MELoc: Indoor localization system integrating MUSIC and EM algorithms

Siming Chen*†‡, Yinnan Zhou*†‡, Hao Zhou*†‡
*School of Computer Science and Technology, University of Science and Technology of China.
†CAS Key Laboratory of Wireless-Optical Communications, University of Science and Technology of China.
‡Deqing Alpha Innovation Institute, Huzhou, Zhejiang, China
Email: chensiming@mail.ustc.edu.cn, yinnanzhou@mail.ustc.edu.cn, kitewind@ustc.edu.cn

***Abstract*—Wi-Fi-based technologies are becoming more popular for indoor localization due to the wide availability of existing infrastructure. To address multipath effects and achieve decimeter-level localization accuracy, path separation solutions have been proposed. However, current solutions still have some shortcomings, including convergence failures caused by improper parameter initialization, and improper direct path selection results when facing multipath interference. In this paper, we introduce MELoc, an indoor localization system that combines Multiple Signal Classification (MUSIC) and Expectation Maximization (EM) algorithms to improve accuracy. We ensure that the EM algorithm converges by using the preliminary estimation results from the MUSIC algorithm as the initial condition. Additionally, we propose a direct path selection mechanism that takes into account the spatio-temporal continuity characteristic of direct paths for better robustness. To enhance localization performance in scenarios with a single access point (AP), we adjust the received signal strength indicator (RSSI) based on the results of the path selection process. Extensive experiments are conducted in an indoor setting with prevalent multipaths. MELoc outperforms other baseline methodologies with median and 90th percentile localization errors of 0.88 m and 1.33 m, respectively.**

***Index Terms*—Wi-Fi Localization, Channel State Information, Path Estimation, Path Selection**

I. INTRODUCTION

Over the past few years, Indoor Localization Systems (ILS) have made remarkable progress, offering various solutions. These solutions use different technologies, such as acoustic [1], infrared [2], UWB [3, 4], sensor [5], RFID [6, 7], mmWave [8], Bluetooth [9, 10], and Wi-Fi technologies [11–20]. However, most of these solutions, except for Wi-Fi-based ones, need additional infrastructure, which can be expensive, thus limiting their practical usage. As a result, Wi-Fi-based localization has become a popular choice for indoor localization since it is widely available, cost-effective, and easy to deploy.

Understanding the characteristics of Wi-Fi signal propagation is essential for achieving high-precision indoor localization, which has numerous practical applications [13, 21]. There are two primary methods for Wi-Fi-based indoor localization: fingerprint identification [22] and parameter estimation [12, 23]. Fingerprint identification requires dense deployment of access points (APs) and significant manual effort to collect the required fingerprint databases, making it less practical. Parameter estimation, on the other hand, is more scalable and requires less manual data collection, making it increasingly popular [11, 12]. As a result, recent research has focused on improving Wi-Fi-based parameter estimation solutions.

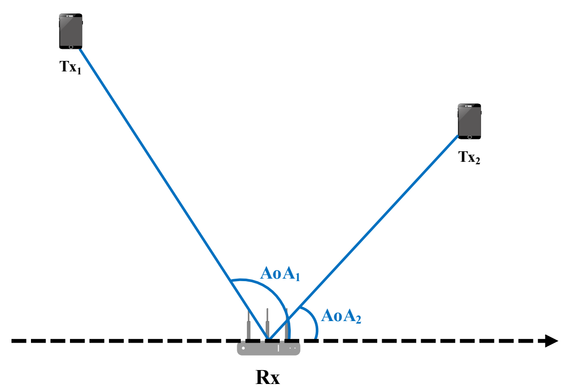


Fig. 1. Localizaiton Framework.

To determine the location of a target device, Wi-Fi Channel State Information (CSI) is used to estimate the parameters of signal transmission paths, such as Angle of Arrival (AoA) and Time of Flight (ToF), as shown in Fig. 1. There are two methods of parameter estimation, i.e., subspace-based and path-separation-based algorithms. For subspace-based algorithms, the Multiple Signal Classification (MUSIC) algorithm is a well-known representative, which estimates AoA by constructing a noise space and identifying spectral peaks. However, this method has high computational demands. For path-separation-based algorithms, the Expectation Maximization (EM) algorithm is a good option, which efficiently estimates multi-dimensional parameters associated with multiple signal transmission paths and offers superior accuracy compared to the subspace-based approaches.

Despite achieving decimeter-level localization accuracy [13, 21], the EM-based path separation solutions face several issues as outlined below.

- Effective initial parameters for the EM-based algorithm. The choice of initial parameters has a significant impact on the iterative process and outcomes of the EM-based algorithm [12]. If the initial values are not suitable, the algorithm may get stuck in local optima. However, commonly used initialization methods often produce sub-optimal results. As a result, it is critical to select effective initial parameters to ensure the convergence of the EM-

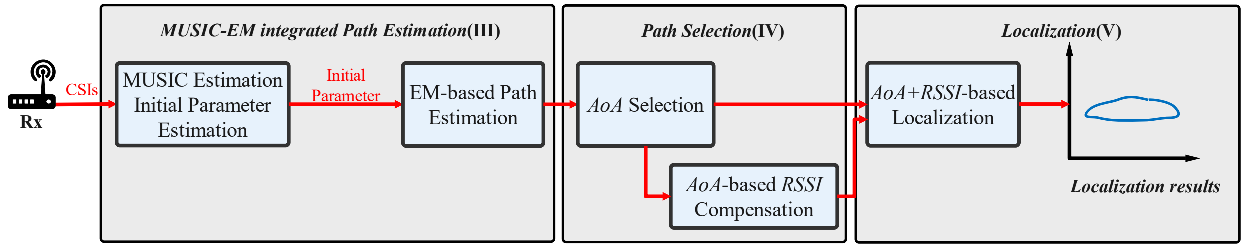


Fig. 2. System Overview.

based algorithm and achieve high-precision indoor mobile localization.

- Robust direct path selection. It is unrealistic to assume that the direct path between the transmitter and receiver always has the strongest signal strength, due to possible obstructions. Therefore, a robust direct path selection scheme is required to maintain localization accuracy when facing multipath interferences. However, this can be a challenging task since typical path estimation results consist of a set of potential paths that lack clear physical interpretations.
- Valid received signal strength indicator ($RSSI$) compensation. The strength of Wi-Fi signals, as measured by $RSSI$, fluctuates significantly when the target is in motion. Unstable $RSSI$ values can lead to errors in distance estimation, subsequently affecting the accuracy and reliability of localization results. To improve the accuracy and reliability of localization, it is important to stabilize the $RSSI$ values.

In this paper, we address these issues and propose an effective **MUSIC-EM** integrated **Loc**alization system, denoted as MELoc. Our contributions are summarized as follows:

1) MELoc is a promising solution for indoor positioning applications as it achieves highly accurate and reliable localization results. Our approach involves using the outcomes of the MUSIC algorithm as initial parameters for the EM-based algorithm to ensure reliable path estimation results. Additionally, we employ a direct path selection strategy that explores the spatio-temporal continuity characteristics. This means that the numerical parameters of the direct path estimated in the current round should remain comparatively consistent with the previous round. To further improve localization performance in single-AP scenarios, we apply $RSSI$ compensation based on the path selection results.
2) We implement MELoc using a single-AP setup, and conduct extensive experiments in various scenarios to evaluate its performance. The experimental results demonstrate that MELoc is highly effective. In a typical indoor environment, the median and 90th percentile localization errors are 0.88 m and 1.33 m, respectively. MELoc outperforms the state-of-the-art solution Widar 2.0, which achieves median and 90th percentile localization errors of 0.99 m and 1.67 m, respectively.

The rest of the paper is organized as follows. First an **System Overview** is presented in Section II. We introduce **MUSIC-EM integrated Path Estimation** in Section III. Then we introduce **Path Selection** and **Localizaiton** in Section IV and Section V, respectively. Experments and evaluation are provided in Section VI. We review **Related Works** in Section VII and **Conclusion** in Section VIII.

II. System overview

As shown in the Fig. 2, the implementation of MELoc consists of three main modules, i.e., the *path estimation* module, *path selection* module, and the *localization* module.

In the first *path estimation* module, there are two components. The first component involves MUSIC estimation, which is employed for estimating the preliminary parameters. Subsequently, the EM-based path estimation serves as the secondary component, utilizing the initial parameters to derive refined parameter estimation outcomes for all paths.

In the second *path selection* module, there are two components. The first component is spatio-temporal continuity-based path selection, used to select the direct path and the corresponding parameters. Then MELoc applies the path selection results to compensate $RSSI$.

In the third *localization* module, MELoc uses an AoA+$RSSI$ based localization framework to transform the parameters into coordinates of the targeted device.

III. MUSIC-EM integrated Path Estimation

A. Traditional EM-based Algorithm

1) Signal Propagation Model: In indoor localization systems, the CSI motion model considers the primary dynamic characteristics of signals, including flight time, arrival angle, Doppler shift, and complex decay. These parameters exhibit intricate interrelationships, collectively forming the comprehensive model for signal propagation in space. To provide a more detailed description of the CSI motion model, we consider discrete CSI measurements, where Wi-Fi cards perform measurements discretely in time, frequency, and space. For a measurement indexed as $\langle i, j, k\rangle$, denoted as $H(i, j, k)$, we express it as a superposition of multipath signals, with the addition of complex Gaussian white noise as

$$\begin{aligned} H(i,j,k) &= \sum_{l=1}^{L} H_l(i,j,k) + N(i,j,k) \\ &= \sum_{l=1}^{L} \alpha_l e^{-j2\pi, f_l(i,j,k)} + N(i,j,k), \end{aligned} \tag{1}$$

where $H_l(i, j, k)$ represents the signal of the l-th path, and $N(i, j, k)$ is complex Gaussian white noise. The variables

τ_l, φ_l, γ_l, and α_l respectively denote the flight time, arrival angle, Doppler shift, and complex decay of the l-th path. The term $f_l(i,j,k)$ represents the signal phase shift relative to the reference point $\langle 0,0,0 \rangle$ as

$$f_l(i,j,k) \approx f_c \tau_l + \Delta f_j \tau_l + f_c \Delta s_k \cdot \varphi_l - \gamma_l \Delta t_i, \quad (2)$$

where f_c is the carrier frequency of the channel, and Δt_i, Δf_j, Δs_k are the differences in time, frequency, and spatial position between $H(i,j,k)$ and $H(0,0,0)$ [11].

This model effectively describes various influences on signals during multipath transmission, laying the foundation for subsequent localization algorithms. In practical applications, accurate estimation of channel parameters and handling phase noise caused by hardware defects are crucial steps [24].

2) Process of the EM-based Algorithm: The conventional EM-based algorithm unfolds through a meticulously structured sequence of steps. In the Initialization phase, the parameters governing each path (τ_l, φ_l, γ_l, and α_l) are systematically initialized to zero. Subsequently, during the Expectation Step (E-step), estimated signals are meticulously computed at discrete measurement indices $\langle i,j,k \rangle$ utilizing the MELoc formula. This computation is predicated on the path parameters obtained during the Initialization phase. The disparity between the estimated signal and the observed value is methodically distributed across each path. Transitioning to the Maximization Step (M-step), the parameters of each path are solved exactly through the meticulous maximization of the likelihood function. Employing a judicious coordinate-update approach for each path, this phase involves the sequential adjustment of individual parameters while holding the others constant. Such an approach serves to effectively decrease the dimension of search space [13, 23].

3) Disadvantages of the EM-based Algorithm: The application of the EM-based algorithm in localization is very important. However, as a localized search algorithm, the performance and convergence of the EM-based algorithm depend heavily on the selection of initial values of parameters [12, 23]. The selection of appropriate initial values plays a crucial role in the performance of the EM-based algorithm. Inappropriate initial values may cause the algorithm to be trapped in the local optimal solution and fail to converge to the global optimal solution.

The Traditional EM-based algorithm usually initializes the path parameters to all zeros and then iterates. However, this fixed and arbitrary choice of initial values is not ideal.

B. MUSIC-EM based path Estimation

1) Basic idea: In order to improve the parameter estimation method, we introduce the MUSIC algorithm to provide the initial parameters of the EM-based algorithm. The MUSIC algorithm is a classical signal processing and spectral estimation algorithm, whose core idea is to obtain the spatial characteristics of the signal by performing spectral analysis of the signal.

We observe that the MUSIC algorithm requires a large amount of computation time due to its algorithmic principle, which requires complex matrix operations and results in large estimation errors because each path is calculated only once. However, the MUSIC algorithm can provide an initial parameter estimation result and is therefore very suitable as an initial value selection based on the EM algorithm.

2) Introduction of MUSIC Algorithm: The AoA of signals through different propagation paths introduce phase differences on the antenna array. This phase difference is related to the AoA and the spacing between antennas. The MUSIC algorithm exploits this phenomenon to estimate the AoA of signals [25].

Specifically, the procedure of the MUSIC algorithm is as follows. First of all, the covariance matrix R of the CSI matrix X is computed, $R = X * X^H$, where X^H denotes the conjugate transpose of X. Next, the covariance matrix R is subjected to eigenvalue decomposition, yielding the eigenvector matrix V and the diagonal matrix Λ, $R = V \Lambda V^H$. The column vectors of the eigenvector matrix V correspond to the signal subspace, while the eigenvalue matrix Λ corresponds to the energy of the signal subspace. Finally, by further analyzing the eigenvalue matrix Λ, the eigenvectors associated with lower energy in the signal subspace can be identified. These eigenvectors correspond to the AoA of the signals.

3) MUSIC-EM integrated Path Estimation: In our research, we utilize the MUSIC algorithm to obtain two crucial localization parameters of Wi-Fi signals, namely AoA and ToF. These parameters are vital for Wi-Fi signal localization as they provide essential information about the signal propagation path. In our application scenario, we set the Doppler frequency shift γ_l to 0, while the final parameter attenuation α_l can be computed based on the first three parameters.

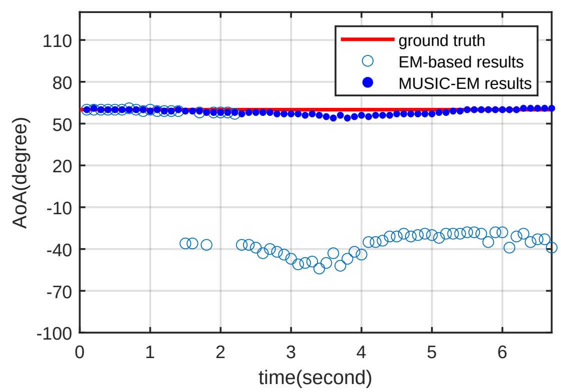
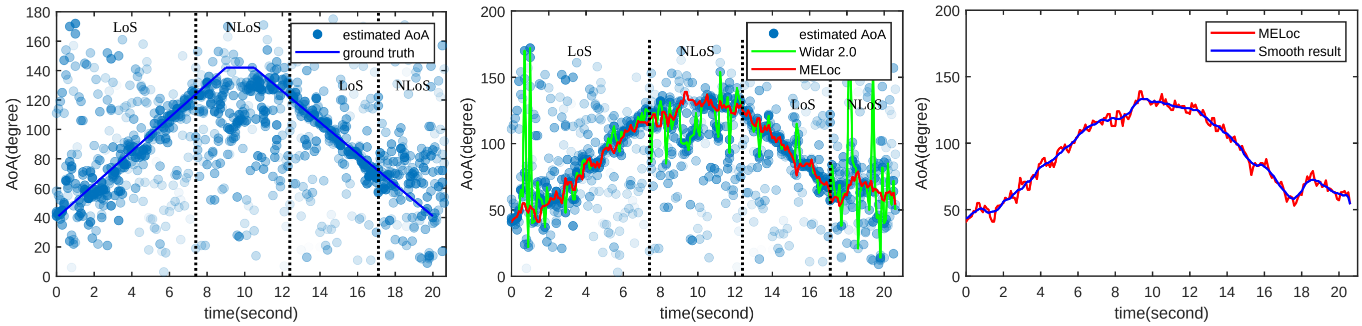


Fig. 3. Example of MUSIC-EM integrated algorithm.

Based on the AoA and ToF parameters obtained through the MUSIC algorithm, we construct a four-dimensional initial parameter vector $\theta_l = [\tau_l, \varphi_l, \gamma_l, \alpha_l]$. In our application scenario, we set the Doppler frequency shift γ_l to 0, and the final parameter attenuation α_l can be computed based on the first three parameters. Therefore, θ_l essentially only contains the initial values of the parameters τ_l and φ_l.

In the first iteration of the EM algorithm, we pass the parameter θ_l as an initial value, thus constructing the estimated signal in the E-Step. In the subsequent M-Step, we adjust



(a) All AoA estimated results of all antennas.
(b) Strongest estimated paths of all antennas.
(c) Best estimated paths of all antennas.

Fig. 4. Example of Path selection.

the path parameters sequentially. Since γ_l is always 0 and α_l can be computed based on the first three parameters in our application scenario, we only need to calculate the parameters τ_l and φ_l by maximizing the likelihood function. Through the iterative process of these two steps, we gradually optimize the parameter θ_l to obtain more refined estimations of Wi-Fi signal localization parameters.

By incorporating the precise estimates of AoA and ToF obtained from the MUSIC algorithm into the EM-based algorithm, we successfully mitigate the problem of the EM-based algorithm being trapped in local optima. This integrated approach holds promise for achieving more accurate and reliable localization results in Wi-Fi signal localization.

4) Results: As shown in the Fig. 3, in a period of consecutive estimation results, the estimation results of the EM-based algorithm with a fixed initial value of 0 produce a large error. However, the accuracy of the estimation results is significantly improved after the initial value is obtained by first estimating the data using MUSIC, which is used as an input to the EM-based estimation algorithm.

IV. Path Selection

A. NLoS Impact on Direct Path Selection

The outcomes of the EM-based algorithm yield multidimensional parameters representing various paths, necessitating the selection of Tx-Rx direct paths. Traditional path selection methods typically rely on signal strength attenuation to determine the optimal path [11, 26], wherein the path with the maximum received signal strength is chosen as the direct path. However, in indoor environments, the presence of NLoS paths exerts an influence on the propagation of wireless signals.

Fig. 4(a) illustrates the outcomes of parameter estimation for all trajectories alongside their respective ground truth in the context of scientific investigation. Notably, in the vicinity of the actual ground truth, certain pathway parameters exhibit subtle complex attenuation. These nuanced variations, indicative of potential authenticity as direct paths, nonetheless evade straightforward selection using elementary metrics. Phenomena such as reflection and refraction from obstacles can result in profound changes in signal strength, thereby rendering the method of selecting the direct path with the strongest attenuation less precise.

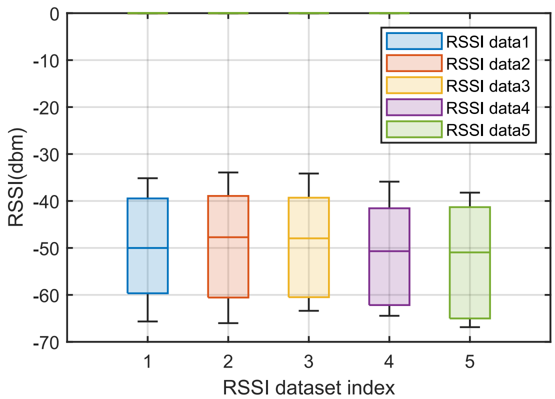
B. Space-time Continuity-based Path Selection

1) Basic idea: To address the shortcomings of traditional path selection methods in the NLoS environment, we propose a more advanced approach, the line chasing principle. In this section, we provide an in-depth description of the working mechanism of the line chasing principle, including how to select the AoA and compensate for the instability of the $RSSI$. The application domain of MELoc involves the localization of mobile devices, which implies that we consider the continuity of the target in both the temporal and spatial domains in an integrated manner. Therefore, our idea is based on spatio-temporal continuity, i.e., optimizing the localization results under NLoS paths by exploiting the relatively accurate path selection results under LoS paths.

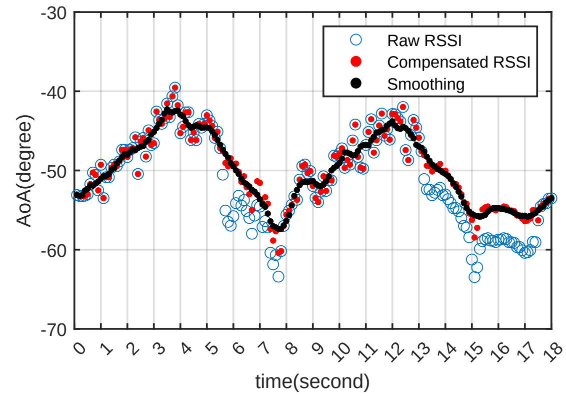
Our algorithm is mainly divided into two parts: path matching and path smoothing.

2) Path matching: We focus on AoA-based path selection because the AoA parameter is more accurate compared to other parameters in the EM-based algorithm. The path matching problem is to select the appropriate AoA at the current moment t from the set of candidate AoA values $\{AoA_l \mid 1 \leqslant l \leqslant L\}$ with reference to the historical sequence of AoA selections from time 1 to $t-1$.

We solve this path matching problem as a discrete problem of $line\ chasing\ problem$. First, we apply quadratic fitting to obtain the predicted AoA (denoted as $AoA^{predict}$) from the historical selection sequence. Then we compute the distance of each candidate from the predicted AoA and select the closest one, $\min_l |AoA_l - AoA^{predict}|$. The $AoA^{predict}$ of the historical selection sequence is obtained by quadratic linear fitting. Ultimately, the distance between each candidate and the predicted value AoA is computed, and the closest candidate is selected, i.e., $\min_l |AoA_l - AoA^{predict}|$. In Fig. 4(b), we showcase the strongest estimated paths obtained from a comprehensive analysis of all antennas in our Wi-Fi localization framework. Remarkably, the paths estimated using the MUSIC-EM integrated algorithm exhibit a notable improvement over those obtained with the Widar2.0 approach. This distinction is especially evident in scenarios characterized by NLoS conditions, underscoring the heightened performance of the MUSIC-EM integrated algorithm in challenging propagation environments.



(a) $RSSI$ fluctuation range.



(b) Public area deployments.

Fig. 5. Example of $RSSI$ compensation.

3) Path smoothing: The iterative steps of path matching are repeated, allowing MELoc to achieve continuous path selection results, thus realizing spatio-temporal continuous localization of mobile devices. The smoothed results presented in Fig. 4(c) emanate from the initial results obtained by the MUSIC-EM integrated algorithm, showing a discernible improvement in curve smoothness.

V. Localization

A. Application scenario

So far, we have obtained the parameters of paths. These figures can be used for subsequent mobile device localization. In this part, we will introduce how to integrate MELoc into single-AP scenarios.

As we know, the path parameter of direct includes ToF (τ_l), AoA (φ_l), doppler shift (γ_l) and complex attenuation (α_l). At first glance, the combinations of AoA and ToF, or AoA and complex attenuation look like good solutions to the localization problem. However, our ToF resolution is 1ns and the corresponding distance resolution is 0.3 m, which makes high-precision localization results at the decimeter-level impossible. Meanwhile, the obtained parameter of Complex Attenuation is a relative value, with a lack of the method to convert it into the distance. Therefore, MELoc selects the combination of AoA and $RSSI$ for device localization in single-AP scenarios.

B. $RSSI$ compensation

It is well known that $RSSI$ signals are highly volatile. When the Wi-Fi signal switches between LoS scenarios and NLoS scenarios, the $RSSI$ will undergo a drastic jump. Such changes can significantly affect the accuracy of $RSSI$-based localization solutions. However, in the previous subsection, we have been able to obtain the AoA steady state through the path selection algorithm, i.e., the AoA is stable and continuous in LoS scenarios while fluctuating and noisy in NLoS scenarios.

We propose a method to compensate $RSSI$ with the help of the above observation. Specifically, when the Wi-Fi signal enters the NLoS scenario from the LoS scenario, the $RSSI$ strength decreases. Therefore, we rescan the AoA selection results to compensate the $RSSI$ value from the LoS scenario into the NLoS scenario. When the Wi-Fi signal enters the LoS scenario from the NLoS scenario, the $RSSI$ intensity increases. Then we reduce $RSSI$ by a certain amount, which is an empirical value collected from the environment.

As shown in Fig. 5(b), the above operation compensates for the unstable situation, i.e., the $RSSI$ value in the NLoS scenarios, which makes the $RSSI$ value closer to the ground truth when converted to distance, thus improving the localization accuracy.

C. Localization Algorithm

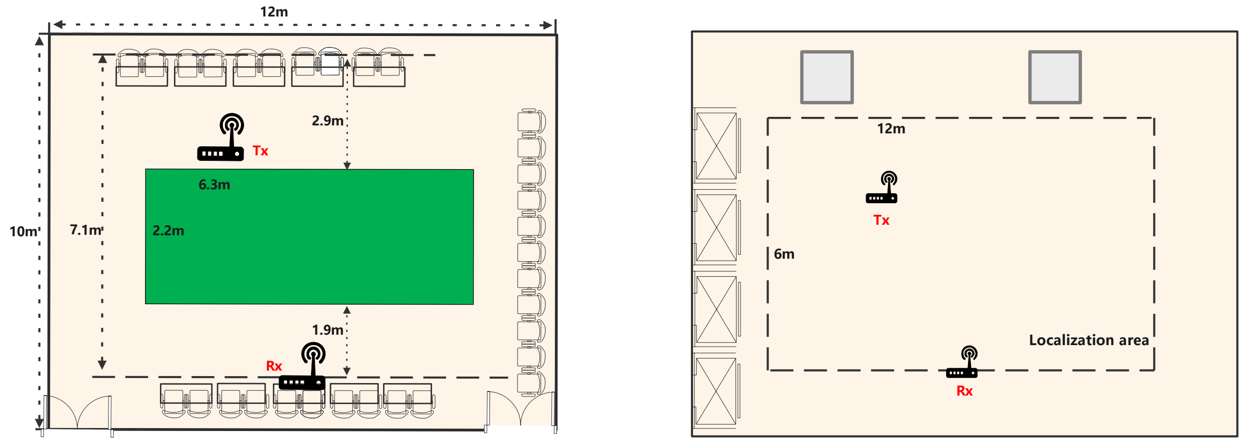
1) Conversion from $RSSI$ to distance: As the first step for $AoA + RSSI$ based localization, we should convert from $RSSI$ to distance d. In the LoS scenarios, we can perform conversion as follows based on the indoor attenuation model of signal [27]:

$$d = 10^\wedge((|RSSI| - A)/10n), \tag{3}$$

where A is the received signal strength (in terms of dBm) 1 meter away from Tx, and n is the signal propagation coefficient. Both parameters could be pre-measured in the target environment.

In NLoS scenarios, there exists obvious obstruction that causes a decrease in $RSSI$ compared to LoS conditions [28]. We conduct $RSSI$ measurements at different places in the room, with continuous LoS/NLoS switching by intentionally blocking the direct path. As shown in Fig. 5(a), the measured $RSSI$ undergo a fluctuation of about 10 to 20 dBm. This is the obstruction caused $RSSI$ reduction, which should be compensated for precise tracking. Therefore, we need pre-processing to measure $RSSI$ in the target indoor environment and obtain the average $RSSI$ reduction factor in NLoS scenarios. As shown in Fig. 5(b), When performing tracking we will apply such compensation factor (e.g., 6dBm in Fig. 5(b)) to the $RSSI$ value in NLoS scenarios, We can clearly see that the $RSSI$ trend is more continuous and also matches the distance trend of the moving trajectory.

2) Target localization: When with AoA (φ) plus distance d (converted from $RSSI$), we can easily obtain the location



(a) Meeting room deployments. (b) Public area deployments.

Fig. 6. Deployments in different environments.

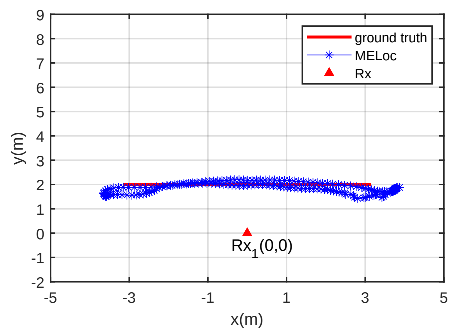


Fig. 7. Linear trajectory localization results.

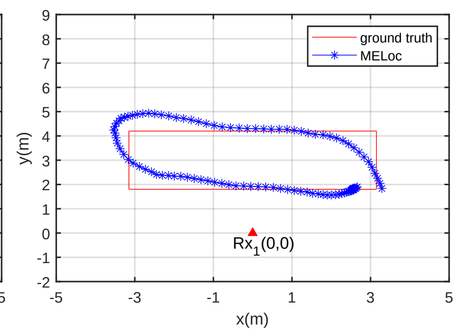


Fig. 8. Rectangular trajectory localization results.

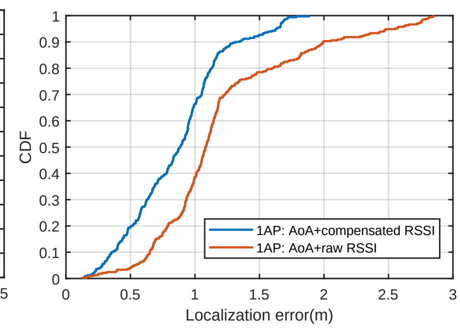


Fig. 9. Overall performance.

of the target in 2D space. We denote the the AP coordinate as $(0,0)$, and the location of mobile device is $(x,y) = d(cos(\pi - \varphi), sin(\pi - \varphi))$.

VI. Performance Evaluation

A. Experiment Setup

1) Experimental environments: To validate the effectiveness of MELoc, experiments are conducted in two distinct types of typical environments. One scenario involves a complex conference room environment with dimensions of 12 m × 10 m, featuring a rectangular conference table at the center surrounded by several chairs, exhibiting strong multipath reflections. The other scenario comprises a simple and spacious public area environment with dimensions of 12 m × 6 m. The specific equipment deployment and tracking areas for both experimental environments are illustrated in Figs. 6(a) and 6(b).

2) Hardware and Software configuration: In each experimental setting, CTOS (Commercial Off-The-Shelf) Wi-Fi devices equipped with Intel 5300 Wi-Fi cards are employed to implement MELoc. The Intel 5300 Wi-Fi cards utilize Linux CSI tools [29] to collect CSI measurement values. The transmitter is equipped with a single antenna, while the receiver features three antennas, with a spacing of 2.6 centimeters between each antenna pair (approximately half a wavelength in the 5 GHz frequency band), forming a uniform linear array. All experiments use the 802.11n protocol on channel 165 at 5.825 GHz, with a data packet transmission rate of 200Hz. An Intel i5-11500 2.70Hz CPU is employed for processing, utilizing Matlab software to process CSI data for localization.

3) Comparison baseline: Evaluations on tracking accuracy and AoA estimation accuracy are conducted in the later subsections. Two algorithms are implemented as the baseline: SpotFi [25] and Widar2.0 [11]. SpotFi is a classical protocol that combines AoA estimates from multiple access points to localize the target. It fuses CSI in spatial and frequency domains, enhancing the resolution of traditional MUSIC and adeptly handling multi-path problems. Widar2.0 introduces a multiple signal parameter estimation and fusion algorithm, extracting multi-dimensional signal parameters from a single Wi-Fi link to improve parameter accuracy and localization precision. SpotFi and Widar2.0 are faithfully reproduced and compared with MELoc under the same experimental scenarios.

B. Overall Performance

We commence by presenting a comprehensive evaluation of the MELoc system, with detailed experimental parameters provided in the subsequent subsections. It is imperative to highlight that all experiments are conducted under uniform conditions, employing a single channel for equitable comparison. MELoc demonstrates robust localization capabilities in a typical indoor environment. The tracked target follows

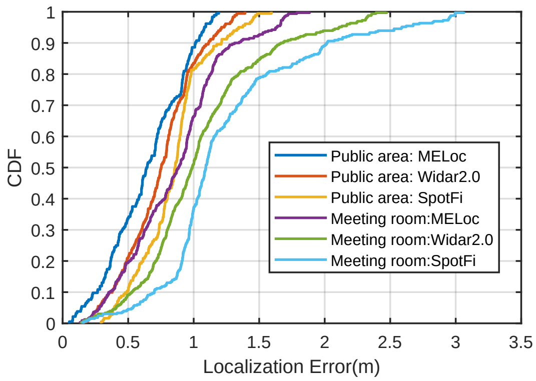


Fig. 10. Impact of environment.

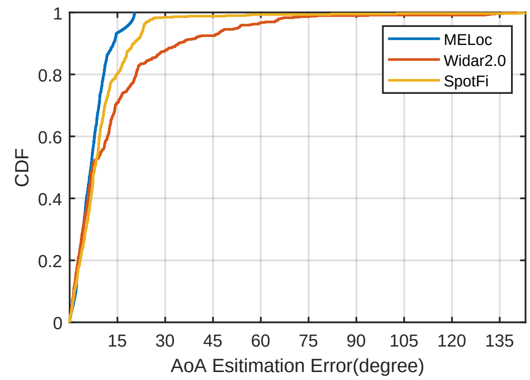


Fig. 11. AoA estimation error.

various trajectories, as illustrated in Figs. 7 and 8, showcasing exemplary tracking results along with the corresponding AP deployment. Notably, our tracking outcomes closely align with the actual trajectories. As shown in Fig. 9, MELoc attains a median localization error of 0.88 meters, exhibiting an improvement of 0.2 m compared to the variant lacking $RSSI$ compensation. Furthermore, it achieves a 90th percentile estimation error of 1.33 meters, outperforming the 2.00 meters observed in the version without $RSSI$ compensation.

C. Accuracy of Tracking

As depicted in Fig. 10, the MELoc system exhibits a median localization error of 0.64 m within an open public area measuring 6 m by 12 m, obtaining good results. In comparison, the median localization errors for SpotFi and Widar2.0 in the same setting are 0.86 m and 0.75 m, respectively.

To assess the resilience of MELoc across diverse environments, we conduct further evaluations in a 10 m × 12 m conference room, representing a typical indoor scenario characterized by abundant multipath effects. The resulting median error is determined to be 0.88 m. The comprehensive results of MELoc in this specific environment are presented in the subsequent table. The influence of multipath effects inevitably induces a degradation in the performance of the localization system. However, MELoc outperforms its counterparts, demonstrating superior performance with a median localization error of 1.09 m and 0.99 m for SpotFi and Widar 2.0, respectively, in the same environment. Furthermore, when considering the 90th percentile error, MELoc exhibits a relatively better performance in localization, achieving a value of 1.33 m, surpassing SpotFi and Widar2.0 by 0.69 m and 0.34 m, respectively. Consequently, MELoc proves its robustness to multipath effects in indoor environments, establishing its suitability for diverse indoor settings.

D. Accuracy of AoA Estimation

In this study, we assess the accuracy of path estimation provided by MELoc. The trajectory of movement is meticulously recorded through the utilization of ground markers, facilitating the subsequent computation of the ground truth of AoAs at various time instances. Consequently, the estimation error is determined by contrasting the ground truths with the estimated AoAs.

To benchmark the accuracy of the direct path AoA in our system, we conduct a comparative analysis with SpotFi and Widar2.0. As illustrated in Fig. 11, our system slightly surpasses both SpotFi and Widar2.0. Specifically, MELoc attains a median AoA accuracy of 7.09 degrees degrees, whereas SpotFi and Widar2.0 achieve 7.85 and 7.19 degrees under identical settings. Simultaneously, the 90th percentile estimation error of MELoc is 14.65 degrees, exhibiting a notable increase compared to SpotFi's 20.17 degrees and Widar2.0's 34.19 degrees.

VII. Related Work

The Wi-Fi active localization domain has witnessed significant strides in research.

A. MUSIC-based algorithm

SpotFi [25] employed the 2D MUSIC algorithm to estimate AoA from multiple APs, achieving a median localization error of 0.4 meters in LoS scenarios using 5 APs, but the error increased to 1.6 meters in NLoS scenarios. SiFi [30] used the MUSIC algorithm to estimate ToF differences between antennas of a single AP, but required the antennas to be placed at a distance. MonoLoco [31] combined AoA, ToF, and angle of departure (AoD) from direct and reflected paths, employing multi-path triangulation. However, it necessitated at least a 3-element antenna array on the transmitter and the receiver.

B. EM-based algorithm

UbiLocate [21] proposed enhanced compressed sensing solutions that achieved a 0.3-meter median localization error in LoS scenarios with 4 APs and escalated to 1.1 meters in NLoS scenarios. Nevertheless, UbiLocate relied on MIMO antenna systems and firmware modifications for fine time measurement (FTM), posing compatibility challenges with most Wi-Fi devices. M^3 [13] utilized frequency hopping to connect non-adjacent Wi-Fi channels, enhancing ToF resolution but potentially impacting wireless communication. NLoC [23] transformed multipath reflections into virtual direct paths, achieving sub-meter localization accuracy with four APs. However, meeting NLoC's deployment density requirements proved challenging in most indoor environments.

VIII. Conclusion

In this paper, we proposed MELoc, a MUSIC-EM integrated localization system. MELoc first utilized the MUSIC algorithm for rough estimation to obtain rough estimation parameters and used the estimation results as the initial parameters of the EM-based algorithm to improve the convergence of the EM-based algorithm. Then MELoc performed path selection based on the spatio-temporal continuity property of direct paths. Finally, MELoc compensated $RSSI$ based on the path selection results. Based on the selected direct path, MELoc fulfilled mobile device tracking under the single-AP deployment.

We developed a MELoc prototype in commercial CTOS Wi-Fi devices and conducted experiments in two different environments. The experiment results suggested that MELoc achieved significant improvement in tracking accuracy as compared with other solutions.

Acknowledgment

The research is partially supported by the "Pioneer" and "Leading Goose" R&D Program of Zhejiang with Grant No. 2023C01143, China National Natural Science Foundation with No. 62172379, Key Research Program of Frontier Sciences, CAS, Grant No.ZDBS-LY-JSC001. Hao Zhou is the corresponding author.

References

[1] Sangki Yun, Yi-Chao Chen, Huihuang Zheng, Lili Qiu, and Wenguang Mao. Strata: Fine-grained acoustic-based device-free tracking. In *Proceedings of the 15th annual international conference on mobile systems, applications, and services*, pages 15–28, 2017.

[2] Yasin Yelkovan, Hilal Güneren, Ahmet Akgöz, Furkan Eybek, Ahmet Türk, İsa Göl, and Ömer Çetin. Infrared beacon based sub-meter indoor localization. In *2014 22nd Signal Processing and Communications Applications Conference (SIU)*, pages 1427–1430. IEEE, 2014.

[3] Sinan Gezici, Zhi Tian, Georgios B Giannakis, Hisashi Kobayashi, Andreas F Molisch, H Vincent Poor, and Zafer Sahinoglu. Localization via ultra-wideband radios: a look at positioning aspects for future sensor networks. *IEEE signal processing magazine*, 22(4):70–84, 2005.

[4] Fadel Adib, Zachary Kabelac, and Dina Katabi. Multi-person localization via rf body reflections. In *12th USENIX Symposium on Networked Systems Design and Implementation (NSDI 15)*, pages 279–292, 2015.

[5] Anil Kumar and Pinhas Ben-Tzvi. Spatial object tracking system based on linear optical sensor arrays. *IEEE Sensors Journal*, 16(22):7933–7940, 2016.

[6] Longfei Shangguan, Zimu Zhou, and Kyle Jamieson. Enabling gesture-based interactions with objects. In *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*, pages 239–251, 2017.

[7] Jue Wang and Dina Katabi. Dude, where's my card? rfid positioning that works with multipath and non-line of sight. In *Proceedings of the ACM SIGCOMM 2013 conference on SIGCOMM*, pages 51–62, 2013.

[8] Yanzi Zhu, Yuanshun Yao, Ben Y Zhao, and Haitao Zheng. Object recognition and navigation using a single networking device. In *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*, pages 265–277, 2017.

[9] Matthew Cooper, Jacob Biehl, Gerry Filby, and Sven Kratz. Loco: boosting for indoor location classification combining wi-fi and ble. *Personal and Ubiquitous Computing*, 20(1):83–96, 2016.

[10] Loizos Kanaris, Akis Kokkinis, Antonio Liotta, and Stavros Stavrou. Fusing bluetooth beacon data with wi-fi radiomaps for improved indoor localization. *Sensors*, 17(4):812, 2017.

[11] Kun Qian, Chenshu Wu, Yi Zhang, Guidong Zhang, Zheng Yang, and Yunhao Liu. Widar2. 0: Passive human tracking with a single wi-fi link. In *Proceedings of the 16th annual international conference on mobile systems, applications, and services*, pages 350–361, 2018.

[12] Yaxiong Xie, Jie Xiong, Mo Li, and Kyle Jamieson. md-track: Leveraging multi-dimensionality for passive indoor wi-fi tracking. In *The 25th Annual International Conference on Mobile Computing and Networking*, pages 1–16, 2019.

[13] Zhe Chen, Guorong Zhu, Sulei Wang, Yuedong Xu, Jie Xiong, Jin Zhao, Jun Luo, and Xin Wang. M3: Multipath assisted wi-fi localization with a single access point. *IEEE Transactions on Mobile Computing*, 20(2):588–602, 2019.

[14] Swarun Kumar, Stephanie Gil, Dina Katabi, and Daniela Rus. Accurate indoor localization with zero start-up cost. In *Proceedings of the 20th annual international conference on Mobile computing and networking*, pages 483–494, 2014.

[15] Jie Xiong and Kyle Jamieson. Arraytrack: A fine-grained indoor location system. In *10th USENIX Symposium on Networked Systems Design and Implementation (NSDI 13)*, pages 71–84, 2013.

[16] Jon Gjengset, Jie Xiong, Graeme McPhillips, and Kyle Jamieson. Phaser: Enabling phased array signal processing on commodity wifi access points. In *Proceedings of the 20th annual international conference on Mobile computing and networking*, pages 153–164, 2014.

[17] Deepak Vasisht, Swarun Kumar, and Dina Katabi. Decimeter-level localization with a single wifi access point. In *13th USENIX Symposium on Networked Systems Design and Implementation (NSDI 16)*, pages 165–178, 2016.

[18] Manikanta Kotaru and Sachin Katti. Position tracking for virtual reality using commodity wifi. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 68–78, 2017.

[19] Xiang Li, Shengjie Li, Daqing Zhang, Jie Xiong, Yasha Wang, and Hong Mei. Dynamic-music: Accurate device-free indoor localization. In *Proceedings of the 2016 ACM international joint conference on pervasive and ubiquitous computing*, pages 196–207, 2016.

[20] Robert K Harle and Andy Hopper. Deploying and evaluating a location-aware system. In *Proceedings of the 3rd international conference on Mobile systems, applications, and services*, pages 219–232, 2005.

[21] Alejandro Blanco Pizarro, Joan Palacios Beltrán, Marco Cominelli, Francesco Gringoli, and Joerg Widmer. Accurate ubiquitous localization with off-the-shelf ieee 802.11 ac devices. In *Proceedings of the 19th Annual International Conference on Mobile Systems, Applications, and Services*, pages 241–254, 2021.

[22] Chi Lin, Pengfei Wang, Chuanying Ji, Mohammad S Obaidat, Lei Wang, Guowei Wu, and Qiang Zhang. A contactless authentication system based on wifi csi. *ACM Transactions on Sensor Networks*, 19(2):1–20, 2023.

[23] Xianan Zhang, Lieke Chen, Mingjie Feng, and Tao Jiang. Toward reliable non-line-of-sight localization using multipath reflections. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 6(1):1–25, 2022.

[24] Xiang Li, Daqing Zhang, Qin Lv, Jie Xiong, Shengjie Li, Yue Zhang, and Hong Mei. Indotrack: Device-free indoor human tracking with commodity wi-fi. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 1(3):1–22, 2017.

[25] Manikanta Kotaru, Kiran Joshi, Dinesh Bharadia, and Sachin Katti. Spotfi: Decimeter level localization using wifi. In *Proceedings of the 2015 ACM Conference on Special Interest Group on Data Communication*, pages 269–282, 2015.

[26] Harold W Kuhn. The hungarian method for the assignment problem. *Naval research logistics quarterly*, 2(1-2):83–97, 1955.

[27] Jiuqiang Xu, Wei Liu, Fenggao Lang, Yuanyuan Zhang, and Chenglong Wang. Distance measurement model based on rssi in wsn. *Wireless Sensor Network*, 2(8):606, 2010.

[28] Mohd Ezanee Rusli, Mohammad Ali, Norziana Jamil, and Marina Md Din. An improved indoor positioning algorithm based on rssi-trilateration technique for internet of things (iot). In *2016 International Conference on Computer and Communication Engineering (ICCCE)*, pages 72–77. IEEE, 2016.

[29] S. Anmol H. Daniel, H. Wenjun and W. David. Linux 802.11n csi tool.

[30] Wei Gong and Jiangchuan Liu. Sifi: Pushing the limit of time-based wifi localization using a single commodity access point. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(1):1–21, 2018.

[31] Dimitrios Arapis, Milad Jami, and Lazaros Nalpantidis. Efficient human 3d localization and free space segmentation for human-aware mobile robots in warehouse facilities. *Frontiers in Robotics and AI*, 10, 2023.