Fast Radio Map Construction and Position Estimation via Direct Mapping for WLAN Indoor Localization System

Caifa Zhou, Andreas Wieser
ETH Zurich, IGP
Stefano-Franscini-Platz 5, 8093 Zurich/Switzerland
Email: caifa.zhou@geod.baug.ethz.ch
andreas.wieser@geod.baug.ethz.ch

Xuezhi TAN
Communication Research Center, Harbin Institute of Technology
Key Laboratory of Police Wireless Digital Communication
Ministry of Public Security, P.R. China
Building 2A, No.2, Str. Yikuang, Dist. Nangang, Harbin
Email: tanxz1957@hit.edu.cn

Abstract—The main limitation that constrains the fast and comprehensive application of Wireless Local Area Network (WLAN) based indoor localization systems with Received Signal Strength (RSS) positioning algorithms is the building of the fingerprinting radio map, which is time-consuming especially when the indoor environment is large and/or with high frequent changes. Different approaches have been proposed to reduce workload, including fingerprinting deployment and update efforts, but the performance degrades greatly when the workload is reduced below a certain level. In this paper, we propose an indoor localization scenario that applies metric learning and manifold alignment to realize direct mapping localization (DML) using a low resolution radio map with single sample of RSS that reduces the fingerprinting workload by up to 87%. Compared to previous work. The proposed two localization approaches, DML and $k$ nearest neighbors based on reconstructed radio map (reKNN), were shown to achieve less than 4.3 m and 3.7 m mean localization error respectively in a typical office environment with an area of approximately 170 m$^2$, while the unsupervised localization with perturbation algorithm was shown to achieve 4.7 m mean localization error with 8 times more workload than the proposed methods. As for the room level localization application, both DML and reKNN can meet the requirement with at most 9 m of localization error which is enough to tell apart different rooms with over 99% accuracy.

I. INTRODUCTION

Indoor localization systems using Received Signal Strength (RSS) of Wireless Local Area Network (WLAN) based schemes have attracted much attention as the implementation of such systems does not require any additional infrastructure, such as additional Wireless Access Points (WAPs), or other extra hardware as opposed to other systems based on RFID, infrared, ultrasonics, etc. [1] [2]. The wide availability of smart devices with WiFi modules contributes further to the attractiveness of WLAN based indoor localization systems (WILSs). Compared to other approaches, fingerprinting based localization algorithms (FLAs) in indoor situations with smart devices are more popular and more feasible than other techniques, which are based on time-of-flight (TOF/TOA) or angle-of-arrival (AOA), see [3].

To build a fingerprinting based indoor positioning system, it is usually required to construct a map of expected RSS values using known location of reference points (RPs) [3] [4]. This map is named radio map. The workload to build the radio map is particularly high if the desired coverage area is large (e.g. a whole mall or airport) or if the environment changes frequently (e.g. on a fair ground or exhibition site). The former requires a large number of RPs and WAPs, and the latter requires frequent updating of the radio map. Whenever the indoor environment undergoes structural changes (e.g. new walls), the radio map may have to be updated by sampling the RSS values at the RPs again. Thus, algorithms focusing on reducing the workload for constructing the radio map while preserving localization performance are of great practical significance.

As presented in previous work, several techniques have been developed to overcome this tricky problem. In [5], Deasy et al. proposed an approach to construct the radio map fast via simulating the indoor propagation model of WLAN signals. This approach needs accurate information about the indoor environment (e.g. geometry, materials and structures of the building, installed facilities and accessories, etc.). Providing comprehensive up-to-date information covering all relevant aspects is typically difficult –if not impossible. So, the radio map constructed in this way is based on approximating assumptions and is therefore an approximation itself. Its use will typically lead to low accuracy of position determination.

Alternatively the RSS fields need to be sampled at known or independently measured positions. To reduce the amount of work and maintain the accuracy, smart devices with built-in WiFi and inertial modules can be applied to accomplish fast sampling of RSS with simultaneous positioning [6]. The methods proposed in [5] and [6] achieved the goal of constructing the radio map quickly, however, the localization accuracy was low. Another approach to reduce the workload for building the radio map is based on semi-supervised machine learning. Various authors constructed the radio map via semi-supervised learning (e.g. compressive sensing, sparse representation, manifold alignment and l-1 optimization) from partial radio maps [2] [7] [8] [9]. Although these works resulted in a sufficient accuracy of positioning while limiting the workload, they are not suitable for large and dynamic indoor environments.

In this work, we aim at designing an innovative direct mapping localization (DML) technique for indoor positioning with the following aspects. First, it can achieve significant performance improvements compared to existing solutions (proposed in [8] and [9]) while only requiring to build a radio map with...
few RPs. The estimated location of the user is computed by mapping the RSS directly to the physical position space via metric learning incorporated with manifold alignment (ML-MA). In this way, the radio map is reduced to low dimension, namely to the dimension of the coordinate system (generally 2D or 3D). Second, fast radio map construction and positioning are reached by using the same mathematical algorithm. The direct mapping process is reversible. So coordinates can be mapped onto RSS directly. It is thus easy to densify a radio map such that it contains more RPs per square meter. To achieve the above two goals, we assume that there are linear or approximately linear relationships between the location of the RPs and the corresponding RSS. Last, but not least, a novel localization approach using \( k \) nearest neighbors based on a densified radio map (reKNN) is proposed.

The organization of the paper is as follows. Section II describes the indoor localization problem. Section III introduces the proposed ML-MA scheme for indoor localization. Experimental results are given and compared to those of other schemes in Section IV.

II. PROBLEM FORMULATION

In this paper, DML using ML-MA is introduced to build radio map that is low complexity and easy to update with low workload. We are going to describe the deployment of a WILS first, including system deployment and data description. Then the datasets, including RSS from users, coordinates, and direct mapping matrix, are described in matrix view. One important definition we want to discuss is resolution analysis, which is a significant conception in following analysis.

A. System Deployment

A typical WILS involves operation in two stages: (a) offline stage and (b) online stage. The online stage comprises positioning using the fingerprinting map. At the offline stage, the hardware is deployed, RPs are defined and possibly marked within the area of interest, and the fingerprinting map is sampled. This stage is the most time-consuming one.

First, a sufficient number of WAPs needs to be available within the area of interest. Usually already existing WAPs can be used without modification if they work according to the IEEE802.11 protocol. Should there be too few WAPs for positioning, additional WAPs have to be installed as radio sources for the WILS. In this paper we assume that the signals of \( N \) WAPs can be received within the entire area of interest.

Second, \( M \) known locations in the area are selected as RPs. We collect their coordinates in the \( M \times D \)-matrix

\[
R^{(m)} = \begin{bmatrix} r^{(1)}; & r^{(2)}; & \cdots; & r^{(M)} \end{bmatrix}
\]

where the \( i \)-th row \( r^{(i)} \) is the \( D \) dimensional row-vector of coordinates of the \( i \)-th RP (e.g. \( r^{(1)} = [x^{(1)} y^{(1)}] \) for the 2D case).

Third, the RSS are sampled at each RP reading SSID, MAC and RSS from the beacon frame of each WAP. The results are stored in the matrix \( S^{(m)} = \begin{bmatrix} s^{(1)}; & s^{(2)}; & \cdots; & s^{(M)} \end{bmatrix} \), where each of the \( M \) rows contains the recorded RSS values of the \( N \) WAPs, i.e. the fingerprint \( s^{(i)} = [RSS^{(i,1)}; RSS^{(i,2)}; \ldots; RSS^{(i,N)}] \). If the coordinates of the RPs are not known and these points are not (yet) marked, the coordinates need to be determined along with the recording of the RSS measurements by employing a suitable positioning technology. The coordinates are then again assumed as known. The sampling results and the known RP coordinates can then be combined into the original radio map? \( ORM \) as defined below.

B. Description of Datasets

The original radio map can therefore be represented as summarized in (1), here given for the 2D case:

\[
ORM = \begin{bmatrix} R^{(m)}; & S^{(m)} \end{bmatrix} \in \mathbb{R}^{M \times (D+N)}
\]

\[
R^{(m)} = \begin{bmatrix} x^{(1)} & y^{(1)}; & x^{(2)} & y^{(2)}; & \cdots; & x^{(M)} & y^{(M)} \end{bmatrix} \in \mathbb{R}^{M \times D}
\]

\[
S^{(m)} = \begin{bmatrix} s^{(1)}; & s^{(2)}; & \cdots; & s^{(M)} \end{bmatrix} \in \mathbb{R}^{M \times N}
\]

\[
s^{(i)} = [RSS^{(i,1)}; RSS^{(i,2)}; \cdots; RSS^{(i,N)}] \in \mathbb{R}^{N}
\]

During the online phase, the \( N \)-dimensional vector \( s^{(i)} \in \mathbb{R}^{N} \) of signal strengths is measured at an unknown location \( r^{(i)} \in \mathbb{R}^{D} \), and the goal is to calculate \( r^{(i)} \) from \( s^{(i)} \) and \( ORM \). For testing and validation we assume that such measurements are actually carried out at \( T \) locations. We collect the measured signal strengths in a matrix \( S^{(t)} \). Furthermore we assume that the corresponding positions, collected in the matrix \( R^{(t)} \), are known or measured independently. We then have a validation data set as summarized in (3), again for the 2D case:

\[
RM^{(t)} = \begin{bmatrix} R^{(t)}; & S^{(t)} \end{bmatrix} \in \mathbb{R}^{T \times (D+N)}
\]

\[
R^{(t)} = \begin{bmatrix} x^{(1)} & y^{(1)}; & x^{(2)} & y^{(2)}; & \cdots; & x^{(M)} & y^{(M)} \end{bmatrix} \in \mathbb{R}^{T \times D}
\]

\[
S^{(t)} = \begin{bmatrix} s^{(1)}; & s^{(2)}; & \cdots; & s^{(M)} \end{bmatrix} \in \mathbb{R}^{T \times N}
\]

\[
s^{(t)} = [RSS^{(t,1)}; RSS^{(t,2)}; \cdots; RSS^{(t,N)}] \in \mathbb{R}^{N}
\]

C. Direct Mapping Matrix

The output of the ML-MA algorithm is the direct mapping matrix \( P \in \mathbb{R}^{N \times D} \), which maps RSS values onto coordinates according to \( \hat{r}^{(t)} = s^{(t)}P \). The derivation of \( P \) will be discussed in the next section.

Using ML-MA the original radio map \( RM \) can be transformed into a potentially denser radio map referring to grid positions, e.g. \( (x_{kl}, y_{kl}) \), for the 2D case where \( k \) and \( l \) are the row and column index within the grid. We will collect these grid positions in a densified matrix \( H \) by stacking the grid points column by column:

\[
H = \begin{bmatrix} x_{11} & y_{11} & \cdots & x_{kl} & y_{kl} \\ x_{21} & y_{21} \\ \vdots & \vdots \\ x_{N1} & y_{N1} \end{bmatrix}
\]

The associated radio map will henceforth be called the reconstructed radio map (RRM). The spacing between the grid points collected with \( H \) can be as small as desired thus giving full control over the spatial resolution of the location algorithm even when using an algorithm of type \( (k) \) nearest neighbor. The RRM can be precomputed (i.e. created during the offline
phase) from the sparsely sampled RSS-field represented by the original radio map. So, ML-MA is a way to reduce the workload and realize fast building of a radio map with the desired resolution.

### III. Metric Learning & Localization Scheme

Manifold alignment is an unsupervised learning method that does not need any correspondence information to align the data sets into a lower dimensional space [8]. In this work, it is not only necessary to handle high dimensional RSS readings, but also to measure the distance between spaces of different dimension, which is possible using metric learning, widely applied in machine learning and computer vision [10]. In this section, we combine metric learning and manifold alignment in the first part, then derive DML with reKNN.

#### A. Metric Learning & Manifold Alignment

General metric learning comprises three steps. First, a coupled metric learning space shared by the different datasets is defined. Then the metric is used to calculate distance in the coupled space is defined. Finally, the distance between the different spaces is computed. Under the scheme of linear metric learning the distance \(d(R^{(i)}, S^{(j)})\) between elements \(R^{(i)}\) and \(S^{(j)}\) of different sets between a D-dimensional position and an N-dimensional RSS-vector can be calculated as follows [6]:

\[
d(R^{(i)}, S^{(j)}) = \sqrt{\sum_{i,j=1}^{M} (f_1(R^{(i)}) - f_2(S^{(j)}))^T A f_1(R^{(i)}) - f_2(S^{(j)}))^{-1}}
\]

where \(f_1\) and \(f_2\) are linear functions mapping \(R\) and \(F\) into the shared space, respectively, and \(A\) is a symmetric matrix defining the metric. The goal of metric learning and manifold alignment is the determination of \(f_1, f_2\) and \(A\) based on chosen criteria. Since \(f_1\) and \(f_2\) are linear the mapping into the shared space can equivalently be expressed as follows:

\[
f_1(R^{(i)}) = P_1'R^{(i)} \\
f_2(S^{(j)}) = P_2'S^{(j)}
\]

where \(P_1'\) and \(P_2'\) are \(D_C \times D\) and \(D_C \times N\) matrices aligning the respective spaces with the \(D_C\)-dimensional common space. Furthermore, since \(A\) is symmetric, it can be expressed as [11]:

\[
A := B^TB
\]

with a suitable matrix \(B \in \mathbb{R}^{D_C \times D_C}\). The matrices \(P_1', P_2'\) used for manifold alignment and the matrix \(B\) used to define the metric can be combined:

\[
P_1 := P_1'B \\
P_2 := P_2'B
\]

and the above distance can be expressed equivalently as:

\[
d(R^{(i)}, S^{(j)}) = \sqrt{(P_1(R^{(i)})^T - P_2(S^{(j)})^T)^T (P_1(R^{(i)})^T - P_2(S^{(j)})^T)}
\]

In this way, the processes of dimension projection and distance measurement are combined into one.

In this paper, we need to realize two kinds of dimensionality mapping. One is mapping from the high dimensional RSS space to the low dimensional coordinate space for localization. The other one is projecting from coordinate space into the high dimensional RSS space for radio map densification. These two mappings can be achieved by ML-MA with one difference: we let \(P_1\) equal the unit matrix, i.e. \(P_1 = I\) for mapping RSS into coordinates (in this case \(D_c = D\)), and let \(P_2\) equal the unit matrix for projecting coordinates into RSS (in this case \(D_c = N\)).

We demonstrate this by applying manifold alignment to the mapping of RSS into coordinates. Manifold alignment helps to achieve two objectives: minimizing the metric learning distance between the original dataset (i.e. \(F\)) and the target dataset (i.e. \(R\)), and minimizing the manifold structure’s variance of the source dataset in the coupled space. The first objective can be expressed as:

\[
J_1(P_2) = \sum_{i=1}^{M} ||R^{(i)}^T - P_2S^{(i)}||_2^2 \rightarrow \min_{P_2 \in \mathbb{R}^{D_c \times N}} \quad (9)
\]

In [9], \(P_1\) has been substituted by the unit matrix as described before. Using the trace, (9) can be rewritten as:

\[
J_1(P_2) = \text{tr}(SP^TP_2S^T + RR^T - 2RP_2S^T) \rightarrow \min_{P_2 \in \mathbb{R}^{D_c \times N}} \quad (10)
\]

The second objective of manifold alignment is to preserve the manifold structure (neighborhood relations) of the source dataset during the process of mapping RSS readings to coordinates. Local linear embedding (LLE) is used to estimate a weight \(w_{ij}\) for each pair \(S^{(i)}, S^{(j)}\) of RSS fingerprints, where a high weight indicates that the two fingerprints are close to each other and a low one that they are not. Preserving the structure of the original dataset can then be taken into account using the cost function:

\[
J_2(P_2) = \sum_{i,j=1}^{M} ||P_2F^{(i)}^T - P_2F^{(j)}||_2^2 w_{ij} \rightarrow \min_{P_2 \in \mathbb{R}^{D_c \times N}} \quad (11)
\]

Collecting the \(w_{ij}\) in the symmetric matrix \(W\) the cost function can be expressed equivalently as:

\[
J_2(P_2) = \text{tr}(FP^T(W - W)P_2F^T) \rightarrow \min_{P_2 \in \mathbb{R}^{D_c \times N}} \quad (12)
\]

where \(W\) is a diagonal matrix with diagonal elements:

\[
W_D(i, i) = \sum_{j=1}^{M} w_{ij} \quad (13)
\]

Achieving manifold alignment using the two objectives [11] and (12) is a multi-objective optimization problem. We reduce it to a more easily handled single objective problem by introducing a weight \(\alpha (\alpha \in [0, 1])\) which expresses a trade-off between minimizing the metric learning distances and preserving the dataset structure:

\[
J(P_2) = \alpha \cdot J_1(P_2) + (1 - \alpha) \cdot J_2(P_2) \rightarrow \min_{P_2 \in \mathbb{R}^{D_c \times N}} \quad (14)
\]
The unconstrained optimization problem \( (14) \) can be solved using the Quasi-Newton BFGS method \([12]\). The result is the optimal mapping matrix \( P_2 \). For mapping RSS fingerprints to coordinates i.e. \( P_2 := \arg \min_{P_2 \in \mathbb{R}_{d \times N}} J(P_2) \). The procedure to compute the optimal radio map reconstruction mapping matrix for mapping from coordinate space to RSS space can be computed accordingly by letting \( P_2 \) equal the unit matrix, i.e. \( P_2 := I \) and minimizing the appropriate cost function for \( P_1 \).

**B. DML and reKNN Approach**

In this part, we will apply the results of the above ML-MA approach to localization and describe procedures to realize DML. Then a similar scheme is used to derive the reconstructed radio map reconstruction matrix and have a new positioning method: reKNN. The first three steps represent the offline stage and are similar for both DML and reKNN:

**First step:** create original radio map ORM with low density of RPs, as well as high density coordinate grid \( H \) according to the definitions in \([1]\), \([3]\), and \([5]\), respectively;

**Second step:** compute the weight matrix \( W \) representing the geometric structure using LLE;

**Third step:** apply Quasi-Newton BFGS to calculate the optimal mapping matrices \( P_1^m \) and \( P_2^l \).

The fourth step represents the online stage and is different for DML and reKNN. DML yields the estimated user location by mapping the RSS fingerprint \( (S^{(m)}_i) \) to the coordinate space via \( P_2^l \), then finds the nearest neighbor from \( H \) as the estimated location of the user. The location can then be computed from:

\[
\hat{x}_i := H_j \quad \text{with} \quad j = \arg \min_{j=1, 2, \ldots, k} \| P_2^l \cdot S^{(m)}_i \|_2^T - H_j \|_2
\]  

(15)

For reKNN, on the other hand, we project the high density coordinates collected in \( H \) to the RSS space first and then estimate the position using the kNN algorithm. The user’s location is estimated as the average of the rows of \( H \) whose corresponding rows of \( S^H \) are the \( k \) nearest neighbors to the measured fingerprints in the RSS space.

**C. Overall Framework of Proposed Approach**

Fig[1] shows the overall framework of the proposed approach. During the offline stage, a low resolution original radio map, treated as a training dataset, is sampled by devices with built-in WiFi module. ML-MA is then applied to the RSS-fingerprints and the coordinates are stored in the original radio map. The result is \( P_1^m \) and \( P_2^l \) which can be applied to reconstruct the radio map and to direct mapping localization, respectively. To reconstruct the radio map the high-density coordinate dataset covering the entire area of interest is extracted from an indoor GIS and transformed into the RSS space using \( P_2^m \). During the online stage the location of a user is estimated by DML and reKNN according to the above algorithms.

**IV. PERFORMANCE ANALYSIS**

In this section, we test our proposed approach using the real measurements from 10th floor of building 2A, Communication Research Center, at Scientific Park of Harbin Institute of Technology, depicted in Fig[2]. There are 8 WAPs in the experimental area, which are attached stably to the wall at a height of 2m from the floor. The red triangles are the RPs of the original radio map. The black dots represent the points selected as test points. They are separated by 0.5m from each other. We apply the proposed approaches in this environment to compare the results with previously proposed fingerprint localization methods.

The data collection was carried out in the same way as described in \([13]\). To test the performance of algorithms as schemes independent, the testing data sets and low resolution radio map are chosen randomly throughout the indoor area.
The mean localization error (average Euclidean distance between estimated and true locations) resulting from the proposed approaches (DML, reKNN) are presented below and compared to those obtained from KNN, unsupervised algorithm with perturbation, unsupervised algorithm without geometry perturbation and raw semi-supervised algorithm which were all proposed in previous work [8] [9]. The results are also shown graphically as cumulative distribution functions of the localization errors obtained by ?All calculations have been carried out using MATLAB (R2013b, 64bit) installed on a laptop with Windows 7.

### A. Comparison of Mean Localization Error and Resolution Analysis

**TABLE I** summarizes the numerical results for different resolutions i.e. different grid size of $H$ as defined in Section II-C. We have several conclusions from **TABLE I**. First, comparing to previous proposed algorithm, the proposed DML and reKNN achieve better mean localization error with respect to similar resolution, as well as the variance. Taking DML as an example, the mean error is $3.75m$, which is $1m$ lower than the best performance of previous proposed methods when the grid size is $1m^2$.

Second, from the simulation result, we could obtain that the performance of KNN is stable, whose mean error equals to $3m$~$4m$, and DML and reKNN achieves comparable mean error with KNN in lower resolution. Third, the performance of reKNN fluctuates greatly along with changing of resolution, as well as variance of positioning error. As the result indicates that reKNN is more likely to achieve better performance in the situation of lower resolution.

Last, comparing the two methods we proposed in this paper, it also achieves different accuracy of localization. From the mean error and variance, DML achieves more stable performance than reKNN, but it has lower accuracy than reKNN when resolution is lower than 0.5 (i.e. grid size is higher than $2m^2$). In this way, the results provide possibility to use these two output to improve the performance via filtering techniques (e.g. particle filtering, Kalman filtering), which we are going to further the research in the future work.

In **TABLE I** it also shows the influence of different resolutions. As the resolution decreased, the number of reference points reduced, as well as workload of building fingerprinting.
DML and reKNN when applying radio map of the different sizes (i.e. varies resolutions).

\[ m \]

and \([9]\). It means that sampling 2 samples at each reference point in the when the resolution equals 1 (i.e. one RP per \( m^2 \)). We randomly select only one samples from data sets to build radio map and testing data sets in the lower resolution (e.g. grid size equals to \( 2m^2 \)). As it presents in TABLE 1, the proposed algorithm achieves much higher accuracy than previous techniques under the condition that reducing 87.5% workload of previous methods. On the other hand, even the resolution is set as 1 (i.e. grid size is \( 1m^2 \)), DML also has better performance than previous proposed algorithm while sampling only one RSS, whose workload is 50% lower than that of previous algorithms.

| Algorithm          | Grid Size \((m^2)\) | Mean \((m)\) | Variance \((m^2)\) |
|--------------------|---------------------|-------------|-------------------|
| DML                | 0.25                | 3.40        | 1.93              |
| \hspace{0.5em}     | 0.50                | 3.61        | 2.21              |
| \hspace{0.5em}     | 1.00                | 3.75        | 2.23              |
| \hspace{0.5em}     | 2.00                | 3.93        | 2.25              |
| \hspace{0.5em}     | 2.25                | 5.34        | 3.15              |
| \hspace{0.5em}     | 3.75                | 4.62        | 2.50              |
| \hspace{0.5em}     | 4.00                | 4.26        | 2.50              |
| \hspace{0.5em}     | 6.25                | 5.34        | 3.31              |
| \hspace{0.5em}     | 9.00                | 7.25        | 4.14              |
| reKNN              | 0.25                | 9.44        | 5.07              |
| \hspace{0.5em}     | 0.50                | 3.84        | 1.91              |
| \hspace{0.5em}     | 1.00                | 9.04        | 4.97              |
| \hspace{0.5em}     | 2.00                | 3.81        | 1.82              |
| \hspace{0.5em}     | 2.25                | 3.98        | 2.13              |
| \hspace{0.5em}     | 3.75                | 3.87        | 1.84              |
| \hspace{0.5em}     | 4.00                | 3.70        | 2.09              |
| \hspace{0.5em}     | 6.25                | 5.22        | 2.89              |
| \hspace{0.5em}     | 9.00                | 5.23        | 2.37              |
| KNN                | 0.25                | 3.09        | 1.74              |
| \hspace{0.5em}     | 0.50                | 3.26        | 1.81              |
| \hspace{0.5em}     | 1.00                | 3.33        | 1.84              |
| \hspace{0.5em}     | 2.00                | 3.59        | 1.87              |
| \hspace{0.5em}     | 2.25                | 3.55        | 2.04              |
| \hspace{0.5em}     | 3.75                | 3.92        | 2.11              |
| \hspace{0.5em}     | 4.00                | 3.59        | 1.90              |
| \hspace{0.5em}     | 6.25                | 3.95        | 2.10              |
| \hspace{0.5em}     | 9.00                | 4.67        | 2.64              |
| Unsupervised       | 1.00                | 20.24       | 13.45             |
| without perturbation | 1.00                | 16.98       | 7.04              |
| Semi-supervised    | 1.00                | 9.58        | 2.53              |
| with crowd sourced | load                | 1.00        | 4.70              |
| load               | 1.00                | 4.70        | 0.58              |

On the one hand, comparing to 1% workload scheme in [8] and [9]. It means that sampling 2 samples at each reference point in the when the resolution equals 1 (i.e. one RP per \( m^2 \)). We randomly select only one samples from data sets to build radio map and testing data sets in the lower resolution (e.g. grid size equals to \( 2m^2 \)). As it presents in TABLE 1, the proposed algorithm achieves much higher accuracy than previous techniques under the condition that reducing 87.5% workload of previous methods. On the other hand, even the resolution is set as 1 (i.e. grid size is \( 1m^2 \)), DML also has better performance than previous proposed algorithm while sampling only one RSS, whose workload is 50% lower than that of previous algorithms.

B. Cumulative Localization Error Analysis

Rather than just analysis the mean error of varies localization techniques, we also simulated the overall performance of DML, reKNN and KNN, including the results with varies grid sizes (i.e. varies resolutions).

In Fig3 and Fig4, it shows cumulative error analysis of DML and reKNN when applying radio map of the different grid size in the indoor environment. From these two figures, we can obtain follow ideas. First, to DML method alone, the shape and size of grid have similar influence on the trend of the specified approach. But to absolute performance, it varies greatly. The localization accuracy decreases from almost 80% to 25% as the grid size increases from \( 0.25m^2 \) to \( 9m^2 \) in Fig3 when error radius is 4 meters. In Fig3B, we conclude that the performance increases as the higher resolution of radio map.

Second, the influence of resolution to reKNN’s performance fluctuates greatly as shown in Fig4. One singularity is that the worst performance of positioning is in the situation of highest resolution, which is contradicted to trend of DML that shown in Fig3. The overall trend shows in the figure is not identical comparing to Fig3, as well as the absolute localization accuracy when error equals to \( 4m \); the highest accuracy is about 65% when the grid size is \( 4m^2 \) in square grid and \( 3.75m^2 \) in rectangle grid when error radius equals to \( 4m \) respectively. Finally, comparing the performance of DML and reKNN as it shows in Fig3 and Fig4, the best performance of DML and reKNN is in the different resolution of reference point, which indicates that both methods have optimized resolutions.

As to the optimized overall performance of proposed approaches comparing to KNN, they can achieve comparable performance to KNN as it shows in Fig3. In the figure, the grid size of DML, reKNN and KNN is \( 4m^2 \), \( 3.75m^2 \) and \( 0.5m^2 \) respectively. After optimizing, DML achieves comparable performance with KNN, the positioning accuracy of both methods are up to 80% when error radius is equals to 4 meter. Considering that, DML reduces 78.5% of workload as it achieves similar performance with KNN. Also, comparing to the workload of previous methods in [8] and [9], the workload of proposed approach is only one-eighth of that. As for the room level locating application (e.g. advertising push), it means to tell apart two different rooms in accuracy is higher than 99%, both DML and reKNN can match this aim within the error about 9 meters.

V. Conclusion

In this paper, we proposed an indoor localization scenario that applies metric learning and manifold alignment (ML-MA) to realize direct mapping localization using low resolution radio map with single sample of RSS. The proposed approach
applies high resolution coordinates set to achieve 12.5% workload to construct radio map of previous work [8]. We proposed two localization approaches: DML and reKNN. They were shown to achieve less than 4.3 m and 3.7 m mean localization error respectively, while the unsupervised localization with perturbation algorithm proposed in [8] was shown to achieve 4.7 m mean localization error with 8 times workload more than proposed methods. As for the room level locating application (e.g. advertising push), it means to tell apart two different rooms in accuracy is higher than 99%, both DML and reKNN can meet this demand within the error about 9 meters. We also would like to facilitate the performance of our proposed algorithms via filtering, transformed domain analyzing and clustering in the future work.

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