After obtain several clusters corresponding to each physical paths [14,15], we need to identify the clustering belongs to direct path. In this paper, we use a weight based direct path identification scheme proposed in [16]. We assign weights for each path as:

$$w_k = f(\omega_c C_k - \omega_\theta \sigma_{\theta_k} - \omega_\tau \sigma_{\tau_k} - \omega_s \tau_k) \tag{13}$$

where f is an increment function, C_k, σ_{θ_k}, σ_{τ_k} and τ_k are the number of extreme points, angle variance, time variance and mean time of the k^{th} clustering, respectively. And ω_c, ω_θ, ω_τ and ω_s are weight factor of extreme points, angle variance, time variance and time mean, respectively. Then, we select path with the largest weights as the direct path and the average angle of the clustering as the direct path AoA.

Usually there is no direct path between target and APs due to obstacle blocking in complex indoor environment. So the selected direct path by the foregoing step is incorrect, so as to avoid this case we need to distinguish LoS and NLoS condition before locating the target. We conduct data collection campaign in LoS and NLoS environment, respectively. The maximum weights calculated by the Eq. (15) were extracted from LoS and NLoS environment respectively, and then we calculate a threshold which can class LoS and NLoS environment. In fact, LoS/NLoS identification can be formulated as a class binary hypothesis test with LoS condition and NLoS condition as following:

$$\begin{cases} H_0 : w \le w_{th} \\ H_1 : w > w_{th} \end{cases} \tag{14}$$

where w_{th} is the optimal threshold.

2.4 Localizing the Target

We use the AoA of direct paths of multiple APs to locate the target and we assume there are R receivers in which receivers are in LoS environment. We measure the deviation using standard least squares cost. Mathematically, we find the location that minimizes the following objective function:

$$\text{location} = \min \sum_{i=1}^{R_{\text{los}}} \left(\hat{\theta}_i - \theta_i\right)^2 \tag{15}$$

where θ_i is the true direct path AoA of i^{th} AP, and $\hat{\theta}_i$ is the estimated direct path AoA at i^{th} AP.

3 Experimental Evaluation

We implemented our system in a typical indoor environment, and we deploy four ProBox23 MS-B083 mini PCs equipped with Intel 5300 commodity Wi-Fi cards which act as access points and one PC in tester act as the target. Each AP possesses an antenna array consisting of three omnidirectional antennas with spaced by half a wavelength and no further hardware modification. The locations of every access points are measured accurately using laser range finder when we install APs on the wall. We use Linux CSI toolkit [10] to collect CFR measurements and then ship the measurement to the localization engineer acted by a computer and Fig. 2 shows our testbed.

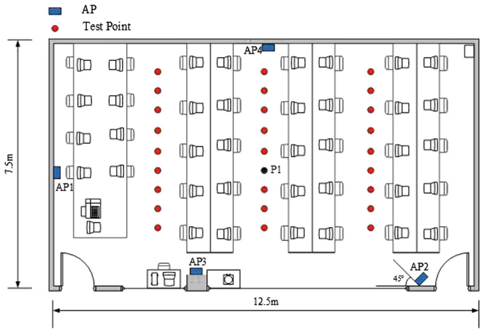
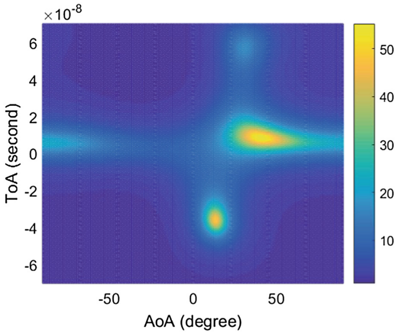
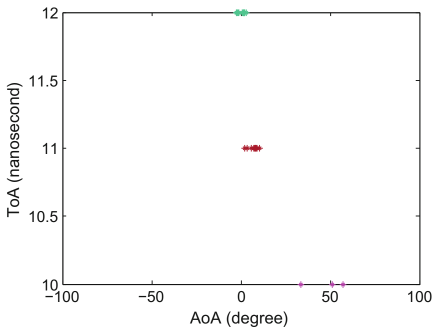


Fig. 2. Experiment tested showing the target locations (red spots) and the AP locations (blue rectangles). The region covering 12.5 m × 7.5 m area, represents typical indoor office environment. (Color figure online)

Estimating direct path AoA: Figure 3 shows the clustering and spatial spectrum at one AP and the test point P1. The data collected at test point P1 is transmitted to the central server. The performance of AoA estimation our algorithm is shown in Fig. 4. From this figure, we can find that our algorithm outperforms the conventional MUSIC algorithm used by SpotFi. Our algorithm is able to achieve the median angle error 5° better than that achieved by SpotFi in the actual static indoor environment. Since our algorithm can resolve more coherent signals comparing to the SpotFi, so the multipath components have lower interference on the AoA estimation of direct path.



(a) Spatial Spectrum.



(b) AoA-ToA clusters.

Fig. 3. Plots spatial spectrum and AoA-ToA clusters respectively.

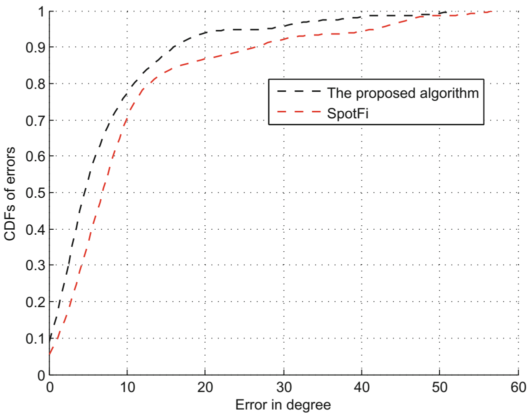
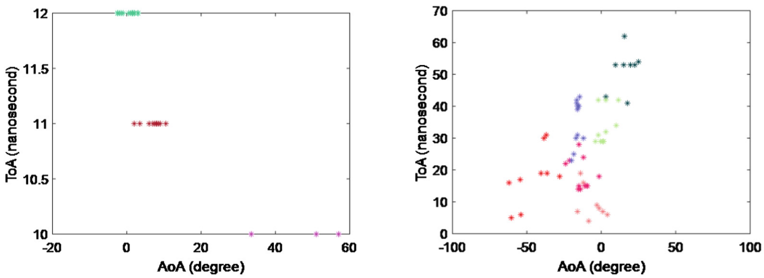


Fig. 4. Plots CDFs of AoA estimation error achieved by proposed algorithm and SpotFi in this paper for the same data.

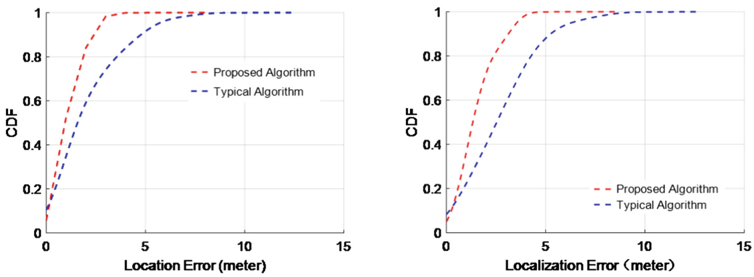
Identifying LOS/NLOS environment: We create a NLoS environment between AP4 and the target at test point P1. Figure 5 shows the result of path clustering with the AP4 at test point P1 in LOS environment and NLoS environment respectively. The clustering result present that the angle clustering map is concentrated in LOS environment while dispersed in NLoS environment.

Localizing the target: Figure 6 shows the localization error accumulation curve in LOS environment and NLOS environment respectively. We can see that in LOS environment median location errors is 0.8 m with proposed super-resolution angle estimation algorithm and the location accuracy reaches sub-meter level while 1.7 m with typical MUSIC algorithm. In NLOS environment, the median location error is 1.3 m with proposed environment recognition algorithm while 2.7 m with typical algorithm.



(a) LOS Environment. (b) NLOS Environment.

Fig. 5. AoA-ToA clusters in LOS environment and NLOS environment respectively.



(a) LOS Environment. (b) NLOS Environment.

Fig. 6. The CDFs of localization error by proposed algorithm and compare with location error by typical algorithm for the same data in LOS environment and NLOS environment respectively.

4 Conclusion

We have presented a sub-meter accuracy indoor localization system only use commodity AP with three antennas. The system firstly provides an OFDM signal based super-resolution AOA estimation algorithm. The algorithm can accurately estimate AoA of multipath signal with no additional hardware modification. And then using a clustering based direct path detection algorithm to pick out direct path. We also expand the direct path information to the scene recognition that can improve the robustness of the localization system. Since the system using multiple antennas and the characteristics of the OFDM signal, such that the algorithm of the present system is readily ported to the LTE system and the upcoming 5G communication system.

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