Avoiding Multipath to Revive Inbuilding WiFi Localization

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ABSTRACT

Despite of several years of innovative research, indoor localization is still not mainstream. Existing techniques either employ cumbersome fingerprinting, or rely upon the deployment of additional infrastructure. Towards a solution that is easier to adopt, we propose $CUPID$, which is free from these restrictions, yet is comparable in accuracy. While existing WiFi based solutions are highly susceptible to indoor multipath, CUPID utilizes physical layer (PHY) information to extract the signal strength and the angle of only the direct path, successfully avoiding the effect of multipath reflections. Our main observation is that natural human mobility, when combined with PHY layer information, can help in accurately estimating the angle and distance of a mobile device from an wireless access point (AP). Real-world indoor experiments using off-the-shelf wireless chipsets confirm the feasibility of CUPID. In addition, while previous approaches rely on multiple APs, CUPID is able to localize a device when only a single AP is present. When a few more APs are available, CUPID can improve the median localization error to $2.7m$, which is comparable to schemes that rely on expensive fingerprinting or additional infrastructure.

Categories and Subject Descriptors

C.2.1 [**Network Architecture and Design**]: Wireless communication; H.3.4 [**Information Storage and Retrieval**]: Systems and Software

General Terms

Design, Experimentation, Performance

Keywords

Wireless, Localization, Cross-Layer, Application,
Indoor positioning

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1. INTRODUCTION

Extensive interest in location-aware services has driven many novel indoor localization techniques [1], yet it is hard to find a solution that is widely deployable. While existing approaches try to address the problem by using several techniques, solutions based on pervasive WiFi systems have remained the dominant theme of localization. Several innovative approaches have employed WiFi fingerprints to design a precise indoor localization system [2–4]. However, the accuracy comes at the cost of expensive, and meticulous war-driving. Such war-driving is not a one time cost because the indoor RF environment can change due to change in layouts and objects, or due to frequent and automatic wireless configuration changes [5, 6]. Attempts to *eliminate* the war-driving requirement have been successful [7–9], but at the expense of performance, or widespread applicability. Realizing this difficulty, there has been efforts to reduce the overhead of war-driving by using crowdsourcing techniques [10, 11]. Apart from being slow to adapt to frequent RF changes, they remain unattractive because of a lack of clear user incentive to share sensor and location information. Thus, despite decades of studies, the tradeoff between accuracy, pervasiveness, and cost has remained the primary challenge in designing a widely deployable indoor localization system. This paper is tasked to break away from this tradeoff, and achieve the accuracy of a fingerprinting-based system, without any war-driving, or crowdsourcing. Although this is a high bar, we demonstrate its feasibility by utilizing wireless physical layer(PHY) information, available from off-the-shelf wireless chipsets.

We explore the candidate solution-space using WiFi, since an approach based on pervasive WiFi will be easier to adopt. Existing WiFi-based approaches typically rely on distance, or angle as the major metric for indoor localization. It is possible to estimate distance using signal strength(RSSI), but RSSI performs poorly indoors primarily because of multipath reflections. Existing *angle-of-arrival(AoA)* estimation algorithms also have similar shortcomings. The key problem is that it is difficult to discriminate between multipath reflections and the *direct path*, i.e., the signal component traversing along the straight line joining the client to the AP (figure 1). Whenever the direct path is relatively weak, RSSI, or AoA is biased by stronger reflected components, which traverses longer distance, and perhaps a different angle than the direct path. If we can somehow accurately estimate the distance, and the angle of the mobile device from only the direct path, localization performance will improve significantly. Our system, *CUPID* distinguishes the direct path from multipath reflections by leveraging PHY layer information along with natural human mobility. CUPID accurately determines the

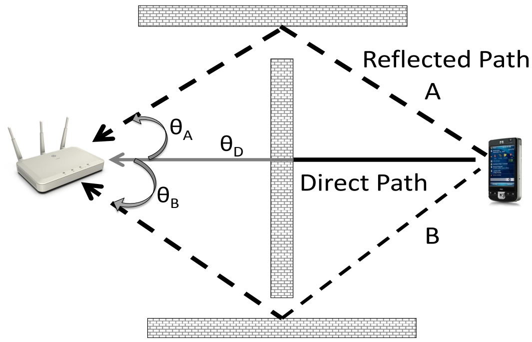


Figure 1: Wireless signal traverses through multiple paths, a direct, and a few reflected paths.

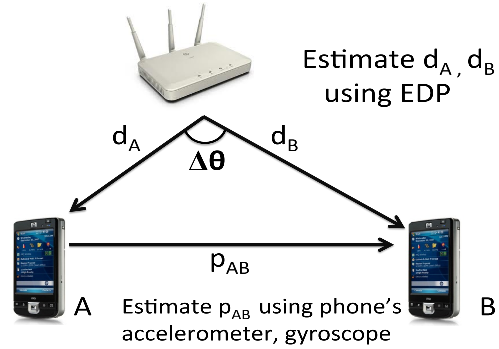


Figure 2: Change in ANDP ($\Delta\theta$) can be computed from the estimated distances – d_A, d_B, and p_{AB}.

distance, and angle of the mobile device from her AP, ultimately yielding her location. CUPID requires no crowdsourcing, or additional hardware, but relies on multiple antennas present in today's commodity wireless APs. Furthermore, it can achieve reasonable accuracy with only a single AP, not to mention multiple APs.

Estimating distance: CUPID relies on only the *energy of the direct path (EDP)* to estimate distance. We find that a PHY layer information called *channel state information (CSI)* exported from Atheros 9390 cards can be used to estimate the EDP of a received signal. Further, we find that it is possible to estimate the propagation characteristics of the signal based on the EDP. Consequently, while converting the energy estimate to distance, CUPID can correctly choose critical parameters such as path-loss exponent. Our experiments show that EDP outperforms RSSI, reducing the mean distance estimation error to $4m$ from $10m$.

Estimating angle: Angle-of-arrival (AoA) techniques, such as MUSIC [12], can estimate the angles at which the transmitted signal arrives at the receiver. Figure 1 shows three such angles. However they cannot determine which of these angles corresponds to the *angle of the direct path(ANDP)*. CUPID leverages human mobility to identify the ANDP, from MUSIC's AoA estimates. We explain our key idea using figure 2. In this example, as the user walks from location A to B, CUPID can track the change in ANDP ($\Delta\theta$). The AP uses the EDP to estimate the distance of the mobile client, d_A, and d_B, when it is at location A and B respectively. It estimates the user's displacement between location A, and B (p_{AB}), by using her phone's inertial sensors – a method called *dead reckoning*. Since d_A, d_B, and p_{AB} are known, CUPID can estimate $\Delta\theta$, which captures the change in ANDP. From MUSIC's AoA estimates at location A, and B, the angle that undergoes a similar change is the actual ANDP. We show that by employing the CSI from the 3 antennas of the Atheros 9390 chipset, CUPID can achieve a mean ANDP estimation error of $20°$.

CUPID combines the client's distance, and angle estimates, yielding her location. By systematically addressing the key issues with WiFi, CUPID enables indoor positioning even with a single AP, making it a practical yet widely deployable solution. Ofcourse, translating the above high level ideas into a working system entails a large number of technical challenges: (1) How does CUPID accurately calculate distance from EDP? (2) How does CUPID deal with errors from EDP, and dead-reckoning, while estimating angle? (3) How does CUPID deal with poor resolution offered by commodity wireless cards? (4) Will CUPID even work if the direct path is very weak? (5) Finally, will CUPID consume a lot of energy? This paper addresses these challenges, and prototypes the system using HP laptops, and Android Nexus S phones. Testbed results from a 4500 square meter building confirm our claim. With a single AP, CUPID can achieve a median localization error of $4.5m$. Ofcourse, with $2-3$ additional APs, CUPID can reduce the error to $2.7m$, remaining robust to dynamic environmental changes. We believe that this could be a promising direction, and with rigorous testing and tuning, a potential candidate for the real-world.

Our main contributions are summarized as follows:

- **We identify the opportunity to utilize PHY layer information to eliminate the effect of multipath reflections in WiFi based localization systems.** We distinguish, and harnesses only the direct path to find the user's location.
- **We demonstrate how the energy of the direct path (EDP) can be a reliable indicator of distance:** Our solution is the first to identify the relationship between EDP and path loss exponent.
- **We combine existing AoA techniques with user mobility to find the angle of the direct path(ANDP):** CUPID is the first to reliably identify the ANDP by leveraging natural human mobility.
- **We implement, and demonstrate our solution using commodity wireless cards:** Our algorithm exploits the CSI information from the 3 antennas of Atheros 9390 wireless chipsets.

In the following sections, we elaborate on our key intuitions, perform controlled measurements, and develop insights to design the CUPID system, followed by performance evaluation. We end the paper with a discussion on open questions, opportunities, and the scope for future work.

2. BACKGROUND AND OBSERVATIONS

This section presents the relevant background material on PHY layer information. Along with wireless propagation foundations, we present our ideas related to extracting the direct path energy.

2.1 Distance Estimation using Wireless Path Loss Equation

A wireless signal traverses in all radial directions, and reflects off walls, furnitures, and other objects. Due to reflections, multiple copies of the same signal arrives at the receiver, each undergoing different delay and attenuation – a phenomena which is commonly called multipath. We define the *direct path* as the straight line joining the transmitter and the receiver. A wireless signal is composed of a direct path, and other reflected components, and suffers attenuation as it propagates from the transmitter to the receiver. Indoors, wireless attenuation is mainly caused by path-loss, and multipath reflections. It is possible to estimate a crude distance between the transmitter and the receiver by using the received energy at the receiver (P_R) in the path-loss equation:

$$P_R = P_0 - 10\gamma log(d) \qquad (1)$$

where P_0 is the received energy at a distance of $1m$ from the transmitter, d is the distance between the transmitter, and the receiver in meters; and γ is the path loss exponent. γ depends on the propagation characteristics of the received signal. Earlier approaches have typically used RSSI as the received energy (P_R) in the above path loss equation. However, RSSI is an union of the energy of all the signal paths – direct as well as multipath reflections. If we use RSSI as P_R, we will need to estimate the propagation characteristics of all the signal paths, to correctly choose the path-loss exponent. Unfortunately, today's WiFi cards do not expose any specific multipath information, making it difficult to choose the correct path-loss exponent. Rather than trying to model the aggregate signal (RSSI), we show that it is easier to only use the *energy of the direct path or EDP*. Since EDP is not sensitive to the energy of the reflected paths, it can be a robust indicator of distance, even in dynamic indoor environments.

Extracting the Direct Path Signal: In search of a mechanism to extract the direct path signal, we found that Atheros 9390 chipsets can export the Channel State Information (CSI) from the PHY layer to the driver. The delay, and attenuation of different signal paths are captured in the CSI. If a transmitter transmits a symbol X, the quality of the received symbol at the receiver, Y, depends on the CSI H:

$$Y = H * X + n \qquad (2)$$

where n captures noise. The CSI is reported as a matrix of complex numbers representing the channel gain for every subcarrier and for every transmit-receive antenna pair. By an appropriate Inverse Fast Fourier Transformation (IFFT), the frequency-domain CSI can be translated into the time-domain *power-delay profile (PDP)*. PDP captures the energy of the different paths incident at increasing delays. Since, the direct path traverses the minimum distance amongst all the received paths, it's energy will likely appear in the earliest component of the PDP. Figure 3 shows the PDP at two different clients which are equidistant from the AP. For the first client (figure 3(a)), the direct path does not pass through obstructions, and thus yields the strongest component. However, for the second client (figure 3(b)), the direct path's trajectory is blocked by a human standing between the client and the AP. Thus the direct path is attenuated, and appears weaker than stronger reflected paths. RSSI cannot discriminate between these scenarios. It will use the same path-loss exponent (in Eq. 2) to measure the distance of both the clients, resulting into large errors. We will show how *CUPID can mitigate the distance error due to multipath by using only the energy of the direct path.*

2.2 Angle-of-arrival Estimation

A wireless transmission from the client arrives at several angles at the AP. If we can determine the *angle of the direct path or ANDP*, it is possible to combine the angle of the client with her distance,

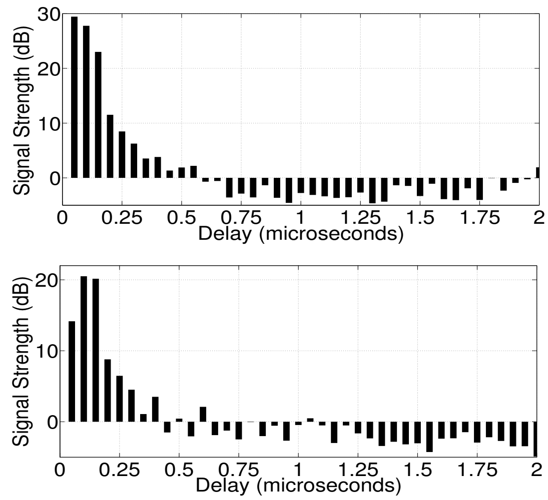


Figure 3: Power delay profiles of two different indoor transmissions: (a) Client has line-of-sight path to the AP, hence its direct path signal is stronger than the reflected, and delayed components. (b) Client's direct path is blocked, hence EDP is also weaker.

ultimately yielding her location. Existing AoA estimation algorithms analyze the received signal on multiple antennas to find out the angular components of the signal [12]. The key idea is to analyze the phase of the received signal, a quantity which changes linearly by 2π for every wavelength (λ) traversed by the signal. For the simplicity of explanation, consider a single path between the transmitter and the receiver. Let us consider that the AP has only two antennas, placed at a distance of $\lambda/2$ (figure 4(a)). Let θ be the angle at which the signal arrives at the two antennas. The signal travels an extra distance before reaching the second (left) antenna. This extra distance(Δd) can be approximated as:

$$\Delta d = \lambda/2\sin(\theta)$$

We know that an extra distance Δd will result into a phase difference($\Delta\phi$):

$$\Delta\phi = 2\pi\Delta d/\lambda$$

Thus, by observing the phase difference ($\Delta\phi$) of the arriving signal, we can find the angle-of-arrival as:

$$\theta = \arcsin(\Delta\phi/\pi)$$

The above explanation assumes that the arriving signal has only one angular component. In reality, a wireless signal will propagate through multiple paths. AoA estimation algorithm can identify the angles of multiple paths by using many antennas. In the interest of space, we omit the details here, but point the reader to [12] for a detailed explanation of a representative AoA estimation algorithm called MUSIC. The output of the MUSIC algorithm is a pseudospectrum(figure 4(b)). Each peak in the pseudospectrum is an estimated *angle-of-arrival(AoA)*. Multiple peaks in figure 4(b) implies incoming signals from different directions, including the direct path, and a reflected path.

Angle Estimation using AoA: How can we locate the peak which corresponds to the direct path in MUSIC's pseudospectrum? The height of a peak may be proportional to the amount of energy incident on the receiver from the corresponding angle [13, 14]. When the receiver is visible to the transmitter, the direct signal path may often be the strongest component. Secureangle [13] uses this intuition. It declares the AoA of the strongest peak of the pseudospectrum as the client's angle. However, this scheme

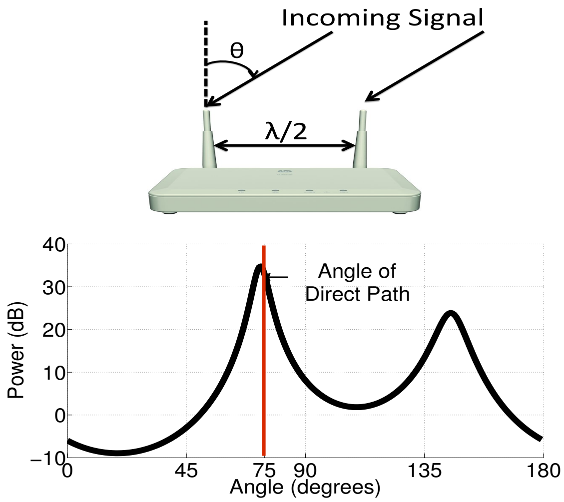


Figure 4: (a) A signal arriving at an angle θ at an AP with two antennas. (b) Output of MUSIC algorithm.

breaks down in indoor environments, where the direct path is often blocked, and hence weaker than a reflected signal. Moreover, a stronger reflected signal may arrive from any random direction, which may be totally unrelated to the angle of the direct path (ANDP). CUPID should only use the ANDP to estimate the location of the client. Otherwise, it will perform poorly whenever it is confused by a stronger reflected component. In this paper, we demonstrate how *human mobility can be combined with MUSIC's AoA estimates to correctly determine the ANDP*.

3. MEASUREMENTS AND SOLUTIONS

In this section, we report measurements from a busy office environment to verify our observations made in the previous section. First, we briefly describe our measurement infrastructure, followed by measurement based analysis of RSSI and AoA. Finally, we develop our key solutions using EDP and ANDP.

3.1 Measurement Infrastructure

We use HP laptops running Linux OS as APs. To enable per-packet CSI measurements at the laptops, we replaced the internal wireless card with Atheros AR9390 chipset. We further attached 3 antennas to the laptop. Ideally, the mobile client should be a smartphone with sensors which can track the user's mobility. The AP should extract the CSI values from the mobile phone's upload packets. However, we found that Atheros AR9390 chipsets export the CSI for packets which have the 802.11n sounding flag turned on in the PHY header. We could not modify the android wireless device driver to add this functionality, and thus could not extract the CSI from regular phone to AP transmissions. To address this challenge, we tape the phone to a laptop and modified the ath9k driver on the laptop to set the sounding flag for uplink transmissions. At the AP, we extract the CSI from the laptop client's transmission, as well as the accelerometer, and gyroscope readings as reported by the phone. We conducted experiments at 500 locations, and analyzed the data to develop our key algorithms.

3.2 Limitations of RSSI-based Distance Estimation

As explained in §2.1, RSSI is the aggregated energy of all the signal paths – direct, as well as multipath reflections. Thus, while translating RSSI to distance, choosing the appropriate path-loss exponent(γ) becomes difficult because γ depends on the time-varying propagation characteristics of the signal. For instance, in a *line-of-sight (LoS)* environment like corridor, the path loss exponent (γ in equation 2) will be close to 2. On the other hand, for complex indoor scenarios the path loss can go upto 4. Figure 5(a) shows the distribution of path loss exponents from 500 known locations in our building Clearly, there is a large range. Even at a single location, we found that the per-packet path loss exponent can vary between 2.1 to 3.4. Since RSSI does not capture any information regarding wireless propagation, choosing the right path-loss exponent for each received packet is difficult. Measuring the path loss exponents at a few locations and using the average of them to estimate distance will likely lead to poor performance (figure 5(b)). We observed up to 100m error while the maximum client-AP distance was 40m.

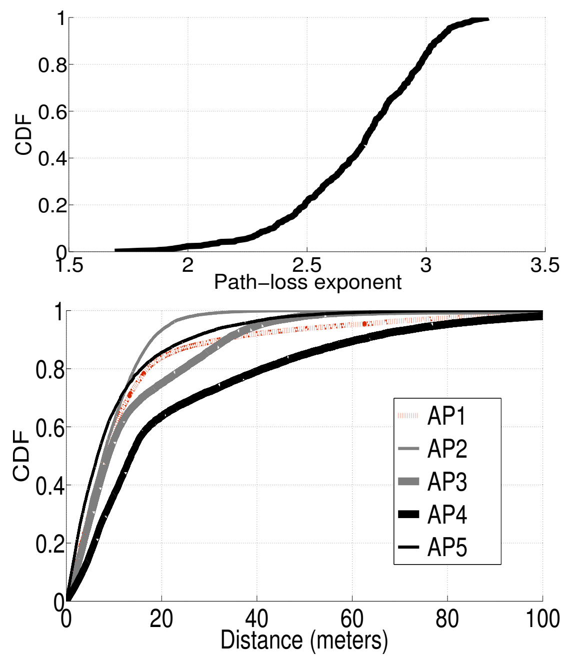


Figure 5: (a) CDF of path loss exponents from 500 known locations. (b) RSSI-based distance estimation error.

3.3 Distance Estimation using EDP

While it is impossible to capture multipath characteristics of a signal using RSSI, the power-delay-profile (PDP) obtained from the CSI information can estimate the same. Due to bandwidth limitations, it is not possible to distinguish every signal path from the PDP. E.g., the resolution of PDP with a 20MHz 802.11n OFDM reception is approximately $50ns$. However, as discussed in § 2.1, the first component of the PDP is likely to contain the direct path signal. The first component may also contain a few other reflected paths, which arrives at almost the same time as the direct path. However, the later arriving components in the PDP correspond to reflected paths which have traversed significantly longer distance (more than $15m$ than the direct path, due to the $50ns$ resolution). Hence these reflected components should be ignored while computing the distance between the transmitter and the receiver. We approximate the energy of the first component of the PDP as the energy of the direct path (EDP). Though not perfect, EDP based distance estimation is more robust than RSSI, since it is much less susceptible to multipath reflections.

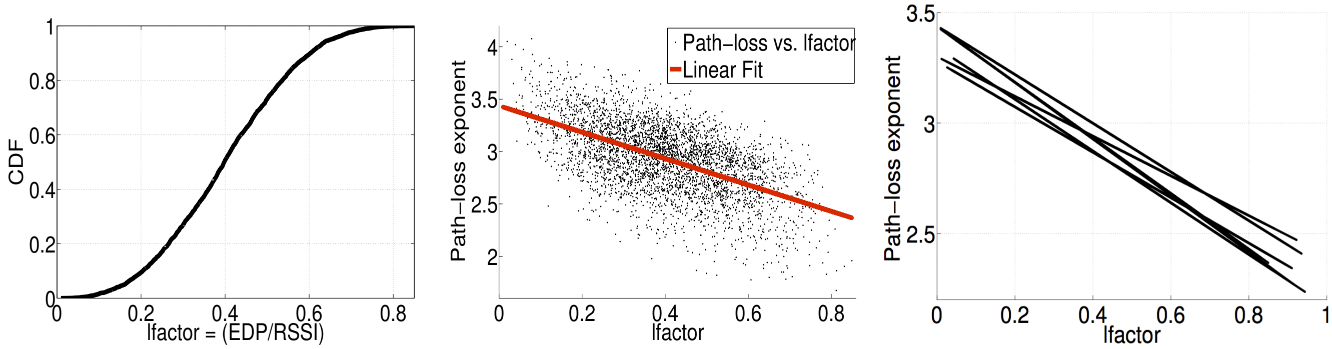


Figure 6: (a) CDF of lfactor values at 500 locations. (b) path loss exponent vs. lfactor at 500 known locations. (c) Relationship between path loss exponent and lfactor for 5 APs.

However EDP is susceptible to shadowing. For example, the direct path between an AP and the mobile device may be blocked by the human carrying the phone. At the same location, the estimated EDP will be higher when the user faces the AP with the phone (*line-of-sight or LoS*, figure 7(a)), versus when she is back-facing it (*non line-of-sight or NLoS*, figure 7(b)). Here, we observe that a blockage on only the direct path may not affect the other reflected components [1]. We use this observation to quantify the likelihood of LoS by computing the *LoS factor (lfactor)* as:

$$lfactor = \frac{EDP}{RSSI} \tag{3}$$

Figure 6(a) demonstrates that a wide range of lfactor values can occur in an indoor setting. A high lfactor will imply that most of the received signal arrives along the direct path, like in a corridor scenario with LoS. On the other hand, if the direct path is blocked, we will witness a low lfactor value. Thus, we expect that the path loss exponent for the direct path will be inversely proportional to lfactor. Figure 6(b) shows the EDP path loss exponent with increasing lfactor for transmissions to a single AP. The trend is clear, and we further observed that the result looks similar at other APs. From these measurements *we can apply linear fitting to establish a relationship between path loss exponent and the lfactor.* We believe we are the first to propose a systematic approach of finding the correct *per-packet path loss exponent* using EDP and lfactor.

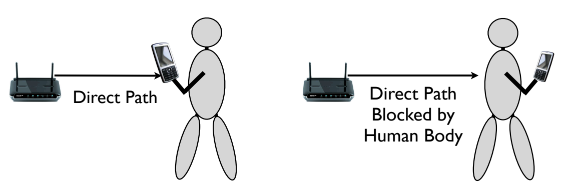


Figure 7: User orientation w.r.t AP: (a) facing (b) blocked

The path loss vs. lfactor relationship may not depend on a particular AP, or even environment. Figure 6(c) plots the path-loss exponent vs. lfactor relationship for 5 different APs. The lines are similar because lfactor directly estimates the environmental factors affecting the EDP, which ultimately governs the path-loss exponent. Hence the relationship between path-loss exponent (γ) and lfactor does not vary much over different environments. Measurements from a few known locations can adequately establish the relation, and we could apply the same relation to other environments as well (§4.4). Of course the lfactor vs. path-loss exponent relationship may not be as straightforward in complex environments, e.g., crowd gathering. However, lfactor may still capture sufficient details of wireless propagation in most scenarios. Later in our evaluation section we will show how lfactor can reduce the distance estimation error in office environments.

To summarize, the AP calculates the EDP and lfactor from the CSI of a client's transmission, and thereafter uses the lfactor-to-γ relation to select a correct path loss exponent for each received packet. The AP then calculates the distance to the client using the path loss equation (Eq. 2) with EDP and path loss exponent as inputs. Note that by choosing the correct path-loss exponent, our solution allows distance estimation to adapt to fast fading on a per- packet basis. Later in our evaluation we show that EDP, along with the use of lfactor, can reduce the median distance estimation error to $4m$, in comparison to $10m$ while using RSSI.

3.4 Limitations of existing AoA Algorithms

In addition to distance, angle is also important for location estimation. Existing angle-of-arrival(AoA) techniques can estimate the angles at which the signal arrives, but cannot determine which of these angles correspond to the angle of the direct path (ANDP). We study the limitations of a representative AoA estimation technique, MUSIC. As discussed in § 2.2, the angle of the highest peak in MUSIC's pseudospectrum may correspond to the ANDP in LoS scenarios. However, whenever the direct path is blocked, the highest peak may correspond to a stronger reflected path, resulting into large errors in angle estimation(figure 8).

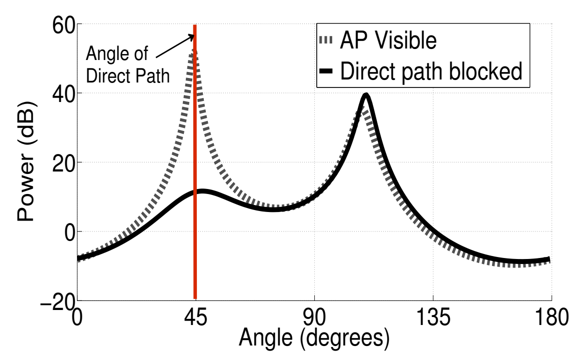


Figure 8: MUSIC's pseudospectrum output at the client when the AP is visible, and when the direct path is blocked by a human. In the later case, MUSIC will mistakenly declare the AoA of a reflected path as the ANDP.

[1] Blockage of all signal components will likely weaken RSSI, which can be separately identified.

How often does this simple scheme fail, and what is the associated error? In figure 9(a), we plot the angle estimation error, if the strongest peak in MUSIC's pseudo spectrum is used for ANDP computation. The estimation error is more then 60° for 40% measurements. Analyzing the data, we found that large errors indeed happen due to a stronger reflected component. To explain this further, figure 9(b) shows that the ANDP estimation error reduces with increasing lfactor. If the lfactor is low, the direct path is weaker than a stronger reflected path, and hence choosing the strongest peak results in large errors. The median lfactor in our measurements is approximately 0.4 (figure 6(a)), indicating rich multipath. Hence, we need to address the multipath issue before we can exploit existing AoA algorithms. However, before exploring such solutions, we need to understand whether any of the AoA peaks actually captures the ground truth ANDP, the actual angle toward the client location. Due to estimation noise, and poor angle resolution due to only 3 antennas, none of the AoA values may exactly match with the ground truth ANDP. Figure 9(a) plots the estimation error if the peak closest to the ground truth is chosen as the estimated ANDP. Clearly, there is opportunity. If we could identify the best peak, the estimation error will decrease to median 20°, contributed mainly by poor angle resolution. We show how it may be possible to identify the best peak by leveraging natural human mobility. We develop our ANDP estimation scheme in conjunction with MUSIC. However, our approach is generalizable to other AoA estimation algorithms as well.

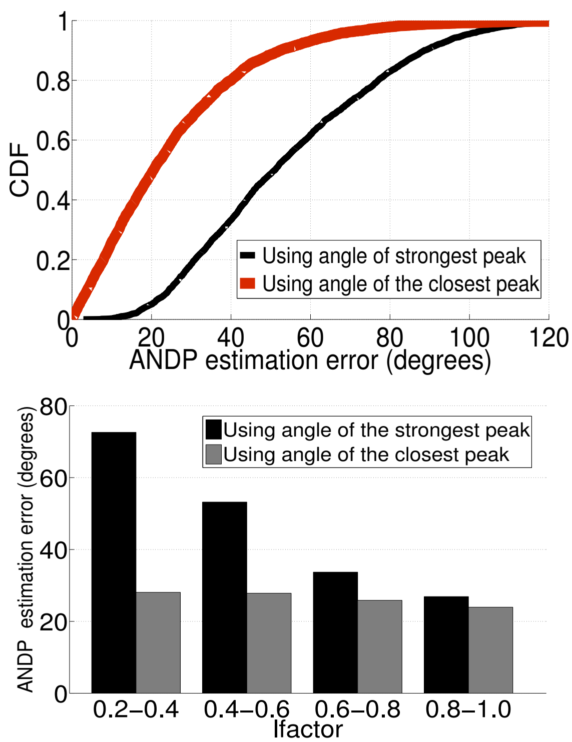


Figure 9: ANDP estimation error using MUSIC (a) CDF, (b) with increasing lfactor value

3.5 Angle Estimation Using Human Mobility

We leverage the observation that by analyzing the AoA values at two different locations that the user has walked through, it is possible to identify the ANDP. The AP computes the AoAs by by employing MUSIC on the CSI estimates of the received uplink packet from the user's mobile device. By analyzing the AoA values from two different locations, we find that two different scenarios may occur (as shown in figure 10). First, it is possible that although the reflected paths are stronger at two different locations, their angles are different. Rather, the weaker direct path is consistent,and hence the ANDP can be approximated as the AoA which remains stable in the pseudospectrums. Second, none of the AoAs in the pseudospectrums from the two locations may closely match. In this scenario, CUPID identifies the ANDP using dead reckoning, and EDP-based distance estimation as described next.

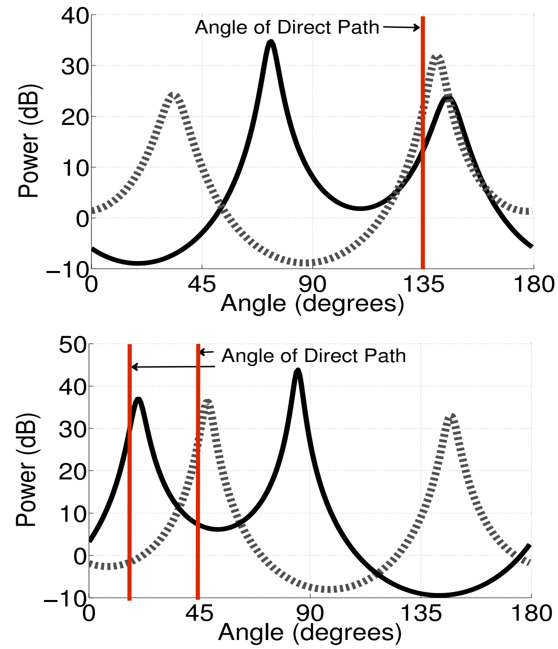


Figure 10: MUSIC pseudospectrum when the client is at two different locations: (a) The ANDP is stable at both the locations, however the reflected angles are different (b) Both ANDP and reflected path angles are different.

We explain our key idea using figure 11. Let us assume that the received signal arrives at two different angles; one component of the signal due to the direct path and another due to a reflected path. When the user is at location A, let the AoA estimates be θ_{A1} and θ_{A2}. When the user moves to position B, let the corresponding estimates be θ_{B1}, θ_{B2}. For the purpose of explanation, let us assume that the signal component which arrives at an angle of θ_{A1} at location A, incidents at an angle of θ_{B1} at location B, and likewise for θ_{A2} and θ_{B2}. Let the EDP-based distance estimate of the client at location A and B, be d_A and d_B respectively. When the user walks from location A to B, we can compute the physical distance between the two locations (p_{AB}) by consulting her phone's accelerometer and gyroscope – a method called *dead reckoning*. The change in ANDP ($\Delta\theta$) is nothing but the angle formed at the AP by the two locations. From the properties of a triangle, $\Delta\theta$ can be computed as:

$$\Delta\theta = \arccos \frac{(d_A^2 + d_B^2 - p_{AB}^2)}{2 * d_A * d_B}$$

The angular change of the i^{th} AoA (ϕ_i), between locations A and B is $\theta_{Bi} - \theta_{Ai}$. We can now identify the AoA (θ_{Bk}) which has experienced the same change as the estimated change in ANDP (($\Delta\theta$)):

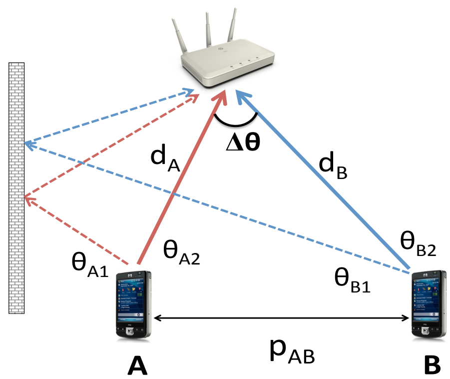


Figure 11: Detecting ANDP exploiting mobility.

$$ANDP = \theta_{Bk}$$
$$\forall i \neq k \; |\Delta\theta - \phi_k| \; < \; |\Delta\theta - \phi_i|$$
$$\forall i \; \phi_i \; = \; \theta_{Bi} \; - \; \theta_{Ai}$$

To identify the ANDP, the AP tracks the AoAs measured at a location, at all subsequent locations the user walks through. We observe that the pseudospectrums from two nearby locations (within $2m-3m$ distance) have similar AoA values. Thus, we can pair an AoA measured at a location, with the closest angle measured from a subsequent location. As the user walks, we can use this correspondence to track each AoA in the pseudospectrum. [2] The AoA which undergoes the same angular change as the direct path is CUPID's estimate of ANDP.

How long does the user have to walk before her ANDP can be identified? If we compare the pseudospectrums at two nearby locations, the change in ANDP ($\Delta\theta$) will be small. A reflected path's angle difference may be similar to $\Delta\theta$ due to estimation noise. To avoid this confusion, ANDP estimation is triggered only when the change, $\Delta\theta$, is more than 20°. Of course, if only a particular AoA value remains stable, the estimate is safely used as the ANDP. Figure 12 shows that the user has to walk only a reasonable distances before her ANDP can be appropriately identified. Observe that, mobility estimation is required only until the ANDP is identified. Once the ANDP is identified it can also be tracked. The AoA close to the previous ANDP estimate can be used as the new ANDP. Although rare, it may be possible that at a new location none of the AoA estimates matches with the previous ANDP. In such scenarios, a fresh round of dead-reckoning and ANDP estimation can be triggered. To our knowledge, we are the first to utilize user mobility to identify the ANDP. Once the ANDP is known, the AP can combine it with the estimated distance to locate the user.[3]

4. DESIGN AND IMPLEMENTATION

Translating the above high level ideas into a functional prototype entails two additional tasks: (1) How to process CSI values from multiple antennas to compute the EDP and AoA values? (2) How to estimate user's mobility to identify the ANDP from the AoA values? The AP can find the location of the client by using the estimated distance, and angle. If multiple APs collaborate, localization performance can be improved. We propose a simple algorithm which can leverage multiple APs. In the next section we will present detailed results on the performance of our scheme.

[2] To deal with estimation noise, we find all the AoA estimates in a window of 2 seconds, and group them based on similarity.

[3] We assume that the location of the AP is known beforehand.

Figure 12: CDF of physical distance walked by the user before the ANDP can be appropriately estimated.

4.1 CSI Processing

802.11n defines a channel sounding mechanism where the transmitter can trigger CSI estimation at the receiver by setting an appropriate flag in the transmitted packet. The receiver can thereafter feedback the estimated CSI to the transmitter for the purpose of calibration, or beamforming. We use this mechanism to extract CSI. We modify the device driver of Atheros 9390 cards to appropriately set the sounding bit of a transmitted packet. On the receiver side, the CSI is estimated for each receive and transmit antenna pair. The Atheros 9390 reports one complex number per subcarrier for 56 out of the 64 available subcarriers, and we only use these for our scheme.

Figure 13 shows the magnitude and phase of the CSI reported for 10 consecutive packets. Since the chipset is MIMO and beamforming capable [4], the three MIMO transceivers are time synchronized and phase locked to run at the same frequency. As a consequence, we find that the reported CSI does not include random phase errors across different receive antennas. The phase difference between the antennas remain stable within the coherence time of the channel, making it appropriate for AoA computation. There might be some error due to downconversion in the PHY layer, which can be mitigated using communication between two APs [17]. We do not apply this optimization in our system. Apart from CSI, we also aggregate the RSSI values from all the antennas as today's WiFi drivers do.

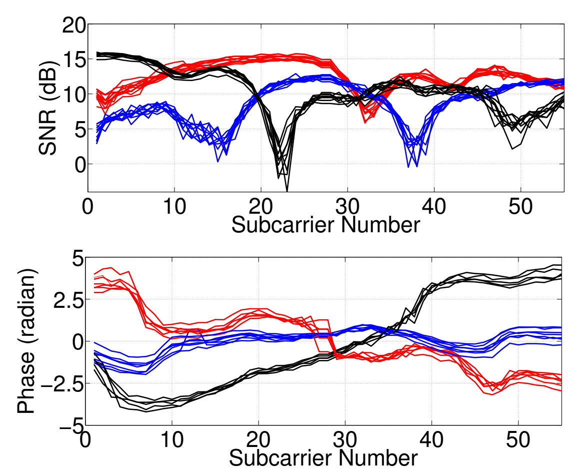


Figure 13: (a) Magnitude and (b) phase of CSI reported for 10 consecutive packets.

[4] Standard for 802.11n and 802.11ac systems [15, 16]

4.2 Location Estimation

CUPID uses the estimated EDP in the path-loss equation (Eq. 2), to determine the distance of the client. We use the highest observed EDP in our measurements as P_0 in equation 2. The AP runs MUSIC algorithm on the CSI to identify the angular components of the received signal. It exploits the mobility pattern of the user to identify the ANDP from the multiple angles reported by MUSIC. We co-opt dead-reckoning techniques to estimate the user's mobility, as described next.

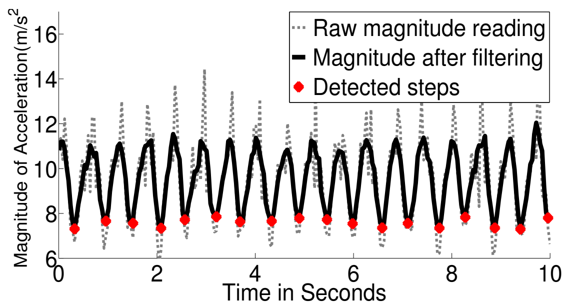
Mobility Estimation using Dead Reckoning

Dead reckoning involves computing the user's displacement from accelerometer, and tracking the direction of movement using the compass. To calculate user's physical displacement, CUPID identifies a human-walking signature from the accelerometer readings, as shown in Figure 14(a). This signature arises from the natural bounce of the human body for each step taken. To identify the steps, we pass the accelerometer readings through a moving average filter, and identify two consecutive local minimas. A legitimate step will cause a significantly strong local maxima between two local minimas. We track the number of steps the user has taken by counting the local maximas. In our experiments, we could achieve a 98% accuracy in step detection. The physical displacement of the user can be computed by multiplying step count with the user's step size, which can be automatically tracked [11].

To estimate ANDP, CUPID calculates the distance between a past location of the user and her current location. Thus apart from physical displacement, orientation information is also required. Past work has demonstrated the feasibility of estimating orientation using smartphone compass. However, compass is vulnerable to indoor magnetic fiends created by metallic and electrical objects. Fortunately, CUPID is only interested in the distance between two locations, the absolute direction is not required. Thus, it only needs to track the angular changes as the user walks from one location to another. Smartphone gyroscope is appropriate for this purpose. It remains unaffected by changing magnetic fields [18], and computes the relative angular velocity. This yields the relative angular displacement of the user when multiplied by the time interval. CUPID can thereafter translate the physical and angular displacement into distance between two locations. Figure 14(b) shows the dead reckoning based distance estimation error between two locations. Errors in step size, along with noisy gyroscope readings increases the error for large distances. However, it is still reasonable (<5m) for up to 50m actual distance, which is the typical range of WiFi APs. In contrast, absolute location estimation using dead-reckoning will require compass angles, which might be erroneous indoors. Thus, in figure 14(b) location estimation error using dead-reckoning increases quickly. We conclude that although dead-reckoning may not be enough for localization, it is adequate for our purpose.

Side Ambiguity with Linear Antenna Placement

CUPID can find the ANDP from MUSIC's AoA estimates by estimating user's mobility using dead-reckoning techniques. In our implementation, we use laptops as APs, which has 3 antennas placed in a straight line, analogous to a linear antenna array. However, a linear antenna array can differentiate between signals from one array side only. This is because the AoA range of a linear array is between 0 and 180. Clients on the two sides of the line formed by the antennas are not differentiable. A circular antenna array type can differentiate signals from all directions. However, it requires almost double the number of antennas to achieve the same accuracy as a linear array. Thus with a linear antenna placement, CUPID needs to address the side ambiguity issue, before it can find the exact client location. We address this by observing the user's turns.



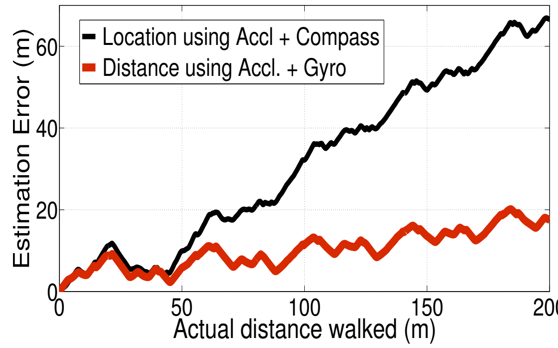


Figure 14: (a) Identifying steps from accelerometer readings. (b) Error from dead-reckoning for increasing distance between two locations.

We explain the key idea using figure 15. Let us assume while walking from location A to C, the user takes a turn at B. The angle of the user (ANDP) increases as he walks from A to C. The linear array cannot distinguish between angles on its two sides. Hence, the change in angle (θ) will be the same if the user walks through ABC or $A'B'C'$. However, the tie between ABC, and $A'B'C'$ can be broken by observing the turn the user undertook. If the gyroscope of the user's phone registered a right turn, she is indeed located in the front of the antenna array. On the other hand, if the user took a left turn, she was walking through $A'B'C'$. In general, it is possible to find out whether the user is located

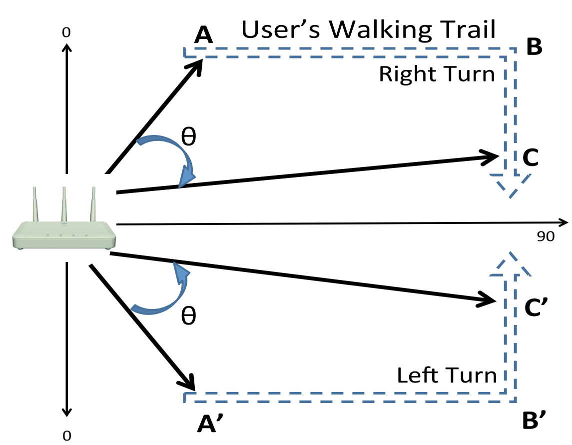


Figure 15: Side ambiguity due to linear antenna array.

in the front, or back side of the antenna array by observing the change in ANDP, and the nature of turn undertaken from her gyroscope (Table 1). The estimated ANDP remains the same if the user is in front. However, if the user is in the back of the array, we use $(-ANDP)$ as the actual angle. Once the angle of the client is determined, the AP can combine the angle with the distance estimate to find the location of the client.

Table 1: Addressing side ambiguity using user turns.

Change in ANDP	Gyroscope Reading	Final Angle
Positive	Right turn	ANDP
Positive	Left turn	- ANDP
Negative	Right turn	- ANDP
Negative	Left turn	ANDP

4.3 Leveraging Multiple APs

An AP can determine the location of all its associated clients by estimating their distances, and angles. However, if multiple APs can overhear a client's upload transmission to it's own AP, they can also independently estimate the location of the client. Of course, it is possible to utilize other APs on different channels if the client performs active 802.11 AP probing over multiple channels. Such active probing is not desirable because it can create throughput degradation and battery drain. Thus, CUPID combines the location estimates across only those APs which can overhear client's transmissions to it's own AP as described next.

Let the d_i be the distance, and θ_i be the angle estimate of a client from an AP (located at $AP_{i,x}, AP_{i,y}$). The AP can utilize the estimated distance, and angle to find the location of the client (x_i, y_i):

$$x_i = AP_{i,x} + d_i \cos\theta_i \quad (4)$$
$$y_i = AP_{i,y} + d_i \sin\theta_i \quad (5)$$

If more than one AP is available, CUPID combines the location estimates across them using a weighted centroid approach:

$$C_x = \frac{\sum x_i EDP_i}{\sum EDPi}, C_y = \frac{\sum y_i EDP_i}{\sum EDPi} \quad (6)$$

where EDP_i is the EDP estimated at AP_i from the client's upload transmission. CUPID announces the weighted centroid (C_x, C_y) as the location of the client. We observe that far away APs may cause large errors in location estimation. For the same angle estimation error, and perfect distance estimation, positioning error is proportional to the distance between the client and the AP. Thus, we optimize the system by ignoring the APs which receives the client's packet at less than $15dB$ signal strength. In this way, CUPID also mitigates distance error due to shadowing effect that is not captured by lfactor, to some extent.

If the client is stationary at the beginning of a new localization attempt, her accurate ANDP information won't be available at every AP. In this case, CUPID solves a system of non-linear equations involving the unknown location of the client (L_x, L_y) and its estimated distance from different APs:

$$|| < AP_{i,x}, AP_{i,y} > - < L_x, L_y > || = d_i \quad (7)$$

i = 1 ... n, where n is the number of APs. Observe that to solve the above multilateration problem, CUPID requires atleast 3 APs which are in range of the client.

4.4 Points of Discussion

Figure 16 presents the overall architecture of CUPID, showing how the distance calculation, ANDP estimation and ANDP database modules collectively mitigate the multipath, LoS/NLoS and side ambiguities to compute the client location. CUPID calculates the distance between the AP and the mobile device using EDP, and lfactor. It also calculates the AoA values of the mobile device using MUSIC. The mobile device shares with the AP its dead-reckoning based distance estimates, as well as past turn information. If the AP had a previous ANDP record for the same mobile device, it declares the AoA which is closest to the past ANDP as the current ANDP. Otherwise, it compares the current AoA with past recorded AoA values to find the ANDP. Whenever the user takes a turn, the AP corrects her ANDP according to the observed gyroscope reading (table 1). If the AP could estimate both distance, and ANDP of the mobile device, it computes an estimated location by using equation 4, and forwards the same to a location server [5]. Otherwise, if the ANDP is not available, the AP sends only the estimated distance value. The location server combines the distance, and ANDP from multiple APs and further refines the user's estimated location. We cover some additional discussion points below in building the real system of CUPID.

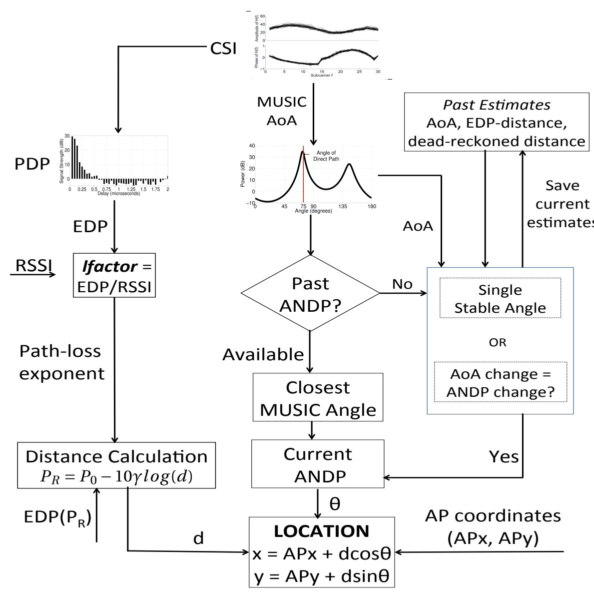


Figure 16: CUPID Architecture

CUPID uses measurements from a few known locations to construct the lfactor to path-loss exponent relation – is this not fingerprinting? We argue that this is certainly not fingerprinting because finding this relationship is a one time effort. Unlike fingerprinting, the relationship may not vary across different locations and environments. We find that a different building within our campus exhibit a very similar lfacor vs. path-loss relation (figure 17). Therefore, we postulate that once the relation is adequately established from any particular building, it can be used in all other locations. Vastly different environments (open desert vs. shopping malls, cold storage vs. indoor office) may show different relation due to the big difference of material or temperature; profiling the relations for such a few representative environments incurs very little cost. In contrast, fingerprinting has to be triggered whenever the environment changes, or the AP changes

[5]One of the APs can participate as the location server.

its channel, or power settings, which can happen very frequently (4 mins) [6].

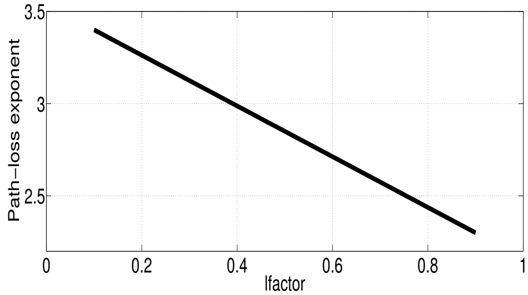


Figure 17: Relationship between lfactor and path-loss exponent for a single AP, estimated from a different building.

CUPID depends on the presence of a direct path signal. Will the direct path signal exist at most locations? It is difficult to evaluate whether the direct path signal exists in all our measurements. However, later we find that the ANDP estimation accuracy falls sharply when the signal strength of a client at the AP is below $15dB$. From this observation, we postulate that for weak clients, it might be difficult to identify the direct path signal. However, if multiple APs are available, CUPID will be able to leverage the nearby APs. Considering the dense AP deployments in typical indoor settings, it's reasonable to expect to have one or more neighboring APs with signals above $15dB$.

Will CUPID work if the user is static? CUPID can still estimate the location of a static client by leveraging her distance estimations. Of course, if the user was walking before becoming stationary, CUPID can estimate her angle from the past ANDP values. In such scenarios, CUPID can find the location of a static user even with a single AP.

Will CUPID consume a lot of energy? CUPID is designed with energy efficiency in mind. Contrary to existing schemes that require power-hungry channel scanning (fingerprinting) or active AP probings (AoA), CUPID can find the location of the client using only a few APs available on the same channel. Further, CUPID uses the client's accelerometer, and gyroscope readings only until her ANDP is known. Thus by eliminating the need of costly AP probing, and continuous scanning, CUPID limits the energy overhead, making it a practical proposition.

5. EVALUATION

We implement CUPID using laptops with Atheros 9390 wireless card and Google Nexus S phone. The phone is time synchronized for timestamping and physically attached to the laptop. It samples the accelerometer at $24Hz$, and the gyroscope at the highest permissible rate, and sends the dead-reckoning based relative location estimate to the AP. The client laptop uses only a single antenna, and it broadcasts packets at $20MHz$ bandwidth in a $5GHz$ band. The APs are also laptops with Atheros 9390 wireless cards, but uses all 3 available antennas. The location estimation logic at the AP is implemented using C in driver, and MATLAB.

5.1 Methodology

We design real-life experiments in an office environment with 5 APs installed at known locations, as shown in figure 18. The APs calculate the distance, and ANDP of a client, and sends them to the location server. The server knows the location of the APs, and can combine the information gathered from multiple APs to estimate the location of the client. We walked around arbitrarily in the building for an hour during normal office hours covering approximately $4500m^2$. As we walked, the client broadcasted 5 packets per second, unless differently specified, and the APs calculated the distance and angles to the client using the received packets. APs use a moving average filter on the distance, and angle estimates to deal with noise. The width of the filter is fixed as the number of packets received in the last 2 seconds; 10 packets by default. We made separate arrangements to collect ground truth (GPS is not availble indoors). Briefly, we pasted markers at known locations (red circles in figure 18). Each marker had a number on them, whenever the user walks through a marker, she records the number. The locations of the markers are known, and between two markers we did interpolation using step-count as the ground truth; we used approximately 1800 ground truth locations. The distance between the ground truth and the estimated location, is CUPID's instantaneous localization error.

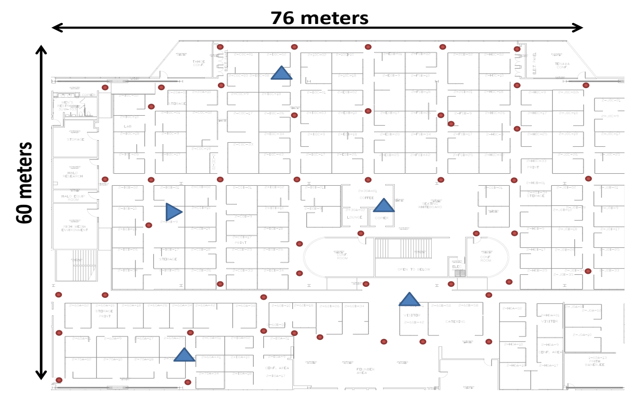


Figure 18: Floorplan of our office building. AP locations are shown as blue triangles, and markers as red circles.

5.2 Distance Estimation Performance

Figure 19(a) shows the distance estimation error of the client at 5 different AP. CUPID greatly reduces distance error compared to the conventional RSSI-based ranging in figure 5(b). It precomputes the lfactor to path-loss exponent mapping function from a few known locations. The accuracy of the function affects the distance estimation process because CUPID uses the path-loss exponent to compute distance. Figure 19(b) shows that even with a few known locations used to generate this function, CUPID performs well. However, the performance is poor at a few client locations. Upon analyzing the data we found that the error is high for weak links (figure 19(c)). This is because of the low fidelity of the CSI estimation process at weaker signal strengths [4].

5.3 Angle Estimation Accuracy

CUPID combines AoA estimation with user's mobility pattern to calculate the angle of the client (ANDP). It further exploits the user's gyroscope to address the side ambiguity introduced by linear antenna placements. Figure 20(a) shows that by using only the angle of the direct path, CUPID's median angle estimation accuracy is 20°. The error in CUPID's angle estimation is mostly due to the poor resolution driven by using only 3 antennas, that commodity 802.11n cards support. We further postulate that some high errors are due to weak links as shown in figure 20(b). Weak links may not have significant energy on the direct path, and hence

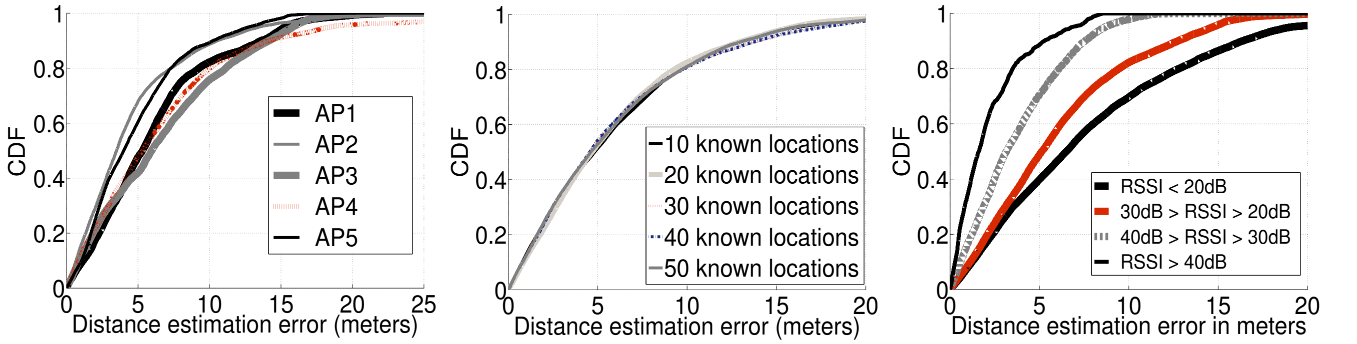


Figure 19: CDF of EDP-based distance estimation error (a) at different APs, (b) for different number of known locations used to find the lfactor-to-γ mapping. (c) Distance estimation error reduces as signal strength increases. Client-AP distance is <= 40m (Fig 19(b)).

are more prone to errors. This led us to exclude weak APs in the design of CUPID.

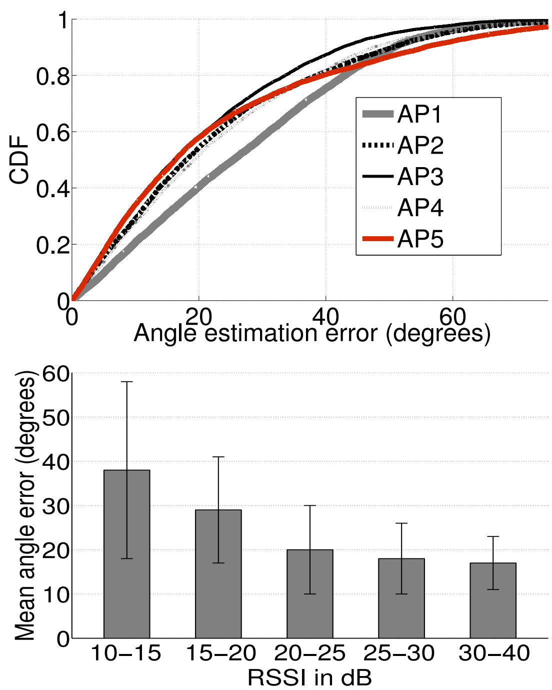


Figure 20: (a) CDF of angle estimation error. (b) Angle estimation error for different RSSI values.

5.4 Localization Performance

By combining the distance, and angle of a client, an AP can find her location. First, we present the localization performance in a single AP scenario. Thereafter we discuss how performance can be improved by leveraging multiple APs.

Single AP Performance

Figure 21(a) demonstrates CUPID's location estimation error by employing only the AP that the client associates with. We plot the distribution of the actual client-AP distance in figure 21(b). Figure 21(a) also demonstrates the effect of number of client's broadcast packets on positioning accuracy. As the client transmits more packets, the moving-average filtering process can be more effective in dealing with noise. However, even with 2 packets per second from the client (total 4 packets in 2 seconds), median localization error is $5m$. We also find that the localization error is large ($> 10m$) at a few locations. To understand this better, we plot the error as a function of RSSI in figure 21(c). We find that most of the errors can be attributed to locations where the strongest AP is less than $15dB$ strong. Thus, while CUPID might be able to locate most of the clients reasonably well, its single AP localization performance degrades at the edge of the wireless network. However, we believe that this is still a significant improvement over previous indoor localization schemes which rely on many APs to attain a reasonable accuracy.

Performance by Leveraging Multiple AP

If multiple APs can overhear the client's upload transmission, CUPID can combine the location estimates from them to further improve the performance. If the user is static, the APs can only find her distance (and not angle). CUPID computes the user's final location by using the per-AP distance estimates in equation 7. As the user moves, accurate ANDP becomes available, and hence CUPID can further refine the user's location. Figure 22(a) shows the comparison of these two forms of localization - evidently the advantage of user mobility is appreciable. Mean localization error reduces from $7m$ when the user is static (thus EDP only), to $2.7m$ when the user has walked a reasonable distance (EDP+ANDP). While the system can use up to 5 APs, we observe that the weak APs can inject large errors in our distance and angle estimation. Hence for better accuracy for mobile users, CUPID uses the location estimate from an AP only if the AP sees signal more than $15dB$ strong; EDP+ANDP plots this case. In our experiments only upto 3 APs satisfied this criteria in 80% of test locations. If CUPID indiscriminately uses all the 5 APs (EDP+ANDP w/o AP selection), localization error may increase - as evident from figure 22(a).

Impact of number of APs: We further analyze CUPID's performance for varying number of APs. We divide the locations into different categories depending on how many APs are visible ($> 15dB$) at each location. Even when a single AP is visible, CUPID can locate the client with an accuracy of $4.4m$ for 50% and $6m$ for 90% (figure 22(c)). As the number of APs increases, the median error quickly goes down to $2m$. Notably, CUPID can locate the client with only 2-3 APs at reasonable accuracy, thus eliminating the need of probing APs across different WiFi channels to use more APs.

Comparison with existing RSSI and AoA: We evaluate if previous RSSI, and AoA-based schemes can achieve similar accuracy as ours. For the RSSI based multilateration, we use RSSI based

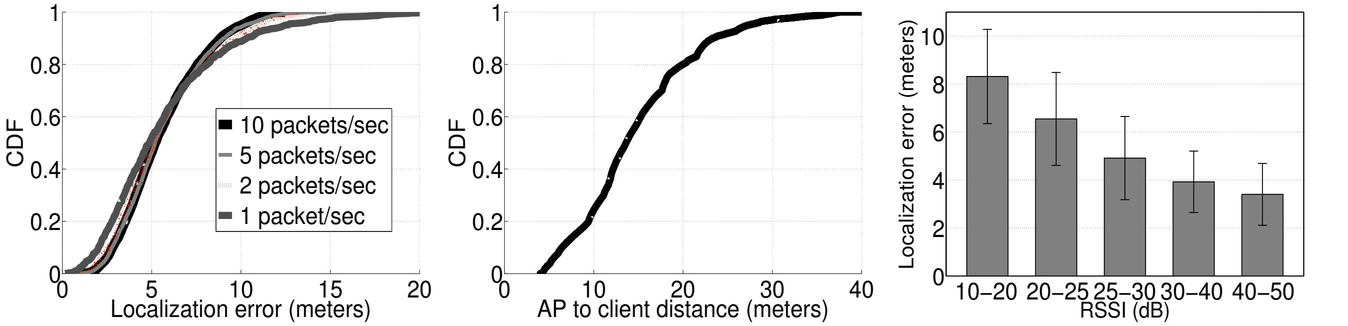


Figure 21: Performance using single AP: (a) CDF of localization error with varying upload traffic. (b) CDF of distance of the client locations from the AP. (c) Localization accuracy increases with signal strength.

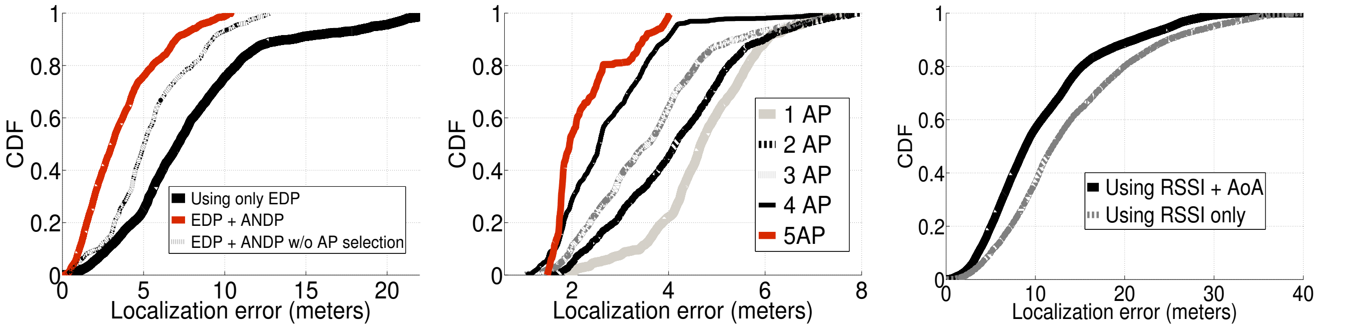


Figure 22: Performance using multiple APs: (a) Localization error in static and mobile scenarios. (b) Localization error with increasing number of APs. (c) Performance of existing RSSI, and AoA schemes.

distance, instead of EDP, in equation 7. The path loss exponent was set to the measured average on a per-AP basis. Since RSSI is a poor estimator of distance, RSSI based multilateration leads to large errors of median $11.5m$ and $> 25m$ for 90% (figure 22(c)). We also explore the possibility of combining RSSI with AoA. The strongest peak in the AoA pseudospectrum was selected as the angle to the client as done by [14]. The previous AoA algorithm cannot address the side ambiguity issue of the linear antenna array. To compare, we sidestep the issue by assuming that the AoA algorithm somehow knows which side the client is in. The combination of RSSI and the strongest AoA does not perform well either (median $9m$ error), confirming the importance of avoiding multipath ambiguity in AoA estimation.

6. RELATED WORK

The indoor localization literature is vast [1, 19]. In the interest of space, we heavily sub-sample this literature, focussing on systems related to CUPID.

RF fingerprinting based localization has been the dominant theme of localization. RADAR [2] was the first to perform detailed site surveys to build a location fingerprint database, based on the AP SSIDs and RSSI reported by wireless devices. Horus [3] proposes enhancements to RADAR by exploiting the structure of RSSI. Place Lab [20] and Active Campus [21] attempt to reduce the overhead of calibration by combining WiFi and GSM signal information. PinLoc [4] demonstrates that by utilizing high resolution CSI fingerprints, it is possible to localize a device with meter scale accuracy. WiFi fingerprints are amenable to environmental changes and periodic WLAN maintenance and configuration changes, requiring frequent wardriving which is expensive, and may not scale over wide areas.

Calibration-free localization: Recent approaches advocate the use of crowdsourcing to reduce the cost of wardriving [10, 11, 18]. However, crowdsourcing either requires a strong user incentive model, or leads to coarse grained fingerprint information which reduces their accuracy. Crowdsourcing further cannot adapt to frequent, and automatic configuration changes as adopted by recent WLAN APs; the default update time settings found in [5, 6] are 10mins and 4mins. Map based particle filtering [9, 22] relies on unique indoor walking paths such as long corridors, making them ineffective in open areas such as airport, auditorium etc. *EZ* [8] was among the first to attempt WiFi based indoor localization without any fingerprinting. Their key intuition is that RSSI based distance estimations from several overheard WiFi APs can find the user's location, provided the mobile device can obtain a few GPS fixes. While GPS can be erratic inside a building, the precise RF signal propagation may also vary over time due to fading. In contrast, CUPID identifies and uses only the direct path, and automatically adapts to environmental variations.

Ranging-based techniques localize nodes by computing the distances between them using a variety of techniques. RSSI-based ranging [23–26] computes inter-node distances based on the observed signal strength. Although appropriate wide-open outdoors, RSSI is susceptible to multipath, resulting into large errors indoors. FILA [27] attempts to utilize the CSI to reduce the error from RSSI based ranging, but stops short of identifying the key issues with multipath and LoS/NLoS ambiguities. Centaur [7] combines RSSI and acoustic ranging. PinPoint [28], and work by Werb et. al. [29] utilize time delays in signal propagation to estimate distances between wireless nodes. TPS [30] uses difference in time of arrival of multiple RF signals from transmitters at known location. Similarly, PAL [31] uses time difference of arrival between UWB signals at multiple receivers to determine location. Cricket [32] and AHLoS [33] utilize propagation delays between ultrasound and RF signals to estimate location of wireless devices. Such solutions require tight time synchronization and/or additional ranging hardware, limiting their applicability.

Angle-of-arrival based techniques use multiple antennas to estimate the angle at which the signal is received, and then employs geometric relationships to locate the wireless transmitter [13, 14, 34–36]. Even with access to raw signal information and using 8 antennas [13, 14], they can be derailed in multi-path rich indoor environments where the direct signal path is often blocked. To address this problem, some AoA based techniques require 6-7 sophisticated antenna systems [14, 37, 38], not possible with low resolution commodity WiFi hardware. Recently the Array-Track system [39] achieves high localization accuracy by utilizing the AoA computed from a rectangular array of 16 antennas. Arraytrack uses spatial smoothing, and time-based AoA grouping to suppress the effect of multipath on AoA based location estimation. While these techniques will certainly improve the accuracy of CUPID, Arraytrack stops short of identifying the actual ANDP, particularly under the constraints of linear antenna arrays offered by commodity WiFi hardware. SpinLoc [40] and Borealis [41] requires the user to make a full 360° turn to find her angle. CUPID's reliance on WiFi alone, along with the ability to extract distance, and angle information from off-the-shelf chipsets, makes it attractive for immediate deployment.

7. LIMITATIONS AND DISCUSSION

Dependence on particular hardware cards: CUPID relies on the availability of CSI information from the wireless chipset. This is not a difficult proposition because the CSI information is already calculated in the hardware for channel estimation, calibration, and beamforming purposes. Moreover for 802.11n, and 802.11ac wireless systems CSI estimation and reporting is a mandatory operation [15, 16]. Hence, although we use a specific a wireless card in our evaluation, we believe that with minor modifications, CUPID can be deployed on other platforms as well.

Phone orientation effect: We have experimented with the phone in hand. Handling arbitrary phone orientations, and their effect on the reported sensor values is an important direction for future research. While magnitude of acceleration may be an orientation-independent feature, gyroscopes may be further leveraged to map an arbitrary orientation to a specific frame of reference.

Localizing clients with heterogeneous hardware: While angle estimation may only depend on the wireless propagation, distance computation using the path-loss equation (Eq. 2), is not independent of the client's transmission power(*txpower*). Mobile devices may use different txpower settings with up to $10dB$ of difference [8]. One way to address this is to let the mobile device report its txpower to the AP. While this requires a minor platform modification, CUPID can employ commercial solutions [42] to identify the type of the device to infer its txpower. In addition, if multiple APs are available, CUPID can utilize existing techniques [8, 24] to infer the location of a mobile device with unknown transmission power.

Angle estimation with only 3 **antennas:** Since CUPID uses commodity off-the-shelf (COTS) chipsets, it suffers from the poor resolution offered by only 3 antennas. CUPID's performance will certainly improve if additional antennas can be leveraged at the AP. A few recent WiFi APs have several antennas, but, they also tend to have multiple radios, such that the number of antennas per radio is around 3. It is extremely difficult to combine the CSI from multiple COTS radios because of the tight phase-synchronization requirement, that is only possible by utilizing raw signals (like in [13, 17]). The upcoming IEEE 802.11ac standard allows up to 8 antennas. However AP vendors tend to mix different antenna polarizations (vertical vs. horizontal), and placements (linear, rectangular, or circular) to maximize the network coverage. Thus, it is reasonable to assume that even in near future, the achievable angle resolution will be similar to that of a linear array of $3-4$ antennas. CUPID is an attempt to improve the capability of WiFi positioning in such practical settings.

Modeling Path-loss: We did not explore sophisticated path-loss models [43] in our system. Our goal was to identify practical heuristics that capture multipath and LoS information directly from each received packet's CSI, instead of trying to tune sophisticated path-loss models at every different location and environment.

8. CONCLUSION

Although attractive for its simplicity, multilateration and triangulation has traditionally suffered from the randomness of multipath reflections, leading to proposals which advocates fingerprinting, or crowdsourcing for the purpose of indoor localization. This paper is an attempt to revisit basic multilateration, and triangulation based techniques using PHY layer information. We find that CSI information, when combined with natural human mobility, can accurately estimate the distance, and angle from only the direct path, ultimately yielding the location of the client from her AP. Our solution system, CUPID, identifies and harnesses only the direct path, avoiding the affect of multipath reflections. Experiments using off-the-shelf Atheros chipsets, and Google Nexus S phones confirm feasibility, demonstrating accuracy comparable to that of expensive fingerprinting based techniques. We believe that CUPID tackles the fundamental issue of multipath ambiquity and can be applied to the other RF-based localization systems that suffer from multipath such as urban outdoor cellular.

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