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Hierarchical fingerprinting and feature extraction for indoor localization

Siyang Liu
Laboratoire des Signaux et Systèmes
Université Paris-Saclay, CNRS, CentraleSupélec
Gif-sur-Yvette, France
siyang.liu@centralesupelec.fr

Raul de Lacerda
Laboratoire des Signaux et Systèmes
Université Paris-Saclay, CNRS, CentraleSupélec
Gif-sur-Yvette, France
raul.delacerda@centralesupelec.fr

Jocelyn Fiorina
Laboratoire des Signaux et Systèmes
Université Paris-Saclay, CNRS, CentraleSupélec
Gif-sur-Yvette, France
jocelyn.fiorina@centralesupelec.fr

***Abstract*—Weighted K nearest neighbor (WKNN) algorithm provides good result for indoor localization by searching for matching fingerprints in the dataset. However, due to the nature of this method, computation load increases as the size of dataset. In this paper, we propose a hierarchical localization method to reduce the computation load during the online phase. A two-level structure first localizes the user to a smaller subset and then position estimation is obtained by WKNN with feature extraction. On a public accessed WiFi fingerprinting dataset, the proposed method achieves a 98% reduction without sacrificing localization performance.**

***Index Terms*—Hierarchical localization, WiFi Fingerprinting, RSS, Principal Component Analysis (PCA), Auto-Encoder (AE), Feature Extraction, WKNN**

I. Introduction

With the increasing number of smart phones and wearable devices, indoor positioning has become a topic of interest [1]. Many techniques have been proposed for indoor localization such as time of arrival (TOA), angle of arrival (AOA), channel state information (CSI), received signal strength (RSS), etc [2]. Comparing to other techniques, RSS has the advantage of being accessible as it does not require additional hardware or synchronization to measure.

Current localization methods can be roughly divided into two categories: propagation model based and fingerprinting based methods [3]. Model based methods estimate distance with propagation model and apply triangulation for positioning. Fingerprinting is a localization solution that exploits the mapping between measurements and positions. RSS measurements from different transmitters such as WiFi Access Points (APs) together provide fingerprints for discrete points in the physical space. With a large number of transmitters and measurements, fingerprinting can mitigate the error caused by RSS fluctuations.

Various algorithms based on machine learning techniques have been proposed for fingerprinting. Deep learning methods have shown excellent results in region classification with sufficient training data and computation power [4], [5]. There are other algorithms that provide good localization performance with less data and resource requirements, such as k-Nearest Neighbor (KNN) [6], [7] and Support Vector Machine (SVM) [8]. These methods suffer from complexity problem during the online phase. Computation time and cost increase with the size of the fingerprinting dataset. This problem can be improved by limiting the number of fingerprints being matched during the online phase [7], [9] or reducing the dimension of each fingerprint [10].

In this paper, we propose a practical and scalable hierarchical localization method to improve the computation load without decreasing localization performance. First, we explore the hierarchical nature of big datasets and divide them into subsets with smaller number of fingerprints using position labels given by the dataset. For each subset, a limited number of representative vectors are generated to increase classification accuracy with a small cost of complexity. Feature extraction is then performed in each subset using principal component analysis (PCA) or auto-encoder (AE). After being classified to a subset, feature dimension of the test RSS sample would be reduced using the corresponding transform matrix or encoder model. Comparing to the commonly applied flat structure which matches the user fingerprint to all fingerprints in the dataset, the proposed method largely reduces both the number and the length of fingerprints being matched during the online phase and hence reduces computation cost.

The remainder of this paper is organized as follows: Section II reviews related work on reducing computation cost for fingerprinting. Section III presents notations and system model. Section IV explains the proposed hierarchical indoor localization method with feature extraction. Section V presents numerical results for performance evaluation, and Section VI concludes the paper.

II. Related work

Over the recent years, different solutions have been proposed in the literature to cope with the computation load problem of fingerprinting on large datasets. Reducing the size of fingerprinting dataset can effectively reduce complexity. By diving the dataset into different subsets using position labels provided by the dataset [11] or clustering algorithms [7], [12], the matching process is limited to one of the subsets which reduces the amount of fingerprints being matched. In a previous result, we used k-means clustering based radio

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mapping to reduce the number of fingerprints related to each reference point [13].

Other attempts on reducing data dimension focus on reducing the size of the feature vector with feature selection and feature extraction. Feature selection uses prior knowledge to select a smaller number of features while keeping the original meaning of them. Jia, Huang, Gao *et al.* prove that when the number of APs increases beyond a certain threshold, localization performance can not be significantly improved [14], providing theoretical support for feature selection in fingerprinting. In paper [15], 30 strongest APs as well as their ID are selected as new features. AP selection can also be performed by minimizing the correlation of selected APs [16].

Feature extraction however, projects the original data into a lower dimensional space. In [8], Principal component analysis (PCA) is used to reduce RSS vector size from 520 to 50 with a minor toll on classification accuracy. Accurate localization can be achieved combining two feature extraction methods: Fisher discriminant analysis (FDA) and PCA [17]. High floor classification accuracy was achieved using an auto-encoder to reduce RSS vector length and training a deep neural network with the reduced data [18]. In [10], a fingerprint is formed by combining 200 RSSI measurements from 4 APs which makes different features in the vector highly correlated and both PCA and auto-encoder (AE) are used for feature extraction.

To our knowledge, previous contributions on reducing data dimension focus only on either reducing the number or the length of fingerprints. Feature extraction tools are usually applied on the entire dataset and not tailored for different parts of the dataset. Furthermore, many auto-encoder based approaches perform localization as position label classification rather than regression. Our work aims to fill these gaps.

III. System model

The process of fingerprinting includes an offline dataset creation phase and an online localization phase as shown in Fig.1. During the offline phase, a fingerprint dataset is built by measuring the received power from different WiFi access points at a series of reference points (RP). Assuming there are M fixed APs in the dataset, a RSS sample i is constituted by the received signal strength indicator (RSSI) of these APs: $RSS_i = [r_i^1, r_i^2, ..., r_i^M]$.

During the online phase, a test sample searches for a matching fingerprint in the dataset. This process can be achieved with similarity functions [6], [7] or other data representation methods [4], [5], [19]. Similarity functions quantify how close two samples are in the feature space. Commonly used similarity measures include Euclidean distance, Manhattan distance, Pearson Correlation Coefficient, etc [20]. In this paper, we adopt the cosine similarity as it provides good performance which will be shown in our numerical results and it is simple to calculate. Similarity value between two samples i and j can be obtained as:

$$s_{i,j} = \frac{\sum_{m=1}^{M} r_i^m r_j^m}{\sqrt{\sum_{m=1}^{M} (r_i^m)^2}\sqrt{\sum_{m=1}^{M} (r_j^m)^2}}. \tag{1}$$

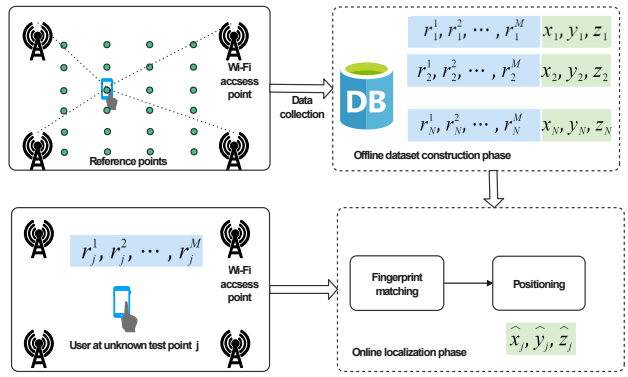

Figure 1. RSS Fingerprinting

In the dataset we used [21], RSSI is expressed in dbM in negative domain. To simplified the calculation of similarity values, positive representation is obtained for RSS value with thresholding as:

$$P(r_i^m) = \begin{cases} r_i^m - r_{min}, & if \quad AP_m \quad is \quad present \quad in \quad RSS_i \\ & and \quad r_i^m > \tau \\ 0, & otherwise, \end{cases} \tag{2}$$

where r_{min} is the lowest RSSI value in the dataset and τ is the threshold value which removes the RSSI value below this threshold.

For test sample j, K fingerprints with highest similarity are selected and WKNN algorithm estimates test sample position as a weighted average of these selected fingerprints. For the indoor environment, vertical label is often a discrete value such as floor number, we can simply just take the floor label of the best matching fingerprint.

A weight function is then used assuming that fingerprints with higher similarity are closer in the physical space. In this paper, the weight function is chosen as:

$$w_k = s_{i,j}^2 \quad (k = 1, ..., K). \tag{3}$$

IV. Proposed method

In this section, the proposed hierarchical localization and feature extraction methods will be presented. During the offline phase, different subsets of fingerprints are created using position labels. Then test sample is then localized with a two-level method during the online phase. Feature extraction is performed on each subset using PCA or AE aiming to better capture the different relationship between features.

A. Feature extraction

In this subsection, two feature extracting methods are presented which reduce the length of feature vectors by projecting the original data to a lower dimension space.

To improve performance of AE, different dimensions of the feature vectors are put into the same scale using min-max scaling as follow:

$$N(r) = \frac{r - r_{min}}{r_{max} - r_{min}}, \tag{4}$$

where r_{min} and r_{max} are the minimum and maximum RSS value in the dataset, respectively. After scaling, the range of each RSS value becomes $[0, 1]$.

1) Feature extraction with PCA: For a fingerprint dataset with N measurements and M APs, the size of feature matrix $\boldsymbol{X}$ is $N \times M$. PCA finds p $(p < M)$ principal components that are orthogonal vectors on which data has the largest variance.

After shifting the mean value of each feature vector to zero, the covariance matrix of original data X can be obtained as: $\boldsymbol{Q}_{M\times M} = \boldsymbol{X}^T\boldsymbol{X}$. To obtain the principle components, we first calculate M eigenvectors of matrix $\boldsymbol{Q}$. Then we sort the eigenvectors in descending order of the corresponding eigenvalues. The first p eigenvectors form the projection matrix $\boldsymbol{T}$. The reduced dataset can be obtained as:

$$\boldsymbol{X}'_{N\times p} = \boldsymbol{X}_{N\times M}\boldsymbol{T}_{M\times p} \tag{5}$$

2) Feature extraction with auto-encoder: The structure of an auto-encoder is shown in Fig.2. The network has a symmetrical structure made up with two parts: encoder and decoder. Usually both the encoder and decoder can have several hidden

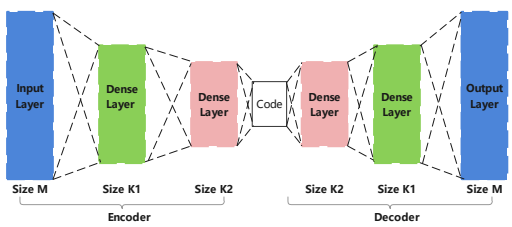

Figure 2. Structure of auto-encoder

layers. To demonstrate the process, we take the simple case in which there is only one hidden layer of each part. Given an input vector RSS with the size $1 \times M$, the encoder generates a code z with smaller dimension p as:

$$\boldsymbol{z} = \sigma(\boldsymbol{W}_e^T RSS^T + b_e), \tag{6}$$

where σ is a nonlinear activation function that allows the neural network to learn the nonlinear mapping of the data. Commonly used activation functions include sigmoid function, Rectified Linear Unit (ReLU), etc. W_e and b_e correspond to the weight matrix $(M \times p)$ and bias vector $(p \times 1)$ of the encoder. Weights and biases are usually initialized randomly, and then updated iteratively during training through backpropagation.

The decoder then takes the code z and try to reconstruct the input as RSS' :

$$\boldsymbol{R}SS' = (\sigma'(\boldsymbol{W}_d^T z + b_d))^T, \tag{7}$$

where the activation function σ', weight W_d and bias b_d can be unrelated to the ones in the encoder. The network is trained in an unsupervised manner by minimizing the error of reconstruction:

$$L(RSS, RSS') = \frac{1}{M-1}\sum_{m=1}^{M}(r^m - r'^m)^2, . \tag{8}$$

For a stacked auto-encoder, we can set hidden layer size as $M > K_1 > K_2 = p$ for reducing vector size from M to p.

B. Two-level hierarchical localization with feature extraction

A fingerprinting dataset covering large area can be divided into small subsets using geometric information provided by the dataset. For example, a dataset covering multiple buildings and floors can be split into subsets each containing one floor of one building. If region labels are not provided, we can apply clustering algorithms on fingerprint coordinates to create additional classification labels. The process of dataset division is shown in Fig.3.

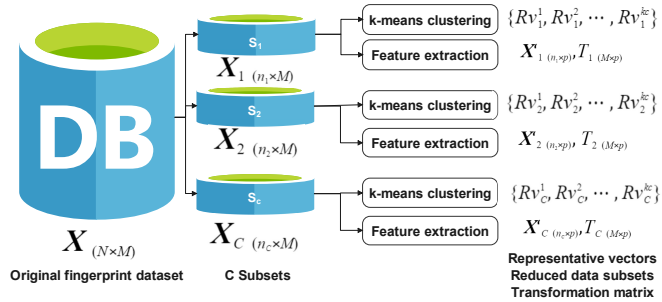

Figure 3. Dataset division

After diving the dataset into C smaller subsets, a centroid fingerprint is usually generated for subset classification. However, one centroid might not be able to well represent the diversity in each subset. To improve classification accuracy, we apply k-means clustering on the RSS samples of each subset to further divide them into k_c clusters and obtain a centroid on each cluster. This way, k_c diverse representative vectors $\{Rv^k\}_{k=1}^{k_c}$ are obtained to represent each subset. Increasing the number of representative vectors improves classification accuracy which is worthy of the small additional computation cost since a misclassification in this early step would result in large localization error.

In each subset, feature extraction is performed separately using PCA or AE to better capture the different distribution of APs over space.

For localizing a user, a two-level structure shown in Fig.4 is adopted as opposed to a flat structure which directly localizes the test sample using the entire fingerprint dataset.

The first level of the hierarchical localization structure localizes the test sample into one of the subsets using Nearest Neighbor (NN) algorithm. Then the dimension of test sample is reduced with transformation matrix or auto-encoder from the corresponding subset. The second level of localization is performed within each subset with reduced data. Test sample position is estimated using WKNN presented in the previous section.

V. Performance Evaluation

In this section, performance of the proposed method is evaluated on a public access WiFi RSS fingerprinting dataset UJIIndoorLoc [21]. This dataset includes three multi-floor building with 520 APs in total providing a training set with 19937 samples and a test set with 1111 samples. Floor height of 4 meters is taken to calculate vertical localization error.

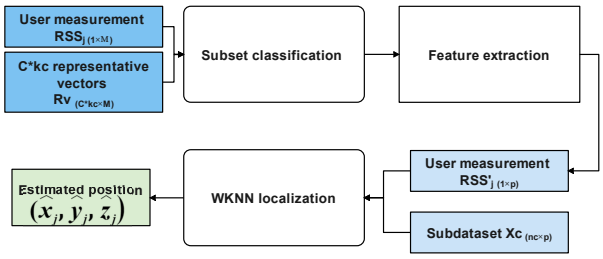

Figure 4. Two-level localization

A. Parameters setting

In the UJIIndoorLoc dataset, RSSI is represented as negative integer values ranging from -104 dBm (extremely poor signal) to 0 dBm. A positive default value 100 is used to denote when an AP was not detected. This value does not reflect the received signal strength or distance to the AP but it will greatly affect the calculation of similarity. Positive representation is drawn from the original data with threshold set as -95 using equation (2). We experimented with different threshold values from -130 to -80 dBM but the details of parameter tuning is out of the scope of this paper.

Auto-encoders with two layers are applied for feature extraction for both flat and hierarchical structure. The first hidden layer size is 100 and the second hidden layer size is set to p which corresponds to expected feature length after extraction. Two single layer auto-encoder were trained separately and then stacked together and fine-tuned as one deep network. As future work, further optimization and hyper-parameter tuning can be performed.

Localization performance of four different similarity functions over different value of K is shown in Fig.5. As shown in the figure, cosine similarity and Pearson Correlation Coefficient provide better results than other two similarity functions. Since cosine similarity is easier to compute, we choose it as similarity function in this paper. Parameter $K = 3$ is also chosen for WKNN to obtain localization results.

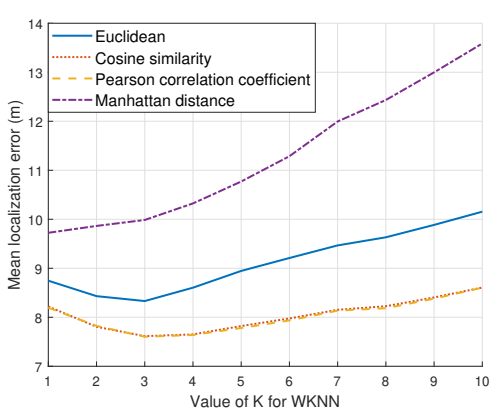

Figure 5. Localization performance over different similarity functions and values of K

B. Results and analysis

Considering data of one floor in one building to be a subset, the entire dataset can be divided into 13 subsets using floor and building labels. For each subset, k_c representative vectors are obtained for subset classification. Since we use the k-means clustering algorithm with random initialization to generate representative vectors, Monte Carlo simulations are conducted. In our simulations, building classification accuracy with different value of k_c is always around 100%. Floor classification results are shown in Fig.6. Comparing to using one centroid vector ($k_c = 1$), a larger number of representative vectors can improve floor classification accuracy. However, for $k_c > 60$, accuracy slowly decreases as k_c increases. If we use all samples in each subset for classification, we can only achieve 92.89% accuracy due to the fluctuation of RSS. The standard deviation of accuracy over 2000 independent trails also decrease as k_c increases.

To balance between computation load and accuracy, in this paper, $k_c = 10$ is chosen. With 130 representative vectors in total, we managed to achieve floor classification accuracy of 95.23% using Nearest Neighbor (NN) method, which outperforms the result with flat structure using the entire dataset and some other results in the literature as shown in Table I.

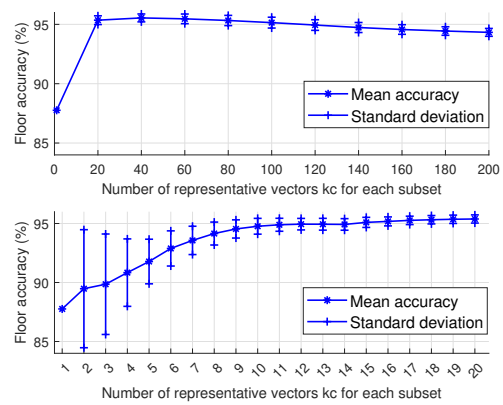

Figure 6. Floor classification accuracy over different values of k_c

Table I
COMPARISON OF CLASSIFICATION RESULTS

Method	*Building accuracy (%)*	*Floor accuracy (%)*
Proposed method	100	95.35
Nearest neighbor on flat structure	100	92.89
WKNN [22]	100	93.74
Deep neural network[11]	99.91	92.80

Localization performance under different data dimension using PCA or AE feature extraction is shown in Fig.7. The results of AE are presented as the mean and standard deviation of different trails. With limited computation power, we conducted 10 trails. The original data has the feature vector size of $M = 520$ and reduced feature vector size p is the

in range of $[100, 300]$. For both PCA and AE, hierarchical localization allows further reduction than flat structure with similar performance. For large feature vector size, hierarchical localization has a slightly smaller mean error than the flat structure due the higher floor classification accuracy. For the limited number of trails we ran, in general PCA provides better performance than AEm especially for small feature vector size ($p < 100$). Performance of AE could be improved with optimization and tuning of the networks.

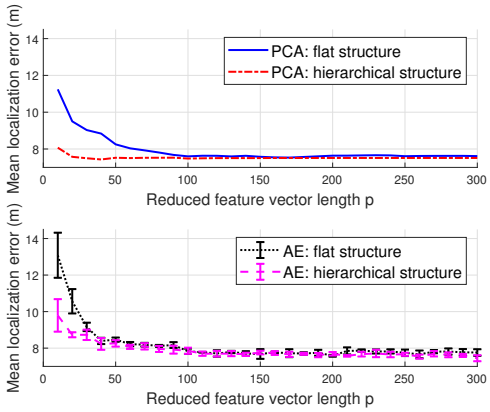

Figure 7. Average localization error under different feature dimension

The comparison of localization performance and computation complexity of WKNN combined with different reduction method is shown in Table II, in which cost* corresponds to number of operations need to calculate similarity matrix between test sample and fingerprints being matched in the dataset. Reduction ratio shows how much the computation cost is reduced using the corresponding method comparing to flat localization with the original dataset.

Complexity of WKNN algorithm is $O(MN)$ in terms of multiplication for similarity calculation and $O(NK)$ in terms of similarity comparison, where M is the length of sample vectors, N is the number of samples and K ($K \ll N$) is the number of neighbors chosen for localization [23]. Given a fixed K, the main factor that impacts complexity is the number operations needed to calculate the similarity matrix. Using feature extraction tools to reduce RSS vector size to p is just a simple multiplication between test RSS vector $RSS_{1\times M}$ and projection matrix $T_{M\times p}$, which has the complexity of $O(Mp)$ in the worst case. Since this complexity is relatively small and it does not grow with the number of test and training samples like WKNN, for simplification we will not take that into account in the complexity analysis.

With feature extraction, sample vector size can be reduced from M to p ($p < M$) resulting in a lower complexity for similarity computation. Applying feature extraction tools directly on the flat structure can reduce computation cost with the ratio of $(M-p)/M$. For $p = 30$, the reduction is 94.22% with an increased localization error. Using AE for feature extraction results in a larger localization error which could be improved if the network is further optimized.

Assuming the dataset is evenly distributed on each floor, adopting the hierarchical structure, the whole dataset is divided into $C = 13$ subsets reducing the number of samples being compared for position estimation to N/C from the original size $N = 19854$. Computation cost of the hierarchical structure can be written as $O(MC + MN/C)$ considering one subset centroid for classification [7]. In this paper, $k_c = 10$ representative vectors are obtained for each subset to improve classification accuracy instead of using just one centroid, so MCk_c similarity calculations are needed for subset classification. To compare with our previous results, we also apply k-means clustering based radio mapping on the full dataset which reduces the number of training samples to $N' = 4202$ and perform localization with a flat structure.

Table II
PERFORMANCE OF DIFFERENT LOCALIZATION METHODS

Method	*Mean error(m)*	*Cost**	*Reduction(%)*
Flat structure	7.62	MN	0
Flat structure+PCA	9.03	pN	94.22
Flat structure+AE	9.16	pN	94.22
Hierarchical structure	7.50	$MCk_c + MN/C$	91.65
Hierarchical structure+PCA	**7.51**	$MCk_c + pN/C$	**98.90**
Hierarchical structure+AE	8.73	$MCk_c + pN/C$	98.90
K-means radio mapping[13]	7.67	MN'	78.84

Using hierarchical structure with PCA feature extraction provides the best result allowing us to reduce computation cost to 98.90% with very little increase in localization error. There is more potential in cost reduction by combining k-means radio mapping and the proposed hierarchical method which can be explore in future work.

VI. CONCLUSION AND DISCUSSION

In this paper, we proposed a hierarchical fingerprinting and feature extraction method to reduce the computation cost without sacrificing localization performance. With a two-level localization, the user is first classified to a subset of the radio map and then WKNN is applied to estimate user position within the subset. This method reduces computation cost for over 90% while slightly decreases localization performance. Applying feature extraction individually in each subset can further reduce the cost up to 98% without sacrificing localization performance.

For subset division, we used floor and building labels given by the dataset which produces a fix number of subsets. Other division method can be studied in the future as well as the trade-off between cluster number, classification accuracy and overall localization error. For feature extraction tools, we compared PCA to auto-encoder. In the given dataset, PCA provides better performance. As future work, further optimization and tuning of the auto-encoder for each subset can be investigated.

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