

CSI Fingerprinting with SVM Regression to Achieve Device-free Passive Localization

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Abstract—Location is an important context on which a broad range of context-aware applications can be built. Most previous approaches require the targets to carry electronic devices, while device-free passive localization is in need on many occasions. This paper proposes a device-free passive localization algorithm based on WiFi Channel State Information(CSI) and Support Vector Machines(SVM). In a physical space covered with WiFi signals, movements of targets may cause observable alteration of CSI. By establishing the nonlinear relationship between CSI fingerprints and target locations through SVM regression, the proposed algorithm is able to estimate the target locations according to the corresponding CSI fingerprints. The algorithm applies Density-Based Spatial Clustering of Applications with Noise(DBSCAN) to reduce the noise in CSI fingerprints, and applies Principal Component Analysis(PCA) to extract the most useful features and reduce the dimension of CSI fingerprints. Evaluations achieved the mean localization error distance of 1.22m, outperforming the Received Signal Strength Indication(RSSI) approach by 43.0%, and outperforming SVM classification and Naive Bayesian by 39.9% and 41.9%.

Index Terms—Localization; device-free; Channel State Information(CSI); Support Vector Machine(SVM)

I. INTRODUCTION

Localization has been the focus of research for years. A common solution to indoor localization is to fingerprint mobile devices in a WiFi infrastructure. Such a solution requires the active participation of mobile devices. However, on many occasions, such as at home or in sensitive areas, the targets may not carry any electronic devices, hence device-free passive(DfP) localization is in need. Device-free passive localization typically makes use of wireless networks to detect and track the targets that do not carry any electronic devices nor participate actively in the localization process.

Current approaches to device-free localization include radar-based systems, computer vision-based systems and radio tomographic imaging. These systems, however, need special hardware and high cost. As WiFi networks are widely deployed, device-free passive localization based on WiFi infrastructures has attracted much attention recently and several such systems have been proposed. The Received Signal Strength Indication(RSSI) is the most commonly used measurement in device-based WiFi localization. The research of [1] shows that RSSI can be used to achieve passive localization, as RSSI is affected by human movements. However, changes in the indoor environment and multipath fading cause instability and declining of its localization accuracy.

Channel State Information(CSI) is a fine-grained value from the physical layer which describes the amplitude and phase of each subcarrier in the frequency domain. Since the Orthogonal Frequency Division Multiplexing(OFDM) technology has been applied to wireless LANs, CSI can be conveniently obtained nowadays. Compared with RSSI, CSI has more fine-grained information about the wireless channel. Researches[1], [2], [3] show that CSI is more temporally stable and provides the capability to benefit from the multipath effect, thus is able to improve the accuracy of device-free passive localization. Several researches have been conducted in this area in a device-based[1], [2] or device-free[3], [4] manner. Novel applications based on CSI are emerging as well, such as human presence detection[5], [6], walking speed estimation[7], crowd counting[8] and activity identification[9], [10], [11].

In order to achieve high accurate device-free passive localization, we propose an algorithm based on the fine-grained physical layer information CSI and the statistical machine learning tool Support Vector Machines(SVM), which solve localization as a regression problem, by going through CSI data collection, feature extraction, model training to set up the nonlinear relationship between CSI fingerprints and locations, and regression to estimate locations according to CSI fingerprints. To remove the noise in CSI data and further improve the accuracy, we propose to apply Density-Based Spatial Clustering of Applications with Noise(DBSCAN) on the CSI data. To reduce the dimension of CSI fingerprints and thus reduce computing complexity, we propose to apply Principal Component Analysis(PCA) to extract the most useful features from the CSI data. Evaluations demonstrate the effectiveness of the proposed methods and show that the CSI-based approach outperforms the RSSI-based approach, and SVM regression can achieve higher accuracy than SVM classification and Naive Bayesian(NB). The main contributions of the paper are summarized as follows:

- 1) apply SVM regression to set up the nonlinear relationship between CSI fingerprints and locations to perform device-free passive localization;
- 2) apply DBSCAN to remove noise in CSI data;
- 3) apply PCA to extract the most useful features from CSI data and reduce the dimension of CSI fingerprints;
- 4) compare localization performance of CSI with RSSI; compare localization performance of SVM regression with SVM classification and Naive Bayesian;

- 5) investigate the parameters that may affect localization performance, such as number of access points, number of antennas, sampling density, and PCA cumulative contribution.

The rest of this paper is organized as follows. Section II reviews the related work briefly. Section III introduces the preliminaries and presents the system model. Section IV proposes the device-free passive localization algorithm in details. Experimental evaluations and discussions are presented in Section V. Section VI concludes the paper.

II. RELATED WORK

A. Device-based localization

Wu et al.[1] designed FILA system based on CSI for device-based indoor localization and claimed to be the first to use CSI to improve localization performance. They developed a refined indoor propagation model representing the relationship between CSI values and distance. By receiving the APs coordinates in network layer and CSI values from physical layer, the mobile device applied the revised propagation model and trilateration method to accomplish the localization. Wu et al.[2] extended the FILA system with a CSI-based fingerprinting approach using maximum likelihood algorithm. For both approaches, evaluations showed that the localization accuracy with CSI outperformed RSSI significantly and could reach submeter level.

B. Device-free localization

Abdel-Nasser et al.[3] introduced MonoPHY as an accurate single stream device-free localization system, which leveraged both the CSI information and the Multiple-Input Multiple-Output(MIMO) information to capture the human effect on signal strength and used a cluster-based fingerprinting approach with maximum likelihood algorithm. Evaluations showed that MonoPHY could achieve an accuracy of 1.36m using a single pair of access point and monitoring point. To further address the noisy wireless channel and the rich CSI information, MonoStream[12], the enhancement of MonoPHY, modeled the device-free localization problem as an object recognition problem, where it treated the CSI profile at different locations as images and extracted novel features that could capture small variations in the effect of the human standing at different locations in the area of interest on the CSI vectors. Classification was through joint boosting classifiers. Evaluations showed that MonoStream could achieve an accuracy of less than 0.95m.

Yang et al.[4] put forward a metric to estimate the sensitivity of a receiver to changes in the detecting area and developed a high-performance indoor device-free passive localization, which employed a Bayesian a posteriori approach and possessed high receiver sensitivity. Experiments showed that the performance could be raised when the receiver was placed at the location with high receiver sensitivity and achieved the accuracy of 0.79m with monostream.

C. Applications based on CSI

Zeng et al.[10] showed that CSI feedback from a client to the access point could be used to recognize different motions of the client. They demonstrated that certain features extracted from CSI could create a unique signature for different types of motions and could uniquely identify them with simple machine learning algorithms. Wang et al.[9] presented device-free location-oriented activity identification at home through the use of CSI. It examined the channel features and could uniquely identify both in-place activities and walking movements across a home by comparing them against signal profiles. Han et al.[11] proposed a passive fall detection method based on time variability and special diversity of CSI as the indicator of human activities.

Xi et al.[8] presented Electronic Frog Eye, device-free crowd counting based on CSI. They proposed a metric, the Percentage of nonzero Elements(PEM), in the dilated CSI matrix and formulated the monotonic relationship between the crowd number and various features of CSI by the Grey Verhulst Model, which was used for crowd counting without a labor-intensive site survey.

To achieve an omnidirectional coverage under link-centric architecture, Zhou et al.[5], [6] proposed the concept of omnidirectional passive human detection utilizing channel frequency response, to detect human presence in a reliable and omnidirectional manner. The rationale was to exploit the rich multipath effect to blur the directional coverage and virtually tuned the shape of the coverage of the monitoring unit.

Jiang et al.[7] proposed a passive crowdsourcing CSI-based indoor localization scheme, C^2IL , which was built upon an innovative method to accurately estimate the moving speed solely based on 802.11n CSI. Knowing the walking speed of a client and its surrounding APs, a graph matching algorithm was employed to extract the RSSI fingerprints and establish the fingerprint map. For localization, they designed a trajectory clustering based localization algorithm to provide precise real-time indoor localization and tracking.

III. SYSTEM MODEL

A. Preliminaries of CSI

CSI is the information that estimates the channel by representing the channel properties of a communication link. To provide CSI, the WiFi infrastructure is required to support OFDM, which uses multiple subcarriers to transmit data, hence OFDM channel measurement at the subcarrier level becomes available. In a narrow band flat-fading channel, the OFDM system in the frequency domain is modeled as:

$$y = Hx + n \quad (1)$$

here, y represents the received vector, x represents the transmitted vector, H denotes the channel matrix, and n is the additive white Gaussian noise vector. The estimated value of H , i.e. CSI of all subcarriers, can be expressed according to equation (1) as:

$$\bar{H} = \frac{y}{x} \quad (2)$$

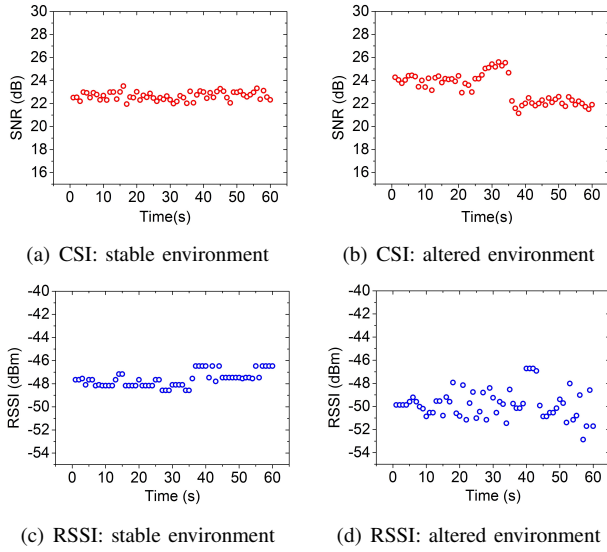


Fig. 1. CSI and RSSI in stable and altered environment.

It is a fine-grained value from the physical layer that describes the channel gain from transmitting baseband to receiving baseband.

A multipath wireless channel is often portrayed as Channel Impulse Response(CIR), which is a linear filter $h(\tau)$:

$$h(\tau) = \sum_{i=0}^{N-1} a_i e^{-j\theta_i} \delta(\tau - \tau_i) \quad (3)$$

where N is the number of paths, a_i denotes the amplitude, θ_i denotes the phase, τ_i represents the delay, of the i -th path, $\delta(\tau)$ represents the Dirac delta function. Channel Frequency Response(CFR) $H(f)$ can be acquired by Fourier Transform of CIR:

$$H(f) = F(h(\tau)) \quad (4)$$

Leveraging commodity network interface card(NIC) with a modified driver[13], a discrete version of CFR

$$H = \{H(f_k)\} \quad (5)$$

can be revealed to the upper layers in the format of CSI, where each $H(f_k)$ is a complex number depicting the amplitude and the phase of subcarrier f_k .

B. Characteristics of CSI for device-free localization

Based on OFDM, channel measurements at the subcarrier level become available. Due to the slight frequency delta, separate subcarriers experience different multipath fading, thus when small movements have altered the multipath environment, the individual subcarrier measurements are more likely to change. Traditional RSSI measurements are a single quantity that represents signal-to-interference-plus-noise ratio(SINR) over the channel, and multipath effects are often averaged out using a single RSSI measurement. Compared with RSSI, physical layer CSI portrays a finer-grained temporal and spectral structure of wireless links and exhibits

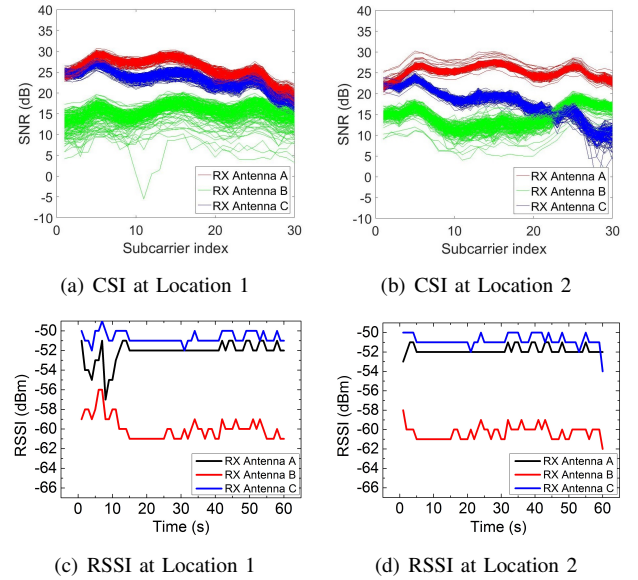


Fig. 2. CSI and RSSI at two locations with 1m distance.

certain characteristics more suitable for device-free passive localization.

- 1) When the environment is not altered, the CSI values are stable over time. Whenever the environment is altered, the CSI values can capture the alteration promptly. Fig. 1 illustrates the characteristics of CSI, with RSSI as a comparison. Fig. 1(a) shows the amplitude of a subcarrier in a stable environment over one minute, more stable than RSSI in Fig. 1(c). When human movements cause the alteration of the environment, the CSI values can capture the change promptly, as shown in Fig. 1(b), more sensitive and accurate than RSSI in Fig. 1(d).
- 2) CSI values exhibit large differences when the target is at different locations. Fig. 2(a) and Fig. 2(b) show the amplitude of subcarriers from three receiving antennas when the volunteer stands at two locations with a distance of 1m. Fig. 2(c) and Fig. 2(d) show the RSSI values from three receiving antennas when the volunteer stands at the same two locations. The CSI values have more variation than the RSSI values, thus more suitable for distinguishing different locations.

In addition, IEEE 802.11n supports MIMO technology, i.e. there are multiple transmitting antennas and multiple receiving antennas, with each pair of transmitting and receiving antennas considered as a separate channel, leading to improved transmission rate and localization performance.

C. System model

The infrastructure of CSI-based device-free passive localization requires WiFi signals to cover the area of interest, which is composed of several wireless Access Points(AP) for data transmission, several Monitoring Points(MP) for data retrieval, and a server for data processing and analysis. The APs are commodity wireless routers supporting 802.11n, i.e.

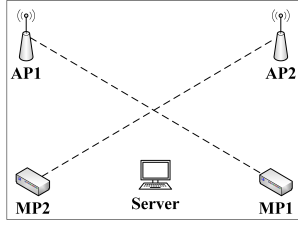


Fig. 3. Placement of access points and monitoring points.

supporting OFDM and MIMO. The MPs are commodity wireless adapters supporting 802.11n as well, with modified drivers to retrieve CSI information. For a complete coverage of the area of interest, each pair of AP-MP forms a diagonal line, as Fig. 3 shows. As supporting MIMO, each AP may have several transmitting antennas and each MP may have several receiving antennas. Each pair of transmitting-receiving antenna, we call it a TX-RX pair, is a channel.

We treat CSI-based device-free passive localization as a regression problem and use the machine learning tool SVM to solve it. The overall process of the system consists of data collection, feature extraction, model training and regression, as illustrated in Fig. 4. During the training phase, the CSI raw data are collected at each reference location for a short period of time, including the number of AP-MP pairs, the number of transmitting and receiving antennas, packet transmission frequency, CSI matrix, and the coordinate of the reference location. As the raw data in the CSI matrix are complex values, they need to be converted to real values. Each channel is a TX-RX pair, having multiple subcarriers and noisy, therefore, we apply the DBSCAN algorithm to each channel to remove noise through clustering. Afterwards, features are extracted from the denoised CSI data through PCA algorithm to obtain the most useful features and reduce the dimension. CSI fingerprints are thus generated and used to establish SVM regression models representing the relationship between CSI fingerprints and locations. During localization, the real-time raw CSI data are measured and processed in the same way as in the training phase, and the location is estimated via regression through the trained SVM regression model.

IV. THE METHODOLOGY

A. CSI data collection

The raw data collected for each channel contain the CSI data that represent the channel frequency response of its multiple subcarriers. Specifically, the raw CSI data contain the number of transmitting antennas N_{tx} , the number of receiving antennas N_{rx} , packet transmission frequency f , and CSI matrix H . Assume N is the number of readable groups of subcarriers in a channel, the CSI matrix H is a $N_{tx} \times N_{rx} \times N$ matrix:

$$H = \begin{pmatrix} H_{11} & H_{12} & \cdots & H_{1N_{rx}} \\ H_{21} & H_{22} & \cdots & H_{2N_{rx}} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N_{tx}1} & H_{N_{tx}2} & \cdots & H_{N_{tx}N_{rx}} \end{pmatrix} \quad (6)$$

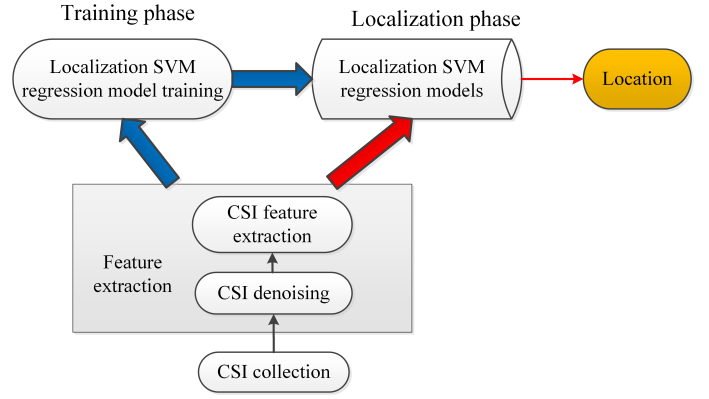


Fig. 4. Overview of the localization algorithm.

where H_{ij} is the information of the channel formed by the i -th transmitting antenna and the j -th receiving antenna, containing the information of the N groups of subcarriers, expressed as

$$H_{ij} = [h_1, h_2, \dots, h_N]^T \quad (7)$$

$$i \in [1, N_{tx}], j \in [1, N_{rx}]$$

The k -th subcarrier can be expressed as

$$h_k = |h_k|e^{j\sin\{\angle h_k\}}, k \in [1, N] \quad (8)$$

where $|h_k|$ is the amplitude response of subcarrier k and $\angle h_k$ is the phase response of subcarrier k . h_k is first converted to its magnitude as a real value and then converted from linear (voltage) space to logarithmic (power) space for the following processing.

B. CSI data denoising

Observations show that raw CSI data have noise. Fig. 5(a) shows the raw CSI data collected from three receiving antennas in a MP, in which the isolated slim curves are noise. In order for improved localization accuracy, we propose to apply the DBSCAN algorithm to detect and remove the noise from the raw CSI data. DBSCAN[14] is a density-based clustering algorithm, which groups points that are closely packed together and marks as outliers that lie alone in low-density regions. It does not require to specify the number of clusters a priori and can be used to detect and remove noise. The two parameters of DBSCAN are the neighborhood radius ε and the minimum number of points required to form a dense region $minPts$, which are of importance to the clustering performance. The values of them are determined by expertise.

DBSCAN clustering is performed on the dataset of each TX-RX channel. An AP-MP pair contains $N_{tx} \times N_{rx}$ TX-RX channels with each channel having N groups of readable subcarriers. We divide the raw CSI dataset into $N_{tx} \times N_{rx}$ data subsets, with each data subset representing a TX-RX channel containing N groups of subcarriers. Assume the data subset for a TX-RX channel is denoted as D , a subcarrier is indexed as $k \in [1, N]$, the algorithm of CSI data denoising with DBSCAN is as follows:

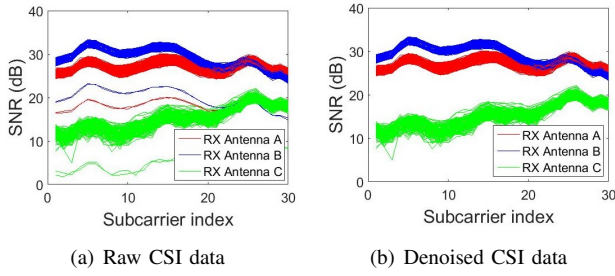


Fig. 5. CSI denoising by DBSCAN.

- 1) Mark all the points in D as "unvisited";
- 2) Select a point $o(k, v)$ arbitrarily from D , marked as "visited", k represents the subcarrier index and v represents the CSI value:
 - a) Check the ε -neighborhood of o , according to the Euclidean distance from the points to o ;
 - b) if the neighborhood contains more than $minPts$ points, o is regarded as a core point. Create a new cluster C and a candidate set N for o , put all the points in the neighborhood of o in the candidate set N ;
 - c) else, i.e. the neighborhood contains less than $minPts$ points, label o as noise;
 - d) iteratively pick a point in N that does not belong to other clusters and put it in cluster C , until the candidate set N is empty, then cluster C is completed;
- 3) Go to step 2) to process the next point;
- 4) The points labeled as noise are removed from D , thus achieving the purpose of data denoising.

After applying the DBSCAN algorithm to remove the noise, the CSI data of the three receiving antennas are shown in Fig. 5(b), which shows that the noise is removed effectively.

C. CSI feature extraction

Consider there are N_{ap} AP-MP pairs and each pair of AP-MP contains $N_{tx} \times N_{rx}$ links, and each link has N groups of subcarriers. Thus each CSI sample has $n = N_{ap} \times N_{tx} \times N_{rx} \times N$ dimensions. In our experimental settings, there are 2 AP-MP pairs, each AP-MP pair has 2 transmitting antennas and 3 receiving antennas, each TX-RX channel has 30 groups of subcarriers, which finally produces 360 dimensions. High dimensionality causes time complexity, thus dimensionality reduction is necessary. As each dimension may have different contribution to the localization problem, we propose to apply PCA algorithm to reduce the dimensions of the CSI data and extract the most effective features. The goal of PCA is to find l ($l < N_{ap} \times N_{tx} \times N_{rx} \times N$) new features, with each one being a linear combination of the original features, so that the new features can reveal the general nature of the original data and thereby compress them.

Suppose the CSI data matrix is H . By PCA algorithm, we can obtain the transformation matrix T , the transformed

matrix S and the feature weights $W = [w_1, w_2, \dots, w_L]$ in descending order, wherein L is the number of the features. The cumulative contribution rate C_i of feature i is defined as

$$C_i = \frac{\sum_{j=1}^i w_j}{\sum_{j=1}^L w_j} \quad (9)$$

If the cumulative contribution rate of the first l features, i.e. C_l , is greater than the predefined threshold C_c , then take the first l features as the extracted features. The first l rows of the transformed matrix S constitute the principal component matrix R , which will be used for the subsequent model training and localization.

Assume the set of CSI fingerprints in the area of interest is $F = \{r_1, r_2, \dots, r_n\}$, n is the total number of fingerprints. Assume the set of reference locations is $P = \{(x_1, y_1), (x_2, y_2), \dots, (x_m, y_m)\}$, m is the number of reference locations. A CSI sample can be expressed as $(r_i, (x_i, y_i))$, where $r_i = (r_{i1}, r_{i2}, \dots, r_{il})$ represents the CSI fingerprint, l denotes its dimension, and (x_i, y_i) represents the coordinate of the sampling location.

D. Localization by SVM regression

Localization can be achieved by SVM regression. SVM is based on statistical learning theory and Vapnik-Chervonenkis(VC)-dimension theory, with the target of minimizing structural risk[15]. SVM can be used for classification—Support Vector Classification(SVC) and regression—Support Vector Regression(SVR). As continuous localization is a regression problem, we propose to apply SVR to solve it. In SVR, the samples are separated into training and testing sets. Each sample in the training set contains one target value and several features. Regression is to establish the functional dependency between the features and the target values and thus able to determine the target values of the testing samples according to their features, based on the training samples.

For the problem of localization, the target values are coordinates and the features are CSI fingerprints after denoising and dimension reduction. Model training is to establish the functional dependency between CSI fingerprints and location coordinates, thus the location coordinates of the objects can be determined according to the CSI fingerprints. As a location coordinate has two dimensions, each coordinate dimension requires a separate regression. Assume n is the number of labeled samples in the training set and l denotes the feature dimension. Each labeled sample consists of a pair $(r_i, (x_i, y_i))$, $i = 1, \dots, n$, where $r_i \in R^l$ is a vector representing CSI fingerprints, $x_i \in R$ denotes the x -coordinate and $y_i \in R$ denotes the y -coordinate where r_i is measured. Model training is to establish the functional dependency f_x between CSI fingerprints and x -coordinates using the empirical dataset $\{(r_i, x_i) | i = 1, 2, \dots, n\}$ and the functional dependency f_y between CSI fingerprints and y -coordinates using the empirical dataset $\{(r_i, y_i) | i = 1, 2, \dots, n\}$. Assume $(r, (x, y))$ is a testing sample, with $r \in R^l$ representing the CSI fingerprint, localization by regression is to determine the values of x

and y with f_x and f_y . Hence, two SVR models are trained by CSI fingerprints to establish the relationship between CSI fingerprints and location coordinates in the area of interest.

The function representing the relationship between CSI fingerprints and coordinates takes the form $f(r) = w^T r + b$, where $w \in R^l$ is a vector representing the direction of the function, $b \in R$ is a constant representing its location, $r \in R^l$ represents a CSI fingerprint. The standard form of SVR is ϵ -SVR[16]. Its goal is to find the function $f(r)$ that has at most ϵ deviation from the actually obtained target values c_i for all the training data $\{(r_1, c_1), (r_2, c_2), \dots, (r_n, c_n)\} \subset R^l \times R$, c_i here represents the target values which are replaced by observed x -coordinates for f_x regression and y -coordinates for f_y regression.

ϵ -SVR needs to specify the desired accuracy of approximation, i.e. ϵ , a priori. However, for localization, we expect the estimation to be as accurate as possible without having to commit ourselves to a specific level of accuracy a priori. Schölkopf et al.[17] introduced a new parameter $\nu \in (0, 1]$ and proposed ν -SVR, which automatically minimizes ϵ . The size of ϵ is traded off against model complexity and slack variables via the constant ν . ν -SVR solves the following problem

$$\begin{aligned} & \text{minimize} \quad \frac{1}{2} \|w\|^2 + C(\nu\epsilon + \frac{1}{n} \sum_{i=1}^n (\xi_i^* + \xi_i)) \\ & \text{subject to} \quad \begin{cases} (w^T r_i + b) - c_i \leq \epsilon + \xi_i \\ c_i - (w^T r_i + b) \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^*, \epsilon \geq 0 \end{cases} \end{aligned} \quad (10)$$

here, r_i is a CSI fingerprint, c_i is a coordinate dimension, the number of samples is n . For each sample an error of ϵ is allowed, everything above ϵ is captured by slack variables ξ_i and ξ_i^* , which are penalized via a regularization constant $C > 0$, chosen a priori. Our implementation adopts ν -SVR, as recommended by Chang et al.[18].

Solving equation (10), we get the function approximating the relationship:

$$f(r) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(r_i, r) + b \quad (11)$$

where, α_i and α_i^* are Lagrange multipliers. Due to the complexity of signal propagation indoors, the relationship between CSI fingerprints and locations should be treated nonlinear. SVR maps CSI fingerprints into a higher dimensional feature space via kernels. We choose Radial Basis Function(RBF) as the kernel function $K(r_i, r)$, which has the form of (γ is the kernel parameter)

$$K(r_i, r) = \exp(-\gamma \|r_i - r\|^2), \quad \gamma > 0 \quad (12)$$

V. EVALUATIONS

A. Testing setup

The experiments were conducted in our research laboratory (6m×7m). We employed a Netgear N300 wireless router and a Cisco RV180W wireless router as the transmitters operating in IEEE 802.11n AP mode, both having two transmitting

TABLE I
PARAMETERS USED IN THE EVALUATIONS.

Parameter	Value	Meaning
N_{rx}	3	Number of receiving antennas per NIC
N_{tx}	2	Number of transmitting antennas per AP
N_{ap}	2	Number of AP-MP pairs
N	30	Number of groups of subcarriers per channel
f	20	Packet transmission frequency (pkts/s)
m	20	Number of reference locations
t	10	Number of testing locations
ϵ	1.2, 2.1	Neighborhood radius of DBSCAN
$minPts$	6	Minimum number of points of DBSCAN
C_c	99%	Cumulative contribution rate of PCA

antennas, and two computers equipped with Intel WiFi Link 5300 NICs as the receivers downloading packets from the APs, each with three receiving antennas. The Intel WiFi Link 5300 NIC implements an OFDM system. Its firmware is modified to export CSI of each packet[19], [13], which contains 30 groups of subcarriers. Fig. 6(a) shows the environment and infrastructure of the evaluations. Two APs (the Netgear and the Cisco wireless routers) and two MPs (two computers) were placed at the corners of the research laboratory to cover the area of interest. The circles are the 20 reference locations, with a distance of 1m between two adjacent locations, and the stars are the 10 testing locations chosen arbitrarily, different from the reference locations for being general. As each Intel WiFi Link 5300 NIC is equipped with three receiving antennas and each wireless router has two transmitting antennas, there are six channels for each AP-MP pair and altogether 12 channels for the testing infrastructure. The packet transmission rate was set 20pkts/s. From each packet, the CSI of 30 groups of subcarriers were extracted. RSSI values were collected at the same time with CSI for the purpose of performance comparison. The key parameters used in the evaluations are summarized in Table I.

B. Data processing and model training

During the training phase, as illustrated in Fig. 4, the testing volunteer traversed each reference location, and the MPs collected raw CSI data from the connected APs during the volunteer standing at each reference location. For each reference location, the raw CSI data were collected for 60 seconds, thus 1200 packets were collected and we took 100 packets from the middle part of the dataset. For all the 20 reference locations, it took 20 minutes to collect the raw data and 2000 training samples were generated.

As there are two AP-MP pairs, each AP with two transmitting antennas and each MP with three receiving antennas, there are $2 \times 2 \times 3 = 12$ channels. Each channel contains 30 groups of subcarriers, thus a CSI sample has a dimension of $12 \times 30 = 360$. After CSI data denoising by DBSCAN and dimension reduction by PCA, 93 features were extracted and constituted a CSI fingerprint, achieving the cumulative contribution rate of more than 99%.

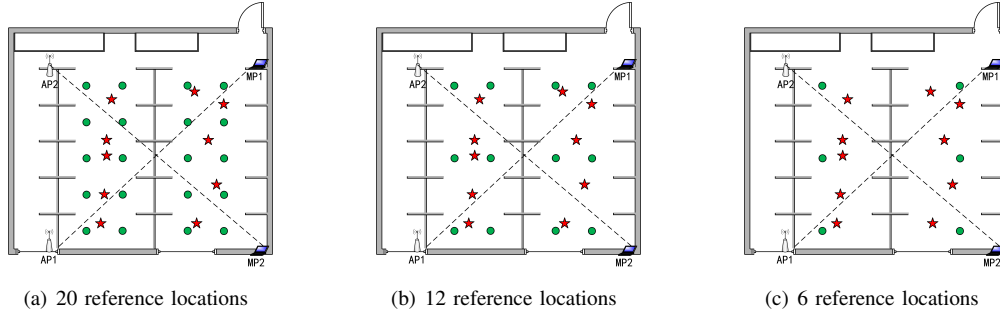


Fig. 6. The testbed. Circles are reference locations and stars are testing locations.

TABLE II
LOCALIZATION ACCURACY WITH CSI AND SVR.

Accuracy	Value	Precision	Value
Mean error	1.22m	Within 0.5m	25.3%
		Within 1.0m	49.5%
Min. error	0.01m	Within 1.5m	58.0%
		Within 2.0m	77.2%
Max. error	2.91m	Within 2.5m	95.9%
		Within 3.0m	100%

For localization with CSI by SVM regression, two SVR models were trained for the x -coordinate and the y -coordinate, respectively. For the purpose of comparison, we implemented localization with CSI by SVM classification and used one-against-one method to extend it to support multi-class classification, which trained $20 \times (20 - 1)/2 = 190$ SVC classifiers. Localization with RSSI was conducted as well, which trained two SVR models and 190 SVC classifiers.

C. Localization

We conducted localization experiments with CSI through SVR. SVR treats localization as a regression problem and estimates the coordinates through the modeled relationship between CSI fingerprints and location coordinates. We collected training data from 20 reference locations, as the circles show in Fig. 6(a), each having 100 samples, thus 2000 training samples altogether. Testings were conducted at 10 testing locations, which were totally different from the reference locations, as the stars show in Fig. 6(a), each having 100 samples, thus 1000 testing samples.

Two metrics are used to analyze the localization performance: (1) accuracy: the mean error distance; (2) precision: the cumulative error probability. The localization results with CSI and SVR are shown in Table. II. The accuracy, i.e. the mean error distance, is 1.22m, and the minimal and the maximal error distances are 0.01m and 2.91m, respectively. The error distance is within 1m with the probability of 49.5%, within 2m with the probability of 77.2%, and within 3m 100%.

In addition to making use of CSI and SVR, the algorithm applies DBSCAN to reduce noise from the CSI data. We made testings to evaluate the data denoising method. The

TABLE III
LOCALIZATION ACCURACY OF DIFFERENT METHODS.

	Method	Max. error	Min. error	Mean error
DBSCAN	With	2.91m	0.01m	1.22m
	Without	2.38m	0.17m	1.56m
PCA	With	2.91m	0.01m	1.22m
	Without	2.66m	0.03m	1.33m
SVR v.	SVR-CSI	2.91m	0.01m	1.22m
SVC v.	SVC-CSI	3.87m	0.34m	2.03m
NB	NB-CSI	3.87m	0.24m	2.10m
CSI v. RSSI	SVR-CSI	2.91m	0.01m	1.22m
	SVR-RSSI	3.86m	0.12m	2.14m
	SVC-CSI	3.87m	0.34m	2.03m
	SVC-RSSI	4.53m	0.34m	2.56m

localization results with and without DBSCAN denoising are shown in Table. III. The mean error distance with DBSCAN is better than without DBSCAN by 0.34m, which is a gain of 21.8%. The comparison between the curves of cumulative error probability of them are shown in Fig. 7(a), in which SVR with DBSCAN outperforms without DBSCAN, demonstrating the effectiveness of the denoising method.

As a raw CSI fingerprint has $N_{ap} \times N_{tx} \times N_{rx} \times N = 2 \times 2 \times 3 \times 30 = 360$ dimensions, which is quite high leading to high computing complexity, we propose to apply PCA to reduce the dimension. By setting a cumulative contribution rate of 99% a priori, the number of dimensions was reduced from 360 to 93, and the regression time of one testing reduced from 2.58ms to 0.45ms. The localization results with and without PCA are shown in Table. III. The mean error distance with PCA is better than without PCA by 0.11m, which is a gain of 8.3%. The comparison between the curves of cumulative error probability of them are shown in Fig. 7(b), in which SVR with PCA outperforms without PCA, indicating that PCA is able to extract the most contributing features and thus reduce the dimensionality and improve the accuracy.

D. Comparison with Bayesian and SVC

Localization can be regarded as a classification problem with each reference location as a class. Localization is to find the reference location that has the most similar signal pattern with the testing sample. Naive Bayesian and SVC

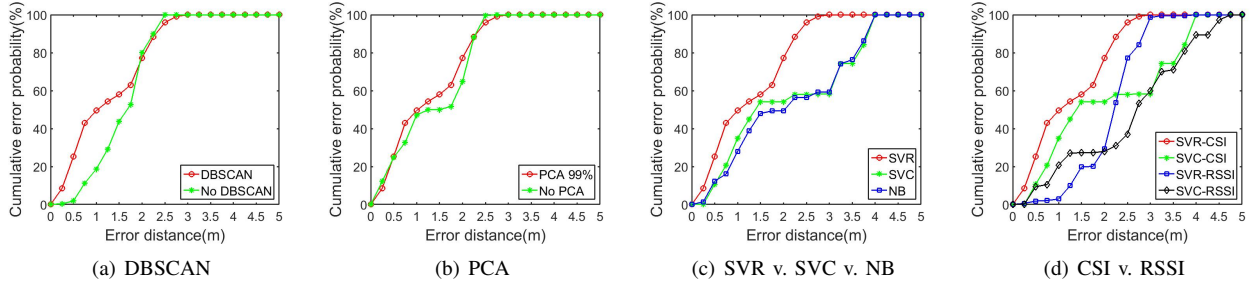


Fig. 7. Localization precision of different methods.

are two common classification algorithms which can solve localization as a classification problem using CSI fingerprints. We made testings with NB and SVC using the same training set and testing set with SVR. The localization results of them are shown in Table III. The mean error distances of SVC and NB are almost equal, 2.03m and 2.10m, respectively, around 40% worse than SVR. The comparison of cumulative error probability of them is shown in Fig. 7(c), in which SVR outperforms SVC and NB significantly, while SVC and NB have comparable performance. The major reason is that localization is a continuous problem instead of a discrete one, thus the regression algorithm SVR suits more appropriately than the classification algorithms SVC and NB.

E. Comparison with RSSI

To compare the performance of CSI with commonly used RSSI, we carried out localization experiments with RSSI using SVC and SVR. The testing environment was the same with CSI experiments, so were the reference locations and the testing locations, as shown in Fig. 6(a). The evaluation results are reported in Table III and Fig. 7(d). The results show that no matter using SVC or SVR, the CSI approach outperforms the RSSI approach significantly, by 43.0% using SVR and 20.7% using SVC, as CSI provides more stable and detailed information than RSSI. SVR outperforms SVC for continuous localization by 40.0% with CSI and by 16.4% with RSSI. These results demonstrate the effectiveness of CSI and SVR for localization.

F. Effect of parameters

Parameters may have effects on localization performance, therefore, we carried out testings to investigate the issues.

1) *Number of AP-MP pairs*: We tested two pairs of AP-MP, one pair of AP-MP using the Cisco router and one pair of AP-MP using the Netgear router. The localization results of the three configurations are shown in Fig. 8(a) and Table IV. One pair of AP-MP is able to provide acceptable localization performance, while using two pairs of AP-MP achieves better accuracy, as more channels provide better coverage and more features. Different types of routers exhibit different localization capability.

TABLE IV
LOCALIZATION ACCURACY WRT. PARAMETERS.

Parameter	Value	Max. error	Min. error	Mean error
AP-MP pairs	2	2.91m	0.01m	1.22m
	1 Cisco	3.16m	0.19m	1.33m
	1 Netgear	3.72m	0.37m	1.50m
Antenna numbers	2TX-3RX	2.91m	0.01m	1.22m
	2TX-2RX	3.44m	0.02m	1.33m
	1TX-1RX	2.51m	0.03m	1.61m
Ref. location numbers	20	2.91m	0.01m	1.22m
	12	3.19m	0.04m	1.38m
	6	2.64m	0.06m	1.60m

2) *Number of antennas*: MIMO technology employed by IEEE 802.11n AP nodes can not only improve the system throughput but also enhance the localization performance. To evaluate the effect of the number of antennas on the performance of localization, we randomly chose 1TX-1RX and 2TX-2RX, and compared with 2TX-3RX. The evaluation results are shown in Fig. 8(b) and Table IV, which show that the localization accuracy can be enhanced by using more antennas. From 1TX-1RX to 2TX-2RX, the localization accuracy is improved by 17.4%; from 2TX-2RX to 2TX-3RX, the localization accuracy is improved further by 8.3%.

3) *Sampling density*: Sampling density of reference locations often has effects on localization accuracy, thus we made investigation on it. We used three sampling density, as shown in Fig. 6(a), Fig. 6(b) and Fig. 6(c), which has 20, 12 and 6 reference locations, respectively. Fig. 8(c) and Table IV compare the accuracy and precision of different sampling density and show that with the increase of the number of reference locations, i.e. with the increase of sampling density, the localization accuracy grows. When the number of reference locations increases from 6 to 12, the accuracy improves 13.8%, and when the number increases further to 20, the accuracy improves further 11.6%.

4) *PCA cumulative contribution*: The value of cumulative contribution rate of PCA determines the dimensionality of the extracted features and thus influences the localization accuracy and computing time. We investigated the issue by setting the cumulative contribution rate as 93%, 95%, 97%, 99% and 100% (i.e. without PCA). Results in Fig. 8(d) and Table V show

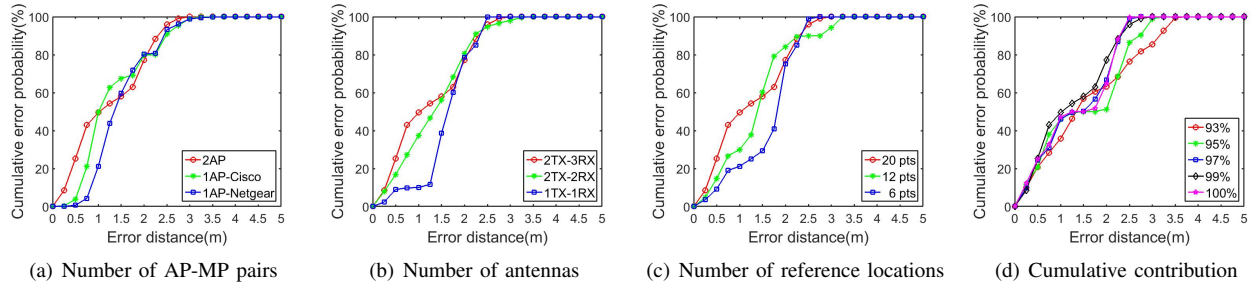


Fig. 8. Localization precision wrt. parameters.

TABLE V
LOCALIZATION ACCURACY AND REGRESSION TIME WRT. CUMULATIVE CONTRIBUTION RATE OF PCA.

Contribution	Features	Time	Max.	Min.	Mean error
93%	19	0.09ms	3.68m	0.00m	1.57m
95%	24	0.12ms	3.08m	0.01m	1.47m
97%	32	0.20ms	2.53m	0.05m	1.34m
99%	93	0.45ms	2.91m	0.01m	1.22m
100%	360	2.58ms	2.66m	0.03m	1.33m

that with the increase of the cumulative contribution rate from 93% to 99%, the localization accuracy grows. The cumulative contribution rate of 99% achieves the best accuracy, even better than 100%. Results in Table V show that with the increase of the cumulative contribution rate, the feature dimensionality and regression time grow. The regression time of one sample for the cumulative contribution rate of 99% is 0.45ms, which is acceptable and much shorter than 100%.

VI. CONCLUSIONS

WiFi fingerprinting has been a solution to indoor localization for years, which often makes use of RSSI for the purpose. ODFM and MIMO technologies make it possible to access physical channel frequency response thus trigger the use of CSI to achieve more accurate device-free passive localization. This paper presents a CSI-based device-free passive localization algorithm and demonstrates its higher localization accuracy and precision than RSSI. SVR is applied to solve the localization problem through regression, which is proved outperforming SVC and Naive Bayesian in the evaluations. DBSCAN is applied to remove data noise and PCA is applied to reduce feature dimensionality, both are proved effective. Evaluations achieve a mean error distance of 1.22m and a probability of 95.9% within 2.5m.

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