MobTrack: Locating Indoor Interfering Radios With A Single Device

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***Abstract*—In this paper, we present MobTrack, a single device system which aims to locate interfering radios on unlicensed ISM band in indoor environments. Compared with existing techniques which require a deployment of dense access points (APs), MobTrack only demands a single device equipped with multiple antennas. The location of an interfering signal source are estimated by computing the angle of arrival (AoA) of Line of Sight (LoS) component using an antenna array. Taking advantage of cyclostationary property, MobTrack differentiates interfering signals from working signals. By moving the device around for a short distance within one meter, it depresses multipath effects and determines the LoS component. Simultaneously, the AoAs on the moving trace are recorded to estimate the location of the interfering radio by triangulation. We evaluate the performance of MobTrack by setting up a prototype experimental system. Compared with recent interference localization schemes, MobTrack has much lower hardware complexity and gets better localization accuracy with a median of 0.55 meters.**

I. INTRODUCTION

As the coming of more wireless devices working on the unlicensed ISM band are produced, this portion of the radio spectrum is becoming more and more crowded, which inevitably leads to interference between these devices. When interference happens, the wireless communication performance may be severely degraded. For example, we all have the experience that though we are close to the WiFi Access Point, our device still experience poor communication performance. Besides WiFi, many other types of devices like Bluetooth speakers, baby monitors, cordless phones and microwave ovens also work on the same frequency band, which causes interference to our WiFi communications from time to time. The interference problem becomes even more crucial especially in some circumstances like hospitals or business environments, where sudden poor wireless performance may lead to serious outcomes.

Nowadays, WiFi has become the predominant wireless communication solution in indoor environments. In this paper, we consider the scenario of WiFi being interfered by one or multiple unknown radios. When interference happens, a quick and accurate method to find and terminate the interfering radio will be helpful. However, in indoor environments, it is not easy to locate the interfering signal.

There are many previous research work on the topic of wireless localization in the literature. However, none of them are applicable for the problem of locating indoor interfering radios. Traditional solutions to the wireless localization problem follows three research lines by measuring the values of Received Signal Strength Indication (RSSI), Time of Arrival (ToA) or Angle of Arrival (AoA). RSSI based solutions [1] [2] collect RSSI values and then use signal propagation models to compute the distances. However, under the circumstance of interference, both interfering and working signals impinge on antennas at the same time and the power is the sum of all incoming signals, which makes it infeasible to differentiate interfering radios from working signals. ToA based ranging solutions [3] [4] require high time resolution measurement and usually rely on dedicated hardware or leverage slower waveforms like acoustic signals. AoA based algorithms [10] [12] rely on antenna arrays to do angle estimation. However, traditional AoA based algorithms cannot address all the challenges encountered by our problem.

Locating indoor interfering radios using AoA based methods has many specific challenges. First, as the nature of the interfering radios are not known to us, nor can we expect cooperation from the interfering radios, a way to differentiate the interfering radios from working signals is needed. On the other hand, because of the multipath phenomenon, too many signal components will impinge on the antenna array simultaneously, which significantly increase the demand for antenna numbers. The second challange is to isolate the LoS componets from Non-LoS (NLoS) components. Among all the multipath components, only the LoS component contributes to calculation of signal source position using AoA, so the LoS component must be isolated from all Non LoS components.

Recent research has made great advances to address these challenges. In Pinpoint [16], an modified Access Point (AP) infrastructure is leveraged to compute LoS AoA. Their algorithms are based on cyclostationary signal analysis to identify the source of interference. To meet the challenge of multipath propagation, they isolate the LoS component by finding the relative delays between LoS and NLoS components and the relative delays between different antennas at APs. However, as the difference of propagation distance between LoS component and the second arriving multipath component is only about several meters, which corresponds to tens of nanoseconds [13], it is hard to differentiate them without expensive dedicated hardware with high sampling rate. Pinpoint uses a modified frontend that was able to send and receive arbitrary waveforms in the entire 100MHz ISM band [17]. Another work ArrayTrack [5] proposes algorithms to eliminate the effects of multipath by paring peaks in AoA spectrum. Their multipath suppression algorithm could make 71% percent of success to find the LoS by moving the mobile device for five centimeters. However, in our scenario, we have no control to

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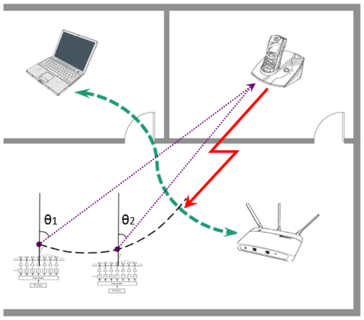

Fig. 1: System Model. WiFi communication between AP and client are working signals. The interfering radio source is a cordless phone which is the target we are trying to locate. MobTrack locates the interfering radio by compute the LoS AoA of the cordless phone at multiple positions on its moving trace.

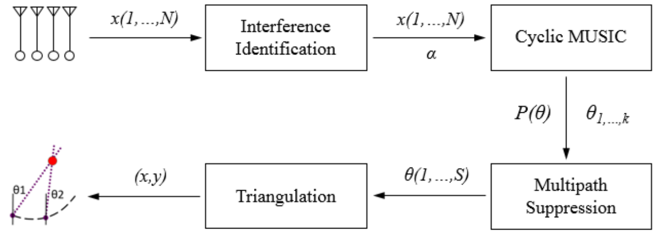

Fig. 2: MobTrack Architecture. Raw samples are phase aligned and then input into the interference detection process, where cyclic frequencies α are extracted. Spacial smoothed cyclic-music algorithm is applied to estimate the AoAs of the multipath components of only the interfering radio. Multipath suppression algorithm is then applied to isolate the LoS component and identify its AoA. LoS AoAs at different points are used to locate the source by triangulation.

the interfering radio and can not move the source arbitrarily, which makes the solution in ArrayTrack not feasible to our problem. These systems achieve sub-meter location accuracy, but the problem is that their performance relies heavily on the number of cooperating APs. However, though the density of WiFi APs has increased largely, it is not necessary and infeasible to deploy 4 to 5 APs on the same channel in a single area because of the distributed channel assignment algorithms by the IEEE standards [18].

In this paper, we present MobTrack, a single device system that locates indoor interfering radios. The goal of designing MobTrack is to provide a lightweight, handheld system that can locate interfering radios with sub-meter accuracy with as less antennas as possible. MobTrack eliminates the dependence on the AP infrastructure. With small antenna array, the cost, complexity as well as size of this device will be also reduced.

MobTrack system model is shown in Fig. 1. A MobTrack device consists of an antenna array, signal processing firmware and our novel algorithms to compute the LoS AoA and estimate the source location. The device is started when an interference is detected. By moving it around, our multipath suppression algorithm can isolate the LoS component from all other impinging components. At the same time, the angles of the LoS component on the movement trace are collected to do triangulation.

Based on cyclosationary signal analysis on existing protocols, we design novel algorithms to classify the signal types and find the cyclic frequencies. Different from PinPoint which creates a dummy signal as the test signature, we analyze cyclostationary signatures of different signal types theoretically and store their cyclostationary signature in bi-frequency domain locally. Thus we don't need to store the dummy signals for every cyclic frequencies. Another difference is that we adopt Cyclic-MUSIC algorithm [11] to calculate AoAs. In contrast, Pinpoint leverages a optimization method, whose target is a residual function of both signal components delays and the angle of arrival. Our algorithms doesn't work on time domain for the purpose of efficiency and designing goal of a lightweight system without dedicated wireless frontends.

To address the problem of multipath propagation, we design a novel algorithm that effectively find the LoS components based on the stability difference of LoS and NLoS components. The key insight of our multipath suppression algorithm is that with the movement of MobTrack device, the values of LoS AoA tend to be continuous, while reflected paths AoA values are more segmented. Using this property, MobTrack finds LoS AoA by selecting the longest continuous AoA line on the angle-movement plane explained in II-C.

The main contributions of this paper are summarized as follows:

- To the best of our knowledge, MobTrack is the first single device indoor interference localization system without the requirement of multiple pre-deployed Access Points.
- We propose a novel algorithm to eliminate the multipath effect in the indoor environment. Our multipath suppression algorithm could robustly and efficiently isolate the LoS component from other reflected components.
- We propose a novel signal type identification algorithm for MobTrack to calculate the AoAs of only interfering radios, which significantly reduces the requirement to antenna numbers and device complexity.

A prototype system of MobTrack is implemented on Ettus USRP platform with 6 antennas as the wireless frontend. The location performances are evaluated on a testbed at 16 points over one floor of our department building. Experimental results show that within a movement of 1 meter, MobTrack achieves a median 55cm location accuracy using data collected from 5 points with an LoS isolation correction of 95%.

The rest of the paper is organized as follows. The system design details are presented in Section II. Implementation is stated in Section III. Section IV elaborates the simulation and experimental results. We discuss related work in Section V and conclude the paper in Section VI.

II. System Design

We describe the system design of MobTrack following the data flow in system architecture in Fig. 2. We assume that the interfered communication is a WiFi link between an AP and a client. The interference to this communication from a nearby device is the signal we want to locate. MobTrack is a movable device equipped with an antenna array. We choose the number of antennas to be 6, which will be explained in Section III. This device is carried by an operator moving around in the interfered area to locate the interfering radio and get an increasing accuracy continuously by moving towards it.

As we have stated in the introduction, there are two major challenges to do indoor interference localization using a single device: to identify the interfering signal type and to isolate the LoS component. Our system design meets these challenges as well as achieve our goal of a lightweight system. By identifying signal type and using Cyclic-MUSIC algorithm, we can significantly reduce the demand for the number of antennas. The system is designed to be a single device, so that we are able to move it to get angles from different points and suppress multipath effect at the same time. The challenges are addressed step by step. We follow the data flow and make a brief introduction to each step first before diving into the details.

1) **Identify the interfering radio type (Section II-A):** MobTrack takes the phase-aligned signal samples as input. It has to eliminate the influence of noise and signals except the interfering radio first. The property it utilizes is the cyclostationarity property of the interfering radio. MobTrack correlates the received signal with pre-stored signal signatures to determine the interfering signal type. Then it picks a cyclic frequency α which is unique to this interfering radio and pass it along with the received samples to the next step.
2) **Calculate the AoAs of only interfering radio (Section II-B):** Cyclic-Music algorithm takes advantage of the signal selection property of cyclic frequencies. If α selected is unique to the interfering radio, all impinging components from other signals are filtered. Only AoAs from the interfering radio are left. Furthermore, multipath components from the same signal source correlate with each other, which degrades the performance of MUSIC algorithm. To handle this problem, a spacial smoothing method is adopted. In this step, we address the fist challenge. The output of this step is the AoAs of impinging components from the interfering radio only.
3) **Isolate the LoS AoA among multiple NLoS AoAs (Section II-C):** At this step, MobTrack can finally address the second challenge. It leverages a novel algorithm called LongestCurveFitting to separate LoS signals from NLoS signals and thus find the LoS AoA of interfering radio. The output of this step is LoS AoAs at multiple points on the device moving trace.
4) **Triangulation to find the interfering radio (Section II-D):** The above steps help MobTrack figure out the relative angle between itself and the targeted interfering radio. It can now tell us the direction of the interfering radio. By triangulation, we use least square method to estimate its location. Thereby we can follow its lead to find the target and turn it off.

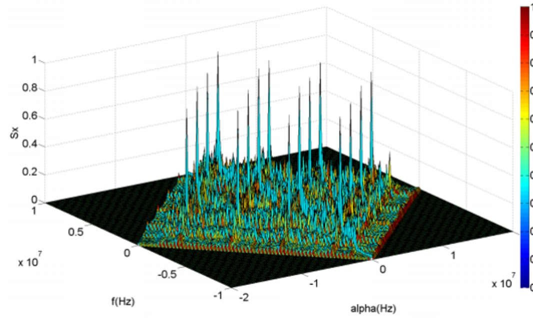

Fig. 3: WiFi SCD Surface by simulation. SCD surface is bi-frequency, with one dimension the frequency and the other the cyclic frequency. The peaks are induced by pilots on the OFDM subcarriers. Sampling frequency is 20MHz with 64 points FFT. The pilots index are -21,-7,7,21 and pilot gain is set to 3db.

A. Interference Identification

WiFi signals are packet based. As we assume that we don't know the nature of the interfering radio, it may be constant or intermittent. Once the samples of a packet are received from the antenna array, we test whether it is interfered using our interference identification algorithm described below. If no interfering radio is detected, the samples are dropped off and MobTrack waits for the next packet. Otherwise, it is analyzed to find its singal type. In this section, we introduce signal cyclostationary properties first, and then we elaborate our interference identification algorithm. The purpose of identifying the interfering radio is to find its cyclic frequencies which are used as input in Cyclic-MUSIC algorithm in Section II-B4.

1) Cyclostationary Property: Different types of signals exhibit different *cyclic signatures*, on which we can rely to detect interference or even determine the interference source type. We first introduce some concept of signal *cyclostationay* properties and then elaborate on the algorithms to find the *cyclic frequency* α.

A signal with the property of *cyclostationay* correlates with a frequency-shifted version of itself, which is named the spectral coherence property. Define a *Cyclic Autocorrelation Function* (CAF) by

$$\mathbf{R}_x^\alpha(\tau) \triangleq < x(t+\tau/2)x^*(t-\tau/2)e^{-j2\pi\alpha t} > \quad (1)$$

where the $< \cdot >$ is the time averaging operation.

If for some α and τ, $\mathbf{R}_{xx}^\alpha(\tau) \neq 0$, then this signal is called a cyclostationary signal. For $\alpha = 0$, $\mathbf{R}_x^0(\tau)$ reduces to conventional autocorrelation function.

Instead of $\mathbf{R}_x^\alpha(t)$, its Fourier transform is more often used in cyclostationary signal analysis because of computation efficiency [14],which is called the *spectral correlation density function* (SCD). SCD is defined by

$$\mathbf{S}_x^\alpha(f) = \int_{-\infty}^{\infty} \mathbf{R}_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \quad (2)$$

In discrete domain, continuous signal $x(t)$ is sampled to be a series $x[n]$. The values of SCD should be estimated from the samples using algorithms like Fast Fourier Transform (FFT) Accumulation (FAM) [19].

The simulated WiFi SCD surface is plotted in Fig. 3. SCD surface is bi-frequency, with one dimension the frequency and the other the cyclic frequency. The peaks are induced by pilots on the OFDM subcarriers. Sampling frequency is 20MHz with 64 points FFT. The pilots index are -21,-7,7,21 and pilot gain is 3db. As [20] shown, WiFi signals exhibit cyclostationary properties because of the OFDM structure like pilots and cyclic prefixes. Similarly, other protocols also exhibit similar cyclostationary properties. With different physical layer implementations, these protocols has their unique cyclic frequencies, on which we rely to differentiate them.

2) Interference Identification : We make a reasonable assumption here that the WiFi signal modulation parameters are known, including the number of subcarriers and the positions of the pilot subcarriers. These parameters define the value of cyclic frequencies.

MobTrack utilizes peak patterns on the SCD surface to differentiate signal types. By doing cyclostationary analysis on the signal universe (including WiFi, Bluetooth, ZigBee, DECT cordless phone, etc), we calculate their possible SCD peak patterns and store the "ideal" SCD surfaces locally. An "ideal" SCD surface take values of only 1 or 0. If there is a peak at a coordinate (α, f), its value is 1. Otherwise, it's 0.

Once the interfered samples are received and the corresponding SCD surface is calculated, We calculate the correlations of the SCD with each stored "ideal" SCD surface. We define a threshold C_{TH}. If a correlation is found over C_{TH}, then we say that the interfering radio of this type exists.

The interference identification algorithm is summarized in Algorithm 1.

Algorithm 1 Interference identification algorithm

1: Analyze signal universe, store "ideal" surfaces $\mathcal{S}_N$
2: Calculate the sample surface S_c
3: **for** each "ideal" surface $S_i \in \mathcal{S}_N$ **do**
4: Calculate the correlation C_{ic} of S_i and S_c
5: **if** $C_{ic} > C_{TH}$ **then**
6: Set S_i as the interfering radio type
7: **end if**
8: **end for**

This algorithm may return two or more signal types. In this situation, we assume more than one interference exists. We can find unique cyclic frequencies for them separately and all these interfering signals can be located. However, in this paper, we focus on the scenario where there's only one interference.

What should be noted is that unlike previous work on signal classification using cyclostationary approaches [24] [17], we don't use machine learning methods. Instead of training the algorithm when interference happens, we analyze the signal universe and store their signatures.

B. AoA spectrum computation

Once the interfering radio is identified, we select a cyclic frequency that is unique to the interfering radio, and use

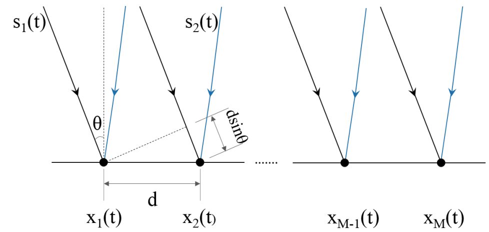

Fig. 4: Phase Array Data Model. Multipath components from multiple sources impinge on the antenna array. Antenna array is a Uniform Liner Array with interval distance $d = \lambda/2$. Propagation phase delay between array elements can be used to infer the incoming angle θ

Cyclic-MUSIC algorithm to calculate the AoA spectrum. Signal components impinging on the antenna array from different directions with different power. AoA spectrum is the incoming signal's power as a function of angle of arrival. We locate the peaks on the AoA spectrum and say that there is a signal component at this direction. However, the directions may or may not be the actual direction of the source because of multipath propagation. Nor the highest peak means that it is the direct path because the direct path signal may be blocked. In this section, we first introduce the concept of phase array model. Then we briefly illustrate MUSIC algorithm and Cyclic-MUSIC algorithm.

1) Array Signal Measurement Model: For simplicity, we use a Uniform Linear Array (ULA) in MobTrack, which consists of M antennas with an interval of d between adjacent antennas. The array signal model is illustrated in Fig. 4. Assume I signals exist in the referred space and for the ith signal, there are K_i multipath components perceptible by the antenna array. Further, we assume that the signal sources are far field sources, which means the impinging signals are plane waves.

The signal received by the mth antenna can be expressed as

$$x_m(t) = \sum_{i=1}^{I} \sum_{k=1}^{K_i} s_{ik}(t - \frac{(m-1)dsin\theta_{ik}}{c}) + n_m(t) \quad (3)$$

where $s_{ik}(t)$ and θ_{ik} are the wavefront of kth component of ith signal impinging on the ULA and its AoA respectively. $n_m(t)$ is additive measurement noise with zero mean value and no cyclostationary property.

Since $d = \lambda/2$, we make the narrowband assumption and the effect of propagation delay is simply a phase shift.

Denoting

$$\mathbf{a}(\theta_k) = [1, e^{-j\pi \sin\theta_k}, ..., e^{-j\pi(M-1)\sin\theta_k}]^T \quad (4)$$

The antenna array signal measurement model can be expressed in a matrix form as

$$\mathbf{x}(t) = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}(t) + \mathbf{i}(t) + \mathbf{n}(t) \quad (5)$$

where $\boldsymbol{x}(t) = [x_1(t), ..., x_M(t)]^T$ is the measurement vector; $\mathbf{s}(t) = [s_1(t), ..., s_K(t)]^T$ is the wavefront vector ; $\mathbf{i}(t) = [i_1(t), ..., i_M(t)]^T$ is uninterested signals vector; $\mathbf{n}(t) = [n_1(t), ..., n_M(t)]^T$ is the measurement noise vector; $\boldsymbol{A}(\boldsymbol{\theta}) =$

$[\mathbf{a}(\theta_1), ..., \mathbf{a}(\theta_K)]$. Note that $\mathbf{x}(t), \mathbf{i}(t), \mathbf{n}(t), \mathbf{a}(\theta_k) \in \mathcal{C}^M$, $\mathbf{s}(t) \in \mathcal{C}^K$ and $\mathbf{A}(\boldsymbol{\theta}) \in \mathcal{C}^{M*K}$ and $()^T$ denotes transpose.

As defined in Equation 4, $\mathbf{a}(\theta)$ is the *steering vector* of the array, which is a function of the AoA of the incoming signals.

2) MUSIC Algorithm: Conventional MUSIC [10] algorithms are based on decomposition of the autocorrelation matrix of the input signal $\mathbf{x}(t) = \mathbf{A}(\boldsymbol{\theta})\mathbf{s}(t) + \mathbf{n}(t)$

$$\mathbf{R}_{xx} \triangleq E\{xx^*\} = \mathbf{A}\mathbf{R}_{ss}\mathbf{A}^* + \sigma^2\mathbf{I} \tag{6}$$

where $\mathbf{A}$ is composed of the steering vectors of the antenna array, and σ^2 is the variance of noise $\mathbf{n}(t)$. $\mathbf{R}_{ss} = E\{\mathbf{ss}*\}$ is the source autocorrelation matrix. If the signals $s(t)$ are modeled as stationary processes, and uncorrelated with the noise, then $\mathbf{R}_{ss}$ is a Hermitian matrix and $\mathbf{A}\mathbf{R}_{ss}\mathbf{A}^*$ is positive semidefinite whose rank is the number of the incoming signals I. MUSIC requires that number of antenna $M > I$.

The autocorrelation matrix $\mathbf{R}_{xx}$ is then eigen-decomposed to get M eigenvalues. The smallest $M - I$ eigenvalues are all equal to noise variance σ^2. Using this property, the number of incoming signals can be estimated.

Corresponding to the eigenvalues, the M eigenvectors span two subspaces: signal subspace $\mathbf{E}_s$ and noise subspace $\mathbf{E}_N$. The eigenvectors whose eigenvalues are σ^2 span the noise subspace. For each $\mathbf{e}_i \in \mathbf{E}_N$, we have

$$\mathbf{R}_{xx}(t)\mathbf{e}_i = \mathbf{A}\mathbf{R}_{ss}\mathbf{A}^*\mathbf{e}_i + \sigma^2\mathbf{e}_i$$

so

$$\begin{aligned} \mathbf{A}\mathbf{R}_{ss}\mathbf{A}^*\mathbf{e}_i &= 0 \\ \mathbf{A}^*\mathbf{e}_i &= 0 \end{aligned} \tag{7}$$

Equation 7 means that for every *steering vector* $\mathbf{a}(\theta_k) \in \mathbf{A}$, $\mathbf{a}(\theta_k) \perp \mathbf{e}_i$. The set of $\mathbf{a}(\theta)$ is named the *array manifold* [12]. For our azimuth-only AoA estimation problem, the array manifold is a one-parameter "line" in the M-dimensional space spanned by the eigenvectors of $\mathbf{R}_{xx}(t)$.

As $\mathbf{a}(\theta_k) \perp \mathbf{e}_i$, the intersections of array manifold $\mathbf{a}(\theta)$ and signal subspace $\mathbf{E}_s$ are the solutions of estimating θ_k. The spacial spectrum function is selected to use the inverts of the distance between a point moving along the array manifolds and $\mathbf{E}_s$, who will peak at the signal AoAs

$$P(\theta) = \frac{1}{\mathbf{a}^*(\theta)\mathbf{E}_N\mathbf{E}_N^*\mathbf{a}(\theta)} \tag{8}$$

3) Spacial Smoothing to eliminate correlation: By selecting cyclic frequency α, we have eliminated the influence of noise and other signals. But in our application scenarios, there is another challenge. Multipath components from the same interference source are apparently correlated. If the multipath components are fully correlated, the rank of $\mathbf{R}_{xx}^{\alpha}$ will be 1. This will degrade the performance of eigen-decomposition based algorithms or even make them infeasible. In order to increase the rank of CAF so that we can estimate all the multipath components, we adopts the *spacial smoothing algorithm* [15] to eliminate the correlation between multipath components. An illustration of spacial smoothing is shown in Fig. 5.

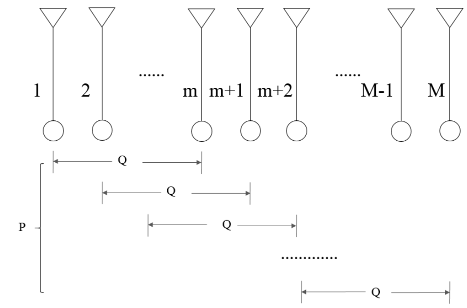

Fig. 5: Subarray Spacial Smoothing Totally M antennas in P groups with Q antennas in each group. $M = P + Q - 1$.

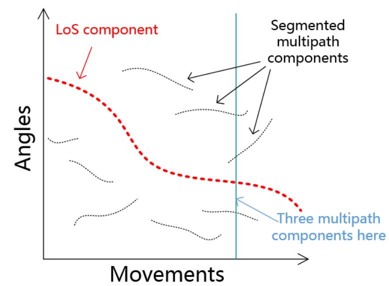

Fig. 6: Multipath Suppression. We record the peaks and plot it as a dot in this figure. With the movement of MobTrack device, the LoS AoA changes continuously, but NLoS components will disappear intermittently. By finding the longest line, we can isolate the LoS component.

4) Cyclic MUSIC Algorithm [11]: The difference between *cyclic MUSIC* algorithm and conventional MUSIC algorithm is that instead of the autocorrelation matrix, the decomposition of the *cyclic autocorrelation matrix* is leveraged here. Assuming that all signals are not fully correlated, we can then choose a cyclic frequency α, at which the K of them exhibit spectral correlation. Because of the frequency selection property of cyclic frequency α, the cyclic autocorrelation matrix of $\mathbf{i}(t)$ and $\mathbf{n}(t)$ are all zeros, and the cyclic cross-correlation between $\mathbf{s}(t)$ and $\mathbf{i}(t)$ and $\mathbf{n}(t)$ are also zeros. So we get

$$\mathbf{R}_{xx}^{\alpha} = \mathbf{A}\mathbf{R}_{ss}^{\alpha}\mathbf{A}^* \tag{9}$$

whose rank is K and $K < M$.

The rest of the cyclic MUSIC algorithm is the same as conventional MUSIC algorithm. It is worth noting that different from autocorrelation matrix, the CAF matrix $\mathbf{R}_{xx}^{\alpha}$ is not a Hermitian matrix. So the eigendecomposition method is not applicable here and the singular value decomposition (SVD) method must be applied.

Because of the signal selection property we stated above, Cyclic-MUSIC does not require higher number of antennas than the number of multipath components. Taking the unique cyclic frequency of interfering radio as input, it successfully output the AoAs of only the interfering radio. Taking advantage of this property, we only need a number of antennas to separate the multipath components from only one signal source. In indoor environments, there are usually 5 multipath components conceptacle. As MobTrack is movable, the blocking effect of LoS is eliminated when moving around. So we

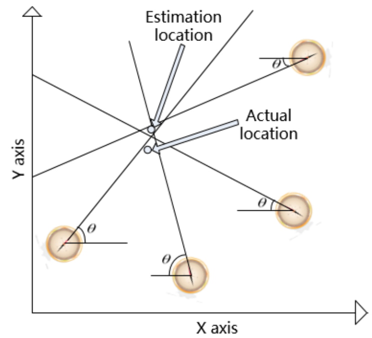

Fig. 7: MobTrack Triangulation. We apply the well-known least square algorithm in linear algebra to calculate a single estimation point. When employing the least square method, the known variables are the 2D locations of the MobTrack and the θs in the figure while the unknown variables are the 2D location of the estimation point.

equip MobTrack with 6 antennas as we can always find places where LoS component is in the strongest three.

C. Multipath Suppression

Now we get the directions of all the components of the interfering radio including both LoS and NLoS components. The next step is to isolate the LOS component in order to find the target interference. The algorithm we employ to achieve multipath suppression is motivated by the observation that LoS components and NLoS components have different stabilities with the movement of the device. As illustrated in Fig. 6, the LoS component is continuous compared to discrete NLoS components when we move MobTrack and record the angle data. This is because if the location of MobTrack change successively, the angle between the target interference and MobTrack will change consecutively. But this is not true for multipath components, which bounce on walls or object surface which is inconsecutively themselves. Based on this observation, we develop an algorithm which can find the longest continuous path in the angle-movement plane, which is the LoS component.

The multipath suppression algorithm is summarized in Algorithm 2. We name this algorithm LongestCurveFitting. It takes the AoA spectrums as the inputs, finds the peaks and records their coordinates. It then uses the Curve Fitting algorithm to test which curve line the peak dots belong to. If a curve line is segmented, it is removed from the candidate set. If there is only one curve line left in the candidate set, we terminate the function and set it as the LoS component.

An experimental result will be presented in Section IV. Using the above algorithm, we are able to find the LoS AoAs within a movement distance less than half a meter.

As long as we find the LoS AoAs from several points, we can estimate the source location using triangulation methods.

D. Triangulation

As MobTrack is a moveable or handheld device, we can simply find the interference by following the direction which MobTrack is pointing to. We run MobTrack continuously at different locations on the movement trace and then we

Algorithm 2 LongestCurveFitting

Set the LoS candidate set $\mathcal{S}$ to be Φ
while The LoS components is not found **do**
    Find the peaks on current AoA Spectrum
    For every peak do CurveFitting
    Find the current longest curve C
    if Length of $C > L_{TH}$ **then**
        C is the line corresponding to LoS AoAs
    end if
end while

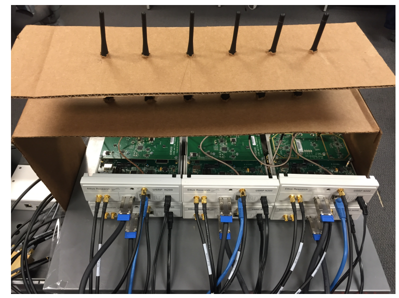

Fig. 8: Prototype implementation. The MobTrack prototype is composed of six USRP radios mounted on a movable case, which form an antenna array. Another USRP works as the phase alignment reference, and one more works as the interferer(not shown in picture).

adopt triangulation to estimate the location of interference with AoAs displayed. As shown in Fig. 7, we observe that the directions which MobTrack points to will not intersect at a single point because of the estimation and measurement errors. Thus, we apply the well-known least square algorithm in linear algebra to calculate a single estimation point. When employing the least square method, the known variables are the 2D locations of the MobTrack and the θs in the figure while the unknown variables are the 2D location of the estimation point. The matrix A and vector b in Ax = b are formed by the 2D locations of the MobTrack and the θs. Because the directions which MobTrack points to can not form a single point, so Ax = b will have no solution. Then we project vector b onto the column space of matrix A to get the projection vector p. By solving Ax = p, we get the single estimation point we desire.

III. Implementation

We implement the MobTrack prototype on Ettus USRP software defined radio platform, as shown in Fig. 8. The system consists of 6 USRP-N200 software defined radio platform. Four of the USRP devices are equipped with a daughterboard XCVR2450, and two of them are equipped with a daughterboard SBX, which provides the support of 2.4Ghz WIFI channel. The distances between antennas are set to be 6.13cm, which is half the wavelength of 2.4G signal.

Fig. 9 explains the connections between the devices of our prototype. Every two of the six USRPs are connected using a MIMO cable, which provide communication as well as synchronization between them. The master USRP in each group is connected to the host computer via a Gigabyte Ethernet switch. Another USRP N200 works as a phase

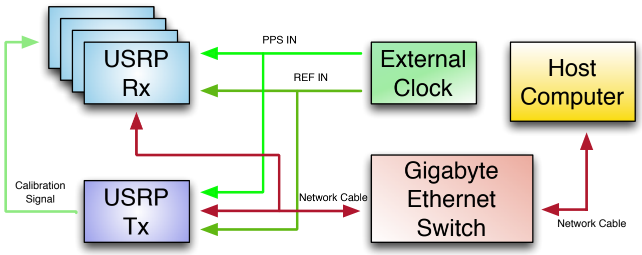

Fig. 9: MobTrack prototype connections.Every two of the six USRPs are connected using a MIMO cable. The master USRP in each group are connected to the host computer via a Gigabyte Ethernet switch. All master USRPs are connected to an external clock for time and frequency synchronization. A phase reference tone is provided by another USRP.

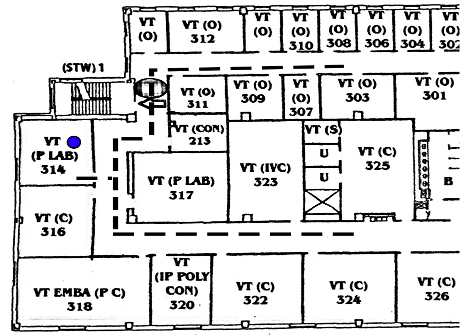

Fig. 10: Testbed. This figure is a part of the floor our lab sits on. The dotted line in this figure is the trace of executed experiments. The blue point in the lab is the interfering radio we would like to locate. Following the trace, we conduct a test per 25 centimeters.

reference tone provider. The transmit antenna of this USRP is cable connected to the six receivers using an SMA splitter. The cables have the same length, which provide the receivers a stable reference tone. The master USRP in each group as well as the reference transmitter are all connected to an external clock, which provides a synchronized 10MHZ reference clock and the PPS signal for the purpose of frequency and time synchronization.

The phase reference tone and signals received over the air are sampled to GNURadio. Two band pass filters are used to split them into separate data streams. The data streams are then transmitted to a Matlab script via a named pipe. The phase differences are calculated from the phase reference tone and compensated to data streams over the air. And then start our interference identification process.

IV. Performance Evaluation

To illustrate the performance of MobTrack in real indoor environments, we present experiment results in this section from the testbed described in IV-A. We first describe the test bed setup methodology. The we present an experimental result of LoS signal stability. After that, we present the location accuracy MobTrack can achieve, comparing with the results of Pinpoint. We also explore the effects of number point we use to do triangulation on the movement trace on the performance of MobTrack.

A. Test bed setup

The location performances are evaluated on a test bed over one floor of our department building, as shown in Fig. 10. The interfering radio is placed at the blue point in Room 314, which is in the same room as the WiFi AP. Our device follows the trace in the figure on the same floor. Most of the test points are in the hall and some of them are in the lab mentioned above. The distance of the whole trace are 20 meters. Along this trace, we take a measurement every 25 centimeters. The ground truth are measured before the experiment with an accuracy of 1cm.

B. LoS Signal stability

To illustrate the difference of stabilities between LoS component and NLoS components, we set up an experiment in our office room. The transmitter works at frequency 2.412GHz and locates in the same room as the MobTrack device. The distance between the transmitter and MobTrack is 172cm. We move MobTrack along the parallel direction of the antenna array and the transmitter. In a distance of 1 meter, we record the angles of arrive estimated by MobTrack, including both LoS and NLoS components. The results are shown in Figure 11. The distance between each location is 2.5cm. As we can see from this figure. The LOS component AoA changes from 0 degree to about -26 degree following a continuous curve. Our curve fitting algorithm finds this line as the longest successfully.

On the other hand, NLoS components change intermittently. We list the percentage of segmented curves in this Fig. 11 using LongestCurveFitting algorithm. From Table I, we can see that most of the distance of multipath components is about 15cm, which means that by moving MobTrack for 15cm, the multipath components almost always change their impinging direction. This experiment verifies that our multipath suppression algorithm is feasible.

TABLE I: Percentage of segmented multipath curves

Distance	5cm	10cm	15cm
Percentage of Segmented	30%	75%	95%

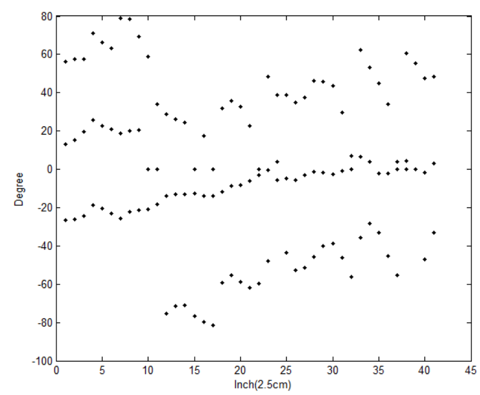

Fig. 11: The stability of LoS and NLoS components. The distance between the transmitter and MobTrack is 172cm. The distance between each location is 2.5cm.

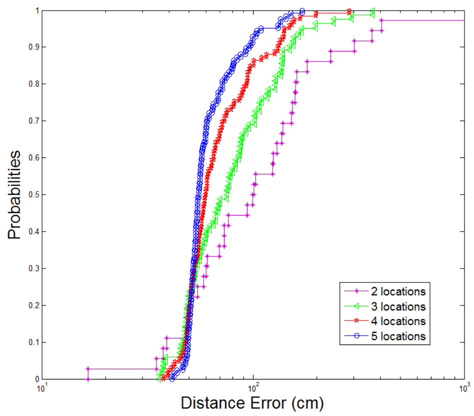

Fig. 12: Localization Accuracy with Different Calculation Points. The median error is 0.55m estimating from 5 locations.

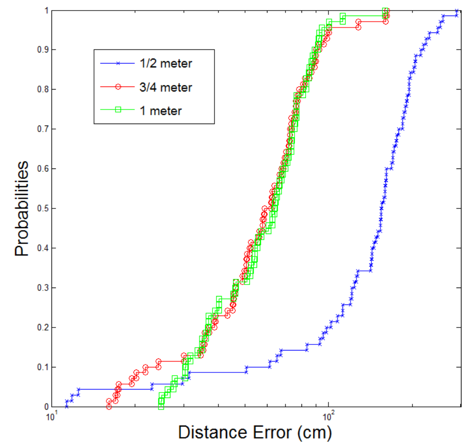

Fig. 13: Localization Accuracy with Different Moving Distance. The longer distance between the calculation points, the more accurate MobTrack achieve.

C. Localization Accuracy with Different Calculation Points

This section presents the localization accuracy changes with different calculation points. In Fig. 12, we estimate the location of interfering radio by the information provided by MobTrack at different locations. We employ respectively 2, 3, 4 and 5 different locations in the triangulation step in our estimation. We can see that the more locations we select to do the calculation, the more accurate results we can achieve. The distances between two locations range from 10cm to 1 meter. We prefer to use longer distance because the longer distance between the points, the better performance it will achieve. Estimating in 5 locations, MobTrack achieves a median localization error of 0.55 meter. Comparing with Pinpoint locating the interfering radio using 5 static APs with accuracy of 0.97 meter, our scheme performs better. The reason for this better performance is that, MobTrack starts estimating the location from the second point and leads moving towards the target. It will perform the estimation repeatedly. At the 5th point, MobTrack has moved 4 meters at most towards the interfering radio. Besides, MobTrack's antenna array contains 6 antennas, while Pinpoint has 4 antennas.

D. Localization Accuracy with Different Moving Distance

As shown in Fig. 13, we also test if we can achieve a valuable estimation within a short distance. We calculate the location from 5 locations within different distances. And the results shows we can achieve an accurate estimation even if we only move around a meter. If we want to make an estimation in half a meter, the accuracy drops, but still it can tell the location with a median location error of 2 meters. This is vital for us, because MobTrack is a single device designed for users to carry with them, with the ability to find the interference in a meter, MobTrack is proved practical.

V. Related work

RSSI based solutions can be archived into two categories. One is the range based algorithms, which estimate the distances from multiple measurement points to the target using wireless signal propagation models and locate the target geometrically [1]. However, it can not distinguish different signals. The other category is fingerprinting based [2] [21] [22] [23] but they need extensive accurate environment calibration workload before system deployment.

ToA based ranging solutions require dedicated hardware with high sampling rate. Instead of measuring signal propagation time directly, researchers usually turn to measuring frequency differences [3] or using slower signals like acoustic signals [4]. However, in order to distinguish LoS signal and NLoS signals, ToA based ranging solutions must apply extremely high sampling rate because the propagation distance difference between LoS component and the second arriving multipath component is only about tens of nanoseconds [13].

AoA based estimation algorithms [10], [12] relies on antenna arrays. Signal samples collected from the antennas are processed using eigenvalue decomposition based methods to estimate signal AoAs. The challenge for AoA is the multipath phenomenon in our scenario. Multipath components from the same source can be highly correlated, which makes eigenstructure based AoA estimation algorithms inaccuracy or even infeasible to estimate the AoAs. Nevertheless, MobTrack follows the AoA based research line and solve the multipath challenge.

Recent techniques require no costly equipments and they can overcome the multipath challenge, but they assume a high density of APs. For instance, EZ [7] utilizes over 100 APs, ArrayTrack [5] leverages several WiFi APs with 7 to 8 antennas and PinPoint [16] assumes 5 APs on a floor. Because of the popularity of WiFi, the density requirement seems to be acceptable. Nevertheless, there exists some practical limitations. First of all, 4 to 5 strong APs with known locations are necessary with multilateraion, which are not realistic in most circumstances such enterprise or hospital network. Second, FCC permits 802.11 b/g/n standard to employ 14 channels in the 2.4GHz frequency band, so it is difficult to find 4 to 5 strong APs on the same channel even if they do exist. And this problem requires WiFi scanning technique, which is an energy hungry operation and can reduce the battery life of mobile devices by over 2-3 time [9] even if the scanning operation is invoked once every 10 seconds for continuous location tracking. Third, when the Aps are operating scanning, regular data communication cannot happen, which impacts the user experience, especially for real-time service like VoIP. In comparison, MobTrack only utilize a single device and thereby will not have the limitations above.

VI. Conclusion and Future Work

MobTrack is a single device system that can locate indoor interfering radios with sub-meter accuracy. Comparing to previous solutions, it significantly reduces the requirement to AP infrastructure and the number of antennas. By moving the device around for a short distance within several meters, it depresses multipath effects and determines the LoS component. Simultaneously, the AoAs at these locations are recorded to estimate the location of the interfering radio by triangulation methods. In order to decrease the physical size of this device and make it suitable for handhold, the method of synthetic array can be explored where the number of antennas can be further reduced to two.

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References

[1] D. Zhang, Y. Liu, X. Guo, M. Gao, and L. M. Ni, "On distinguishing the multiple radio paths in rss-based ranging," in INFOCOM, 2012 Proceedings IEEE, march 2012, pp. 2201-2209.

[2] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in INFOCOM. IEEE, March 2000, tel Aviv, Israel.

[3] Fadel Adib, Zachary Kabelac, Dina Katabi, and Robert C. Miller, "3D tracking via body radio reflections," in NSDI, 2014, USENIX Association, Berkeley, CA, USA, 317-329.

[4] Hongbo Liu, Yu Gan, Jie Yang, Simon Sidhom, Yan Wang, Yingying Chen, and Fan Ye, "Push the limit of WiFi based localization for smartphones," in Mobicom, 2012, ACM, New York, NY, USA, 305-316

[5] Jie Xiong and Kyle Jamieson, "ArrayTrack: a fine-grained indoor location system," in NSDI, 2013, USENIX Association, Berkeley, CA, USA, 71-84.

[6] Nandakumar, Rajalakshmi, Krishna Kant Chintalapudi, and Venkata N. Padmanabhan. "Centaur: locating devices in an office environment." Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012. APA

[7] Chintalapudi, Krishna, Anand Padmanabha Iyer, and Venkata N. Padmanabhan. "Indoor localization without the pain." Proceedings of the sixteenth annual international conference on Mobile computing and networking. ACM, 2010.

[8] Sen, Souvik, et al. "Avoiding multipath to revive inbuilding wifi localization." Proceeding of the 11th annual international conference on Mobile systems, applications, and services. ACM, 2013.

[9] Anand, Arjun, et al. "A quantitative analysis of power consumption for location-aware applications on smart phones." Industrial Electronics, 2007. ISIE 2007. IEEE International Symposium on. IEEE, 2007.

[10] Schmidt, R.O., "Multiple emitter location and signal parameter estimation," Antennas and Propagation, IEEE Transactions on , vol.34, no.3, pp.276,280, Mar 1986

[11] S. V. Schell, Calabretta, and W. A. Gardner, "Cyclic MUSIC algorithms for signal selective DOA estimation," in Proc. IEEE Int. Conf. Acoust., Speech Signal Process., 1989, pp. 2278C2281.

[12] Roy, R.; Kailath, T., "ESPRIT-estimation of signal parameters via rotational invariance techniques," Acoustics, Speech and Signal Processing, IEEE Transactions on , vol.37, no.7, pp.984,995, Jul 1989

[13] Takeuchi, T.; Sako, M.; Yoshida, S., "Multipath delay estimation for indoor wireless communication," Vehicular Technology Conference, 1990 IEEE 40th , vol., no., pp.401,406, 6-9 May 1990

[14] Gardner, W.A, "Exploitation of spectral redundancy in cyclostationary signals," Signal Processing Magazine, IEEE , vol.8, no.2, pp.14,36, April 1991

[15] Tie-Jun Shan; Wax, M.; Kailath, T., "On spatial smoothing for direction-of-arrival estimation of coherent signals," Acoustics, Speech and Signal Processing, IEEE Transactions on , vol.33, no.4, pp.806,811, Aug 1985

[16] Kiran Joshi, Steven Hong, and Sachin Katti, "PinPoint: localizing interfering radios'" in NSDI, 2013, USENIX Association, Berkeley, CA, USA, 241-254.

[17] S. Hong, S. Katti, "DOF: A Local Wireless Information Plane," in ACM SIGCOMM, 2011.

[18] Alex T. Mariakakis, Souvik Sen, Jeongkeun Lee, and Kyu-Han Kim, "SAIL: single access point-based indoor localization," in MobiSys, 2014, ACM, New York, NY, USA, 315-328.

[19] Roberts, R.S.; Brown, W.A; Loomis, H.H., "Computationally efficient algorithms for cyclic spectral analysis," Signal Processing Magazine, IEEE , vol.8, no.2, pp.38,49, April 1991

[20] C. Du, H. Zeng, Y.T. Hou, W. Lou, "On Cyclostationary Analysis of WiFi Signals for Direction Estimation", IEEE ICC 2015, June 8-12, 2015, London, UK.

[21] Youssef, Moustafa, and Ashok Agrawala. "The Horus WLAN location determination system." Proceedings of the 3rd international conference on Mobile systems, applications, and services. ACM, 2005.

[22] Rai, Anshul, et al. "Zee: zero-effort crowdsourcing for indoor localization." Proceedings of the 18th annual international conference on Mobile computing and networking. ACM, 2012.

[23] Sen, Souvik, et al. "You are facing the mona lisa: spot localization using phy layer information." Proceedings of the 10th international conference on Mobile systems, applications, and services. ACM, 2012.

[24] K. Kim, I. A. Akbar, K. K. Bae, J.-S. Um, C. M. Spooner, and J. H. Reed, "Cyclostationary approaches to signal detection and classification in cognitive radio," IEEE DySpan 2007, Jan. 29 2007-Feb. 2 2007, La Jolla, CA, USA