Pseudo Lateration: Millimeter-Wave Localization Using a Single Infrastructure Anchor

by

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ABSTRACT

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While radio-based indoor localization schemes achieve decimeter-scale accuracy, they typically require precise reference measurements or multiple infrastructure nodes with redundant localization anchors. In this paper, we propose Pseudo LATeration (PLAT), an indoor localization protocol that requires only a single infrastructure anchor and does not require prior knowledge of the environment. PLAT leverages the directionality and propagation characteristics of millimeter-wave transmissions to relax the requirement of multiple infrastructure anchors and constructs pseudo anchors for multilateration from reflected signal paths. By combining these pseudo anchors with time-of-flight measurements for distance estimation, PLAT can localize user devices in indoor environments with only a single infrastructure node. Our evaluation reveals centimeter scale location accuracy for typical office environments. In testbed measurements and simulations, localization errors are below 10 cm for distances up to 1.5 m and beamwidths below 10°. Although accuracy decreases with distance, we show that multiple reflection paths can mitigate this effect.
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Chapter 1

Introduction

In this paper, we design, implement, and experimentally evaluate Pseudo LATeration (PLAT), the first indoor localization protocol that requires only a single infrastructure node, such as an AP, and does not require knowledge of the localization environment. PLAT eliminates the need for multiple infrastructure nodes, as employed by prior work, by substituting IAs with pseudo anchors (PAs) from environmental reflectors. These PAs are identified using sector diversity in a highly directional millimeter-wave environment that lacks the rich scattering and multipath common in bands below 60 GHz. Moreover, with limited ability to penetrate walls and objects for millimeter-wave bands, a client may often be in range of only a single IA for a WLAN deployment.

PLAT is a three-step localization protocol. First, the AP performs a sector-level sweep using a narrow beam, and the user reports the received signal strength (RSS) for each sector. Similar to the IEEE 802.11ad standard, the AP transmits a short beacon in rapid succession in different sectors defined by codebook entries [1, 2]. In PLAT, the user reports the RSS for all overheard beacons, even in those sectors that will not be used for data transmission. Consequently, the AP can analyze both LOS and reflected paths and select sectors with high RSS for localization. Second, the user refines its received beam for the selected localization sectors and reports their angular offsets. As illustrated in Figure 1.1, the pairs of sectors and angular offsets between the AP and user define a directed set of LOS and NLOS paths over which communication is possible. In the final protocol step, the AP and user cooperatively
measure the time of flight for each localization sector. With all of this information, the
AP estimates the locations of reflected paths and assigns them as PAs which replace
IAs in multilateration. Consequently, PLAT localizes the user using the mix of the
LOS path and reflected paths along with all of their angular offsets and times-of-flight.

Figure 1.1: Idealized scenario in which PLAT uses both the LOS path and NLOS
pseudo anchors from existing environmental objects to localize a user.

To demonstrate the performance of our approach, we implement PLAT and evalu-
ate the localization accuracy in over-the-air testbed experiments and simulations.
The testbed provides traces from an office, while the simulation provides a ray-tracing
analysis of custom environments. Using a combination of both, we compare PLAT
against traditional multilateration, and test several scenarios with varying degrees
of distance uncertainty, beamforming inaccuracy, and sector diversity. Our results
indicate that PLAT achieves centimeter scale accuracy for close transceivers and
decimeter scale for distances greater than approximately 1.5 m for beamwidths below
10°.

The remainder of this paper is organized as follows. First, we discuss our system
model and protocol in Chapter 2. We describe our evaluation environments for the
protocol including a modified 802.11ad simulator and a custom-built millimeter-wave
testbed in Chapter 3. Afterwards, we experimentally evaluate PLAT in Chapter 4.
We then classify the different existing techniques for indoor localization in Chapter 5.

Finally, we conclude the thesis in Chapter 6.
Chapter 2

PLAT Localization Protocol

In this chapter, we present PLAT, an indoor localization protocol that localizes a user using millimeter waves and only a single IA. In particular, we start with a brief description of the system requirements. Afterwards, we give a high level overview of how PLAT works. Finally, we discuss the three key aspects of PLAT in greater detail: extended sector level sweep, distance measurements, and the post-processing needed for localization.

2.1 System Requirements

We consider protocol, device, and opacity constraints as illustrated by a system architecture that uses commercially available off-the-shelf devices that are IEEE 802.11ad compliant at both the user and infrastructure. The key aspects that affect PLAT are as follows.

- **Codebook-based beamforming.** IEEE 802.11ad adopts codebook beamforming to reduce the overhead cost of beamforming. With a fixed beamforming codebook, devices employ a discrete set of virtual sectors and can rapidly switch beams within short beamforming interframe spacing (SBIFS) (1 μs) [1]. Both link end points sweep among the sectors and adaptively select the strongest sender-receiver sector pair.

- **Single RF chain.** Codebook-based beamforming can be achieved with a single
RF chain and multiple radio-frequency phase shifters. This design architecture significantly reduces cost for large arrays achieving high directivity as analog-digital conversion is increasingly costly at higher frequencies.

2.2 Overview

PLAT is designed to localize a user in an indoor environment with a LOS path and a moderate number of reflected paths. A fixed AP inside the service region serves as an IA with a known position. For the remainder of this paper, we assume that the IA is an AP that uses 802.11ad and PLAT, but any millimeter-wave node with a known position and orientation may be used instead. The overall flow of our localization scheme is described in Figure 2.1. Instead of deploying additional IAs in the environment, PLAT infers the presence of PAs based on environmental reflectors that the AP and user can use to communicate. We consider PLAT as a localization protocol that is only run on demand (not continuously). Our protocol features three key stages: sectorwise sweeping, distance measurements, and a post-processing localization algorithm.

The AP divides the localization region into multiple discrete virtual sectors. Each sector corresponds to the narrowest possible beamwidth defined in its codebook. APs typically have many antennas, such that a narrow beamwidth is feasible. The AP does not require any prior knowledge of the environment to localize the user. The user’s beamforming codebook is assumed to be calibrated such that the user knows the angular offset between the center of the main lobe of each codebook entry’s beamforming pattern. This calculation depends on the codebook implementation.

For ease of exposition, we assume that beamforming codebooks are formed based on a 1-D array of half-wavelength spaced antenna elements, and various beamwidths
are generated by adding or removing active antenna elements. However, alternative beamforming codebooks are also applicable to PLAT. For a 1-D linear array, the steered direction $\theta_d$ can be extracted with the weight ($W_n$) and index number of one of the antenna elements ($n$) in the codebook as

$$\theta_d = \arccos\left(\frac{\ln(W_n)}{jn\pi}\right)$$

(2.1)

The remainder of this chapter describes each stage of PLAT in detail.

### 2.3 Extended Sector Sweep

To localize a user, PLAT first performs an extended sector level sweep between the AP and the user to establish which sectors to use for localization as shown in Figure 2.2a.
Figure 2.2: An example timeline of PLAT transmissions between the AP and user. (a) The AP beacons “B” in all of its sectors. The user reports the observed RSS by sector ID, and the AP selects the localization sectors $L_A$. (b) For the chosen localization sectors, the AP continuously beacons while the user sweeps through its sectors. (c) A rapid bit exchange is used to measure the distance along each localization sector.

This process is cooperative and is intended to establish as many non-contiguous sectors as possible. The AP beacons along each of its sectors while the user passively listens for beacons in pseudo-omnidirectional mode. Afterwards, the user reports both the sector IDs and RSS measurements for each sector it successfully decodes. The AP finds the RSS peaks and selects those as AP localization sectors—for a large planar surface like a wall, an RSS peak typically refers to a perfect reflection point, and for a smaller object, an RSS peak represents the sector that is the closest to pointing directly at the reflector. We collect the sector IDs of these AP localization sectors in set $L_A = \{L_{A0}, L_{A1}, ..., L_{Ai}, ..., L_{A(N-1)}\}$, where $N$ represents the total number of selected localization sectors. The AP also selects the localization sector with the strongest RSS as a reference sector and defines it as $L_{A0}$. Afterwards, the AP sends $L_A$ to the user.
Next, the user must sweep using its narrowest beamwidth and pair one of its sectors with each of the selected AP localization sector. In other words, the user must find its own set of localization sectors \( L_U = \{L_{U0}, L_{U1}, \ldots, L_{Ui}, \ldots, L_{U(N-1)}\} \). This process is shown in Figure 2.2b. To find \( L_{Ui} \), the AP beacons continuously in \( L_{Ai} \) while the user sweeps through its sectors, noting the RSS of each decoded beacon by user sector.

At the end of this process, the user reports the angular offset \( (\alpha_i) \) between the user sectors with respect to the strongest AP sector \( L_{A0} \). For example, \( \alpha_0 = 0^\circ \) because \( L_{U0} \) pairs with \( L_{A0} \). Additional information about the user’s orientation is not needed. In contrast, since the AP is often a stationary entity in the room, we assume that the \( 0^\circ \) sector’s orientation is known at the AP. Accordingly, we define \( \theta_i \) as the angular offset between the AP’s \( 0^\circ \) sector and the center of the localization sector \( L_{Ai} \). An example of these angles is shown in Figure 2.3 where \( \phi_i = \theta_i - \theta_0 \).

![Figure 2.3](image.png)

Figure 2.3 : An example of an AP and user who have established the LOS sector along with one NLOS sector numbered \( i \). The NLOS sector serves as a pseudo anchor. PLAT measures \( \phi_i, \alpha_i, d_0 \) and \( d_i \) to approximate the location of the user without prior knowledge of the environment.

In the event that the user is very close to the AP and the non-line-of-sight (NLOS)
sector is very weak (whether by poor reflection materials or long propagation distance from the reflector), the LOS path may dominate the NLOS path, despite beamforming in the NLOS sector. When this occurs for NLOS sector \( i \), the user will direct its beam at the LOS orientation for the NLOS localization sector as well. PLAT removes the NLOS sector when it detects this so that this error does not affect localization accuracy.

2.4 Distance Measurements

After selecting localization sectors, the AP and user now have a set of communication paths. Finally, PLAT measures the approximate distance between the AP and user along each of these communication links with time difference of arrival techniques. The set of distances are defined as \( D = \{d_0, d_1, ..., d_i, ..., d_{(N-1)}\} \). We design the AP such that it sends a series of bits to the user on one channel, and the user simply reflects those bits back towards the AP on a second channel as shown in Figure 2.2c. The time difference between when the AP sends the bits and when it receives the response serves as the round-trip time (RTT) used to measure the distance. For the example in Figure 2.3, \( d_0 \) is directly measured via RTT, whereas \( d_{AP,i} \) and \( d_{PU,i} \) are not directly measurable. Nonetheless, \( d_i = d_{AP,i} + d_{PU,i} \) is also directly measured.

We assume that users are able to measure the time of arrival with a precision of within 1 ns. This is a modest assumption that reduces the uncertainty of any distance measurement to within 15 cm. Currently, off-the-shelf UWB chips by DecaWave known as Scensor (DW1000) are able to achieve an accuracy of 10 cm with time of flight measurements [3], so a time of flight to distance accuracy of 15 cm is a feasible assumption. Alternatively, Rasmussen and Capkun have shown that this is achievable by adding an additional specialized module [4]. The fundamentals of
distance measurements and distance bounding can be found in other works [5, 6]. If the processing time at the user is fixed and known, the RTT uncertainty may be less than 1 ns by calibrating the two devices to account for this processing time. The effects of this assumption will be evaluated later in the paper.

2.5 Post-Processing Localization

With the angular offsets at the AP ($\phi_i$) and user ($\alpha_i$) known for all localization sectors from Chapter 2.3, and the distance measurements in Chapter 2.4, PLAT now has enough information to localize the user.

PLAT considers the localization sector with the shortest measured distance to be the LOS path. Ideally, this should validate that $L_{A0}$ and $L_{U0}$ are the LOS sectors, but if it does not, all angular offsets $\alpha_i$ are adjusted so that the localization sector with the shortest measured distance is the point of reference. For an AP beamwidth of $B_{AP}$, PLAT nominates multiple linearly spaced candidate orientations for the LOS sector (centered at $\theta_0$). We define candidate $j$ as the user position at the exact geometric angle of $\theta_{0j}$ between the APs and the candidate $j$, where $\theta_{0j}$ is constrained as $\theta_0 - 0.5B_{AP} \leq \theta_{0j} \leq \theta_0 + 0.5B_{AP}$. With the measured LOS distance $d_0$ and $\theta_{0j}$, candidate user position $j$ can then be calculated using geometry as

\[
X_j = AP_x + d_0 \cos(\theta_{0j}) \\
Y_j = AP_y + d_0 \sin(\theta_{0j}).
\]

The set of these candidate positions is defined as $C = \{C_0, C_1, ..., C_j, ..., C_{(M-1)}\}$ where $M$ is the total number of candidates and $C_j = (X_j, Y_j)$. In contrast to an extremely narrow laser-like beamwidth, the point-to-point distances for PLAT can
be large. The goal of the remainder of PLAT is to identify which candidate position is the most likely location of the user.

If \( N \) localization sectors are available, then \( N - 1 \) localization sectors are NLOS created by PAs. In an ideal scenario in which beamwidths approach zero and time of flight measurements are perfect, PLAT can calculate the exact position of the \( i \)th PA as \( P_i = (P_{xi}, P_{yi}) \) (\( i > 0 \) indicates a NLOS localization sector). We first assume that the PA is created by a 1st order reflection, which creates the triangular geometry shown in Figure 2.3. Geometry can then be used to calculate each localization sector’s propagation distance as

\[
\begin{align*}
    d_{AP,i} &= d_i \frac{\sin(\alpha_i)}{\sin(\beta_i)} \\
    d_{PU,i} &= d_i \frac{\sin(\phi_i)}{\sin(\beta_i)}
\end{align*}
\] (2.3)

where \( \beta_i \) is the only unknown angle in the triangle from Figure 2.3. With these distances, the position of the PA can be calculated as

\[
\begin{align*}
    P_{x,i} &= AP_x + d_i \cos(\theta_i) \\
    P_{y,i} &= AP_y + d_i \sin(\theta_i)
\end{align*}
\] (2.4)

where \( AP_x \) and \( AP_y \) are the \((x,y)\) coordinates of the single known IA at the AP.

This process can be repeated for all PAs. However, in a system with non-negligible beamwidths, error in the true LOS orientation \((\theta_0, \phi_i)\) and angular offset at the user \((\alpha_i)\) cause errors when approximating \( P_i \). Therefore, we construct a minimization problem over different LOS orientations and angular offsets at the user.

For a given candidate position \( C_j \) and user beamwidth of \( B_U \), the user’s angular offset \((\alpha_{i,k})\) can be any angle within \( \alpha_i - B_U \leq \alpha_{i,k} \leq \alpha_i + B_U \), such that \( \alpha_{i,k} > 0 \). The
upper bound on $\alpha_{i,k}$ is $B_U$ because the worst case scenario is when the LOS orientation is half a beamwidth from the center and when the NLOS orientation is also half a beamwidth from the center. For each $\alpha_{i,k}$, PLAT uses Equation (2.3) to calculate $\hat{d}_i$. We then calculate the absolute difference between the measured distances and the geometrically calculated distance as $\delta d_i = |\hat{d}_i - d_i|$. This process is repeated for all $\alpha_{i,k}$, and the minimum $\Delta d_i$ represents the best PA$_i$ position for the candidate position $C_j$. This entire process is repeated for all PAs for the candidate position $C_j$. To approximate the probability that the user is at $C_j$, we sum the absolute errors for all localization sectors for a candidate as $\epsilon_j$.

By the end of the localization process, each candidate position $C_j$ has its own $\epsilon_j$. PLAT assumes that the candidate position with the smallest $\epsilon$ is the most probable position for the user.

Alternate minimization problems may be posed to find the user’s position. For instance, PLAT can collect historical information via prior localizations to statistically characterize the localization environment and gain a better estimate of the user’s position. In this thesis, we assume no prior knowledge of the localization environment and thus do not carry information over from prior localizations. This technique may offer an improvement on PLAT’s localization accuracy but requires a training period to statistically characterize the propagation environment. We choose to not assume prior knowledge of the localization environment, meaning the accuracy of PLAT presented in this thesis is the initial deployment accuracy of a system that does collect historical information.
Chapter 3

PLAT Implementation

Our implementation of PLAT consists of two parts. First, we present PLAT as part of our custom-built millimeter-wave wireless testbed. Afterwards, we describe our custom millimeter-wave simulator, written in MATLAB, that is used to test extended cases. These implementations use our software implementation of PLAT as defined in Chapter 2.

3.1 Millimeter-Wave Testbed Implementation

The practical key components of PLAT, namely sectorization and the localization algorithm, are implemented on our custom-built millimeter-wave testbed which combines a commercial VubIQ / Pasternack transmitter and receiver pair with two Wireless open-Access Research Platform (WARP) boards [7]. Because of clocking limitations, noisy distance measurements are fed to the testbed to complete the localization process instead of over-the-air measurements, and the accuracy of these distance measurements are varied based on existing round-trip distance measurement literature [4]. Figure 3.1 shows the hardware setup of our millimeter-wave testbed. One WARP board generates modulated analog baseband signals for transmission, which is passed to the VubIQ transmitter following a baseband conversion from single-ended to differential signaling. The VubIQ transmitter upconverts to the 60 GHz carrier frequency and then transmits wirelessly to the VubIQ receiver. The receiver downconverts the
analog signal back to baseband, the signal is filtered using a low-pass filter, and the second WARP board samples the result. All remaining processing and modulation is done using WARPLab.

![Diagram of hardware setup showing the interconnection of WARP and the millimeter-wave transceivers.](image)

Figure 3.1: Hardware setup showing the interconnection of WARP and the millimeter-wave transceivers.

Although our platform is flexible enough to support any higher order quadrature amplitude modulation (QAM) scheme, we only use binary phase-shift keying (BPSK) for simplicity. A Barker Sequence is implemented as the preamble for packet detection. At a distance of 2 m, we achieve 0% bit error rate (BER) for the LOS case. The testbed does incur some phase noise, so any BER measurements shown are slightly narrower than what would be achieved in a normal 802.11ad system. As a proof of concept, we use narrowband single-carrier transmissions. Directionality is achieved using directional horn antennas.

The testbed features two micro-stepping rotating tables with sub-degree precision along the azimuth orientation and a Cinetics linear rail with sub-millimeter precision. This setup allows us to position and rotate the transmitter and receiver accurately during our localization tests.
3.2 Millimeter-Wave Simulator

To explore additional performance factors, we implement a custom millimeter-wave simulator that combines the link budget and path loss models from the 802.11ad conference room channel models with ray-tracing [8].

We discretize an empty test room into virtual sectors, and test PLAT with various user positions. If the RSS at the user position is enough to support the MCS-0 threshold specified in 802.11ad, we consider it usable for communication. Beamforming is accomplished using a linear 1-D array of antenna elements as a proof of concept with half wavelength spacing. The number of antenna elements in the beamforming array on both parties is varied between 4 and 32 antenna elements depending on the experimental goal, which produces beamwidths between 4.3–36° (IEEE 802.11ad specifies the minimum beamwidth sector as ∼3° [1]). Using more antenna elements allows the device to achieve narrower beamwidths, and using a single antenna element produces omnidirectional mode with no beamforming gain.
Chapter 4

PLAT Evaluation

In this chapter, we combine simulations with testbed traces to test the localization granularity of PLAT compared to traditional multilateration with multiple APs.

4.1 Proof of Concept & Number of Localization Sectors

As a proof of concept, we deploy the millimeter-wave testbed implementation of PLAT in an office and localize a user at several test points in that office. We also use the test data to test localization accuracy as a function of the number of available localization sectors.

Figure 4.1: The office environment used for testing localization accuracy and sector selection accuracy. Measurements are taken on top of the office desks, approximately 100 cm above the ground. The AP rotates 180° whereas the receiver is stationary, pointed at the AP. The walls are made of plasterboard.
4.1.1 Experimental Setup

This experiment uses the millimeter-wave testbed previously described in Chapter 3.1. We deploy the wireless millimeter-wave transmitter at one end of an office shown in Figure 4.1. We then deploy the millimeter-wave receiver in several positions in the room to collect RSS traces at different positions in the room. The peaks of these RSS traces are chosen as localization sectors and run through the PLAT localization algorithm. The localization distances are calculated geometrically (not over the air) from the known office environment of the room for evaluation purposes only. Prior to localizing with PLAT, all distance measurements are perturbed with a random amount of normally distributed noise with a mean of 0 and a standard deviation of 3.75 cm, which corresponds to the 15 ns assumption from Chapter 2.4. This represents realistic distance measurements.

The AP (transmitter) uses a narrow beamwidth of 7°. During the AP’s sweep, the user (receiver) uses a wide beamwidth of 80° to collect as many alternate paths as possible. During the user’s sweep, the AP maintains its 7° beamwidth, and the user narrows its beam to a 20° beamwidth. The AP’s sweep is conducted in increments of 5° via the electronic rotating table, and the user averages 100 RSS values for each swept sectors. The user sweeps at 10° steps.

For comparison purposes, we remove the localization sector with the weakest RSS in a separate data set to observe how accuracy scales with number of localization sectors available.

4.1.2 Experimental Results

Table 4.1 shows the results when combining the testbed RSS traces with the simulator geometric distance measurements. For the maximum number of reflectors (3),
Table 4.1: Localization error for 4 office positions with testbed measurements averaged over 100 trials (with 95% confidence intervals).

<table>
<thead>
<tr>
<th>Position</th>
<th>Error for 3 Sectors (cm)</th>
<th>Error for 2 Sectors (cm)</th>
<th>LOS Distance (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4.87 ± 0.40</td>
<td>4.62 ± 0.44</td>
<td>85</td>
</tr>
<tr>
<td>2</td>
<td>4.69 ± 0.53</td>
<td>5.45 ± 0.50</td>
<td>135</td>
</tr>
<tr>
<td>3</td>
<td>4.87 ± 0.54</td>
<td>11.73 ± 1.48</td>
<td>285</td>
</tr>
<tr>
<td>4</td>
<td>4.87 ± 0.46</td>
<td>18.62 ± 2.03</td>
<td>328</td>
</tr>
</tbody>
</table>

Localization accuracy is on the centimeter scale for the given test positions, which is comparable with many indoor localization schemes. Larger distances will introduce more error to PLAT due to sector expansion. This trend is clearly visible when using only 2 localization sectors. However, the results also show that additional localization sectors provide higher resolution and can help overcome this error, as the localization error is nearly unaffected by LOS distance when using 3 sectors. This mimics the effect that localization improves with additional IAs in traditional techniques, such as multilateration and fingerprinting. On the other hand, PLAT’s PAs are completely passive and do not require any additional infrastructure.

4.2 Codebook Calibration & Sector Selection Errors

PLAT always assumes a perfect codebook (i.e., the center of the main lobe is calibrated to be perfectly in a specific orientation). However, manufacturing defects and differences from device-to-device can cause errors in the codebook’s main lobe orientation. In this section, we use the wireless testbed to explore the impact of a non-perfect codebook on PLAT’s localization accuracy since PLAT ignores these imperfections.
4.2.1 Experimental Setup

In this experiment, we use the same test setup as Chapter 4.1. We use position 2 in Figure 4.1 throughout this section for evaluation. However, we introduce angular uncertainty $\gamma$ to the main lobe of each codebook entry where $0 \leq \gamma \leq \gamma_{\text{max}}$ and $\gamma_{\text{max}}$ is half the angular step size to the next codebook entry. $\gamma$ perturbs the codebook center as a normally distributed random variable centered at 0 within these bounds with a standard deviation of $\gamma_{\text{max}}/4$. If the random variable produces $\gamma > \gamma_{\text{max}}$, then we cap $\epsilon$ at the max value.

To characterize the results, we calculate the cross-correlation of RSS sector sweeps for a baseline perfect codebook and a perturbed beam as described previously. The cross-correlation is a measure of the similarity in the shape of the RSS sector sweep results. Since localization sectors are selected based on local maxima of the RSS sector sweep results, the shape of the RSS map is more important to PLAT’s accuracy than the actual magnitude of the RSS. The closer the cross-correlation is to 1, the more similar the shapes, and the less likely that there will be errors selecting the localization sectors. Afterwards, based on the sector selection errors, these errors propagate into the localization algorithm, and we observe the effect of these errors on localization accuracy.

4.2.2 Experimental Results

The results from the cross-correlation between a perfect codebook and 5 imperfect codebook sweeps are compiled in Table 4.2. As a point of comparison, the transmit RSS map at position 1 (0.85 m from the AP) produces a cross-correlation of 0.9130 with the transmit RSS map of position 2 (1.35 m from the AP), as marked in Figure 4.1. The results for this experiment show a consistently high cross-correlation for
all runs, despite the imperfect codebooks.

Table 4.2: Cross-correlation of a sector sweep’s RSS map with codebook errors, and the observed localization sector selection errors caused by these scenarios (mean with 95% confidence intervals).

<table>
<thead>
<tr>
<th>Sweep Setup</th>
<th>Cross-Correlation</th>
<th>Observed Errors</th>
</tr>
</thead>
<tbody>
<tr>
<td>AP Tx Sweep</td>
<td>0.9802 ± 0.0098</td>
<td>Lost weakest Tx sector</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2/5 cases)</td>
</tr>
<tr>
<td>Rx Sweep</td>
<td>0.9739 ± 0.0142</td>
<td>10° error in Rx sector</td>
</tr>
<tr>
<td>(LOS AP)</td>
<td></td>
<td>(2/5 cases)</td>
</tr>
<tr>
<td>Rx Sweep</td>
<td>0.9817 ± 0.0061</td>
<td>20° error in Rx sector</td>
</tr>
<tr>
<td>(NLOS 1 AP)</td>
<td></td>
<td>(1/5 cases)</td>
</tr>
<tr>
<td>Rx Sweep</td>
<td>0.9886 ± 0.0034</td>
<td>No observed errors</td>
</tr>
<tr>
<td>(NLOS 2 AP)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

However, sector selection errors are still introduced despite the high cross-correlation. For the AP transmit sweep, 2/5 runs lost the weakest (most distant) localization sector because the RSS was too close to the noise floor of the testbed platform. On the receive side, we observe up to 2 step sector selection errors for some runs (10° step size between sectors). This can propagate errors up to 10°–20° in \( \alpha \) (user angular offset from the reference sector) depending on where the error occurs.

The potential impact of these errors in sector selection is compiled in Table 4.3. The first three rows show the mean localization error when AP sector selection loses no sectors, and errors in \( \alpha \) vary from 0°-20°. Noticeably, the localization error minimally increases by only roughly 3–3.5 cm. The last three rows show the mean localization error when the AP loses its weakest localization sector. Similarly, the localization error stays close to 5–6 cm. These results suggest that the errors introduced by the imperfect codebook have a smaller impact on localization accuracy than other factors.
Table 4.3: Inaccuracy introduced by non-ideal sector selections from imperfect codebooks (mean with 95% confidence intervals).

<table>
<thead>
<tr>
<th>Error Scenario</th>
<th>Localization Error (cm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Tx Sectors, $</td>
<td>\delta\alpha</td>
</tr>
<tr>
<td>All Tx Sectors, $</td>
<td>\delta\alpha</td>
</tr>
<tr>
<td>All Tx Sectors, $</td>
<td>\delta\alpha</td>
</tr>
<tr>
<td>Lost Tx Sector, $</td>
<td>\delta\alpha</td>
</tr>
<tr>
<td>Lost Tx Sector, $</td>
<td>\delta\alpha</td>
</tr>
<tr>
<td>Lost Tx Sector, $</td>
<td>\delta\alpha</td>
</tr>
</tbody>
</table>

4.3 LOS Blockage Detection

PLAT requires the LOS sector to localize the user because localization with only NLOS paths is an under-constrained problem. However, communication via a LOS path cannot always be guaranteed, especially in millimeter-wave systems where penetration and diffraction are weaker than traditional WiFi bands. In this section, we observe the behavior of PLAT when the LOS path is blocked.

4.3.1 Experimental Setup

This experiment uses the same data and test positions as Chapter 4.1, but simply removes all LOS information prior to localizing the user. We observe the sum of absolute errors $\sum \epsilon$ for the remaining NLOS sectors to see how well the sum of absolute errors can detect geometric inconsistencies given that PLAT has no prior information on the localization environment (office from Figure 4.1). Accordingly, PLAT incorrectly uses the next shortest measured path as the LOS path.
4.3.2 Experimental Results

The results for the LOS blockage experiments are compiled in Table 4.4. For the tested positions, the sum of absolute errors is very small when the LOS sector is not blocked (less than 10 cm). However, blocking the LOS sector and attempting to localize with two NLOS sectors creates a much larger sum of absolute errors for all positions (all greater than 6 m). This shows that geometric inconsistencies can be inferred, and the sum of absolute errors can be used to detect when the LOS path is blocked. In these cases, PLAT outputs an “unable to localize” response.

Table 4.4: Sum of absolute errors ($\sum \epsilon$) for different user positions averaged over 100 trials (with 95% confidence intervals).

<table>
<thead>
<tr>
<th>Position</th>
<th>No Blockages $\sum \epsilon$ (m)</th>
<th>LOS Blockage $\sum \epsilon$ (m)</th>
<th>LOS Distance (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$0.0141 \pm 0.0043$</td>
<td>$6.1767 \pm 0.0103$</td>
<td>0.85</td>
</tr>
<tr>
<td>2</td>
<td>$0.0097 \pm 0.0009$</td>
<td>$7.5552 \pm 0.0150$</td>
<td>1.35</td>
</tr>
<tr>
<td>3</td>
<td>$0.0025 \pm 0.0002$</td>
<td>$13.0233 \pm 0.0375$</td>
<td>2.85</td>
</tr>
<tr>
<td>4</td>
<td>$0.0154 \pm 0.0047$</td>
<td>$7.2688 \pm 0.0225$</td>
<td>3.28</td>
</tr>
</tbody>
</table>

4.4 Infrastructure Anchor-User Distance

To test an extended number of cases beyond the testbed possibilities, we use our millimeter-wave simulator to simulate PLAT in a conference room environment. In this section, we compare PLAT against traditional multilateration in the same room.

4.4.1 Simulation Setup

To quantify localization granularity, we simulate PLAT with a fixed AP on one end of the room and nomadic user. The key parameters are shown in Table 4.5 and the
topology is shown in Figure 4.2. This topology is non-optimal for PLAT, as the AP loses a potential reflector by being placed against a wall.

<table>
<thead>
<tr>
<th>Table 4.5 : Key simulation parameters.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Tx Sector Size</strong></td>
</tr>
<tr>
<td><strong>Rx Sector Size</strong></td>
</tr>
<tr>
<td><strong>Wall Material</strong></td>
</tr>
<tr>
<td><strong>Room Dimensions</strong></td>
</tr>
<tr>
<td><strong>Test Point Spacing</strong></td>
</tr>
</tbody>
</table>

As outlined in Chapter 2, the AP performs a fine-beamwidth sector level sweep, and the user reports the sectors it overhears above the 802.11ad MCS-0 threshold to the AP along with the measured RSS. Based on this information, the AP identifies the localization sectors as the RSS peaks and calculates the angular offsets from the strongest RSS sector as previously described for PLAT. The AP then re-beacons using the chosen localization sectors, while the user performs his own sweep. We fix the user beamwidth at 17.4° (8 antenna elements) and vary the AP beamwidth. All distance measurements include a random amount of normally distributed noise with a mean of 0 and a standard deviation of 3.75 cm. This 15 cm range corresponds to a processing time uncertainty of 1 ns, which has already been achieved in existing distance measurement implementations [3, 4].

To evaluate the accuracy of PLAT, we use multilateration with 3 IAs in the same environment, as shown in Figure 4.2, corresponding to 3 APs in the room. Each multilateration anchor’s distance uncertainty uses the same distribution as PLAT’s single IA, and the IAs are distributed as shown in Figure 4.2. The multilateration position is calculated based on the Gauss-Newton algorithm, and the initial guess is
the center of the overlapping circular regions created by each IA’s distance measurement. Like with PLAT, no prior information about the environment is needed for multilateration.

Figure 4.2: Simulations are conducted in an empty room with walls made of plasterboard. The AP is fixed on the left wall and discretizes the room into multiple sectors between $-90^\circ$ to $90^\circ$. The beam centers are uniformly distributed throughout these boundaries, and the angular step size is set to equal the AP beamwidth. The user nomadically moves around the region to evaluate localization, but the user is considered stationary during the localization process. LOS multilateration with three IAs is used for comparison against PLAT.

4.4.2 Simulation Results

Figure 4.3 shows the localization error for different AP beamwidths along with the 3-AP multilateration scheme for comparison. Each tested user position is partitioned into 5 bins based on AP-user distance, and the average localization error for the entire bin is plotted at the shortest distance within the bin.

The results indicate that multilateration is always more accurate than PLAT when there are three multilateration IAs in the room, which is expected given that there is no error in the true position of the multilateration anchor, whereas PLAT must infer...
the position of a PA, which is not guaranteed to be perfectly accurate. Nonetheless, PLAT comes within 10–15 cm of the accuracy of three-anchor multilateration between around 2–3 m. However, prior multilateration and angle-of-arrival (AoA) techniques were designed for bands below 6 GHz. Since multiple APs are often not in the same room as the user, the LOS distance is not guaranteed to be measured. This can create localization errors on the order of decimeters (roughly 0.1–0.4 m) in localization, even with NLOS suppression algorithms [10].

For PLAT, closer users tend to have less error than farther users. This is because PLAT nominates candidate positions for the user that are within the beamwidth of the LOS sector. This creates an upper bound on the potential error that PLAT can achieve. As propagation distance increases, the upper bound on errors also rises.

Note that localization errors at very close user positions are almost indistinguishable. This is because of the trend observed in Figure 4.4. At close range, potential PAs are frequently masked by the LOS sector because the LOS and the NLOS sectors are very close. Because transmissions are conducted with a finite codebook and a non-negligible beamwidth, this means that PLAT must localize these users with only
a single localization sector (i.e. it simply assumes that the user is in the center of the LOS sector). As expected, narrower beamwidths lead to more localization sectors on average, and moving further away from the AP likewise increases the number of distinguishable localization sectors. This suggests that the ideal operating distance is above 1 m in this environment. The upper limit on this operating distance depends on the AP beamwidth, and centimeter scale accuracy is achievable at all points in the simulated environment for narrow beamwidths, such as 4.3°.

![Figure 4.4: Number of localization sectors available for PLAT based on propagation distance and AP beamwidth.](image)

**4.5 User Beamwidth**

The prior section shows that PLAT’s accuracy changes based on the AP beamwidth. In this section, we simulate PLAT under different user beamwidths to observe how localization accuracy scales with various user beamwidths, which are traditionally less narrow than the AP’s beamwidth.
4.5.1 Simulation Setup

We once again use the same simulator and topology as in Chapter 4.4. The key difference is that we vary the user’s beamwidth from 8.6–36°. Since users are typically mobile devices, they have less antenna elements and must use a wider beamwidth. We fix AP beamwidth at 8.6°.

4.5.2 Simulation Results

![Localization Accuracy Graph]

Figure 4.5: Localization accuracy based on user beamwidth and distance from the AP.

Figure 4.5 shows the results of the simulation. Based on these results, user beamwidth has no conclusive link to PLAT’s localization accuracy. This is because PLAT does not include the user’s beamwidth when nominating candidate positions for the user. Instead, the user beamwidth is only used to select which candidate is the most probable position for the user (i.e., it serves as a refinement). Furthermore, PLAT only uses relative angles at the user and accounts for potential errors in relative angles by minimizing over a range of relative angles for a given PA. Noting that user beamwidth minimally affects localization accuracy is a beneficial property for PLAT.
because a user’s beamwidth traditionally is wider than the AP because a user usually has less antenna elements than an AP.

4.6 Distance Uncertainty

Although all other evaluation uses a reasonable RTT distance uncertainty of 15 cm, we test the limits of PLAT by altering the distance uncertainty. The user and AP can ideally pre-calibrate to reduce this uncertainty below 15 cm since most of the uncertainty in RTT is a fixed processing time at the user. However, PLAT can also suffer from worse uncertainty depending on the underlying hardware.

4.6.1 Simulation Setup

In this section, we use the same test setup as Chapter 4.4 with an AP beamwidth of 8.6° and a user beamwidth of 11.6°. Distance uncertainty is varied from 0–60 cm.

4.6.2 Simulation Results

Figure 4.6: Localization error by AP-user distance for various distance uncertainty measurements.

The results of the simulation are shown in Figure 4.6. As previous results have
already shown, localization error for PLAT increases with AP-user distance. Furthermore, additional distance uncertainty adds to the localization error. One important note is that PLAT does not achieve perfect accuracy with perfect distance measurements because there is still angular uncertainty from the sectorization. The error for 60 cm is not plotted because PLAT could not converge on a solution with small sum of absolute errors. This suggests that uncertainty must be maintained within at least 45 cm or less for PLAT to localize a user.
Chapter 5

Related Work

Existing work on localization falls into five main categories of indoor localization: multilateration, angle-of-arrival, radio frequency (RF) fingerprinting, and camera and sensor based approaches. In the remainder of this chapter, we outline related work in these categories and further discuss existing object tracking in millimeter-waves.

5.1 Multilateration

In multilateration, multiple infrastructure devices are deployed indoors which periodically announce their own known location. Based on the difference in time-of-arrival and angle-of-arrival, the user is able to infer its position. Typically, the user must hear beacons from at least three different sources to trilaterate a location. If the user hears more than three infrastructure devices, this generalizes as multilateration.

Early work using multilateration focuses on multi-sensor ad-hoc systems where multiple nodes are available as potential IAs. These nodes traditionally use RF omni-directional transmission [11]. Recent work focuses on tackling the implicit assumptions of multilateration, such as perfect IA position availability [12], and implementing hardware that can measure time difference of arrival accurately [4].

Researchers have also explored using multilateration for non-sensor (indoor) scenarios. ToneTrack addresses the strict timing requirements of multilateration with frequency-agile radios [13]. GPS also falls into the category of multilateration, but is
more commonly used outdoors. Recently, researchers are using visible light communication to implement multilateration indoors, because lights are readily available as IAs. Examples include Pharos [14] and Luxapose [15].

Unlike multilateration, PLAT uses highly directional millimeter-waves for localization and only use a single IA to localize the user.

5.2 Angle-of-Arrival (AoA)

This technique estimates the AoA at a known IA to find the position of a user. The main goal of this technique is to identify the LOS path between the user and the IA by accessing physical layer signals and then using algorithms such as MUSIC [16]. Afterwards, time of arrival information is used to estimate the position of the user. One earlier example of AoA indoor localization is simulated in [17] with high SNR and achieves an accuracy of around 1–2 m. However, in an indoor environment, multipath can cause errors when the environment is not known, so ArrayTrack proposes increasing the number of APs that serve as IAs to suppress the effects of multipath and NLOS errors [18].

Unlike AoA, PLAT only uses a single RF chain and does not compute phase offsets. Instead, it uses the 802.11ad sector sweep mechanism to infer directional information.

5.3 RF Fingerprinting

This method involves wardriving the service region to create a location database. When wardriving at a discrete location, the database lists all traditional RF APs that can be heard along with the average RSS for each AP. The accuracy of this method depends on the granularity of the wardriving and the diversity of the mapping
of hearable APs and RSS values in each location. Some popular methods include RADAR [19], HORUS [20], and SPOT localization [21].

First, PLAT does not require any prior environmental knowledge nor wardriving. Second, PLAT only relies on one existing infrastructure device, whereas fingerprinting relies on the diversity of multiple existing infrastructure devices.

5.4 Camera-Based Approaches

Mobile camera-based techniques were proposed to mitigate the startup time and cost needed for multilateration and fingerprinting. The developers of Ubicarse use stereo vision algorithms to geotag landmarks in indoor settings [22]. This allows the user to build an indoor map as traveling indoors. Travi-Navi implements a similar idea for indoor navigation [23]. These methods are typically intended for self-navigation and are often used for backtracking when camera data is available. In contrast, PLAT aims to localize a user regardless of his prior location history by reusing an off-the-shelf 802.11ad radio instead of a camera.

5.5 Millimeter-Wave Object Tracking

Prior work has suggested using the short wavelength of millimeter-waves for object tracking. mTrack is able to achieve sub-centimeter accuracy of a small passive object (pen) in a small yet open space by tracking the RSS and phase changes of a reflected impulse as the object move from one location to another [24]. Chen et. al. focus on identifying centimeter-sized objects with their 3D-imaging millimeter-wave system [25].

Nightcrawler tracks larger objects than the previously described works. Nightcrawler uses millimeter-wave transmissions to detect the presence, shape, and material of ob-
jects in a wide space for robotic motion [26].

In object tracking, the object is typically completely passive, meaning multiple IAs are needed to track it, similar to multilateration. In contrast, PLAT solves a localization problem, where the user being tracked has at least one radio device, which allows PLAT to only use a single infrastructure device. This is a different problem than tracking an object of known material and shape.
Chapter 6

Conclusion

Although indoor localization has been heavily studied in environments with anchor coverage redundancy, we propose PLAT, the first indoor localization protocol that works with a single infrastructure anchor with no prior environmental knowledge. By leveraging the propagation characteristics of millimeter-waves, PLAT relaxes the requirement of multiple localization anchors for multilateration and replaces infrastructure anchors with pseudo anchors from signal reflections. Our evaluation based on wireless testbed experiments and customized millimeter-wave simulations with the 802.11ad channel models shows that PLAT achieves centimeter to decimeter scale accuracy in both an office and a conference room with only a single IA. This accuracy is comparable to existing multilateration and angle-of-arrival localization protocols in literature when only a single LOS IA is available.
Bibliography


