Angle-of-Arrival Positioning System Based on CSI Virtual Antenna Array

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Abstract. Traditional Wi-Fi positioning systems usually use the signal intensity for fingerprint localization. However, the intensity of the received signal varies with time. And it is also easily affected by the indoor multipath environment. This paper presents a positioning system using Channel State Information (CSI) exposed by commodity Wi-Fi chips without any hardware adjustments. The core modules of this system include an Angle of Arrival (AOA) and Time of Flight (TOF) estimating algorithm using CSI, along with a clustering algorithm to identify the direct path in multipath environment. In this paper, we employ affine propagation clustering to avoid disadvantages of traditional K-means algorithm. The experiment results show the proposed system achieves an accuracy of about 1 m in a multipath-rich indoor environment.

Keywords: Indoor positioning · Channel state information · Angle of arrival

1 Introduction

As an important part of pervasive computing and Internet of Things (IOT), location technology is attracting more and more attention. Although Global Navigation Satellite System (GNSS) can provide high precision localization services in outdoor environment, satellite signals will decay due to wall obstructing and so on indoors [1]. As the GNSS is not able to achieve high positioning accuracy, indoor localization technology has received more attention.

In recent years, many indoor positioning technologies have been developed, such as Wi-Fi, Base-station, Ultra-wide bandwidth (UWB) based localization systems [2, 3]. With the development of Multiple-Input Multiple-Output (MIMO) technology, Angle of Arrival (AOA) based systems have been paid much attention. This kind of systems generally estimates the AOA of multipath signal at each wireless Access Point (AP), and then use triangulation method to locate the target. For example, Wang and Ho proposed an AOA-based system using hybrid AOA-TDOA positioning [4], which extends the source range to 90 m and maintains the estimation accuracy. But this system requires preliminary measurement of unique positions. A novel autofocusing approach for Direction of Arrival (DOA) estimation, proposed by Pal and Vaidyanathan, applies modified focusing matrices in the coherent methods for wideband DOA

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estimation using 8 antennas and exhibits satisfactory performance in comparison to the existing algorithms [5]. While the hardware of the autofocusing algorithm is difficult to deploy.

Channel State Information (CSI) is a kind of Physical layer (PHY) information, which extends Received Signal Strength Indication (RSSI) to frequency domain with phase information per subcarrier per antenna. Thus CSI is a kind of fine-grained information. Zhou used a deterministic CSI fingerprinting method and a threshold-based method separately to detect human presence in an omnidirectional manner [6]. Li Mo measured the CSI of multiple subcarriers in the coherent time of the channel, making it possible to achieve a median accuracy of sub-meter level [7]. However, these systems require strict time synchronization of all APs, which is impossible in commodity Wi-Fi infrastructure.

In this paper, the CSI of subcarrier is used to establish one-dimension Multiple Signal Classification (MUSIC) algorithm [8] in frequency domain. To meet the number requirement of antennas in AOA based system, an AOA and Time of Flight (TOF) joint estimation MUSIC algorithm is applied to expand the number of antennas by using spatial smoothing technique [9, 10]. In addition, affinity propagation clustering method is applied to cluster the paths, and a weight allocation based method is used to recognize Line of Sight (LOS) path. At last, the least square algorithm is used to locate the target with AOA and LOS information of multiple APs.

2 Preliminary

2.1 MUSIC Algorithm

Considering a uniform linear array (ULA) with N antennas, d is the distance of adjacent sensor, M is the number of uncorrelated signal sources ($M < N$), θ_k is the AOA of the k^{th} source. The sampled data vector $x(t)$ obtained at time t by ULA is:

$$x(t) = As(t) + n(t) \tag{1}$$

where A is the $N \times M$ steering matrix, $s(t)$ is the $M \times 1$ signal vector, $n(t)$ is the additive white Gaussian noise vector.

$$A = [a(\theta_1), a(\theta_2), \cdots, a(\theta_M)] \tag{2}$$

$$a(\theta_k) = \left[1, e^{2\pi d \sin\theta_k/\lambda}, \cdots, e^{2\pi(N-1)d\sin\theta_k/\lambda}\right]^T \tag{3}$$

$$s(t) = [s_1(t), \cdots, s_M(t)]^T \tag{4}$$

$$n(t) = [n_1(t), n_2(t), \cdots, n_M(t)]^T \tag{5}$$

where λ is the wavelength of signals, $a(\theta_k)$ is the steering vector of the k^{th} propagation path.

Since the incident signals on each sensor are uncorrelated with the noise, the $N \times N$ covariance of vector $x(t)$ is:

$$\begin{aligned} R &= E\left[x(t)x^H(t)\right] \\ &= AE\left[s(t)s^H(t)\right]A^H + E\left[n(t)n^H(t)\right] \\ &= APA^H + \sigma^2 I \end{aligned} \tag{6}$$

where I is an identity matrix and diagonal matrix $P = E[s(t)s^H(t)] \in C^{N \times N}$. Note that the rank of A is M, so is the rank of P, which is less than N, therefore:

$$\left|APA^H\right| = 0 \tag{7}$$

For A full rank and P positive definite, APA^H is nonnegative definite. Therefore, R is Hermitian matrix. Conducting the singular-value decomposition (SVD) of R, we have:

$$R = U_s \Sigma_s U_s^H + U_n \Sigma_n U_n^H \tag{8}$$

where $U_s = [u_1, u_2, \cdots, u_M] \in C^{N \times M}$ is the matrix composed of the signal eigenvectors and $U_n = [u_{M+1}, u_{M+2}, \cdots, u_N] \in C^{N \times (N-M)}$ is the matrix composed of the noise eigenvectors. The columns of U_s and U_n span the signal subspace and its orthogonal subspace respectively. According to definitions, $span(U_s) = span(A)$ and $span(U_n) \perp span(A)$. Together with (6) and (7), we have:

$$RU_n = \sigma^2 U_n \tag{9}$$

$$RU_n = APA^H U_n + \sigma^2 U_n \tag{10}$$

Therefore, $APA^H U_n = 0$ and:

$$U_n^H APA^H U_n = \left(A^H U_n\right)^H PA^H U_n = 0 \tag{11}$$

Since P is full-rank, $A^H U_n = 0$. Using this property, the AOAs of M signals can be found as:

$$P_{MUSIC}(\theta) = \frac{1}{a^H(\theta) U_n U_n^H a(\theta)} \tag{12}$$

2.2 CSI Phase Correction

Since Wi-Fi network is built based on a burst communication mechanism, each received CSI packet will introduce packet detect delay (PDD). Compared with 10 ns-level mean propagation delay, PDD is much higher [7]. As a result, the acquired CSI phase cannot be used directly. By applying linear least square fitting method, the influence of PDD can be eliminated. We can build the model of CSI phase as [11]:

$$\varphi(s) = \varphi(s) + 2\pi s \Delta f \delta + \beta \tag{13}$$

where $\widehat{\varphi}(s)$ and $\varphi(s)$ are the measured CSI phase and the true CSI phase of the s^{th} subcarrier, respectively. Δf is the frequency interval between subcarriers. δ_i is the PDD of i^{th} packet and β is the phase noise. Let $\psi_i(n,s)$ denote the unwrapped CSI phase from the i^{th} packet at the s^{th} subcarrier of the n^{th} antenna, the optimal slope of unwrapped CSI phase is obtained by:

$$\widehat{\delta}_i = \arg_{\delta_i} \min \sum_{n,s=1}^{N,S} \left(\psi_i(n,s) - \widehat{\varphi}(s)\right)^2 \tag{14}$$

where N denotes the number of antennas and S denotes the number of subcarriers. Then subtract phase offset $\widehat{\delta}_i$ caused by PDD from unwrapped CSI phase and obtain modified CSI phase $\widehat{\psi}_i(n,s)$:

$$\widehat{\psi}_i(n,s) = \psi_i(n,s) - s\widehat{\delta}_i \tag{15}$$

Figure 1 indicates the phase of unwrapped CSI (left) and modified CSI (right). After CSI phase correction, the CSI phase of two consecutive packets match basically in spite of different PDDs.

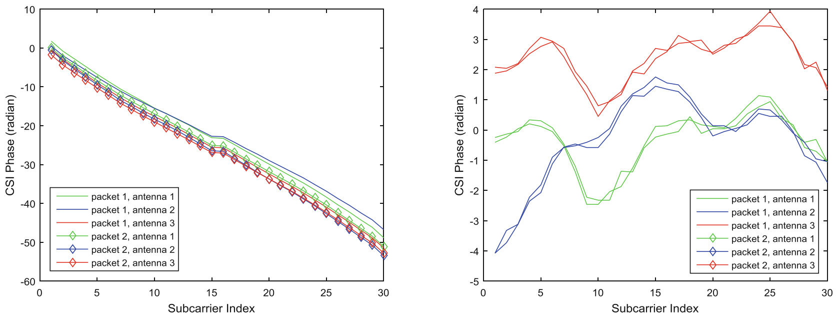

Fig. 1. Comparison of unwrapped CSI phase and modified CSI phase.

3 System Design

The workflow of the positioning system in this paper is illustrated in Fig. 2. The system estimates the AOA and TOF of multipath signals arriving at APs from the target using CSI information obtained from Wi-Fi Network Interface Cards (NICs). Then, the system identifies the most possible direct propagation path from the target to AP based

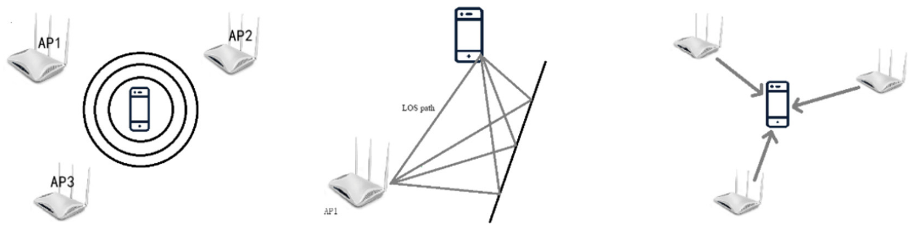

Fig. 2. Workflow of the system: First, collect CSI data from all the APs in range. Then the system estimates the AOA and TOF of all propagation paths from the target to each AP and identify the LOS path between the target and the AP. Finally, the system locates the target with AOA data of multiple APs.

on the weight of each path. Finally, by combining AOAs of all direct paths, the system estimates the target's position.

3.1 Estimating AOA and TOF

Let's denote S as the number of subcarriers of each antenna, and assume that there are L propagation paths. θ_k is the angle between the k^{th} path and the antenna. To the Wi-Fi signal of a propagation path, the largest phase shift between subcarriers introduced by the distance between antennas can be expressed as:

$$\Delta\varphi = 2\pi \times (3 - 1) \times \left(f_i - f_j\right) \times d \times \sin\theta / c \tag{16}$$

where f_i and f_i denote the frequency of the i^{th} and the j^{th} subcarrier. Assuming that d = $\lambda/2$, where λ denotes the wavelength of the subcarrier, in order to avoid pseudo peak values [12]. Previous studies have shown that the number of significant multipath signals in indoor environment is usually 6–8 [13]. Here we remodel the CSI matrix of N antennas by introducing TOF to connect the phases of each subcarrier:

$$\begin{bmatrix} csi_{1,1} \\ \vdots \\ csi_{1,S} \\ csi_{2,1} \\ \vdots \\ csi_{2,S} \\ \vdots \\ csi_{N,1} \\ \vdots \\ csi_{N,S} \end{bmatrix} = \begin{bmatrix} 1 & \cdots & 1 \\ \vdots & \ddots & \vdots \\ e^{-j2\pi\times(S-1)\Delta f\tau_1} & \cdots & e^{-j2\pi\times(S-1)\Delta f\tau_L} \\ e^{-j2\pi f_1 d\sin\theta_1/c} & \cdots & e^{-j2\pi f_1 d\sin\theta_L/c} \\ \vdots & \ddots & \vdots \\ e^{-j2\pi\times(S-1)\Delta f\tau_1} e^{-j2\pi\times f_1 d\sin\theta_1/c} & \cdots & e^{-j2\pi\times(S-1)\Delta f\tau_1} e^{-j2\pi\times f_1 d\sin\theta_L/c} \\ \vdots & \cdots & \vdots \\ e^{-j2\pi\times f_1\times(N-1)d\sin\theta_1/c} & \cdots & e^{-j2\pi\times f_1\times(N-1)d\sin\theta_L/c} \\ \vdots & \ddots & \vdots \\ e^{-j2\pi\times(S-1)\Delta f\tau_1} e^{-j2\pi\times f_1\times(N-1)d\sin\theta_1/c} & \cdots & e^{-j2\pi\times(S-1)\Delta f\tau_1} e^{-j2\pi\times f_1\times(N-1)d\sin\theta_L/c} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_L \end{bmatrix} \tag{17}$$

where $\beta_k = \alpha_k \times e^{-j2\pi f_1\tau_k}$. We can see that the number of sensors has been expanded to $N \times S$. However, an indoor environment is usually filled with coherent signals, thus the CSI value we obtained from (17) across antennas is not independent. Therefore, the noise subspace will spread to the signal subspace, resulting in the performance degradation of the algorithm. Traditional MUSIC algorithm solves this problem at the cost of the number of antennas [9]. Different from the traditional method, we apply a two-dimensional spatial smoothing method. If we divide the two dimensional array with $N \times S$ sensors into subarrays of size $N_{sub1} \times N_{sub2}$, then the channel frequency response matrices of all subarrays are obtained. Finally we expand the number of sensors to $(N - N_{sub1} + 1) \times (S - N_{sub2} + 1)$. We can conduct two dimensional MUSIC algorithm on the smoothed CSI matrix and get estimated AOA and TOF.

Figure 3 illustrates the simulation results of AOA estimation by both traditional MUSIC algorithm and our modified MUSIC algorithm. It should be mentioned that the modified MUSIC estimator has been shown to perform better than traditional MUSIC estimator with higher precision.

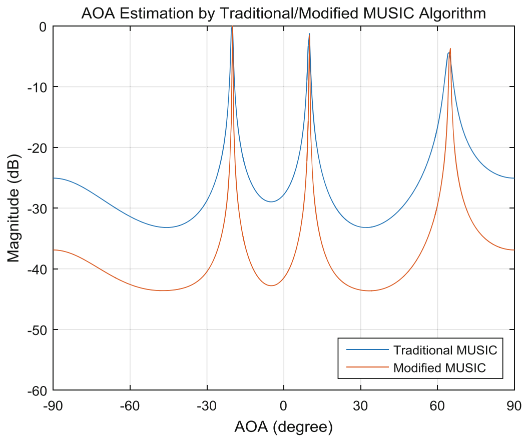

Fig. 3. Comparison between traditional MUSIC algorithm and modified MUSIC algorithm.

3.2 Identifying Direct Path

Typically, there are about 5 significant multipath signals [14]. However, in the actual situation, the number of paths that each AP receives at different times may change, and the number of fixed classes in the clustering algorithm may lead to a decrease in the positioning accuracy. The clustering method used in this paper is affine propagation clustering [15]. Compared to traditional clustering algorithms, such as K-means clustering, affine propagation clustering does not need to select the number of clusters in advance, and the number of paths can be determined adaptively. At the same time, the clustering effect will not be reduced because of the improper selection of the initial cluster center.

We normalize the data in time and angle dimensions, and let similarity $s(i, j)$ denotes the negative squared error (Euclidean distance) between extreme points as similarity:

$$s(i,j) = -\left\|\Omega_i - \Omega_j\right\|_2, \forall i,j \neq i \in \{1,2,\cdots,N_{data}\} \tag{18}$$

where Ω_i and Ω_j are two random extreme points, N_{data} is the number of data points. After calculating the similarity of all extreme points, the similarity is stored as a $N_{data} \times N_{data}$ matrix. Similarly, let $s(k, k)$ denotes the self-similarity:

$$s(k,k) = \frac{\sum_{i,j=1,i\neq j}^{N_{data}} s(i,j)}{N_{data} \times (N_{data} - 1)}, 1 \leq k \leq N_{data} \tag{19}$$

Set the input of clustering algorithm to be matrix $s(i, j)$ and $s(k, k)$. Let $r(i, j)$ and $a(i, j)$ denote the "degree of attraction" sent from i to j and the "degree of belonging" sent from j to i, $r(i, j)$ reflects the degree of suitability of extreme point j being the cluster center of i, $a(i, j)$ shows how appropriate it is for i to select j as the cluster point.

Table 1. Process of affine propagation clustering algorithm

Affine propagation clustering algorithm.
Input: random $s(i, j)$.
Parameter initiation: $a(i,j)$=0; maximum iteration number $M_{iteration}$
1. Calculate $r(i,j)$ between extreme points: $$r(i,j) = s(i,j) - \max\{a(i,j) + s(i,j)\}$$ 2. Calculate $a(i,j)$ between extreme points: $$a(i,j) = \min\left\{0, r(i,j) + \sum_{i \neq i,j} \max\{0, r(i,j)\}\right\}$$ 3. Calculate $a(k,k)$ of extreme points: $$a(k,k) = \sum_{i \neq j} \max\{0, r(i,j)\}$$ 4. $j' = \arg\max_{j \in \{1,2,\cdots,N_{data}\}} \{a(i,j) + r(i,j)\}$, if i=j', select j' as the cluster center, otherwise select i as the cluster center. 5. Repeat step 1-4 until the cluster center no longer changes or reaches the maximum number of iterations.
Output: Classes of all extreme points and corresponding cluster centers.

The process of affine propagation clustering algorithm can be described in Table 1. After path clustering, the system allocates weights to different classes to identify direct path.

The likelihood of the k^{th} propagation path being the LOS path is calculated as [16]:

$$likelihood_k = f(w_c n_k - w_\theta \sigma_{\theta_k} - w_\tau \sigma_{\tau_k} - w_s \bar{\tau}_K) \tag{20}$$

where f(·) is an increasing function, e.g. exp(·). n_k is the number of extreme points of the class representing the k^{th} path. σ_{θ_k} and σ_{τ_k} are the variance of AOAs and TOFs of the k^{th} class, respectively. w_c, w_θ, w_τ and w_s are corresponding weight parameters. The system selects the path with the highest likelihood as the LOS path. Figure 4 illustrates the result of affine propagation clustering. The blue squares with a black circle around them represent the LOS path. It can be seen that among the 6 propagation paths, the system identifies the path with smallest fluctuation in both AOA dimension and TOF dimension.

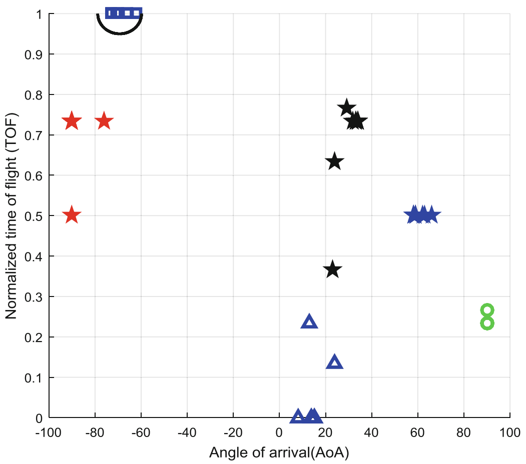

Fig. 4. Result of affine propagation clustering. (Color figure online)

3.3 Localizing the Target by Multiple APs

After obtaining the estimated values of AOA and TOF of LOS paths from multiple APs, AOA based positioning is achievable. Assuming that there are H APs, the position of the target can be estimated by least square method:

$$position = \arg \min_{p} \sum_{i=1}^{H} \left[\widehat{\theta}(i) - \theta(i)\right]^2 \tag{21}$$

where $\widehat{\theta}(i)$ and $\theta(i)$ denote the estimated and actual AOA of the i^{th} AP, respectively.

4 Experimental Evaluation

To test the performance of the system, we implement the system using laptop with 3-antenna Intel 5300 Wi-Fi NICs as AP and a mobile phone hotspot as sender. In this paper, $N = 3$, $S = 30$, $N_{sub1} = 2$, $N_{sub2} = 15$. All experiments are conducted as follows:

1. Linux CSI Tool [17] is used to obtain CSI value for each packet.
2. The Intel 5300 NIC works under 802.11n mode and operates in 5 GHz Wi-Fi spectrum with a bandwidth of 40 MHz.
3. The AP operates in monitor mode.

In the test, a coordinate system is set up first. The distance between the test point and the AP is measured by a tape. The angles between the test points and the APs are calculated. Then, keeping the sender at the same position, a set of CSI information of one position is collected. Repeat this step and change the position of the AP, more CSI data will be obtained to establish the fingerprint database. Finally, all CSI data is processed in the server and the estimated position is given.

We deploy the system in a typical indoor environment: student dormitory. The positioning accuracy of the system depends on many factors. For example, the number of the furniture, the material of the walls, the multipath. Therefore, we choose a typical indoor environment of a square area of roughly 5 × 7 square meters and deploy 3 APs in this area as Fig. 5 shows.

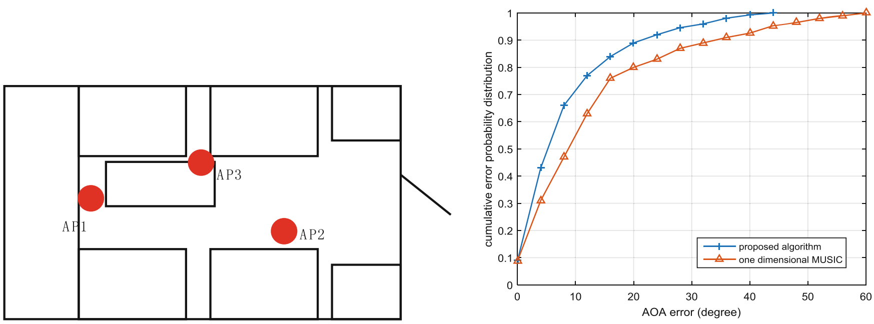

Fig. 5. The space of experimental environment (left) is about 5 × 7 square meters and it contains furniture, walls and other obstacles. Identify performance of different AOA estimation algorithm (right).

To test the positioning performance, we choose test positions randomly and use the laptop to obtain CSI information at selected AP position. Then, the laptop is moved to the next AP position. The method of calculating the angle estimation error is to find the extreme points closest to the real angle in the space spectrum, and to calculate the absolute value of the difference between the measured value and the actual value. Then we employ a multi-AP joint positioning algorithm to estimate the target position after identifying AOA of LOS path.

Figure 5 indicates that the proposed algorithm has a smaller range of AOA estimation error and is more robust against multipath-rich environment. Figure 6 illustrates that compared with ArrayTrack [18], the proposed algorithm has smaller maximum positioning error and higher positioning accuracy. It is observed that the median positioning error of the proposed system achieves 1.7 m under the condition of 3 APs.

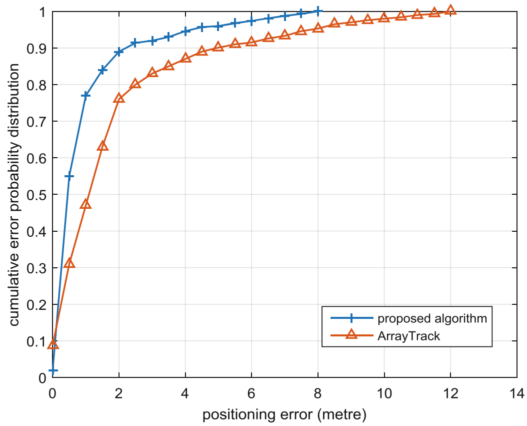

Fig. 6. Positioning performance of different algorithms.

5 Conclusion

In this paper, we design an Angle-of-Arrival positioning system based on CSI virtual antenna array using commodity Wi-Fi NICs such as Intel 5300 with three antennas. After having obtained AOA and TOF by modified MUSIC algorithm, the system employs its phase correction algorithm to eliminate PDD. Affine clustering method is applied identify LOS path. We prototype the system in typical indoor scenario. The result shows that our system achieves a meter level accuracy without any hardware and firmware modifications.

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