Integrated Segmentation and Subspace Clustering for RSS-Based Localization under Blind Calibration

Zheng Xing[1], Junting Chen[1], and Yadan Tang[2]
[1] School of Science and Engineering (SSE) and Future Network of Intelligence Institute (FNii)
Guangdong Provincial Key Laboratory of Future Networks of Intelligence
The Chinese University of Hong Kong, Shenzhen, Guangdong 518172, China
[2] Shenzhen Eachitech Technology Co. Ltd, Guangdong, China

***Abstract*—Indoor localization is important for many location-based services. The fundamental challenge is the high deployment cost for device, infrastructure, and calibration. This paper develops a blind calibration approach for received signal strength (RSS)-based localization. The essential idea is to employ a device that visits each region exactly once in an indoor area to complete a blind data collection process without recording the route, locations, and timestamps. Thus, the key challenge is to cluster the blind training data into groups and extract the key features to identify the location regions. Classical clustering algorithms fail to work as the data naturally appears as non-clustered due to mutipaths and noise. In this paper, an integrated segmentation and subspace clustering method is developed to exploit both the sequential data structure from the blind data collection process and the signal subspace structure due to the segmented propagation environments. Based on real measurements from an office space, the proposed scheme reduces the region localization error by roughly 50% from a weighted centroid localization (WCL) baseline. In addition, the performance is also comparable to k-nearest neighbor (KNN) and support vector machine (SVM) that require labeled data for calibration.**

I. Introduction

Many technologies have been developed for indoor localization. However, most of them are expensive in hardware or calibration effort required. On one hand, triangulation approaches based on time-of-arrival (TOA), time difference of arrival (TDOA), or angle of arrival (AoA) can achieve a sub-meter-level localization accuracy [1]. However, some of these methods may require complicated hardware, such as multiple antenna systems for AoA-based localization, and some others may need expensive infrastructure, such as access point (AP) networks where high accuracy time synchronization is required for TDOA localization [1]. In addition, these approaches mostly require a line-of-sight (LOS) propagation condition, which is challenging to meet in an indoor environment. On the other hand, fingerprint-based approaches may provide meter-level accuracy, and they do not require dedicated hardware or LOS conditions. However, fingerprint-based methods require tedious laboring efforts on data collection and calibration for constructing a fingerprint database [2], [3].

However, many applications are sensitive to hardware and calibration cost, where accuracy is only a secondary consideration. For example, there has been a strong demand for hospitals and factories of tracking the locations of equipments and visitors, where it is acceptable to localize the target up to a small region. In an indoor exhibition, the organizer may want to track the crowd of visitors and localize them up to a certain region, where the targets are usually *non-cooperative* in the sense that the APs may not be able to decode the signal from a target except for extracting the received signal strength (RSS) of the target. However, it is still challenging to conduct RSS-based localization with limited calibration effort.

This paper aims at reducing the calibration effort while providing a good localization performance for non-cooperative targets. Specifically, it focuses on RSS-based indoor localization using sensor networks with *blind calibration*. An existing calibration-free approach is the weighted centroid localization (WCL), which localizes the target by computing the RSS-weighted average of the sensor locations [4]. A special case is the *max-RSS* approach which takes the sensor location that captures the highest RSS as the estimate of the target location. However, these approaches are strongly affected by signal blockage and the topology of the AP network. Other approaches allow some sorts of calibration, but aim at reducing the calibration effort as much as possible. For instance, the authors in [2] proposed a Generative Adversarial Network based scheme to complete the localization task with reduced RSS measurements. The work [3] uses a small amount of labeled data and a large amount of unlabeled data, and employs Kriging interpolation to recover the label. Despite these efforts, the remaining calibration effort is still substantial and possibly not affordable in some application scenario.

In this paper, a blind calibration approach is developed for indoor localization with coarse performance requirement. First, the area of interest is divided into a number of regions according to the layout and the sensor deployment. Then, a mobile device follows an arbitrary route to visit each region exactly once to complete the calibration process. Note that, except for tracking the RSS of the device, the sensor network is *blind* to the location of the device and the timestamps when the device enters each region. As a result, this is a blind training

The work was supported in part by the Key Area R&D Program of Guangdong Province with grant No. 2018B030338001, by the National Key R&D Program of China with grant No. 2018YFB1800800, by National Science Foundation of China No. 92067202 and No. 62171398, by Guangdong Research Project No. 2017ZT07X152 and Grant No. 2019QN01X895, by the Shenzhen Science and Technology Program No. KQTD20200909114730003 and JCYJ20210324134612033, and by the Guangdong Provincial Key Laboratory of Future Networks of Intelligence.

process, and only negligible laboring effort is required.

The main challenge is to learn the signal feature for each region from the blind training process that collects the RSS data without any location information. This is naturally cast into a clustering and matching problem, where one needs to first assign labels to the RSS data and then extract the feature for each region. Conventional clustering approaches include subspace clustering [5], K-means clustering [6], spectral clustering [7] and Gaussian mixture model (GMM) [8]. However, these clustering methods fail to work for the RSS-based localization, because the RSS data for each indoor region has huge divergence due to the randomness caused by signal obstruction and the multipath effect. As a result, the RSS data appears as non-clustered, leading to large errors for conventional clustering algorithms.

To overcome the above challenge, this paper develops an *integrated segmentation and subspace clustering* method that exploits both the sequential data structure from the proposed data collection process and the signal subspace structure due to the partition of the regions. With the location labels recovered from the proposed clustering method, a region classifier is built to localize the target to the regions. Intuitively, the finer the regions, the better the localization performance, but more sensors are required. Based on real measurements from an office space, we demonstrate that the proposed scheme reduces the region localization error by roughly 50% from a WCL scheme. In addition, the proposed method achieves comparable performance with the state-of-the-art supervised-learning-based localization methods k-nearest neighbor (KNN) and support vector machine (SVM) which require substantial calibration effort to collect labeled RSS data.

II. System Model

A. A Blind Calibration Model

Suppose that there are D sensors deployed in an indoor area. The sensors, such as WiFi APs, are capable of measuring the RSS of the signal emitted by a wireless device, although the sensors may not be able to decode the signal of the device. Consider partitioning the indoor area into K non-overlapping regions. For example, a room or a semi-closed space separated by large furniture can be naturally considered as a region, as in the example shown in Fig. 1.

Intuitively, signals emitted from the same region is believed to share some common feature due to the proximity of the transmission. In addition, the common environment, including walls and large furniture, may also shape specific features for radio signals emitted from the region. Note that the region partition method is not the focus of the paper. Instead, this paper focuses on extracting the *common feature* of the RSS measured by the sensor network of the radio signals emitted from the same region.

Consider a blind calibration approach, where a mobile device follows an arbitrary route to visit all the K regions without repetition. Without loss of generality, assume that the mobile device visits from region 1 to region K in sequence. Meanwhile, the mobile repeatedly transmits radio signals.

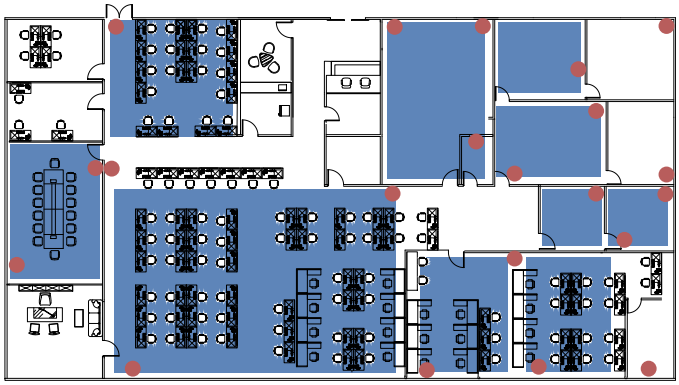

Figure 1: Ten non-overlapping rooms and semi-closed spaces (blue square) are separated by large furniture and walls in a 30×16 m^2 indoor layout with 21 sensors (red circle).

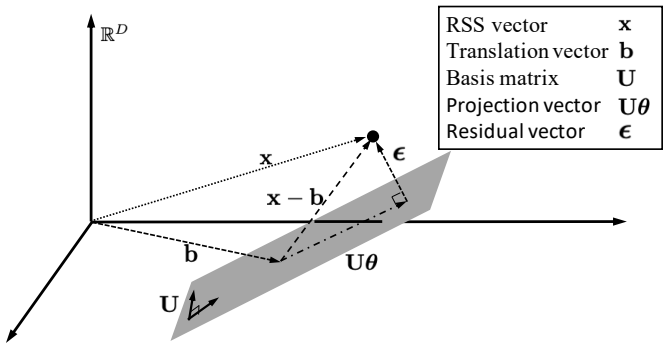

Figure 2: The projection of the sample $\mathbf{x}$ on a two-dimensional affine subspace in $\mathbb{R}^D$.

Note that the route and the location of the mobile, and the sojourn time that the mobile spends in each region are *unknown* by the sensor network. Instead, only the RSS of the signal emitted by the mobile is recorded. Denote the RSS measured by the sensor network at time slot n as $\mathbf{x}_n \in \mathbb{R}^D$. Denote $\mathcal{X} = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_N\}$ as the set of data samples and $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N]^{\mathrm{T}} \in \mathbb{R}^{N \times D}$ as the data matrix. The remaining part of the paper aims at extracting the common feature for each region from the data matrix $\mathbf{X}$ for RSS-based localization.

B. Affine Subspace

In a static environment, the RSS vector $\mathbf{x}$ due to the radio signal emitted from a region k can be intuitively and approximately perceived as a point in a two-dimensional manifold embedded in $\mathbb{R}^D$, although this remains as an assumption to be verified in practice. This is because the mobile has only 2 degrees of freedom to move around in the region, and for any two locations i and j that are sufficiently close to each other, the RSS vectors $\mathbf{x}_i$ and $\mathbf{x}_j$ are also close in $\mathbb{R}^D$. For example, if the first sensor is installed in the first region, then the first entry $x_{n,1}$ in the vector $\mathbf{x}_n = (x_{n,1}, x_{n,2}, \ldots, x_{n,D})$ is relatively larger than most of other entries $x_{n,i}$ for each data sample $\mathbf{x}_n$ measured in the first region.

We consider to use affine subspace to approximate the data manifold as shown in Fig. 2. Let d_k be the dimension of the kth subspace for the kth region. Let $\mathbf{U}_k \in \mathbb{R}^{D\times d_k}$ be a semi-unitary matrix, where the d_k columns $\{\mathbf{u}_{k,i}\}_{i=1}^{d_k}$ are orthogonal. In addition, denote $\mathbf{b}_k \in \mathbb{R}^D$ as the translation vector of the kth affine subspace. The RSS vector $\mathbf{x}$ that is taken from the kth region is thus modeled as

$$\mathbf{x} = \mathbf{U}_k\mathbf{y} + \mathbf{b}_k + \boldsymbol{\epsilon} \tag{1}$$

where $\mathbf{y} \in \mathbb{R}^{d_k}$ is a set of coefficients related to the specific measurement location (unknown) for $\mathbf{x}$, and $\boldsymbol{\epsilon}$ is a random component that captures the residual due to the affine subspace approximation to the manifold and the signal fluctuation due to the variation of the propagation environment. The random component $\boldsymbol{\epsilon}$ is treated as noise with zero mean.

Under the affine subspace model, the vectors $\{\{\mathbf{u}_{k,i}\}_{i=1}^{d_k}, \mathbf{b}_k\}$ serve as the *common feature* for the RSS data taken from the kth region. Note that the subspace bases $\mathbf{U}_k$ for different regions are *not* necessarily orthogonal, because they depend on the locations of the sensor and the layout of the environment.

Remark 1. (Default Choice of d_k): As the user has 2 degrees of freedom to move around in the area, the RSS vector $\mathbf{x}$ may be modeled as a point on a two-dimensional hyper-surface $\mathcal{S}$ embedded in a $\mathbb{R}^D$ space. Therefore, for a small area, an affine subspace with dimension d_k= 2 or 3 can be locally a good approximation of $\mathcal{S}$. This is also verified by our numerical results.

C. Integrated Segmentation and Subspace Clustering

As there is no location label for the data matrix $\mathbf{X}$ in the blind calibration process, we propose to group the rows of $\mathbf{X}$ into K clusters using a clustering algorithm. Two properties from the blind calibration approach and the affine subspace model can be exploited: First, the data samples $\{\mathbf{x}_i\}_{i=1}^N$ belong to each region $k = 1, 2, \ldots, K$ in sequence. As result, a clustering problem is essentially a segmentation problem that determines the segment boundaries $1 < t_1 < t_2 < \cdots < t_{K-1} < N$. Consequently, with the blind calibration approach, we can reduce to $K-1$ clustering variables t_k, instead of computing N variables to assign each sample $\mathbf{x}_i$ to a cluster in a conventional clustering approach.

Second, based on the affine subspace model, one can assign measurement samples $\mathbf{x}_i$ to affine subspace $\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K$ based on the distance between $\mathbf{x}_i$ and the subspace, where the squared-distance between a measurement vector $\mathbf{x}$ and an affine subspace ($\mathbf{U}$, $\mathbf{b}$) is derived as

$$\varepsilon(\mathbf{x}, \mathbf{U}, \mathbf{b}) = ||\mathbf{x} - \mathbf{b} - \mathbf{U}(\mathbf{U}^{\mathrm{T}}\mathbf{U})^{-1}\mathbf{U}^{\mathrm{T}}(\mathbf{x} - \mathbf{b})||_2^2 \tag{2}$$

where $||\cdot||_2$ denotes the l_2-norm. The physical meaning of (2) is illustrated in Fig. 2. The projection of $\mathbf{x} - \mathbf{b}$ to the affine subspace is $\mathbf{x} - \mathbf{b} - \mathbf{U}\mathbf{y}$. Since the projection line is perpendicular to the basis $\mathbf{U}$, we have $\mathbf{U}^{\mathrm{T}}(\mathbf{x} - \mathbf{b} - \mathbf{U}\mathbf{y}) = \mathbf{0}$. So, the coefficients $\mathbf{y} = (\mathbf{U}^{\mathrm{T}}\mathbf{U})^{-1}\mathbf{U}^{\mathrm{T}}(\mathbf{x} - \mathbf{b})$ can be obtained by solving a least square problem. The projection vector $\mathbf{U}\mathbf{y}$ can be written as $\mathbf{U}(\mathbf{U}^{\mathrm{T}}\mathbf{U})^{-1}\mathbf{U}^{\mathrm{T}}(\mathbf{x} - \mathbf{b})$, and the residual vector can be written as $\mathbf{x} - \mathbf{b} - \mathbf{U}(\mathbf{U}^{\mathrm{T}}\mathbf{U})^{-1}\mathbf{U}^{\mathrm{T}}(\mathbf{x} - \mathbf{b})$.

The integrated segmentation and subspace clustering problem is formulated as follows,

$$\begin{aligned} \underset{\{t_k\}_{k=1}^{K-1}, \{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K}{\text{minimize}} \quad & \sum_{k=1}^{K} \sum_{i=t_{k-1}+1}^{t_k} \varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k) \\ \text{subject to} \quad & 0 < t_1 < t_2 < .... < t_{K-1} < N \end{aligned} \tag{3}$$

where $\varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k)$ is the clustering residual of the ith sample to the kth subspace, and $\{t_k\}_{k=1}^{K-1}$ are the segmentation index indices to be determined. For notation convenience, we set $t_0 = 0$, $t_K = N$.

Remark 2. Under $d_k = 0$, the proposed formulation degenerates to integrated segmentation and K-means clustering. In addition, while the formulation (3) was discussed based on the affine subspace model, the proposed framework can be extended to integrating segmentation with other clustering methods, such as GMM, mean shift clustering, and spectral clustering. For instance, to formulate an integrated segmentation and GMM clustering, one may modify the objective in (3) to maximize the likelihood that the ith sample belongs to the kth cluster.

III. Clustering Algorithm for Sequential Data

Observed that there are two blocks of variables in (3). The variable $\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K$ is dependent on $\{t_k\}_{k=1}^{K-1}$, and $\{t_k\}_{k=1}^{K-1}$ is dependent on $\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K$. Consider alternating optimization. Problem (3) can be divided into two subproblems

$$\underset{\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K}{\text{minimize}} \quad \sum_{k=1}^{K} \sum_{i=t_{k-1}+1}^{t_k} \varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k) \tag{4}$$

and

$$\begin{aligned} \underset{\{t_k\}_{k=1}^{K-1}}{\text{minimize}} \quad & \sum_{k=1}^{K} \sum_{i=t_{k-1}+1}^{t_k} \varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k) \\ \text{subject to} \quad & 0 < t_1 < t_2 < .... < t_{K-1} < N. \end{aligned} \tag{5}$$

This alternating optimization has some admirable advantages: firstly, problem (4) has a closed-form solution; secondly, while (5) is non-convex with integer variables, it can be solved based on gradient descent and weighted local polynomial regression.

A. Obtaining the Subspace Feature

We first focus on solving (4) with the given segmentation index, that is fixing $\{t_k\}_{k=1}^{K-1}$ to $\{t_k^{(n)}\}_{k=1}^{K-1}$, and updating $\{\mathbf{U}_k^{(n+1)}, \mathbf{b}_k^{(n+1)}\}_{k=1}^K$ by solving (4). Denote the objective function of (4) as $\mathcal{J}_1(\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K)$. If we set the derivation of $\mathcal{J}_1(\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K)$ on $\mathbf{b}_k$ as zero, that is $\partial\mathcal{J}_1(\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K)/\partial\mathbf{b}_k = 0$, we have

$$\mathbf{b}_k^{(n+1)} = \frac{1}{t_k - t_{k-1}} \sum_{i=t_{k-1}+1}^{t_k} \mathbf{x}_i \tag{6}$$

Next, we consider $\{\mathbf{U}_k^{(n+1)}\}_{k=1}^K$ with the given $\{\mathbf{b}_k^{(n+1)}\}_{k=1}^K$. If we restrict $\mathbf{u}_{k,j} \in \mathbb{R}^D, j = 1, 2, ..., d_k$ to be unit orthonormal vectors, we have $\mathbf{U}_k^{\mathrm{T}}\mathbf{U}_k = \mathbf{I}$, where $\mathbf{I}$ is a d_k-by-d_k identity matrix. So the residual function can also be written as $\varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k) = ||(\mathbf{I} - \mathbf{U}_k\mathbf{U}_k^{\mathrm{T}})(\mathbf{x}_i - \mathbf{b}_k)||_2^2$. Given $\mathbf{b}_k$, minimizing $||(\mathbf{I} - \mathbf{U}_k\mathbf{U}_k^{\mathrm{T}})(\mathbf{x}_i - \mathbf{b}_k)||_2^2$ is equivalent to maximizing $||\mathbf{U}_k\mathbf{U}_k^{\mathrm{T}}(\mathbf{x}_i - \mathbf{b}_k)||_2^2$. In this way, finding unit orthonormal basis vectors $\mathbf{u}_{k,1}, ..., \mathbf{u}_{k,d_k}$ is equivalent to finding the best rank-d_k approximation $\mathbf{U}_k\mathbf{U}_k^{\mathrm{T}}$ of the covariance matrix $\mathbf{S}_k$, where

$$\mathbf{S}_k = \frac{1}{t_k - t_{k-1}} \sum_{i=t_{k-1}+1}^{t_k} (\mathbf{x}_i - \mathbf{b}_k)(\mathbf{x}_i - \mathbf{b}_k)^{\mathrm{T}}$$

So, given $\{\mathbf{b}_k^{(n+1)}\}_{k=1}^K$, problem (4) can be reformulated as

$$\underset{\{\{\mathbf{u}_{k,j}\}_{j=1}^{d_k}\}_{k=1}^K}{\text{maximize}} \quad \sum_{k=1}^K \sum_{j=1}^{d_k} \mathbf{u}_{k,j}^{\mathrm{T}} \mathbf{S}_k \mathbf{u}_{k,j}$$

The solution is given by taking the eigenvectors of $\mathbf{S}_k$ that correspond to the d_k largest eigenvalues.

B. Solving for the Segmentation Index using Weighted Local Polynomial Approximation

We now obtain the segmentation index based on the feature of the subspace, that is, fixing $\{\mathbf{U}_k, \mathbf{b}_k\}_{k=1}^K$ to $\{\mathbf{U}_k^{(n+1)}, \mathbf{b}_k^{(n+1)}\}_{k=1}^K$, and updating $\{t_k^{(n+1)}\}_{k=1}^{K-1}$ by solving (5).

Denote $\mathbf{H} \in \mathbb{R}^{N \times K}$ as a residual matrix, where (i,k)th entry given by $H_{ik} = \varepsilon(\mathbf{x}_i, \mathbf{U}_k, \mathbf{b}_k)$. Define $f(\mathbf{t})$ as the value of $\sum_{k=1}^K \sum_{i=t_{k-1}+1}^{t_k} H_{ik}$ at $\mathbf{t}$, where $\mathbf{t} = [t_1, t_2, ..., t_{K-1}]^{\mathrm{T}}$. The function $f(\mathbf{t})$ appears as staircase in each variable t_k due to the fact that t_k's take integer values, where the derivative is zero almost everywhere. In addition, the noise and outlier in dataset lead to a lot of local optimums in (5), which is challenging to solve (5) by using gradient descent method directly. To tackle these challenges, we adopt weighted local polynomial approximation to compute the approximate gradient of $f(\mathbf{t})$. Its workflow is to build a function by point-by-point fitting a simple model to a local subset of data to describe the deterministic element of the variation in the data. Denote $f_k(t)$ as the partial function of $f(\mathbf{t})$ with fixed t_j, $j = 1, 2, ..., K-1$, $j \neq k$. The local polynomial fitting of $f_k(t)$ at point t_k is

$$\min_{\boldsymbol{\theta}_k} \quad \sum_{q=-Q}^{Q} \left(f_k(t_k + q) - \sum_{m=0}^{M} \theta_{k,m} q^m \right)^2 \kappa_b(q) \tag{7}$$

where polynomial parameters $\boldsymbol{\theta}_k = [\theta_{k,0}, \theta_{k,1}, ..., \theta_{k,M}]^{\mathrm{T}}$, and the polynomial approximation of $f_k(t)$ at t_k is $\sum_{m=0}^M \theta_{k,m} q^m$. The parameter Q control the size of the local subset. The kernel function $\kappa(\cdot)$ assigns weights to data points and it also has a bandwidth b, which is usually set to be $2Q$, to control the size of the local neighborhood, $\kappa_b(q) = \frac{1}{b}\kappa\left(\frac{q}{b}\right)$.

Note that if the kernel function is a constant, problem (7) becomes an original polynomial fitting around t_k. Epanechnikov kernel function is used in this paper

$$\kappa(\mathbf{x}) = \frac{D(D+2)}{2S_D}(1 - x_1^2 - \cdots - x_D^2)_+$$

where D is the dimension of data, which is also the number of the sensor, $S_D = 2\pi^{\frac{D}{2}}/\Gamma(\frac{D}{2})$ is the area of the surface of the D-dimensional unit ball and Γ is the Gamma function [9]. The first-order fitting is needed for the gradient descent method, so the polynomial order M is set to be 1 and $\theta_{k,1}$ can be seen as the gradient of the function $f_k(t)$ at point t_k. Then, problem (7) can be written as

$$\min_{\theta_{k,0},\theta_{k,1}} \quad \sum_{q=-Q}^{Q} (f_k(t_k + q) - (\theta_{k,0} + \theta_{k,1} q))^2 \times \frac{\Gamma(\frac{D}{2}) D(D+2)}{4\pi^{\frac{D}{2}} b} \left(1 - |\frac{q}{b}|^2\right)_+ .$$

The parameter t_k, $k = 1, ..., K-1$ are updated simultaneously according to

$$t_k^{n+1} = t_k^n - \lfloor \eta \theta_{k,1} \rfloor \tag{8}$$

where η is a step size, and $\lfloor \cdot \rfloor$ denotes the rounding down operation. Consider the constraint in (5), we sort the elements of $\mathbf{t}^{n+1}$ in an increasing order after each updating of t_k^{n+1}, $k = 1, 2, ..., K-1$.

The proposed gradient descent algorithm based on the weighted local polynomial approximation is likely to obtain a locally optimal solution since problem (5) is non-convex, but we can try different initial points to find the best local minimum with minimal objective function value among local optimal points.

IV. Localization

A. Matching the Signal Subspace and Indoor Regions

The clustering results obtained from Section III are blind to the region locations, and therefore, the subspace features $\{\mathbf{U}_k, \mathbf{b}_k\}$ need to be associated with regions. We employ the idea of WCL to estimate the region locations.The clustering results obtained from Section III are blind to the region locations, and therefore, the subspace features $\{\mathbf{U}_k, \mathbf{b}_k\}$ need to be associated with regions. We employ the idea of WCL to estimate the region locations.

Let $\mathbf{o}_q \in \mathbb{R}^2$, $q = 1, ..., D$ be the position of sensors. Denote $\mathcal{D}_k \subset \mathbb{R}^2$ as the area for region k. For each data sample $\mathbf{x}_n = (x_{n,1}, x_{n,2}, ..., x_{n,D})$ in the mth subspace, the estimated location of $\mathbf{x}_n$ is $\mathbf{z}_n = \sum_{q=1}^Q w_{n,q}\mathbf{o}_q$, where the weight $w_{n,q} = \frac{10^{(x_{n,q}/20)}}{\sum_{j=1}^Q 10^{(x_{n,j}/20)}}$. Then, a majority vote is applied to determine the region corresponding to the mth subspace. Specifically, if most data samples are found to region k, i.e., $\mathbf{z}_n \in \mathcal{D}_k$, then associate this mth subspace with region k.

B. Localization Schemes

1) Localization based on subspace classification: One scheme is to complete the localization task based on integrated segmentation and subspace clustering and subspace classification. Specifically, once we collect new RSS measurement, we explore subspace classification method to search the best matching subspace feature, which has been obtained by integrated segmentation and subspace clustering, to the current RSS measurement $\mathbf{x}$. It is operated by comparing the similarity between the online RSS measurement vector and the subspaces to identify the subspace to which the online readings belong. The clusters with the largest similarity values are selected as the candidate clusters. Given a new coming RSS measurement $\mathbf{x}$, the nearest subspace to $\mathbf{x}$ is

$$\hat{k} = \underset{k\in\{1,2,\ldots,K\}}{\operatorname{argmin}} ||(\mathbf{I} - \mathbf{U}_k(\mathbf{U}_k^{\mathrm{T}}\mathbf{U}_k)^{-1}\mathbf{U}_k^{\mathrm{T}})(\mathbf{x} - \mathbf{b}_k)||$$

2) Localization based on DNN classifier: Another scheme is to use the clustering result of integrated segmentation and subspace clustering to train a multi-layer perceptron neural network and then use the network to predict the location the new coming RSS measurement. The input of the model is D RSS measurement form D sensors. The network contains three hidden layers, each consisting of 32 nodes with the rectified linear unit (ReLU) as the activation function. There are K nodes in the output layer corresponding to K classes with softmax as the activation function. The cross-entropy loss function, which is calculated between the predicted category probability output and the actual category.

V. Experiments

A. Environment Configuration and Data Collection

We conduct experiments to test the proposed integrated segmentation and subspace clustering with real-world datasets. As shown in Fig. 1, a mobile device follows an specific route to visit all the 10 non-overlapping regions (ranging from 3-by-$3\mathrm{m}$ to 8-by-$5\mathrm{m}$) without repetition in an office space area of dimensions 30-by-$16\mathrm{m}$ ($480\mathrm{m}^2$) with 21 sensors. Meanwhile, the mobile repeatedly transmits radio signals and only the RSS of the signal emitted by the mobile is recorded. To evaluate the generalization capability under a change of environment, we separate the data collection in two periods ranging for 3 days. The data collected in the first day is used as Training Dataset, and the data collected in the second and third day is used as Test Dataset I and Test Dataset II respectively. The environments are considered to be slightly different, since there are people walking around and small furnitures can be moved.

B. Clustering Performance Evaluation

We compare the proposed integrated segmentation and subspace clustering method with the state-of-the-art clustering approaches, including subspace clustering [5], K-means clustering [6], spectral clustering [7] and GMM [8]. We define the average clustering error rate is defined as

$$R_\epsilon = (1 - \frac{1}{N}\sum_{i=1}^{N}\delta(m_i, \mathrm{map}(\hat{m}_i))) \times 100\%$$

where $\mathbf{x}_i$ is collected in the m_ith region and grouped to the $\hat{m}_i$th cluster, $\delta(x, y) = 1$ if $x = y$, and $\delta(x, y) = 0$ otherwise, and $\mathrm{map}(q_i)$ is the best mapping function that permutes clustering labels to match the ground truth labels. As shown in Table. I, the proposed method shows the lowest clustering error percentage 1.33%.

Table I: Clustering Performance Evaluation on Training Dataset.

Metric	K-means [6]	GMM [8]	Spectral Clustering [7]	Subspace Clustering [5]	Proposed
R_ϵ [%]	18.05	32.20	29.19	30.24	1.33

Table II: Localization result on Test Dataset I and II. Proposed (subspace) is the localization scheme based on subspace matching and Proposed (DNN) is the localization scheme based on DNN classifier.

Type	Method	Test Dataset I		Test Dataset II	
		E_{RC} [regions]	E_{RL} [meter]	E_{RC} [regions]	E_{RL} [meter]
Unsupervised	Max-RSS	0.4740	1.4006	0.4802	1.0767
	WCL [4]	0.5844	1.9035	0.5961	1.6663
	Proposed (subspace)	**0.2352**	**0.4857**	**0.3462**	**0.7210**
	Proposed (DNN)	0.2496	0.7207	0.3663	1.0011
Supervised	KNN [10]	0.2804	0.8096	0.3781	0.9200
	SVM [11]	0.3620	0.8131	0.3751	**0.7019**

C. Localization Performance Evaluation

We compare the localization performance with the max-RSS and WCL [4] schemes. In addition, for performance benchmarking, we also evaluate the performance of KNN [10] and SVM [11], which are supervised learning methods that require labels.

1) Region classification error: The region classification error of the ith sample is $C_{m_i,\hat{m}_i}$ if $\mathbf{x}_i$ is collected in the m_ith region and predicted to be collected in the $\hat{m}_i$th region, where $C_{m_i,\hat{m}_i}$ equals to the normalized distance of the shortest path connecting region m_i and region $\hat{m}_j$ in which there is a direct "path" between region m_i and region m_j if the two regions are *not* separated by concrete walls according to the layout in Fig. 1. The average length of such direct paths is normalized to 1 in the region classification error metric. The average region classification error is $E_{\mathrm{RC}} = \frac{1}{N}\sum_{i=1}^{N} C_{m_i,\hat{m}_i}$.

2) Region localization error: The region localization error of the ith sample is $e_i = \|\mathbf{p}_{m_i} - \mathbf{p}_{\hat{m}_i}\|_2$ if $\mathbf{x}_i$ is collected in the m_ith region and predicted to be collected in the $\hat{m}_i$th region, where $\mathbf{p}_k$ is the center position of the kth region. The average region localization error is $E_{\mathrm{RL}} = \frac{1}{N}\sum_{i=1}^{N} e_i$.

The parameters of baseline methods were determined and tuned using a ten-fold cross validation. For KNN, the optimal

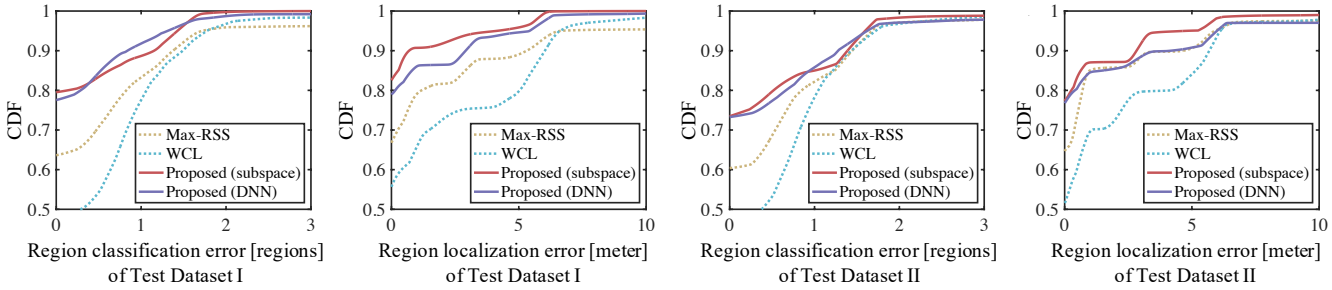

Figure 3: Accumulative region classification error and region localization error on Test Dataset I and Test Dataset II.

number of neighbors was found to be 8. A Gaussian kernel was used for SVM. The neighbor size Q in proposed clustering method is set to be 10, and the step size η in proposed gradient descent method is set to be 0.1. The subspace dimension d_k is chosen from 1 to 3 according to the number of sensors located in the region as shown in Fig. 1.

As shown in Table. II, our proposed subspace-based localization scheme outperforms all of the state-of-arts. For Test Dataset I, the proposed subspace-based localization scheme has the smallest average region classification localization error 0.2352m and region localization error 0.4857 than the supervised method, which implies that the RSS data collected from the same region locate in a same subspace and the proposed clustering model (3) can effectively extract the subspace feature from the dataset. Although the data collected in different regions cross together and even the supervised classifiers, e.g., KNN and SVM, do not show good partition performance, the proposed subspace-based scheme can group the data according to the subspace feature. In addition, the traditional calibration-free localization methods, e.g., Max-RSS and WCL, show large localization error, because they are not suit for the indoor complicated environment with the irregular sensor installment. Finally, the proposed localization schemes also outperform the existing supervised and unsupervised methods with the time going. As we all know, the localization error of RSS-based method will become larger and larger without any environment adaptation. Because Test Dataset II is collected later than the Test Dataset I, the error of Test Dataset II is larger than the error of Test Dataset I. Although the performance of all the methods become worse, the proposed scheme still shows the lowest localization error.

Fig. 3 shows the accumulative region classification error and region localization error of testing datasets. For Test Dataset I, almost 80% of data are classified correctly based on the proposed localization scheme, which is better than Max-RSS and WCL. In addition, the region classification error of the proposed subspace-based scheme is 0.0144 smaller than the region classification error of the proposed DNN-based scheme, but the proposed subspace-based scheme shows 0.235 smaller region localization error than the proposed DNN-based scheme. This implies that the wrong prediction region of the proposed subspace-based scheme is always near to the true region in geometry.

VI. Conclusion

This paper presented an integrated segmentation and subspace clustering method that exploits both the sequential data structure from the blind data collection process and the signal subspace structure due to the partition of the regions. The core idea is to learn the subspace feature from the RSS measurement under the prior knowledge of the sequential data structure. First, an affine subspace clustering model for sequential data is proposed, and a two-step alternating algorithm is designed to obtain the subspace feature and clustering label simultaneously. Then, with the location labels recovered from the proposed clustering method, a subspace classifier and a DNN-based classifier are built to localize the target to the regions. Finally, numerical results demonstrated that the proposed localization schemes show lower region error than the existing state-of-arts.

References

[1] F. Zafari, A. Gkelias, and K. K. Leung, "A survey of indoor localization systems and technologies," *IEEE Commun. Surv. Tutor.*, vol. 21, no. 3, pp. 2568–2599, Apr. 2019.

[2] K. M. Chen and R. Y. Chang, "A comparative study of deep-learning-based semi-supervised device-free indoor localization," in *Proc. IEEE Global Commun. Conf.*, Dec. 2021, pp. 1–6.

[3] Y. Li, Y. Nishikawa, and T. Nobukiyo, "Dividing-and-kriging method for wireless RSS fingerprint based indoor localization," in *Proc. IEEE Global Commun. Conf.*, Dec. 2019, pp. 1–6.

[4] S. Phoemphon, C. So-In, and N. Leelathakul, "Fuzzy weighted centroid localization with virtual node approximation in wireless sensor networks," *IEEE Internet Things J.*, vol. 5, no. 6, pp. 4728–4752, Dec. 2018.

[5] E. Elhamifar and R. Vidal, "Sparse subspace clustering: Algorithm, theory, and applications," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 35, no. 11, pp. 2765–2781, Nov. 2013.

[6] A. Likas, N. Vlassis, and J. J. Verbeek, "The global K-means clustering algorithm," *Pattern Recognit.*, vol. 36, no. 2, pp. 451–461, Feb. 2003.

[7] U. Von Luxburg, "A tutorial on spectral clustering," *Statistics and computing*, vol. 17, no. 4, pp. 395–416, Aug. 2007.

[8] X. He, D. Cai, Y. Shao, H. Bao, and J. Han, "Laplacian regularized Gaussian mixture model for data clustering," *IEEE Trans. Knowl. Data Eng.*, vol. 23, no. 9, pp. 1406–1418, Sep. 2010.

[9] J. Fan and I. Gijbels, *Local polynomial modelling and its applications*. Routledge, 1996.

[10] S. Sadowski, P. Spachos, and K. N. Plataniotis, "Memoryless techniques and wireless technologies for indoor localization with the internet of things," *IEEE Internet Things J.*, vol. 7, no. 11, pp. 10 996–11 005, Nov. 2020.

[11] R. C. Luo and T.-J. Hsiao, "Indoor localization system based on hybrid WiFi/BLE and hierarchical topological fingerprinting approach," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 10 791–10 806, Nov. 2019.