FUSELOC: A CCA BASED INFORMATION FUSION FOR INDOOR LOCALIZATION USING CSI PHASE AND AMPLITUDE OF WIFI SIGNALS

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ABSTRACT

With the growth of location based services, indoor localization is attracting great interests as it facilitates further ubiquitous environments. In this paper, we propose FuseLoc, the first information fusion based indoor localization using multiple features extracted from Channel State Information (CSI). In FuseLoc, the localization problem is modelled as a pattern matching problem, where the location of a subject is predicted based on the similarity measure of the CSI features of the unknown location with those of the training locations. The system exploits both the amplitude and phase information of CSI over multiple antennas from Orthogonal Frequency Division Multiplexing (OFDM) system for localization. Specifically, FuseLoc implements a discriminative feature extraction from measured CSI for pattern matching, where an effective feature fusion is performed using Canonical Correlation Analysis (CCA) by maximizing the pairwise correlations across the feature sets. Finally a similarity measure is performed to find the best match to localize a subject. Experimental results show that FuseLoc can estimate location with high accuracy which outperforms other state-of-the-art approaches.

***Index Terms*—** Indoor Localization, CSI, Amplitude, Phase, Canonical Correlation Analysis

1. INTRODUCTION

Indoor positioning has become a hot topic now-a-days with the growth of context-aware computing. Almost all our daily aspects, such as where I am, what I am doing, and who I am with can be covered through the learning of human context information. It thus leads to revolutions in different domains, such as healthcare, entertainment, transportation, and social networks. Among different indoor localization approaches that are reported in literature, wireless signal based fingerprinting [1–3] is most widely used. Fingerprinting approach relies on the recording of the signal feature and stores this information in a database along with the known location of the target. During the localization phase, the current feature vector of wireless signal at an unknown location is compared to those saved in the fingerprint. The best match is returned as the estimated location. Therefore, choosing an appropriate feature is one of the crucial factors in fingerprinting based approach.

Most of the fingerprinting based localization approach relies on coarse-grained Received Signal Strength (RSS) [1,2], which not only varies over distance on the order of the signal wavelength but also fluctuates over time even at a static link, resulting in localization with lower accuracy [4]. With the aim of realizing high accuracy indoor localization, recently fine grained PHY layer CSI has gained significant attention for different wireless applications [5, 6], which is available in several Wi-Fi network interface cards (NIC) [7,8]. Unlike RSS, in IEEE 802.11n communication, OFDM system provides CSIs with amplitude and phase for subcarrier level channels. Therefore, CSI is richer in multipath information and more stable than RSS for a given location [4, 9]. Different methods are reported [9–11] for CSI based localization. [9] leverages the weighted average CSI amplitude as feature for fingerprinting based localization. In [10] CSI from a single antenna is utilized whereas [11] exploits CSI from multiple antennas. However, all these approaches rely only on CSI amplitude data. Recently, CSI phase is exploited in [12] for line-of-sight (LOS) identification. In [13], it is shown that phase difference for two receiver antenna is more stable with 5GHz Intel 5300 NIC.

In this paper we propose to exploit multimodal features of CSI in terms of the amplitude and the phase data from commodity WiFi device for fingerprinting based localization. Specifically, in addition to amplitude information, we use relatively stable estimated angle of arrival (AOA) obtained from the difference in phase data among receiving antennas from 5GHz NIC. This AOA does not change if the transmitter and receiver positions remain unchanged, hence is relatively stable. Utilizing both the amplitude and the phase information from CSI enables to exploit the complete multipath features to achieve a higher accuracy in localization. Furthermore, we exploit a discriminant feature of CSI for indoor localization, using the Canonical Correlation Analysis (CCA) based information fusion. CCA is one of the multi-data processing methods that deals with linear relationship between two or more multidimensional variables [14]. CCA has been used as a standard tool in the fields of neuroscience, machine learning, and signal processing [15–18]. Recently, feature fusion based on CCA has attracted the attention in the area of image recognition [17, 18]. In CCA based feature fusion, the correlation between two sets of features are used to find two sets of transformations such that the data co-variation of the transformed features is maximized across the two feature sets. In this work we employ CCA to combine multiple features extracted from CSI measurements in order to achieve a more discriminant feature over the individual ones. Multiple features extracted from the same CSIs reflect different characteristics of the patterns of CSIs affected by the presence of a subject at different locations. CCA based feature fusion not only keeps effective discriminant information of multiple features, but also eliminates redundant information to some extent. Finally the system employs euclidean distance based similarity measure to find the best match to localize a subject. To the best of our knowledge, ours is the first approach that utilize CCA based feature fusion to incorporate both the amplitude and the phase of CSIs for localization. Extensive experiments performed on CSI measurements in a typical research lab verify the effectiveness of FuseLoc which outperforms the state-of-the-art localization approaches.

The rest of the paper is structured as follows. Section 2 presents the preliminaries on CSI and feature extraction. Section 3 describes FuseLoc system. Section 4 describes the experimental setup of the system and evaluates the performance of proposed method. Finally, the concluding remarks are discussed in Section 5.

2. PRELIMINARIES

2.1. Channel State Information

In Multiple Input Multiple Output (MIMO) Orthogonal Frequency-Division Multiplexing (OFDM) technology, the narrow-band flat fading channel is modeled as, $y = Hx + n$, where y and x are the received and the transmitted signal vectors respectively, n is the noise vector and H denotes the channel matrix. The channel matrix $\hat{H}$ can be estimated by,

$$\hat{H} = \frac{y}{x}, \tag{1}$$

where $\hat{H}$ represents the PHY layer CSIs over multiple sub-carriers. For one antenna, $\hat{H}$ is a $N \times S$ matrix, where N is the number of measurements and S denotes the number of subcarriers for each antenna pair. CSI of a single subcarrier i is a complex value, $h_i = |h|e^{jsin\theta}$, where $|h|$ is the amplitude and θ is the phase of each subcarrier. We group CSIs of all transmission/receiving antenna pairs as,

$$H = [\hat{H}_1 \ \ \hat{H}_2 \ \ \ldots \hat{H}_l], \tag{2}$$

where l is the index of transmission/receiving antenna link and $\hat{H}_l \in R^{N \times S}$. Therefore, in (2), $H \in R^{N \times d}$, where $d = S \times l$, the total number of subcarriers from all transmission/receiving antenna pairs.

2.2. CSI Phase Information

CSI phase data extracted from the Intel 5300 NIC is highly random. The direct use of this phase data results in high error for indoor localization. This error stems from the hardware imperfection, specifically from the lack of synchronization of time and frequency of the transmitter and receiver. In order to overcome the error due to phase randomness, in this work we exploit the difference in phase values between two receiver antennas. For data packets that are received consecutively, this phase difference between two receiver antenna is highly stable. The measured CSI phase value θ_i from any subcarrier i can be expressed as [19, 20],

$$\theta_i = \phi_i + i(\lambda_{PB} + \lambda_{SF}) + \lambda_{CF}, \tag{3}$$

where ϕ_i is the original phase of subcarrier i caused by the channel propagation, i is the subcarrier index, λ_{PB}, λ_{SF}, and λ_{CF} are phase errors resulted from the packet boundary detection (PBD), the sampling frequency offset (SFO), and central frequency offset (CFO), respectively. We aim to obtain the phase value ϕ_i by eliminating the impact of error parameters λ_{PB}, λ_{SF}, and λ_{CF}.

Phase error λ_{PB} is caused by the time shift τ_{PB} from the packet boundary detection uncertainty while the phase error λ_{SF} is generated due to the offset of the sampling frequencies of the sender and the receiver. On the other hand, due to the hardware imperfection, the central frequency offset compensation is incomplete, which can cause CSI phase error λ_{CF}. Based on [20], it can be shown that,

$$\begin{aligned}
\lambda_{PB} &= 2\pi\Delta\tau N, \\
\lambda_{SF} &= 2\pi(\frac{T_r - T_t}{T_t})\frac{Ts}{Tu}, \\
\lambda_{CF} &= 2\pi\Delta f T_s n,
\end{aligned} \tag{4}$$

where N is the FFT size, $\Delta\tau$ is the packet boundary detection delay, T_r and T_t are the sampling periods of the receiver and the transmitter, respectively, T_u is the data symbol length, T_s is the total length of the guard interval and the data symbol, n is the current packet sampling time offset, Δf is the difference of center frequency between the transmitter and receiver. However, the value of $\Delta\tau$, T_r and T_t, n, and Δf in (4) are unknown, since only physical layer CSI data are received from the off-the-shelf devices. Furthermore, $\Delta\tau$ and n are different for different packets, which causes variation in λ_{PB}, λ_{SF}, and λ_{CF} over time. Hence, the original phase can not be properly detected by the measured CSI phase.

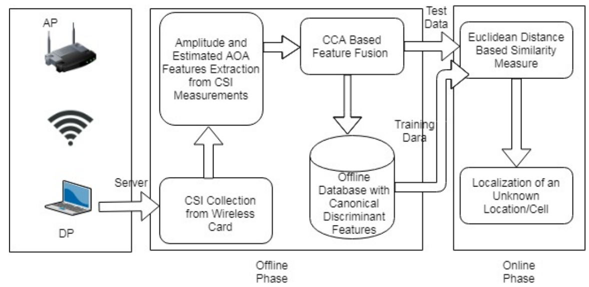

Fig. 1. System Architecture.

However, the difference in measured CSI phase values on a particular subcarrier between two receiver antennas in MIMO OFDM system is stable. This stability stems from the same clock and the same down-converter frequency of the receiver antennas of a particular Intel 5300 NIC device. For a particular subcarrier i, this in turn, results in the same central frequency difference, same delay in packet detection and same sampling period for the measured CSI phase [13]. Hence, the difference in measured CSI phase between two antennas at subcarrier i, can be approximated as,

$$\Delta\theta_i \approx \Delta\phi_i, \tag{5}$$

where $\Delta\phi_i$ is the phase difference of original phase on subcarrier i. From (5) it can be seen that the effect of random phase errors are minimized since the random terms $\Delta\tau$, T_r, T_t, n and Δf associated with λ_{PB}, λ_{SF}, and λ_{CF} are eliminated. Consequently, over different packets, $\Delta\theta_i$ becomes more stable compared to the measured CSI phase value.

3. THE FUSELOC SYSTEM

The overall system architecture of FuseLoc is shown in Fig. 1. FuseLoc consists of three hardware elements in a WLAN infrastructure: access points (AP), detecting points (DP) and a server. The overall localization is performed through an offline phase and an online phase as described below.

3.1. Offline Phase

3.1.1. Feature Extraction

Exploiting multimodal features of CSI, in terms of the amplitude and the phase from commodity WiFi device facilitates to utilize complete multipath features to achieve a high precision indoor localization system. To obtain the CSI based features for different location, the area is considered as a grid of small square cells and there are c cells in that area of interest. First, the system collects CSI for each cell, with a subject present in this cell. A CSI amplitude feature matrix H_c is generated for each cell as,

$$H_c = |H_{sbj}|_c, \tag{6}$$

where, H_c represents the effect of the presence of an entity on the CSI amplitude in a particular position or cell, c.

To generate the CSI phase based feature matrix for each cell, the difference in measured CSI phase between two antennas of the receiver is calculated. The system then translates this phase difference into an estimated angle of arrival for subcarrier i as,

$$\gamma_i = \arcsin(\Delta\theta_i \lambda / 2\pi d), \tag{7}$$

where d is the distance between two consecutive antennas at the NIC and λ is the wavelength. The value of d is set as 0.5λ in the experiment. The AOA in (7) lies in the range $[0, \pi]$. This AOA is highly stable due to the higher stability that arises from utilizing the difference in phase data between receiver antennas.

3.1.2. *Feature Fusion Using Canonical Correlation Analysis*

For multi-data processing, Canonical Correlation Analysis (CCA) is considered as one of the useful tools for finding a linear relationship between two sets of variables. For each set, CCA creates new variables by maximizing the pairwise correlation between these variables. In this work, we apply CCA for indoor localization using channel state information. Suppose that N training feature vectors from two different modalities of CSI are denoted by two matrices $X \in R^{s\times N}$ and $Y \in R^{t\times N}$, with dimension s and t for each sample, respectively. CCA finds the linear combinations, $A = U^T X$ and $B = V^T Y$ such that the pair-wise correlation, ρ, across the two feature sets are maximized:

$$\rho = \frac{cov(A,B)}{var(A).Var(B)} = \frac{U^T C_{XY} V}{U^T C_{XX} U.V^T C_{YY} V}, \tag{8}$$

where C_{XX} and C_{YY} are the within-set covariance matrices and C_{XY} is the between-set covariance matrix. A and B are known as canonical variates, which are uncorrelated within each feature set. CCA transformation matrices, U and V are obtained by solving the following optimization problem [14]:

$$\begin{aligned} \text{minimize} \quad & \|U^T X - V^T Y\|_F^2 \\ \text{subject to} \quad & \frac{1}{N} U^T X X^T U = I, \frac{1}{N} V^T Y Y^T V = I, \\ & \frac{1}{N} U^T X Y^T V = I. \end{aligned} \tag{9}$$

Here I is the $D \times D$ identity matrix with $D \leq min(s,t)$. The solution to (9) can be simplified as [21],

$$\begin{aligned} C_{XX}^{-1} C_{XY} C_{YY}^{-1} C_{YX} \hat{U} = R^2 \hat{U} \\ C_{YY}^{-1} C_{YX} C_{XX}^{-1} C_{XY} \hat{V} = R^2 \hat{U}, \end{aligned} \tag{10}$$

where, $\hat{U}$and $\hat{V}$ are the eigenvectors and R^2 is the diagonal matrix of eigenvalues or squares of the canonical correlations.

Once the transformation matrices are obtained, the system consolidates the feature sets obtained from multiple feature extractors into a single feature set using CCA based feature fusion. The CCA based feature fusion maximizes the information out of the two feature extractors. In [17], feature fusion is defined as the combinatorial feature obtained by either concatenation or summation of the transformed feature vectors:

$$Z_1 = \begin{pmatrix} A \\ B \end{pmatrix} = \begin{pmatrix} U^T X \\ V^T Y \end{pmatrix} = \begin{pmatrix} U & 0 \\ 0 & V \end{pmatrix}^T \begin{pmatrix} X \\ Y \end{pmatrix}, \tag{11}$$

$$Z_2 = A + B = U^T X + V^T Y = \begin{pmatrix} U \\ V \end{pmatrix}^T \begin{pmatrix} X \\ Y \end{pmatrix}, \tag{12}$$

where Z_1 and Z_2 are called the Fused Features, FF-I and FF-II, respectively. This feature fusion not only finds effective discriminant information over the two features but also eliminates redundant information within the features.

The CCA based feature fusion described above usually suffers from the problem of small sample size. In real time applications of localization, the number of samples might be less than the number of features ($N < s$) or ($N < t$). Consequently, the covariance matrices become singular and non-invertible, which in turn results in a major problem for inverting the C_{XX} and C_{YY} matrices used in Eq. (10). To overcome this issue the dimensionality of the feature vectors should be reduced before applying CCA. Therefore, to surmount the small sample size problem we perform Principle Component Analysis (PCA) and extract the top-k PCA components of the amplitude and AOA features of CSI and then fuse them using CCA based feature fusion.

3.2. Online Phase

In the online phase, A random subject appears at a location/cell and the FF-I and FF-II corresponding to that location of interest are collected following the same procedure of offline phase. In order to find the class/cell label of test location i, a simple but efficient Euclidean Distance based classifier is employed. We find the matching training cell that satisfies

$$\underset{j}{\text{argmin}} \|Z_{if} - Z_{jf}\|_2, \tag{13}$$

where, $j \in [1, 2, ..., c]$ and $f = 1, 2$, the fusion method used.

4. EXPERIMENTAL STUDY

4.1. Experimental Configuration

The FuseLoc system is implemented with Intel 5300 commodity Wi-Fi device and extensive experiments are conducted to valid its effectiveness. Fig. 2 shows the experimental configuration of FuseLoc. The system uses a TL-WR940N wireless router, mounted at a fixed location, which works as the AP. The DP is a mobile device equipped with Intel 5300 Network Interface Card (NIC). The operating system is Ubuntu desktop 14.04 LTS OS. Using the Linux 802.11n tool [7, 8], the DP collects the CSI data for 30 subcarriers for each transmitter-receiver link. 3×3 transmission/receiving antenna pairs with only one AP-DP link is utilized. A host PC (Intel i7-4790CPU 3.60 GHz, 8GB RAM) serves as the centralized server for location estimation.

FuseLoc is verified in a research laboratory with an area of $6m \times 5m$ in the CoRE Building of Rutgers University during weekdays. The lab is a cluttered environment, equipped with typical office facilities like desks, shelfs, desktops, chairs etc. and hence is a subject of rich multipaths. We virtually partition the area into 15 uniform square grids/cells, each of which is $0.75m \times 0.75m$ in size, which is typical walking step size for adults. The CSI packets are received at 1s interval and we record for 5 minutes for each cell. We take 300 packet samples for each cell position. We conduct 10 independent measurements on different days and compute the mean value for performance evaluation.

4.2. Accuracy of Localization

First the performance of FuseLoc system is evaluated in terms of mean distance error, standard deviation and mean processing time

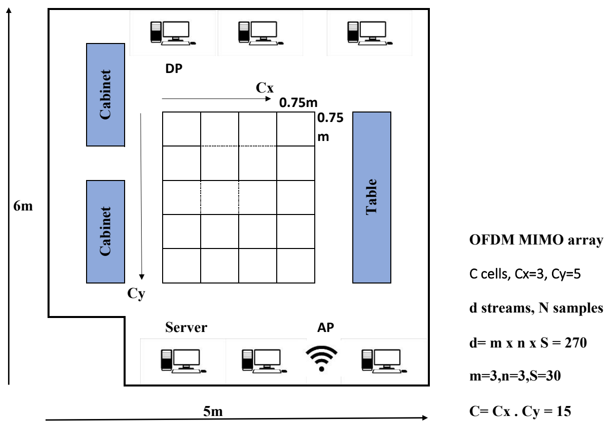

Fig. 2. The Layout of the Testbed in a Research Laboratory.

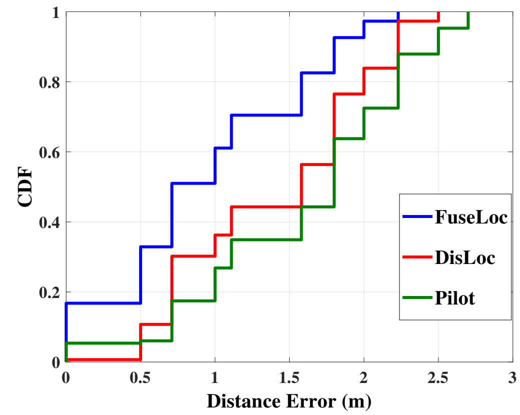

Fig. 3. CDF of Distance Error

Table 1. Comparison of mean error, STD and processing time for different schemes in the laboratory environment

Algorithm	Mean error (m)	Std. dev. (m)	Mean processing time (s)
FuseLoc	0.71	0.7420	0.2348
DisLoc	1.12	0.8001	0.6720
Pilot	1.20	0.76	3.2188

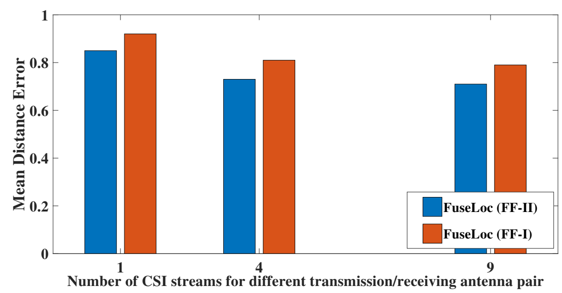

Fig. 4. Mean Distance Error for Different No of Antenna Pairs

and are compared with the CSI-based approach DisLoc [16] and Pilot [22]. Table 1 shows that, the mean error of FuseLoc is 0.71 m and the STD error is 0.7420 m for the 15 test cells. FuseLoc outperforms the other methods with the smallest mean error, as well as with the smallest standard deviation error. In addition, the online processing time is compared for all the schemes. Results show that FuseLoc achieve the smallest mean processing time of 0.2348 s, which outperforms Disloc and Pilot by a large margin. Therefor, the FuseLoc system is also computationally efficient than the other state-of-the-art approaches.

Fig. 3 presents the CDF of distance errors for different methods in the laboratory environment. FuseLoc has about 60% of the test locations having an error less than or equal to 1 m, while that for the other methods is 38% or less. We also find that approximately 97% of the test locations for FuseLoc have an error under 2 m, while the percentage of test locations having a smaller error than 2 m are 85%, and 73%, for Disloc, and Pilot, respectively. This is because the other methods are either designed to work with single antenna and/or use only a single feature for localization, while FuseLoc exploit CSIs from multiple antennas and fuse both the amplitude and phase difference based AOA features of CSI into a single feature, which is more discriminative than the individual ones. This feature fusion method reduces the redundant information between two input feature vectors, and therefore will be more effective.

4.3. Impact of Different Number of Antenna Pairs

We also evaluate the performance in terms of cell estimation accuracy for different number of transmission/receiver antenna pairs as shown in Fig. 4. Results show that the cell estimation accuracy of FuseLoc increases as we increase the number of antenna pairs. Accuracy of our system with FF-II can be extended to 91.8% while we increase the number of transmission/receiver antenna pair to 3×3, which corresponds to 9 CSI streams. This is because the more the number of transmission/receiver antenna pairs, the more the number of CSI streams and the more the information we have about the environment and hence better accuracy is achieved. Furthermore, we see that, with a single AP, FuseLoc can obtain a higher accuracy compared to the other methods. Thus, we consider using one AP with all antennas for the FuseLoc system in order to achieve the higher localization accuracy with lower device cost.

5. CONCLUSION

In this paper, we presented FuseLoc, the first information fusion based indoor localization that uses both the amplitude and the phase of CSI. In FuseLoc, CSI information for all the subcarriers from MIMO channels are collected from the commodity WIFi device and along with amplitude features, AOA features are estimated from the phase difference of receiver antennas. The system exploits an information fusion approach based on canonical correlation analysis of the feature sets. It aims to find transformations by maximizing the pair-wise correlations across the two feature sets. These characteristics make FuseLoc an effective approach for indoor localization using pattern matching. Moreover, FuseLoc is computationally efficient and can be employed in real-time applications. Extensive experiments are performed in an indoor environment. Experimental results show that the FuseLoc can estimate location with higher accuracy, which outperforms the benchmark localization approaches.

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