Re-Implementing SpotFi for WiFi localization Using the WILD-v2 Dataset

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Accurate indoor localization using commodity WiFi hardware remains a challenging problem due to multipath propagation, limited antenna arrays, and hardware-induced phase distortions. Prior work, most notably SpotFi, demonstrated that super-resolution Angle-of-Arrival (AoA) estimation combined with Time-of-Flight (ToF) information can enable decimeter-level localization using off-the-shelf WiFi devices. In this project, we aim to re-implement the SpotFi localization pipeline using the WILD-v2 dataset, which differs significantly from the original Intel 5300 CSI dataset in terms of hardware configuration, antenna layout, and measurement conditions. We implement a MUSIC-based AoA estimation framework, adapt SpotFi's signal model to the new dataset and analyze AoA behavior along known ground-truth trajectories. This report presents the background, algorithmic foundations, and dataset characteristics underlying our approach, and lays the groundwork for a quantitative evaluation of localization performance.

CCS Concepts: • **General and reference** → *Experimentation*; *Evaluation*; *Design*; • **Hardware** → **Wireless integrated network sensors**; *Beamforming*; • **Computing methodologies** → *Model verification and validation*; *Simulation evaluation*.

Additional Key Words and Phrases: Localization, WiFi, Angle of Arrival, Time of Flight, Super Resolution

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1 Introduction

Indoor localization using radio-frequency (RF) signals remains a challenging problem due to sever multipath propagation, non-line-of-sight conditions, and the limited sensing capabilities of nommodity wireless hardware. While global navigation satellite systems provide reliable localization outdoors, their performance degrades significantly indoors, motivating the development of alternative localization techniques. WiFi-based localization is particularly attractive because of the widespread availability of WiFi infrastructure. However, traditional approaches based on received signal strength (RSS) typically achieve only meter-level accuracy and are highly sensitive to environmental changes. Current methods utilize channel state information (CSI) to extract physical propagation parameters such as Angle-of-Arrive (AoA) and Time-of-Flight (ToF), enabling substantially improved localization accuracy.

Among these approaches, SpotFi showed that super-resolution localization is possible commercially available WiFi devices by jointly estimating AoA and ToF through subspace-based methods. SpotFi exploits phase differences across antennas and subcarriers to form a virtual antenna array, enabling the application of the Multiple Signal Classification (MUSIC) algorithm to resolve multipath components with high angular resolution. While SpotFi reports decimeter-level localiztion accuracy, its evaluation is limited to a specific hardware platform and dataset. This raises the question of how well the SpotFi approach generalizaes to datasets collected under different conditions and hardware configurations.

In this project, we aim to re-implement the SpotFi localization pipeline using the WILD-v2 dataset, which differs substantially from the original Intel 5300 CSI dataset used in prior work. Our goal is not only to reproduce the core algorithmic ideas behind spotfi, but also to evaluate the robustness and limitation of these ideas when applied to a new dataset. We focus on implementing a MUSIC based AoA estimation framework, analyzing AoA behavior along known ground-truth trajectories, and identifying the challenges that arise when transferring the algorithm across datasets.

2 Background and Related Works

Early WiFi localization systems primarialy relied on RSS fingerprinting, in which signal strength measurements are match against a pre-collected database of labeled locations. While simple ti implement, these systems suffer from limited accuracy and poor robustness, as RSS measurements are highly sensitive to environmental dynamics such as furniture movement or human presence. To address these limitation, subsequent work explored the use of CSI, which provides per-subcarrier complex channel measurments and captures richer propagation information then RSS alone.

Several CSI-based localization approaches use amplitude and phase information to improve fingerprinting or infer coarse spatial information. However, naive use of CSI phase is problematic due to hardware-induced distortions such as sampling time offset (STO) and carrier frequency offset (CFO), which introduce unknown phase shifts across packets and subcarriers. As a result, many early CSI-based systems either discard phase information or rely on extensive calibration.

SpotFi represents a significant advancement by demonstratin that CSI phase can be sanitized and exploited for super-resolution localization. By combining antenna arrays with OFDM subcarriers, SpotFi effectively constructs a large virtual sensor array that enables joint AoA-ToF estimation using MUSIC. Related works have explored similar subspace-based or sparsity-based techniques, including ESPRIT and compressed sensing methods, as well as hybrid systems that fuse RF measurements with inertial sensors [Roy and Kailath 1989][Malioutov et al. 2005][Vasisht et al. 2015][Woodman

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and Harle 2008]. Despite these advances, most prior work evaluates performance on a single dataset or hardware platform, leaving open question about generalization and robustness.

3 Algorithmic Foundations

The SpotFi localiztion framework models the WiFi channel as a suerposition of multiple propagation paths, each characterized by and AoA and a ToF. For a receiver equipped with M antennas and an OFDM system with N subcarriers, the measured CSI can be represented as a joint antenna-frequency observation. Let $x_{m,n}$ denote the CSI measurement at antenna m and subcarrier n. Assuming L dominant multipath components, the received signal can be modeled as

$$x_{m,n} = \sum_{k=1}^{L} \alpha_k \exp\left(-j2\pi(m-1)\frac{d}{c}\sin\theta_k f_n\right)\exp(-j2\pi f_n \tau_k) + n_{n,m} \tag{1}$$

where α_k is the complex gain of the k-th path, θ_k and τ_k denote its AoA and ToF respectively, d is the antenna spacing, c is the speed of light, f_n is the frequency of the n-th subcarrier, and $n_{m,n}$ represents additive noise. This expression highlights how AoA induces a phase progression across antennas, while ToF induces a phase progression across subcarriers.

By stacking CSI measurements across all antennas and subcarriers, the received signal can be written in vector form as

$$\mathbf{x} = \sum_{k=1}^{L} \alpha_k \mathbf{a}(\theta_k, \tau_k) + \mathbf{n} \tag{2}$$

where $\mathbf{a}(\theta, \tau) \in \mathbb{C}^{M,N}$ is the joint steering vector corresponding to AoA θ and ToF τ. This formulation effectively treats the antenna-subcarrier grid as a virtual sensor array, significantly increasing the dimensionality available for parameter estimation.

To estimate the unknown AoA and ToF parameters, SpotFi employs the Multiple Signal Classification (MUSIC) algorithm, a subspace-base super-resolution method. Given multiple CSI snapshots, a sample covariance matrix is formed as

$$\mathbf{R} = \frac{1}{K}\sum_{i=1}^{K} \mathbf{x}_i \mathbf{x}_i^H \tag{3}$$

where K is the number of snapshots. An eigenvalue decomposition of $\mathbf{R}$ yields

$$\mathbf{R} = \mathbf{E}\mathbf{\Lambda}\mathbf{E}^H \tag{4}$$

where the eigenvectors corresponding to the largest eigenvalues span the signal subspace, while the remaining eigenvectors span the noise subspace. Let $\mathbf{E}_n$ denote the matrix of noise-subspace eigenvectors.

The MUSIC psuedospectrum is then defined as

$$P(\theta, \tau) = \frac{1}{\mathbf{a}(\theta, \tau)^H \mathbf{E}_n \mathbf{E}_n^H \mathbf{a}(\theta, \tau)} \tag{5}$$

which exploits the fact that the true steering vectors corresponding to physical propagation paths are approximately orthogonal to the noise subspace. Peaks in $P(\theta, \tau)$ therefore correspond to candidate AoA-ToF pairs.

In practice, applying MUSIC to commercial WiFi CSI presents several challenges. Hardware-induced phase distortions like STO introduce unknown linear phase shifts across subcarrier and must be mitigated through phase sanitation. Additionally, the limited number of physical antennas necessitates spatial smoothing techniques to de-correlate multipath components and increase the effective number of sensors. In this work, we primarily focus on AoA estimation as a first step toward full joint AoA-ToF localization, using the above formulation ans the algorithmic foundation for our implementation on the WILD-v2 dataset.

4 Dataset Description

The WILD-v2 dataset consists of over 17,000 WiFi measurements collected in an indoor environment with known ground-truth transmitter locations. Each measurement includes complex channel frequency response values across multiple antennas and OFDM subcarriers, along with metadata describing antenna spacing, center frequency, and subcarrier indices. Ground-truth positions are provided in two dimensions, enabling detailed analysis of spatial consistency and localization performance.

Unlike the Intel 5300 CSI dataset used in SpotFi, the WILD-v2 dataset exhibits different hardware characteristics and measurement conditions. These differences include variations in antenna configuration, frequency parameters, and noise properties, which impact the stability and interpretability of CSI phase measurements. Additionally, the dataset contains a singular trajectory through the environment, which makes analysis of AoA behavior along known paths difficult because there is only one sample for each location. We addressed this problem by clustering multiple nearby samples, treating them as measurements from one location.

These characteristics make WILD-v2 a suitable but challenging testbed for evaluating the generalizability of the SpotFi approach. By re-implementing the SpotFi pipeline on this dataset, we aim to understand how dataset-specific factors influence AoA estimation performance and to identify the adaptations necessary for reliable localization across different WiFi measurement platforms.

5 Results

Although we went to work with wildv2 dataset, we encountered very significant difficulty in implementing the dataset for the SPOTFI algorithm. We realised that the CSI data was very difficult to get reasonable accurate AoA using MUSIC. This could be because there could be external artifacts in the CSI, which hasn't been cleaned yet. To show if the MUSIC algorithm is not working, we implemented FFT as well. For a particular user location, the following figure will show how FFT and MUSIC algorithms compare. In the figure, the actual user location is shown in purple diamond, the ground truth direction towards this user is shown in dottedn green line, from each AP. Also, the predicted directions using FFT and MUSIC algorithm are shown in purple and cyan respectively. The error of FFT is much lower than that of MUSIC. Even then both methods' AoA estimation is significantly worse. The average AoA error from FFT and MUSIC are 23.5° and 54° respectively. Since, in this particular case (not so when we average over multiple locations as we shall see) FFT has

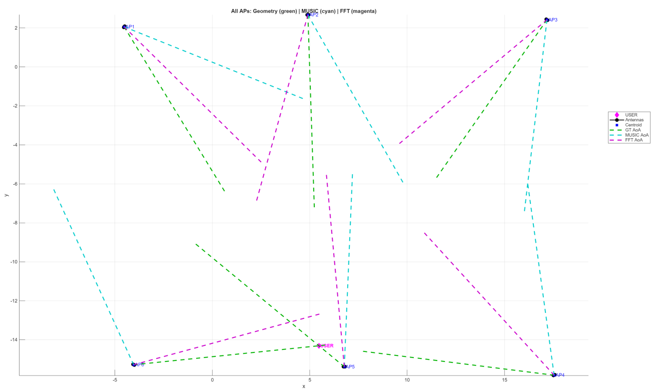

Fig. 1. Comparison of AoA estimation using FFT and MUSIC for a fixed user location in the WILD-v2 dataset.

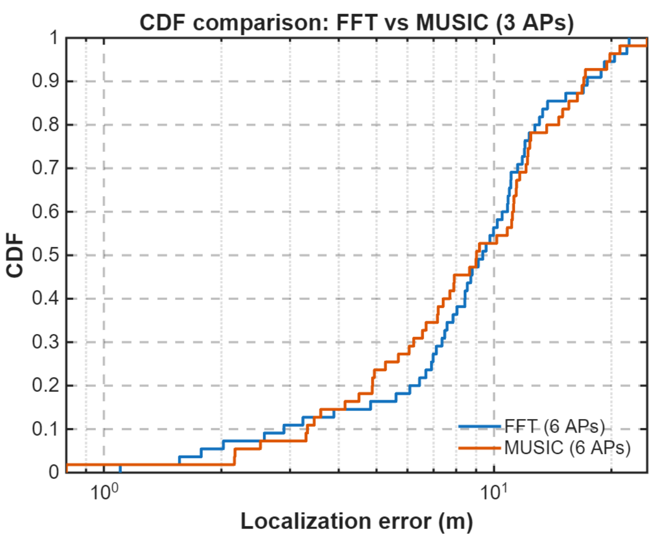

Fig. 2. Comparison of absolute localization error using FFT and MUSIC algorithm for 55 user locations and using 6 APs

much better performance than MUSIC so, we decided to show the performance of FFT as well.

We want to inform that we noticed mostly single AoA from both of these algorithms, hence we are only focusing on AoA and not the time-of-flight (ToF). Hence the FFT and MUSIC we implement here are not 2D AoA-ToF MUSIC or FFT, instead they are only for AoA. The sole reason why SPOTFI implements ToF based 2D MUSIC is to have better resolution in finding the direct path AoA. Since our dataset seem to contain only a single (mostly) angle (even though it is highly incorrect most probably due to external factors), we decided not to use the 2D algorithms.

Next, although we have 17000 new user locations, SPOTFI works with only 55 locations, so we also used the first 55 locations to generate the CDF of the absolute errors. The following figure shows the CDF plot of MUSIC and FFT. Although the figure 1 showed the FFT performed better, here for localization of 55 locations, they both

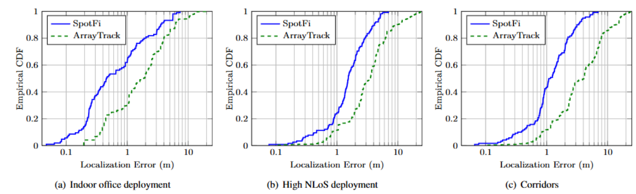

Fig. 3. SPOTFI paper results

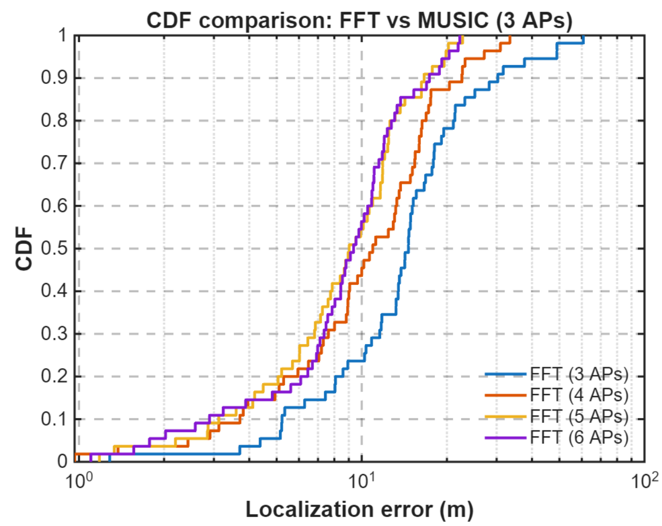

Fig. 4. CDF plot of FFT using different number of APs

seem to be performing similarly. The median error is around 0.9 meters.

As for SPOTFI results, they show at different scenes. For indoor scens, their median error is around 0.4 meters, but for outdoor and bigger scenarios like corridors, the median error is more than 1m. The SPOTFI figure is shown below: Now since our result is comparable with outdoor scens, we can say that our error is slightly better than SPOTFI.

next, we wanted to study the effect of having different number of APs for localization. The figure below shows effect of multiple APs.

We see that when we increase the number of APs from 3 to 6, the error slightly reduces. We did the same for MUSIC as well. However, for MUSIC, there doesn't seem to be much improvement, it could be because there was so much error in MUSIC to begin with, as shown in figure 1.

next, we checked if the error reduces when using more receiver locations. Below shows the figure that uses multiple locatins. Unfortunately we don't see performance improvement. It could be because each location has high error and all locations seem to have similar errors and this way the statistics didn't change.

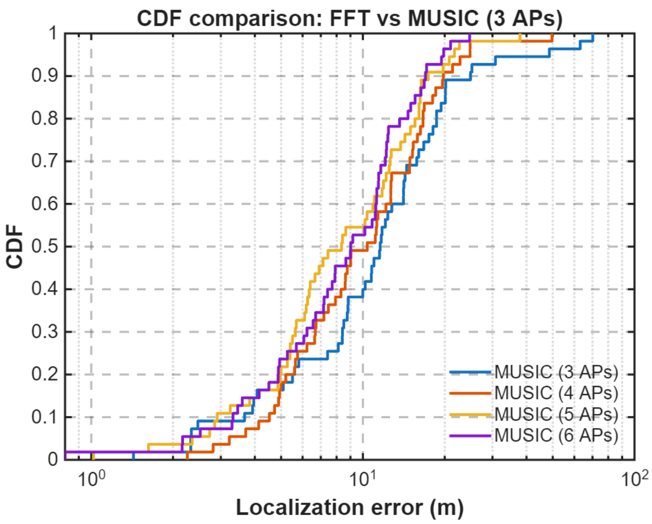

Fig. 5. CDF plot of MUSIC using different number of APs

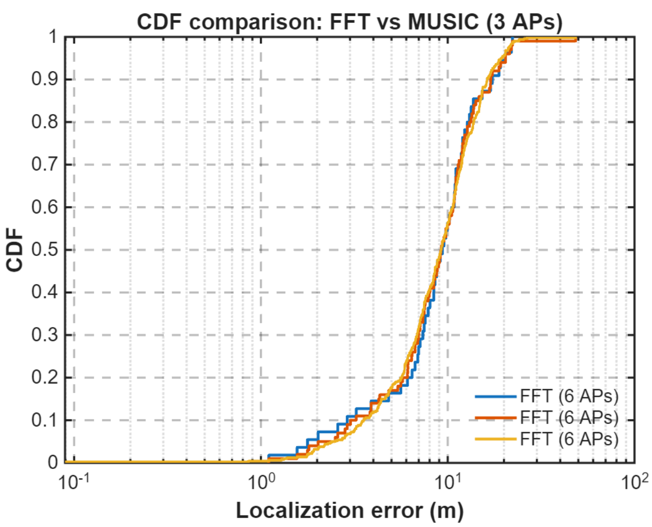

Fig. 6. CDF plot of FFT using different number of user locations

6 Conclusion

In this project, we were able to implement the SPOTFI algorithm. We searched online for a new dataset and implemented this new dataset. Also, by analyzing the nature of the dataset, we managed to bypass some of the steps used in the SPOTFI algorithms. Also, our performance was comparable to SPOTFI results in outdoor scenarios. We also performed ablation studies on the effect of different number of APs and different number of datasets.

Acknowledgments

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