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AUTOCALI: ENHANCING AOA-BASED INDOOR LOCALIZATION THROUGH AUTOMATIC PHASE CALIBRATION

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ABSTRACT

Recent advancements in WiFi indoor localization have demonstrated the potential for achieving decimeter-level accuracy based on Angle of Arrival (AoA). However, existing commercial WiFi Access Points (APs) suffer from phase offset across different antennas, which significantly degrade the performance of AoA-based methods in practical deployment. Previous work either relied on labor-intensive manual calibration or involved inaccurate and non-robust automatic calibration. In this paper, we propose AutoCali, an accurate and robust automatic phase offset calibration system. The key insight is to utilize the binary nature of phase offsets and the property that triangulation exhibits higher convergence when the correct combination of phase offsets is employed. Extensive experiments demonstrate that AutoCali outperforms state-of-the-art methods by 22.1% in median localization error for simple scenarios and by 37.1% for complex multipath scenarios.

Index Terms— Angle of Arrival (AoA), WiFi Localization, Automatic Phase Calibration

1. INTRODUCTION

Indoor localization using commercial WiFi devices has gained significant attention due to its cost-effectiveness and widespread implementation [1]. With the increasing number of antennas equipped on commodity WiFi devices, it has been demonstrated that AoA-based localization [2–6] could achieve promising results. However, the accuracy of AoA-based methods is hindered by the initial phase offsets across different RF chains introduced by imperfect inertial circuit contamination. Those offsets, referred to as the phase-locked-loop (PLL) initial phase offsets [7], introduce phase distortion that results in significant errors in AoA estimations, as illustrated in Fig. 1.

To tackle this challenge, lots of methods have been investigated in recent years. Existing manual calibration methods [2, 8, 9] utilize coaxial cables and power splitters to connect the transmit and receive chain, creating an ideal channel

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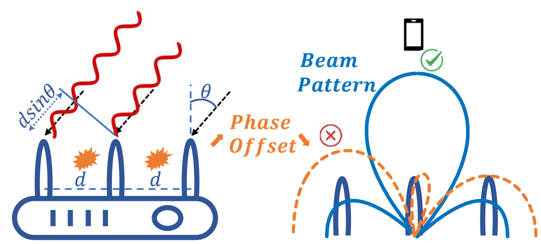


Fig. 1: PLL initial phase offset leading to incorrect AoA estimation.

for directly measuring the PPL initial phase offsets across the antennas. Given that the phase offsets between each antenna pair are constant across time, these methods can efficiently calibrate the phase offsets in raw Channel State Information (CSI) and achieve accurate AoA estimation. However, a notable drawback of those approaches is the necessity for recalibration after each system restart or channel switch, which demands a considerable amount of manual effort.

To overcome this limitation, automatic calibration methods have emerged. On one hand, some automatic calibration systems estimate PPL phase offsets by measuring specific location or angle information, which still incurs additional manual labor costs. For instance, Phaser [10] relies on transmitting signals from known positions for phase offset calibration, while D-MUSIC [11] proposes multiplying conjugate CSI from different positions to mitigate phase offsets and measurement noise. On the other hand, some systems, such as AutoLoc [12], achieve automatic calibration without human effort by leveraging the constraints of triangulation. However, AutoLoc still encounters certain challenges in practical deployments, especially complex scenarios with numerous multipath reflections. Firstly, AutoLoc employs the complex conjugate multiplication of CSI collected from reference and target locations to remove phase offsets. This process can introduce additional virtual multipath, diminishing the algorithm's effectiveness. Secondly, AutoLoc estimates the phase offsets based on channel measurements. It still exhibits deviations in the phase offsets compared to the true values, limiting the precision of localization.

In this paper, we propose a novel approach, referred to as AutoCali, for automatic and accurate phase offset calibration in AoA-based WiFi localization system. The key insights lie in the underutilized binary nature of PLL phase offsets [7] and the convergence properties of triangulation. Specifically, the PLL phase offset between adjacent antennas has only two possible values, according to [7]. Based on this observation, we can easily obtain all 2^{n-1} possible phase offset combinations for one AP, where n represents the number of antennas. This observation largely simplifies the phase offset calibration and turns it into a classification problem. Then, we systematically explore all $2^{N\times(n-1)}$ possible combinations of phase offset calibration for N APs and conduct triangulation. Those triangulation results tend to converge more effectively when the correct combination is applied. In order to select the optimal combination from $2^{N\times(n-1)}$ possibilities, we carefully design a confidence-aware triangulation selection algorithm. To the best of our knowledge, AutoCali is the first automatic phase offset calibration system that achieves calibration accuracy matching ground truth values.

Extensive experiments are provided to demonstrate the effectiveness of the proposed automatic phase offset calibration method. The proposed system can achieve enhanced AoA estimation accuracy and significantly reduce the localization errors introduced by initial phase offsets. This research contributes to the practical application of AoA-based indoor localization systems, facilitating their deployment in real-world scenarios without the burden of frequent manual recalibrations.

2. CSI MODEL

Consider a typical scenario in which the WiFi signal propagates from a single transmitting antenna to a receiver equipped with an array of M uniformly spaced antennas. During propagation, the WiFi signal encounters L propagation paths. Additionally, the WiFi channel is divided into K different subcarriers, each with a frequency denoted as f_k, where $k = 1, 2, \ldots, K$. Thus, the received CSI signal can be expressed as:

$$h(t,m,k) = \sum_{l=1}^{L} \alpha_l(t,m,k) e^{-j2\pi f_k \tau_l(t)} \times e^{-j2\pi f_k \frac{(m-1)d\sin\theta_l(t)}{c}} \tag{1}$$

where t, m, k, and l denote the index of time, antenna, subcarrier, and propagation path; $\alpha_l(t,m,k)$ is the complex attenuation coefficient; d is the space interval between two adjacent antennas; c is the speed of light; $\theta_l(t)$ and $\tau_l(t)$ denote the AoA and Time of Flight (ToF) of the l-th path, respectively.

Various parameter estimation algorithms such as MUSIC [13], and beamforming [14, 15] can be applied to estimate the geometric characteristics of all paths, including AoA and ToF. In our current implementation, we select the beamforming algorithm to achieve joint AoA-ToF estimation, since beamforming is robust to various environments and can be quickly calculated through Fast Fourier Transform (FFT).

In practice, however, the CSI obtained from commercial WiFi chips characterizes wireless channel frequency response, containing various phase distortions introduced by imperfect inertial circuits. Considering all known phase distortions [16–19], CSI can be represented as:

$$\begin{aligned}\overline{h}(t,m,k) =& e^{-j2\pi(f_{\mathrm{CFO}}t + k\Delta f(\tau_{\mathrm{SFO}}(t)+\tau_{\mathrm{PDD}}(t)))} \\ &\times e^{j\varphi_m} h(t,m,k),\end{aligned} \tag{2}$$

where Δf represents frequency spacing between subcarriers; f_{CFO}, τ_{SFO}, and τ_{PDD} denote Carrier Frequency Offset (CFO), Sampling Frequency Offset (SFO), and Packet Detection Delay (PDD); φ represents the initial PLL phase. In Eq. 2, CFO, PDD, and SFO have little impact on AoA estimation performance, due to their consistency across RF chains. In contrast, the initial phase of PLL, denoted as $\varphi_{m1} - \varphi_{m2}$, varies among RF chains and needs to be calibrated.

The AoA-based localization methods utilize the phase differences among different antennas to estimate the AoA and then perform triangulation for target localization. As shown in Fig. 2, the unknown phase offsets significantly degrade the AoA estimation performance, rendering them from obtaining accurate AoA values on commercial WiFi Network Interface Cards (NICs).

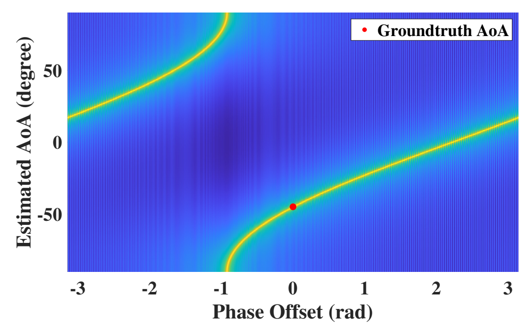


Fig. 2: Estimated AoA for a 2-antenna array with phase offset ranging from $-\pi$ to π.

3. AUTOCALI DESIGN

3.1. The Binary Nature of Phase Offset

The unknown initial phase offset significantly degrades the performance of AoA estimation. [10] indicates that the phase offset between two antennas is fixed when the WiFi system locks onto a specific frequency. However, the phase offset will change randomly each time the system restarts. The authors in [7] further point out that after the WiFi system restarts, the phase offset indeed changes, but it settles to one of two fixed values, with a difference of π. Furthermore, for chips of the same model, the phase offsets are approximately the same.

Based on this insight, we can transform the phase calibration task into a classification problem by pre-measuring the

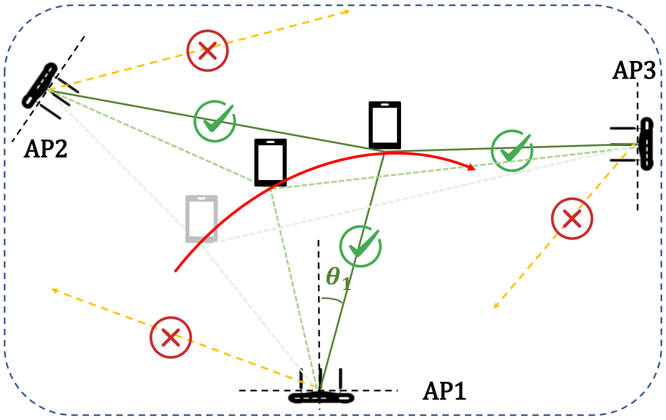


Fig. 3: System Overview: Orange arrows represent triangulation after calibration using incorrect phase offset, while green arrows represent triangulation calibrated by the correct phase offset. We determine the correct phase offset by observing the degree of convergence in triangulation.

phase offsets among all adjacent antennas of the AP. Specifically, for all APs in the localization system, we can measure one possible phase offset combination using coaxial cables and power dividers, and deduce all other possible combinations based on the characteristic of their π difference. Compared with existing phase calibration methods, the proposed AutoCali requires only one manual measurement, and thus the human effort is significantly reduced.

3.2. The Convergence Property of Triangulation

Now that we have obtained all possible phase offset combinations, the next crucial question is to find the correct one. The presence of multiple fixed APs with known positions is a significant aspect of a localization system. Hence, automatic calibration can be conducted by jointly considering multiple APs without the necessity of prior knowledge about the terminal's location. The key insight is that, under ideal conditions, the triangulated results from the accurate combination of phase offsets tend to converge at a single point.

Specifically, by leveraging the binary nature of phase offsets, we can obtain 2^{n-1} possible phase offset combinations for each AP, denoted as $\mathbf{S}$, (APs of the same model share the same $\mathbf{S}$). For $s \in \mathbf{S}$, we directly calibrate the collected raw CSI and perform 2D-beamforming on the calibrated CSI, resulting in 2^{n-1} AoA-ToF spectra $P(\theta, \tau)$, with only one being correct. Subsequently, we transform each AoA-ToF spectrum into a probability density function concerning angles. Here, we directly select the peak with the smallest ToF value (denoted as τ_{min}) in the AoA-ToF spectrum as the direct path, which is simple yet efficient. Then, we compute the probability density function:

$$P(\theta) = \frac{P(\theta, \tau_{min})}{\sum_{\theta=-\pi/2}^{\pi/2} P(\theta, \tau_{min})}. \tag{3}$$

By utilizing $P(\theta)$ coupled with CSI from multiple APs, the confidence level associated with each location can be determined through a confidence-aware triangulation. This confidence level serves as an indicator of how multiple APs effectively converge during triangulation at a given location. Specifically, we conduct grid point searches on the two-dimensional plane to be localized. For each grid point, the confidence level of that position is computed:

$$P(x, y) = \prod_{i=1}^{N} P_i(\theta_i(x, y)), \tag{4}$$

where i represents the i-th AP, $\theta_i(x, y)$ represents the AoA between point (x, y) and the i-th AP, which can be calculated based on the geometric relationship between that point and the AP:

$$\theta_i(x, y) = \arccos \frac{(x_i - x, y_i - y) \cdot \boldsymbol{n}}{||(x_i - x, y_i - y)|| \times ||\boldsymbol{n}||}. \tag{5}$$

Here, (x_i, y_i) is the location of i-th AP, $\boldsymbol{n}$ represents the unit directional vector of the antenna orientation. For each candidate phase offset combination, we can generate a confidence spectrum on the two-dimensional localizing plane by triangulating, with a total of $2^{N(n-1)}$ possibilities. We compare the maximum confidence from each spectrum and consider the candidate phase offset combination associated with the highest confidence among all maxima as the correct phase offset.

However, in practical scenarios, some environmental factors such as noise and multipath can significantly affect the robustness of the calibration algorithm. This is intuitively reflected in the higher convergence of incorrect phase offset combinations during the triangulation process. To tackle this problem, we introduce a multi-packet processing scheme. Specifically, we superimpose and average the maximum confidence levels of multiple packets corresponding to each combination of phase offsets:

$$\overline{p}^j_{max} = \frac{\sum_{i=1}^{N} p^{i,j}_{max}}{N}, \tag{6}$$

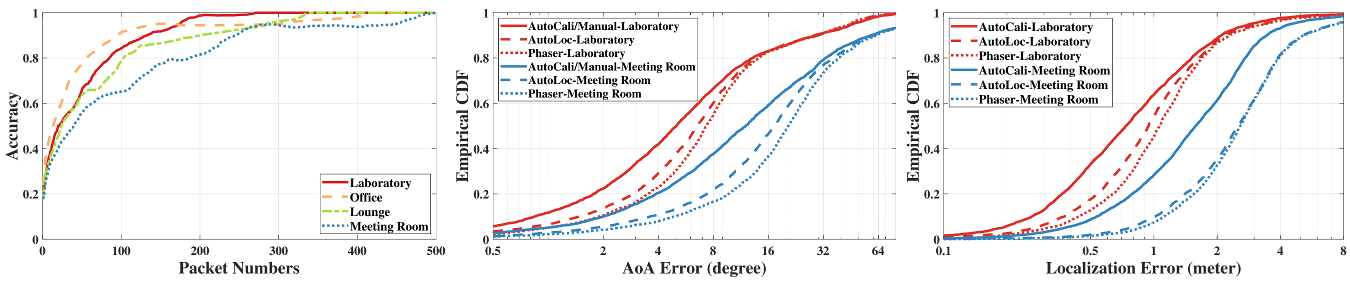
where i, j, and p_{max} represent the i-th packet, j-th triangulation spectrum, and the maximum confidence level of the spectrum, respectively. Similarly to single-packet processing, we consider that the phase offset combination corresponding to the maximum $\overline{p}_{max}$ is the correct one. This yields a more robust calibration result, a necessity that is further confirmed by subsequent experiments.

4. EXPERIMENTS

4.1. Experiment Setup

We implement our method on a human-held device WiFi localization dataset[1], which consists of approximately 120k

[1]For details on the scenario setup, please refer to [20].



(a) (b) (c)

Fig. 4: Performance of AutoCali. (a) Phase offset calibration accuracy. (b) AoA estimation performance comparison. (c) Localization performance comparison.

Number of APs	Laboratory	Office	Lounge	Meeting Room
3	271 (28s)	421 (43s)	338 (34s)	500 (50s)
4	433 (44s)	736 (74s)	608 (61s)	891 (90s)

Table 1: Minimum packet count (seconds) required to achieve 100% calibration accuracy.

data points collected from ten volunteers with a sampling rate of $10Hz$ across four classic indoor scenarios: laboratory, lounge, office, and meeting room. This dataset uses an Ultra-Wideband (UWB)-based localization system with an accuracy of ten centimeters to obtain ground truth location data.

4.2. Phase Offset Calibration Accuracy

AutoCali utilizes the binary nature of phase offset to transform the calibration problem into a classification problem. We implement our method in four different scenarios to evaluate the accuracy rate of the phase offset calibration. As illustrated in Fig. 4(a), the accuracy rate of phase offset calibration increases with the number of packets, reaching 100% with at most 500 packets. With the sampling rate of $10Hz$, calibration can be accomplished within a 50-second timeframe. This implies that AutoCali can automatically, accurately, and quickly complete the phase offset calibration task across four common indoor scenarios.

4.3. AoA Estimation Accuracy

We conduct a comparison of AoA estimation performance between our AutoCali and two other methods: AutoLoc [12] and Phaser [10] in simple and complex scenarios, respectively. As Fig. 4(b) illustrates, AutoCali achieves median errors of $5.0°$ in the simple laboratory scenario and $12.0°$ in the complex meeting room scenario, which significantly outperforms Phaser and AutoLoc. It is worth noting that AutoCali exhibits performance identical to the ground truth calibration, which is achieved by the coaxial cables and power splitters (manual calibration). This implies the accuracy advantage of AutoCali compared with other automated calibration methods.

4.4. Localization Accuracy

We conduct localization accuracy experiments in a simple laboratory scenario and complex meeting room scenario to evaluate our AutoCali. As shown in Fig. 4(c), AutoCali exhibits superior performance compared with AutoLoc [12] and Phaser [10]. Specifically, in the simple laboratory scenarios, the median localization errors for AutoCali, AutoLoc, and Phaser are 0.73m, 0.94m, and 1.06m, respectively. Furthermore, in complex meeting room scenarios, AutoCali achieves a remarkable 1.57m median localization error, significantly outperforming AutoLoc's 2.51m and Phaser's 2.58m. This implies that in the meeting room scenario with rich multipath reflections, AutoLoc and Phaser encounter challenges, while AutoCali significantly enhances calibration robustness.

4.5. Impact of AP Numbers

We evaluate the impact on the phase calibration of the number of APs. Table 1 illustrates the minimum packet count to achieve 100% calibration accuracy of our AutoCali in four scenarios under varying numbers of APs, along with the corresponding CSI collection times. With an increasing number of APs, the minimum required packet count remains low, taking up to 90 seconds to complete calibration.

5. CONCLUSIONS

In this paper, we investigated the PLL phase calibration problem and proposed AutoCali, a confidence-aware phase calibration system, that can automatically, accurately, and robustly calibrate the phase offset among antennas. To the best of our knowledge, AutoCali represents the first automatic calibration system that achieves the same level of precision as manual calibration. Real-world evaluations demonstrate that AutoCali outperforms state-of-the-art methods by 22.1% in median localization error for simple scenarios and by 37.1% for complex multipath scenarios. We believe AutoCali's salient advantages will promote more AoA-based indoor localization systems to be deployed in the real world.

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