Available online at www.sciencedirect.com
ScienceDirect
Procedia Computer Science 34 (2014) 392 – 399
Procedia
Computer Science

The 11th International Conference on Mobile Systems and Pervasive Computing (MobiSPC-2014)

CA^{2}T: Cooperative Antenna Arrays Technique for Pinpoint Indoor Localization

Xuyu Wang[a], Shiwen Mao[a,*], Santosh Pandey[b], Prathima Agrawal[a]

[a] *Department of Electrical and Computer Engineering, 200 Broun Hall, Auburn University, Auburn, AL 36849-5201 USA*
[b] *Cisco Systems, Inc., 170 West Tasman Dr., San Jose, CA 95134 USA*

Abstract

Location-based service has a great potential in the indoor environment, making it important to develop accurate indoor localization techniques. In this paper, we consider AOA based indoor localization, which can generally achieve higher accuracy of localization than other approaches. We propose to use cooperative APs with antenna arrays for accurate indoor localization. With the proposed Cooperative Antenna Arrays Technique (CA^{2}T), we first estimate the arriving angles for all the multipath components using the MUSIC algorithm, and then exploit the geometric relationship among the angles to identify the LOS angles. The user location can be computed with the LOS angles and the accurate, known distance between the two APs. The proposed scheme is validated with simulations and is shown to outperform an existing scheme with considerable gains.

Selection and peer-review under responsibility of Conference Program Chairs
Keywords: Indoor localization, antenna array, cooperation, MUSIC, LOS identification, Optimization.

1. Introduction

With the proliferation of mobile computing devices, location-based services have attracted considerable interest, with many localization techniques proposed recently [1]. Global positioning system (GPS), as the most popular localization technique, can offer an accurate localization service when there are Line-Of-Sight (LOS) paths to the satellites. Such outdoor localization techniques have found broad applications in car navigation, land surveying, military monitoring, and so on. On the other hand, location-based service also has a great potential in the indoor environment. For example, with accurate localization, a smartphone App can help a user to find the nearest ATM machine in a shopping mall, guide a user to his/her seat in a football stadium, or push ecoupons to a customer around certain sections in a department store. Since GPS service is not available in such indoor environments, there is a critical need for accurate indoor localization techniques for fully harvesting the high potential of location-based service.

Many existing localization methods are based on angle of arrival (AOA) [2], time of arrival (TOA) [3], time difference of arrival (TDOA) [4], and received signal strength (RSS) [5]. The AOA based approach can generally achieve higher

* Corresponding author. Tel.: +1-334-844-1845 ; fax: +1-334-844-1809.
E-mail address: smao@ieee.org

Selection and peer-review under responsibility of Conference Program Chairs
doi:10.1016/j.procs.2014.07.044

accuracy of localization than other approaches[6]. An AOA based scheme uses an antenna array to estimate angles of incoming waves, and then exploits the geometric relationship to determine a user's position. In the scheme proposed in[7], a node transmits a signal to its surrounding beacons. The beacons then detect the signal directions with an AOA method and return the estimated directions to the node to compute its location. In[6], the authors propose a virtual array technique that uses an iterative AOA method to improve localization accuracy. These existing AOA based methods only consider the LOS waves for angle estimation and may not be effective for indoor localization, because the indoor environment is usually highly complex where Non-Line-Of-Sight (NLOS) propagation due to the refection, diffraction and scattering greatly affects the precision of AOA based localization.

Due to NLOS propagation, the errors from NLOS paths and noises become the major factors affecting the accuracy of AOA based indoor localization. The problem of mitigating the impact of NLOS paths and identifying the LOS path has been addressed in several recent works[8,9,10,11]. These prior work can be classified into two groups: (i) schemes using the strongest peak in the power spectrum[8,9], and (ii) schemes exploiting user mobility[10,11]. In[8], the authors propose an indoor 802.11-based localization scheme, where the base stations use directional antennas to transmit to a user, and the user then uses the strongest signal strength to estimate the AOA, The SecureAngle scheme[9] is proposed to determine the user's position using physical layer information such as channel state information (CSI), and again the strongest signal is used. These two schemes are effective when the LOS signal is the dominant component. On the other hand, the authors in[10] utilize an antenna array with eight elements to achieve a high accuracy of 36 cm, assuming the direct path peak does not change while the other multipath peaks change when the user moves. In[11], rich multipath propagation is dealt with by using CSI and angle identification with a geometric method. It is worth noting that both schemes require users to move.

In this paper, we propose to use cooperative APs with antenna arrays for accurate indoor localization. We focus on how to effectively identify the LOS angles and pinpoint the user's position with two MIMO APs in rich multipath environments, while not requiring the user to move. With the proposed Cooperative Antenna Arrays Technique (CA^2T), we first estimate the arriving angles for all the multipath components using the MUSIC algorithm. Once the angles are obtained, we then exploit the geometric relationship among the angles to identify the LOS angles by minimizing an estimation error. Finally the user's location can be computed based on the detected LOS angles and the accurate, known distance between the two APs. We evaluate the performance of the proposed CA^2T scheme with simulations and provide a comparison study with a benchmark scheme SecureAngle[9]. We find that although both schemes achieve good performance when the LOS path is not blocked, the proposed scheme outperforms SecureAngle with a considerable margin when the LOS path is obstructed.

The remainder of this paper is organized as follows. We first present the preliminaries in Section 2. We then formulate an optimization problem for the proposed localization scheme and derive a two-stage solution algorithm in Section 3. Simulation results are presented in Section 4. Section 5 concludes this paper.

2. Preliminaries

2.1. Indoor Path-loss Model

In the outdoor environment, an electromagnetic wave propagates more likely through an unobstructed line-of-sight (LOS) path from a transmitter and a receiver. The RSS can be effective for distance estimation (e.g., according to a free space propagation model) in such cases. In the indoor environment, however, a wireless signal usually traverses many different media with different propagation properties, such as walls, floors, pedestrians, and other objects, leading to rich refection, diffraction and scattering. The signal attenuation is mainly due to path-loss, multipath reflections and absorption. Usually more sophisticate propagation models are needed for the complex indoor environment.

In this paper, we adopt a widely used indoor path-loss model from the literature[11,12], which is defined as

$$P_{r,dB} = P_{0,dB} + 10\gamma \log(d) + X_{\sigma}, \tag{1}$$

where $P_{r,dB}$ denotes the path loss at distance d (dB), $P_{0,dB}$ is the reference path loss at the first meter (dB), γ is the path-loss exponent, d is the distance between the transmitter and receiver (m), X_{σ} represents the shadowing effect (dB). With this indoor path-loss model, we can estimate the distance d between the transmitter and receiver with detected path loss $P_{r,dB}$.

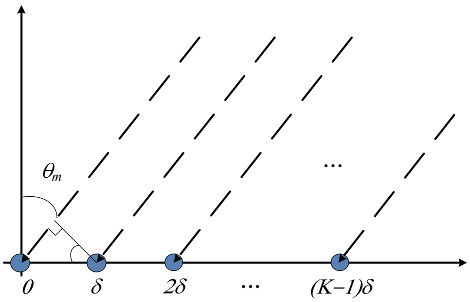

Fig. 1. A multipath element with AOA θ_m arriving at the K-element antenna.

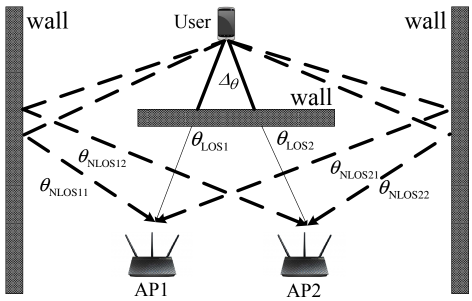

Fig. 2. A typical scenario of indoor localization where the LOS components are blocked by a wall.

2.2. AOA Estimation with MUSIC

We next briefly review the well-known Multiple Signal Classifier (MUSIC) scheme for AOA estimation [13]. Consider a K-element linear antenna array, which receives M multipath signals from a narrowband transmitter (such as a Wi-Fi station) in an indoor environment. The signal $s_m(t-\beta_m)$, for $m = 1, \cdots, M$, which arrives at the antenna array from direction θ_m with the propagation delay β_m at time t, is assumed to be a plane wave due to the far-field model, as shown in Fig. 1. The received signal can be expressed by a $K \times 1$ complex vector as [13]

$$\vec{x}(t) = \sum_{m=1}^{M} \vec{a}(\theta_m) \cdot s_m(t-\beta_m) + \vec{n}(t) = \mathbf{A} \cdot \vec{s}(t) + \vec{n}(t), \tag{2}$$

where $\vec{a}(\theta_m)$ is the $K \times 1$ steering vector for the mth multipath component defined as $\vec{a}(\theta_m) = [1, \exp(-j\frac{2\pi}{\lambda}\delta\sin\theta_m), \exp(-j\frac{2\pi}{\lambda}2\delta\sin\theta_m), \cdots, \exp(-j\frac{2\pi}{\lambda}(K-1)\delta\sin\theta_m)]^T$, δ is the distance between two neighboring antenna elements, and λ is the wavelength of the source signal; $\mathbf{A} = [\vec{a}(\theta_1), \vec{a}(\theta_2), \cdots, \vec{a}(\theta_M)]$; $\vec{s}(t) = [s_1(t-\beta_1), s_2(t-\beta_2), \cdots, s_M(t-\beta_M)]^T$; and $\vec{n}(t)$ is the $K \times 1$ noise vector. In the indoor environment, the difference in propagation delays for the narrow-band multipath signals is usually negligibly due to small distances. We therefore assume that $\beta_m \approx 0$, for all m, as in prior work [10] in the remaining part of this paper. It follows that $\vec{s}(t) \approx [s_1(t), s_2(t), \cdots, s_M(t)]^T$.

In order to analyze the incoming waves, the data correlation matrix $\mathbf{R}_{xx}$ can be derived as

$$\mathbf{R}_{xx} = \mathbf{E}\left[\vec{x}(t) \cdot \vec{x}(t)^H\right] = \mathbf{E}\left[(\mathbf{A} \cdot \vec{s}(t) + \vec{n}(t)) \cdot (\mathbf{A} \cdot \vec{s}(t) + \vec{n}(t))^H\right] = \mathbf{A}\mathbf{R}_{ss}\mathbf{A}^H + \sigma_n^2\mathbf{I}. \tag{3}$$

In a real wireless system, it is not feasible to obtain $\mathbf{R}_{xx}$ due to the realtime constraint. However, the ensemble average $\hat{\mathbf{R}}_{xx}$, computed as $\hat{\mathbf{R}}_{xx} = \frac{1}{N}\sum_{t=1}^{N} \vec{x}(t) \cdot \vec{x}(t)^H$, can be used to approximate $\mathbf{R}_{xx}$ when the number of snapshots N is sufficiently large, due to the ergodicity hypothesis. In addition, the ensemble average $\hat{\mathbf{R}}_{xx}$ can be decomposed into the orthogonal signal subspace and noise subspace with eigenvalue decomposition (EVD) [13], denoted as $\hat{\mathbf{R}}_{xx} = \mathbf{E_S}\mathbf{\Lambda_S}\mathbf{E_S}^H + \mathbf{E_N}\mathbf{\Lambda_N}\mathbf{E_N}^H$, where $\mathbf{E_S}$ and $\mathbf{E_N}$ are the signal subspace eigenvectors and the noise subspace eigenevectors of $\hat{\mathbf{R}}_{xx}$, respectively, and $\mathbf{\Lambda_S}$ and $\mathbf{\Lambda_N}$ are the signal subspace eigenvalues and the noise subspace eigenvalues, respectively. Since the signal subspace is orthogonal to the noise subspace, we can estimate the angles of the multipath waves by searching for the peaks of the power spectrum function, which is given by [13]

$$\mathcal{P}(\theta) = \frac{\vec{a}^H(\theta)\,\vec{a}(\theta)}{\vec{a}^H(\theta)\,\mathbf{E_N}\mathbf{E_N}^H\vec{a}(\theta)}. \tag{4}$$

3. Indoor Localization with Cooperative Antenna Arrays

3.1. LOS Identification and Localization

From the power spectrum function $\mathcal{P}(\theta)$, we can identify the angles of the multiple signal paths, including the direct path, which is indicative of the distance, and the reflected paths. How to identify the direct path angle among many incoming angles is an important problem, because the result will determine the precision of the AOA based localization. Most of the prior papers, such as SecureAngle[9], assume that the strongest peak of the power spectrum corresponds to the direct path. In fact, this assumption is true if the direct path is not blocked. However, in indoor environments, the direct path is usually obstructed; some reflected paths may have stronger peaks than the direct path. In such cases, there will be large localization errors with the existing techniques.

In this paper, we consider using two collaborative APs for identifying the direct path (or, the LOS) angle in rich multipath environments. An example is given in Fig. 2, where AP1 receives three signals with arriving angles θ_{LOS1}, θ_{NLOS11}, and θ_{NLOS21}, and AP2 receives three signals with arriving angles θ_{LOS2}, θ_{NLOS12} and θ_{NLOS22}. Note that unlike Fig. 1, these angles are between the incoming path and the x-axis. Both direct paths, i.e., θ_{LOS1} and θ_{LOS2}, are blocked by the wall. If a traditional scheme is used to identify the strongest peak of the power spectrum as in MUSIC, it will highly likely ignore the two direct paths, which have weaker peaks in the power spectrum due to the effect of the wall. As a result, there will be large localization errors.

With collaborative APs, every AP with an antenna array can first estimate its incoming angles based on the MUSIC algorithm. We can then identify the LOS components based on the geometric relationship among the angles, as

$$\Delta_\theta = \theta_{LOS2} - \theta_{LOS1}. \tag{5}$$

In addition, Δ_θ can be estimated by the following equation as

$$\Delta_\theta = \arccos\left((d_{1u}^2 + d_{2u}^2 - d_{12}^2)/(2d_{1u}d_{2u})\right), \tag{6}$$

where d_{1u} is the distance between AP1 and the user, d_{2u} is the distance between AP2 and the user, and d_{12} is the distance between AP1 and AP2. The AP–user distances can be estimated as $d_{1u} = 10^{(P_{r1,dB}-P_{0,dB})/(10\gamma)}$ and $d_{2u} = 10^{(P_{r2,dB}-P_{0,dB})/(10\gamma)}$, respectively, based on the propagation model (1).

Once the LOS angles θ_{LOS1} and θ_{LOS2} are determined, we then use them to pinpoint the user's location. Let (x_1, y_1) be the coordinates of AP1, (x_2, y_2) the coordinates of AP2, and (x_u, y_u) the coordinates of the user. It can be seen that the two LOS angles satisfy equations $\tan(\theta_{LOS1}) = (y_u - y_1)/(x_u - x_1)$ and $\tan(\theta_{LOS2}) = (y_u - y_2)/(x_u - x_2)$. The user's location can be computed by solving these two equations, as

$$x_u = (x_1 \tan(\theta_{LOS1}) - x_2 \tan(\theta_{LOS2}) + y_2 - y_1)/(\tan(\theta_{LOS1}) - \tan(\theta_{LOS2})) \tag{7}$$

$$y_u = ((x_1 - x_2)\tan(\theta_{LOS1})\tan(\theta_{LOS2}) + y_2 \tan(\theta_{LOS1}) - y_1 \tan(\theta_{LOS2}))/(\tan(\theta_{LOS1}) - \tan(\theta_{LOS2})). \tag{8}$$

Among the three distances, d_{1u} and d_{2u} are not accurate since they are estimated using the indoor path-loss model, while d_{12} is precisely known. By exploiting the cooperative APs, the LOS components can be identified more accurately. This is because except for the two LOS angles, the other reflected path angles are less likely to satisfy the relationship (5), due to the random reflections in the rich multipath environment. The main difference between this work and CUPID[11] is that we use two APs to cooperatively identify the LOS components based on two crude distance estimates d_{1u} and d_{2u}, as well as one accurate distance d_{12}, and then use the two accurate LOS angles to pinpoint the user's position. In CUPID, only one AP is utilized to identify the LOS component based on three crude distance estimates. CUPID then estimates the user's location based on one accurate LOS angle and one crude AP–user range. Thus, the proposed scheme can achieve a better performance over CUPID in LOS identification.

3.2. Optimal LOS Angle Identification

We next show how to identify the LOS angles with the two cooperative APs. Since the estimated distances between the APs and the user are not precise, equation (5) only holds true approximately. In other words, the estimation error $|\ \theta_{LOS2} - \theta_{LOS1} - \Delta_\theta\ |$ is not always zero. The idea is to minimize this error term among all the identified incoming angles with MUSIC, while the minimizer yields the LOS angles.

Let $\Theta_1 = \{\theta_{11}, \theta_{12}, \cdots, \theta_{1m}\}$ be the set of arriving angles to AP1, and $\Theta_2 = \{\theta_{21}, \theta_{22}, \cdots, \theta_{2n}\}$ the set of arriving angles to AP2 identified by MUSIC. As discussed, the sets of angles can be detected by finding the peaks in the power spectrum function. Define index variables x_{1j} and x_{2k} as follows: $x_{1j} = 1$ if θ_{1j} is the LOS component at AP1, and $x_{1j} = 0$ otherwise, for $j = 1, 2, \cdots, m$; $x_{2k} = 1$ if θ_{2k} is the LOS component at AP2, and $x_{2k} = 0$ otherwise, for $k = 1, 2, \cdots, n$. Since each AP can have only one LOS angle, we have constraints $\sum_{j=1}^{m} x_{1j} = 1$ and $\sum_{k=1}^{n} x_{2k} = 1$. We then formulate the LOS identification problem as follows.

$$\text{minimize} \left| \sum_{k=1,\ \theta_{2k}\in\Theta_2}^{n} x_{2k}\cdot\theta_{2k} - \sum_{j=1,\ \theta_{1j}\in\Theta_1}^{m} x_{1j}\cdot\theta_{1j} - \Delta_\theta \right| \tag{9}$$

$$\text{subject to:}\ \Theta_1 = \left\{ \theta \ \middle|\ \arg\max_\theta \{\mathcal{P}_1(\theta)\},\ \mathcal{P}_1(\theta) = \frac{\vec{a}_1(\theta)^H \vec{a}_1(\theta)}{\vec{a}_1(\theta)^H \mathbf{E_{N1}} \mathbf{E_{N1}}^H \vec{a}_1(\theta)} \right\} \tag{10}$$

$$\Theta_2 = \left\{ \theta \ \middle|\ \arg\max_\theta \{\mathcal{P}_2(\theta)\},\ \mathcal{P}_2(\theta) = \frac{\vec{a}_2(\theta)^H \vec{a}_2(\theta)}{\vec{a}_2(\theta)^H \mathbf{E_{N1}} \mathbf{E_{N2}}^H \vec{a}_2(\theta)} \right\} \tag{11}$$

$$d_{1u} = 10^{(P_{r1,dB}-P_{0,dB})/(10\gamma)} \tag{12}$$

$$d_{2u} = 10^{(P_{r2,dB}-P_{0,dB})/(10\gamma)} \tag{13}$$

$$\Delta_\theta = \arccos\left((d_{1u}^2 + d_{2u}^2 - d_{12}^2)/(2d_{1u}d_{2u})\right) \tag{14}$$

$$\sum_{j=1}^{m} x_{1j} = 1 \tag{15}$$

$$\sum_{k=1}^{n} x_{2k} = 1 \tag{16}$$

$$x_{1j} \in \{0,1\},\ \text{for } j = 1,2,\cdots,m,\quad x_{2k} \in \{0,1\},\ \text{for } k = 1,2,\cdots,n, \tag{17}$$

where $\mathcal{P}_1$ ($\mathcal{P}_2$) denotes the power spectrum function of AP1 (AP2), $\vec{a}_1(\theta)$ ($\vec{a}_2(\theta)$) is the steering vector of AP1 (AP2), $\mathbf{E_{N1}}$ ($\mathbf{E_{N2}}$) are the noise subspace eigenvectors of AP1 (AP2), and Θ_1 (Θ_2) is the set of angles that are the local maximizers of the power spectrum function $\mathcal{P}_1$ ($\mathcal{P}_1(\theta)$). The formulated problem is a non-linear integer programming problem, which is NP-hard. To reduce the computational complexity, we next show how to decompose it into two sub-problems in the following.

3.3. Two-Stage Algorithm

To solve the formulated optimal LOS angle identification problem, we decompose it into two sub-problems: (i) angle estimation and (ii) LOS angle identification. We first utilize MUSIC to estimate the incoming directions by searching for the peaks of the power spectrum. Once the incoming angle sets are computed, the LOS angles can be selected by solving the reduced problem.

3.3.1. Angle Estimation

We first use MUSIC to estimate all the arriving angles at the two APs. The distance between two neighboring antenna elements is half of the carrier wavelength. For angle estimation, we compute the data correlation matrix $\hat{\mathbf{R}}_{xx}$ based on received signals. Then by decomposing $\hat{\mathbf{R}}_{xx}$ into the signal subspace and the noise subspace, we obtain the power spectrum function. To obtain the set of arriving angles at the APs, we use (10) and (11) to find all the peaks in their power spectrum function. Since it is difficult to obtain closed-form expressions for Θ_1 and Θ_2 by maximizing the power spectrum functions, we adopt an approximation method to find all the maximal value points in the power spectrum function, by exploiting the fact that every peak point is greater than the values in its neighborhood.

We also use (12), (13), and (14) to estimate the angle between the two LOS paths. In fact, we need to obtain the AP–user distances with the maximum likelihood (ML) estimation method [14] to overcome the shadowing and multipath effects. Moreover, the RSS of every AP is the superposition of powers of all arriving signals. Traditionally, RSS can be used to estimate the AP–user distance by minimizing the sum square error between the measured RSS and estimated RSS with the ML method. Thus d_{1u} can be estimated as $d_{1u} = \arg\min_d \|P_{r1,dB} - P_{0,dB} - 10\gamma\log(d)\|^2$, and d_{2u} can be estimated as $d_{2u} = \arg\min_d \|P_{r2,dB} - P_{0,dB} - 10\gamma\log(d)\|^2$. The angle estimation algorithm as described above is presented in Algorithm 1.

Algorithm 1: Angle Estimation

Initialize normalized antenna array space vector $\vec{\delta}' = \vec{\delta}/\lambda = [0 : 0.5 : (K-1) \times 0.5]$;
Compute data correlation matrix $\hat{\mathbf{R}}_{xx} = \frac{1}{N}\sum_{t=1}^{N} \vec{x}(t)\vec{x}(t)^H$;
Obtain noise subspace eigenevectors $\mathbf{E_N} = \text{EVD}(\hat{\mathbf{R}}_{xx})$;
for ($i = 0$ to 180) **do**
  $\vec{a}(i) = \exp(-j2\pi\vec{\delta}' \sin(\pi/180 i))$;
  $\mathcal{P}(i) = \frac{\vec{a}^H(i)\vec{a}(i)}{\vec{a}^H(i)\mathbf{E_N}\mathbf{E_N}^H\vec{a}(i)}$;
end
Let $m = 0$;
for ($i = 1$ to 179) **do**
  if ($\mathcal{P}(i) > \mathcal{P}(i+1)$ and $\mathcal{P}(i) > \mathcal{P}(i-1)$) **then**
    $\Theta(m) = i$;
    $m = m + 1$;
  end
end
$d_{1u} = \arg\min_d ||P_{r1,dB} - P_{0,dB} - 10\gamma \log(d)||^2$;
$d_{2u} = \arg\min_d ||P_{r2,dB} - P_{0,dB} - 10\gamma \log(d)||^2$;
$\Delta_\theta = \arccos\left((d_{1u}^2 + d_{2u}^2 - d_{12}^2)/(2d_{1u}d_{2u})\right)$;
Return Θ and Δ_θ ;

3.3.2. LOS Angle Identification

After all the angles are identified, we then find out the LOS angles that can minimize the error term. The original problem is reduced to the following problem.

$$\text{minimize} \quad \left| \sum_{k=1,\ \theta_{2k}\in\Theta_2}^{n} x_{2k} \cdot \theta_{2k} - \sum_{j=1,\ \theta_{1j}\in\Theta_1}^{m} x_{1j} \cdot \theta_{1j} - \Delta_\theta \right| \tag{18}$$

$$\text{subject to:} \quad \sum_{j=1}^{m} x_{1j} = 1 \tag{19}$$

$$\sum_{k=1}^{n} x_{2k} = 1 \tag{20}$$

$$x_{1j} \in \{0,1\} \text{ for } j = 1,2,\cdots,m, \quad x_{2k} \in \{0,1\} \text{ for } k = 1,2,\cdots,n. \tag{21}$$

It can be seen that the reduced problem is still a non-linear 0-1 integer programming problem, which is NP-hard. Since usually the sets Θ_1 and Θ_2 of the estimated incoming angles are not very big, we can use exhaustive search to check out all the angle combinations. In particular, we first compute the errors as in (18) for all angle pairs. We then rank all the error values to find the minimum error, which is indicative of the two LOS angles. Once we obtain the LOS angles, the user's position can be accurately determined as in (7) and (8). The LOS angle identification and localization algorithm is presented in Algorithm 2.

Note that we can easily extend the above approach to more than two cooperative APs. In this case, the exhaustive search approach may incur high computational times. We then develop effective sub-optimal algorithms to obtain highly competitive solutions. We omit the results for more than two cooperative APs due to lack of space.

4. Performance Evaluation

We conduct extensive simulations in MATLAB to evaluate the performance of the proposed scheme. For the results presented in this section, each data point is the average of 10,000 individual experiments with different random seeds, along with 95% confidence intervals plotted as error bars. It can be seen that the confidence intervals are all negligible, indicating that the results are convergent. We consider the case of two cooperative APs each with 4 antenna

Algorithm 2: LOS Angle Identification and Localization

Execute Algorithm 1 to obtain Θ_1, Θ_2, and Δ_θ ;
Let $\vec{d_c}$ be an $m \times n$ vector and set $k = 1$;
for $(i = 1 : m)$ **do**
  for $(j = 1 : n)$ **do**
    $\vec{d_c}(k) = |\, \Theta_2(i) - \Theta_1(j) - \Delta_\theta \,|$;
    $k = k + 1;$;
  end
end
Get the index of the minimum error $p = \arg\min(\vec{d_c})$;
Get LOS1=$\Theta_1(\lceil p/n \rceil)$, LOS2=$\Theta_2(\mathrm{mod}(p, n))$;
Determine the user's position (x_u, y_u) according to (7) and (8) ;

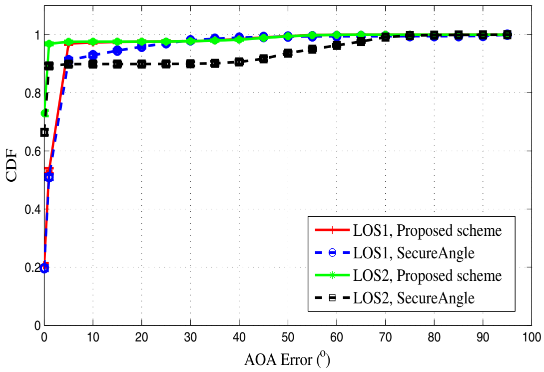

Fig. 3. Angle estimation in unobstructed LOS environments.

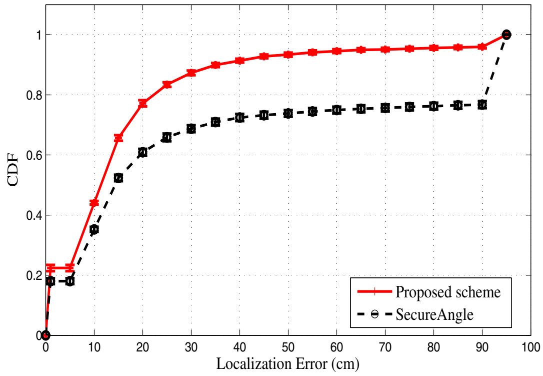

Fig. 4. Localization in unobstructed LOS environments.

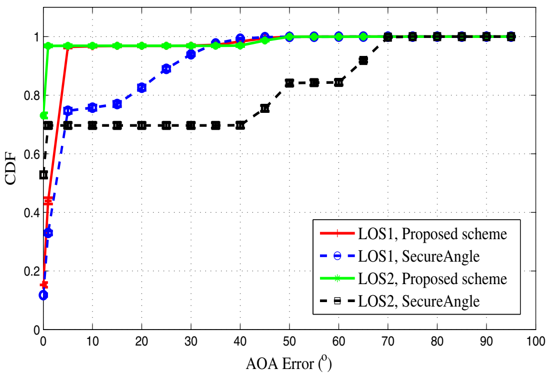

Fig. 5. Angle estimation in obstructed LOS environments.

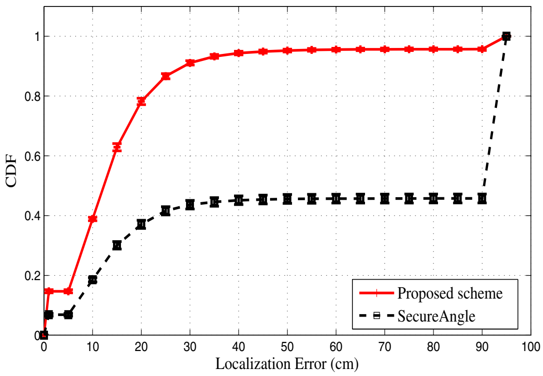

Fig. 6. Localization in obstructed LOS environments.

elements, one located at (0, 0) and the other at (500 cm, 0). In addition, we assume that AP1 receives three incoming waves with arriving angles $[0, 30, 60]$, respectively, and AP2 receives three incoming waves with angles $[35, 15, -30]$, respectively. We compare the proposed scheme with the SecureAngle method[9] in the following two experiments.

In the first experiment, we consider the case that the LOS path is not blocked. The simulation results on angle estimation and localization are presented in Figs. 3 and 4, respectively. In the simulations, the SNRs of the received signals at the two APs are 5 dB, the LOS signal strength is 17 dB higher than the other incoming waves, the number of snapshots N is 512, and the path-loss exponent γ is 2.0. It can be seen from Fig. 3 that both schemes perform well on identifying the LOS angle in this scenario. However, with the proposed method, the cumulative distribution function

(CDF) approaches 97% when the angle error is over 5°. With SecureAngle, the CDF approaches 97% when the angle error is in the range of 30° to 40°. Similarly, from Fig. 4, we find that the localization error of the proposed method is about 55 cm when the CDF reaches 93%. With SecureAngle, the error is 55 cm when the CDF exceeds 75%. Both methods achieve fine localization precisions in unobstructed indoor environments.

In the second scenario, the LOS path is blocked by a wall. The angle estimation and localization results are presented in Figs. 5 and 6, respectively. In these simulations, the LOS signal strength is 5 dB lower than the other incoming waves, the path-loss exponent γ is 3.3, and all the other parameters are the same as that in the previous scenario. It can be seen that the proposed scheme still performs well in the obstructed scenario. With the proposed scheme, the CDF of angle estimation approaches 97% when the angle error is above 5° and the localization CDF is over 97% when the error is above 50 cm. On the other hand, SecureAngle does not perform well in the obstructed scenario, as indicated by the large AOA and localization errors. Apparently, using the strongest peak of the power spectrum leads to wrong LOS angle selections and large localization error in this case.

5. Conclusion

In this paper, we consider the problem of indoor localization in rich multipath environments. We propose to adopt two cooperative APs with antenna arrays to improve the precision of LOS angle identification. The proposed scheme is based on the traditional MUSIC algorithm to identify the multipath angles. It then exploits the simple geometric relationship among the multiple angles and the accurate distance between the two APs to accurately identify the LOS angles, leading to accurate localization for the user. The proposed scheme is validated with simulations and outperforms an benchmark scheme with considerable gains, especially when the LOS path is blocked.

Acknowledgements

This work is supported in part by Cisco Systems, Inc., and by the US NSF under grant CNS-1247955 and the NSF I/UCRC Broadband Wireless Access & Applications Center (BWAC) site at Auburn University.

References

1. H. Liu, H. Darabi, P. Banerjee, and J. Liu, “Survey of wireless indoor positioning techniques and systems,” *IEEE Trans. Syst., Man, Cybern. C*, vol. 37, no. 6, pp. 1067–1080, Nov. 2007.
2. D. Niculescu and B. Nath,“Ad hoc positioning system (APS) using AOA,” in *Proc. IEEE INFOCOM’03*, San Francisco, CA, Mar./Apr. 2003, pp. 1734–1743.
3. M. Kanaan and K. Pahlavan,“A comparison of wireless geolocation algorithms in the indoor environment,” in *Proc. IEEE WCNC’04*, Atlanta, GA, Mar. 2004, pp. 177–182.
4. Y. T. Chan and K. C. Ho,“A simple and efficient estimator for hyperbolic location,”*IEEE Trans. Signal Process.*, vol. 42, no. 8, pp. 1905–1915, Aug. 1994.
5. L. Cong and W. Zhuang,“Hybrid TDOA/AOA mobile user location for wideband CDMA cellular systems,”*IEEE Trans. Wireless Commun.*, vol. 1, no. 3, pp. 439–447, July 2002.
6. S. Kawakami and T. Ohtsuki, “Localization using iterative angle of arrival method sharing snapshots of coherent subarrays,” *EURASIP J. Adv. Signal Process.*, vol. 2011, no. 46, 2011.
7. Z. Shan and T. S. P. Yum, “Precise localization with smart antennas in ad-hoc networks,” in *Proc. IEEE GLOBECOM’07*, Washington, DC, Nov. 2007, pp. 1053–1057.
8. D. Niculescu and B. Nath, “VOR base stations for indoor 802.11 positioning,” in *Proc. ACM MobiCom’04*, Philadelphia, PA, Sept. 2004, pp. 58–69.
9. J. Xiong and K. Jamieson, “SecureAngle: Improving wireless security using angle-of-arrival information,” in *Proc. ACM HotNets’10*, Monterey, CA, Oct. 2010, pp. 415–416.
10. J. Xiong and K. Jamieson, “ArrayTrack: A fine-grained indoor location system,” in *Proc. USENIX NSDI’13*, Lombard, IL, Apr. 2013, pp. 71–84.
11. S. Sen, J. Lee, K. H. Kim, and P. Congdon, “Avoiding multipath to revive inbuilding WiFi localization,” in *Proc. ACM MobiSys’13*, Taipei, Taiwan, June 2013, pp. 249–262.
12. T. S. Rappaport. *Wireless Communications: Principles and Practice (2nd Edition)*. Prentice Hall: Upper Saddle River, NJ, 2002.
13. R. Schmidt, “Multiple emitter location and signal parameter estimation,” *IEEE Trans. Antennas Propag.*, vol. 34, no. 3, pp. 276–280, Mar. 1986.
14. A. Coluccia and F. Ricciato, “On ML estimation for automatic RSS-based indoor localization,” in *Proc. ISWPC’10*, Modena, Italy, May. 2010, pp. 495–502.