GrassMA: Graph-Based Semi-Supervised Manifold Alignment for Indoor WLAN Localization
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Abstract—Wireless local area network (WLAN) fingerprinting has been extensively studied for indoor localization due to the formidable deployability of WLAN in indoor environment, but one major bottleneck of its practical implementation is the extensive calibration effort required to construct the radio map through the fingerprinting which is time consuming and labor intensive. In response to this compelling problem, we newly design the graph-based semi-supervised manifold alignment approach which relies on the concept of graph construction to construct a cost-efficient radio map with a small number of labeled fingerprints. In addition, the unlabeled user traces are also considered to compensate for the sparsity of the raw radio map as well as enhance its robustness to the environmental change. The extensive experiments conducted in an actual indoor WLAN environment demonstrate the performance improvement (by 27% at most with respect to the confidence probability of errors within 3 m) by our system compared with the existing ones using the fingerprints solely.

Index Terms—WLAN, indoor localization, radio map construction, semi-supervised learning, manifold alignment.

I. INTRODUCTION

THE rapid development of mobile devices (e.g., smartphones, tablets, and laptops) has caused the proliferation of various Location-based Services (LBSs) [1]. Due to the weak received signal strength (RSS) from the satellites, the Global Positioning System (GPS) [2] cannot provide high enough localization accuracy in indoor environment, and thereby the indoor localization systems based on Wireless Local Area Network (WLAN) [3], Radio-frequency Identification (RFID) [4], ultrasound [5], Bluetooth [6], ultra-wideband [7], motion sensors [8], vision images [9], and audible sound [10] have been significantly studied in recent decade. By considering the advantages of ubiquitous coverage and inexpensive devices to set up the infrastructure, the indoor WLAN localization is recognized to be particularly effective by using the RSS measurement [11], which is very appealing for the commercialization over the Angle-of-Arrival (AoA) [12], Time-of-Arrival (ToA) [13], and Time-Difference-of-Arrival (TDoA) [14] measurements.

The indoor WLAN localization systems using the RSS measurement can be divided into two main categories. The first one is based on the propagation model [15], while the second one makes use of location fingerprinting [16]. Since the propagation model to be matched with the indoor environment is difficult to be constructed, the location fingerprinting is much preferred. The location fingerprinting generally consists of two phases, namely offline phase and online phase [17]. In offline phase, The RSS measurements from all the hearable Access Points (APs) in target environment are collected at each Reference Point (RP). Most often, a considerable number of RSS measurements are required to be collected at each RP to capture RSS variation property especially when considering the antenna patterns in different orientations. After that, the RSS measurements and the corresponding locations are aligned to form the fingerprints, and then construct the radio map of the target environment. In online phase, each newly-collected RSS measurement is matched against the pre-constructed radio map to estimate the locations of the target.

As can be easily inferred from the description above, let alone the tedious process of manual RSS measurements collection, the huge time and labor cost for radio map construction becomes the most expensive bottleneck facing the feasible commercialization of indoor WLAN localization especially when the dimensions of the target environment is significantly large (e.g., in airports, railway stations, and giant shopping malls). Then, the solutions towards reducing this cost are of extreme importance with the rapid development of LBSs. In this paper, we provide a solution by constructing a graph-based semi-supervised radio map with the substantially reduced fingerprints calibration cost in offline phase, while providing the high enough localization accuracy in online phase. Specifically, we design a new Graph-based Semi-supervised Manifold Alignment (GrassMA) approach to physically label the sporadically-collected user traces by using a small number of labeled fingerprints. The basic idea behind the proposed approach is to exploit the inherent correlation relations of different RSS measurements to reduce the number of required labeled fingerprints. In addition, the concept of Graph Construction Based on Labeled Data (GCBLD) [18] is applied to construct neighborhood graph for semi-supervised manifold alignment.

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The three main contributions of this paper are summarized as follows. First of all, the overhead of the tedious process of manual RSS measurements collection becomes acceptable since the proposed radio map requires a small number of labeled fingerprints. Second, the newly-designed GrassMA approach which relies on the neighbor weight matrices combined with the GCBLD scheme to construct radio map not only achieves high localization accuracy, but also enhances the robustness of radio map to the environmental change. Third, the extensive experimental results conducted in an actual indoor WLAN environment have verified the effectiveness and efficiency of our system.

The rest of the paper is organized as follows. Some related works are reviewed in Section 2. In Section 3, we illustrate the Laplacian Eigenmap problem in manifold alignment. Section 4 discusses the steps of performing the GCBLD to construct neighborhood graph for manifold alignment. Then, in Section 5, we present the most important contribution of this paper, the idea of using the proposed GrassMA to construct a cost-efficient radio map for indoor WLAN localization. Section 6 shows the experimental results, and finally the conclusion of the paper is given in Section 7.

II. RELATED WORK

As mentioned in the previous section, the indoor WLAN localization systems are mainly based on the propagation model or location fingerprinting [19]. The propagation model scheme usually assumes that the AP locations are known, and meanwhile the relations between the RSS and the distance from each AP can be characterized by a closed-form solution. Although the propagation model scheme is independent of manual RSS measurements collection, its performance easily suffers from the multi-path fading and environmental change [20]. On the contrary, the location fingerprinting scheme has been widely studied in many literatures using the deterministic or probabilistic inference approach [21]–[23]. The deterministic inference approach represents each fingerprint as a statistic RSS (e.g., mean, median, and maximum of RSS), and then performs features matching to infer the localization of the target with a very small number of location fingerprints. As mentioned in the previous section, the indoor WLAN localization systems are mainly based on the propagation model or location fingerprinting [19].

The process of fingerprints calibration normally requires huge time and labor cost, which hinders its widespread application. In this circumstance, the semi-supervised learning approach using a limited number of labeled fingerprints to achieve acceptable performance attracts significant attention. Compared with the labeled fingerprints, the unlabeled ones are more easily to be collected by crowdsourcing. A new generative and discriminative semi-supervised learning approach is proposed in [32] to enrich the raw sparse radio map by the help of a large number of unlabeled fingerprints, but the temporal relations of the consecutive unlabeled fingerprints are not considered. Majeed et al. [33] rely on the Hidden Markov Model (HMM) to explore the RSS changing regularity on each unlabeled user trace for radio map enrichment, but the HMM works in an iterative manner which may result in the local minimum. The manifold learning not only uses the RSS as distance metric between the AP and target, but also takes the topological structure of the APs and labeled locations into account, and thereby it has been widely studied in recent years due to its potential ability of achieving high localization accuracy.

The semi-supervised localization approach in [34] constructs a hybrid fingerprint database by fusing the labeled and unlabeled fingerprints with the assumption that the similar RSS data are much likely to be collected at nearby locations. Goldshtein et al. [35] perturb the local geometries of the destination data set during the semi-supervised manifold alignment to locate the target with a very small number of location fingerprints. Zhang et al. [36] use a graph-based semi-supervised learning approach to exploit the correlation relations of RSS data at nearby locations to infer the optimal RSS value at each location in terms of errors, and meanwhile utilize the RSS difference between different locations to construct a cost function for performance evaluation. Pan et al. [37] present a manifold regularization approach to track mobile nodes in wireless sensor network, while the related experimental environment is only based on the simple Line-of-sight (LOS) condition. Wang et al. [38] rely on the semi-supervised manifold learning to design a new WiFi-only Outdoor Localization (WOLoc) system, which utilizes the crowdsensed WiFi labels to improve localization accuracy. However, the graph Laplacian considered in these two literatures [37], [38], is constructed from RSS measurements solely, and thereby their performance may seriously deteriorate when the RSS changes abruptly at neighboring locations.

Different from the studies above, the proposed GrassMA well preserves the neighborhood relations of the data in both the signal and physical spaces during the radio map construction. Specifically, we make use of the RSS measurements, location information of labeled data, as well as timestamp information of unlabeled data to construct Laplacian graph, so that the neighborhood relations of the locations at which the RSS changes abruptly can be well preserved. Here, the timestamp information is used to enhance the neighborhood relations of the consecutive RSS data on each user trace.

III. PROBLEM FORMULATION

As an effective dimensionality reduction approach, the manifold alignment learns the transfer relations of the data in the signal and physical spaces with the same underlying manifold [39]. The effectiveness of transfer relations learning is guaranteed based on the two main conditions below. The first one is to preserve the neighborhood relations of the data in both the signal and physical spaces, which indicates that the neighboring data are with stronger neighborhood relations compared with the one far apart. The second one is that the data in both the signal and physical spaces have the same underlying manifold even though they exhibit different data structures in the raw spaces.

We propose to use the Laplacian Eigenmap [40] to perform manifold alignment for radio map construction, which assumes that the similarity between the unconnected data is zero and the connected one is as close as possible after dimensionality
In our system, there are two types of data, namely labeled and unlabeled data. The former one consists of the RSS data and the corresponding location coordinates, while the latter one without physically labeling is collected on each user trace, which contains the RSS data and the corresponding timestamps. In target environment, by assuming that there are $N$ APs in total and $n$ RSS data collected at each RP (with the total number of $n$), the sets of $N_l (= n \times m)$ RSS data and the corresponding location coordinates, while labeled and unlabeled data. The former one consists of the reduction. In our system, there are two types of data, namely

$$L \times \text{timestamps.}$$ 

By setting the derivative of objective function to be zero, the location coordinates of the RSS data collected on user traces can be estimated by

$$q = (J_q + \gamma \mathbf{L})^{-1} J_q \mathbf{y} \quad (3)$$

From (3), we can find that $q$ is determined by $L$, which is calculated from $W$, and then the most important step of the proposed GrassMA is the construction of $G$ for the calculation of $W$.

IV. GCBLD FOR NEIGHBORHOOD GRAPH CONSTRUCTION

A. GCBLD

The conventional way of constructing $G$ is by using K-nearest Neighbor (KNN) approach to connect every two RSS data, $x_i$ and $x_j$, when $x_j \in N_{k}(x_i)$ or $x_i \in N_{k}(x_j)$, where $N_{k}(x_i)$ is the set of the $k$ nearest neighbors of $x_i$. This process does not take the location coordinates of labeled fingerprints into account, whereas their physical labeling information can help a lot in recognizing the prior information for semi-supervised manifold alignment, and thereby it plays an important role in neighborhood graph construction. Based on this, we propose a new neighborhood graph construction approach, namely GCBLD, by incorporating the physical relations of labeled fingerprints. To achieve this goal, in the GCBLD, the mutual neighbors which are close to labeled RSS data are chosen to be connected with the corresponding closest labeled RSS data, and then the smaller distance of connections indicates the more informative mutual neighbors corresponding to the connected labeled RSS data. In this case, the labeled data become the hubs of neighborhood graph, which facilitate the physical labeling propagation. The target of the GCBLD is to choose the most informative mutual neighbors to minimize the objective function below.

$$\min \sum_{i,j=1}^{N_l+T_p} (S_{ij} + \min (S_{ij})) \quad \text{s.t. } S_{ij} \geq 0 \quad (4)$$

where $S_{ij}$ is the similarity between $x_i$ and $x_j$ and min $(S_{ij})$ represents the minimum of the similarities between $x_j$ and its connected labeled data $x_i$. We rely on the Bray-Curtis distance (also named as Sorensen distance) [42], which is proved to be more effective than the Euclidean distance in complex indoor environment [43], to measure the similarity between different RSS data. The Bray-Curtis distance is calculated by the sum of the absolute subtraction between the RSS data over the sum of their absolute addition, as shown below.

$$S_{ij} = \frac{\sum_{m=1}^{N} |rss_{im} - rss_{jm}|}{\sum_{m=1}^{N} |rss_{im} + rss_{jm}|} \quad (5)$$

The steps of performing the GCBLD to construct neighborhood graph are as follows. Step 1: Use the k-d tree.
algorithm [44] to construct the similarity matrix $S = \{S_{ij}\}((N_l + T_p) \times (N_l + T_p))$ with the reduced computation complexity, which will be further discussed in the following section; Step 2: For each RSS data $x_i$, find its $k_e$ nearest neighbors with the sorted Bray-Curtis distances in ascending order; Step 3: For each nearest neighbor of $x_i$, $x_j$, find its $k_e$ nearest neighbors with the sorted Bray-Curtis distances in ascending order, and then if the Bray-Curtis distance between $x_i$ and its $k_e$-th nearest neighbor is larger than $S_{ij} (= S_{ji})$, $x_i$ and $x_j$ are defined as the mutual neighbors. Step 4: Construct the set of labeled RSS data belonging to the set of the $k_e$ nearest neighbors of $x_j$, $\Psi(x_j)$, and then recalculate the similarity between $x_i$ and $x_j$ as $DS_{ij} = S_{ij} + \min(1, S_{ji})$. Step 5: Connect $x_i$ with its first $k_i$ mutual neighbors with the smallest value $DS_{ij}$, and then the weight of the connection between $x_i$ and its $j$-th mutual neighbor is defined as $W_r(i, j) = e^{-\frac{DS_{ij}}{\theta_{r}}}$, where $\theta_{r}$ is the kernel parameter for mutual neighbors, which is determined by kernel alignment function [45]. In addition, if there is no connection between $x_i$ and $x_j$, we set $W_r(i, j) = 0$. Finally, the neighbor weight matrix is constructed as $W_r = \{W_r(i, j)\}((N_l+T_p) \times (N_l+T_p))$. In general, the GCBLD prioritizes the connections between the mutual neighbors which are close to labeled RSS data, which facilitates the physical labeling of unlabeled one. Fig. 1 shows an example of performing the GCBLD to construct neighborhood graph. In Fig. 1(a), the $k_e = 15$ nearest neighbors of the data of interest, $x_i$, are found in the dashed circle. Then, in Fig. 1(b), the value $DS_{ij}$ is calculated for each nearest neighbor as described in Step 4, where $x_{4m}(m = 1, \ldots, 4)$ represents the 4 labeled RSS data with respect to $x_i$. Finally, in Fig. 1(c), the $k_i = 3$ mutual neighbors with the smallest value $DS_{ij}$ (within the dotted ellipse) are connected with $x_i$ in neighborhood graph.

B. Computation Complexity

Based on the previous study in [46], the number of multiplications required for constructing the k-d tree is $O(N_l(N_l + T_p) \log(N_l + T_p)) \approx O(N_l \log(N_l + T_p))$ under the condition of $N_l + T_p \gg 2^{N_l}$. In addition, for each RSS data, searching for its $k_e$ nearest neighbors takes $O(k_e \log(N_l + T_p))$ multiplications, and therefore the number of multiplications for all the RSS data is $O(k_e(N_l + T_p) \log(N_l + T_p))$.

Finding the mutual neighbors with respect to $x_i$ takes $O(k_e \log(N_l + T_p))$ multiplications since it is required to check whether $x_i \in N_k(x_j)$ for each nearest neighbor. In addition, the process of calculating the $k_e$ smallest value $DS_{ij}$ needs $O(k_e (N_l + T_p) \log(N_l + T_p))$ multiplications. Therefore, the number of multiplications involved in constructing the connections for all the RSS data is $O(k_e \log(N_l + T_p) + k_i (N_l + T_p) \log(N_l + T_p))$.

Finally, the total number of multiplications required by the GCBLD equals to $O((N_l + T_p) \log(N_l + T_p)) + O(k_e(N_l + T_p) \log(N_l + T_p)) + O(k_e \log(N_l + T_p) + k_i (N_l + T_p) \log(N_l + T_p))$ under the condition of $k_e \gg k_i$, which is much smaller than the one by the conventional KNN, $O(N(N_l + T_p)^2)$ [46].

V. GRASSMA FOR RADIO MAP CONSTRUCTION

A. Neighbor Weight Matrices

Considering the location coordinates of labeled fingerprints as well as the timestamps of unlabeled RSS data on each user trace, we construct the neighbor weight matrices with respect to the location coordinates of labeled RSS data, $L_{loc}$, and timestamps of unlabeled one, $T'$, as $W_{loc} = \{W_{loc}(i, j)\}_{N_l \times N_l}$ and $W_{t} = \{W_{t}(i, j)\}_{T_p \times T_p}$ respectively, as shown below.

$$W_{loc}(i, j) = \begin{cases} \frac{e^{-\frac{d(i,j)^2}{\theta_{dist}}}}{0}, & \text{if the } i\text{ }\text{th and } j\text{ }\text{th data are connected} \quad (6) \\ 0, & \text{otherwise} \end{cases}$$

where $\theta_{dist}$ is the kernel parameter for location coordinates.

$$W_{t}(i, j) = \begin{cases} \frac{e^{-\frac{|t_i-t_j|^2}{\theta_{t}}}}{0}, & \text{if } |t_i-t_j| \leq T_{thr} \quad (7) \\ 0, & \text{otherwise} \end{cases}$$

where $T_{thr}$ is the threshold for timestamps and $\theta_t$ is the kernel parameter for timestamps.

B. Radio Map Construction

The key step of radio map construction is to use (3) to estimate the location coordinates of unlabeled RSS data on user traces. To achieve this goal, we first rewrite $W_r$ in
Input: $X_j$, $L_{loc}^j$, $X_T$, and $T^u$

Output: Radio map

1. Construct the neighbor weight matrix $W_r$ by the GCBLD;
2. Construct $W_{loc}^j$;
3. Construct $W_r^r$;
4. Construct $W_l^l$ and $W_u^u$;
5. Construct $L$;
6. Calculate $q$, where $q(N_i+1:N_i+T_p, 1:2)$ is the result of physical labeling of unlabeled RSS data;
7. Construct radio map based on $X$, $L_{loc}^j$, and $q(N_i+1:N_i+T_p, 1:2)$.

Fig. 2. Pseudocode of the proposed GrassMA for radio map construction.

partitioned matrix form as $W_r = \begin{bmatrix} W_r^l & W_r^{lu} \\ W_r^u & W_r^r \end{bmatrix}_{(N_t+T_p) \times (N_t+T_p)}$, where $W_r^l$ is the former $N_t$ rows and $N_t$ columns of $W_r$, which represents the neighbor weight matrix with respect to labeled RSS data, $W_r^u$ is the latter $T_p$ rows and $T_p$ columns of $W_r$, which represents the neighbor weight matrix with respect to unlabeled RSS data, $W_{loc}^{lu} = \{W_{loc}^{lu}(i, j)\}_{N_t \times T_p}$ is the former $N_t$ rows and latter $T_p$ columns of $W_r$, which represents the neighbor weight matrix between labeled and unlabeled RSS data, and $W_r^{ul} = \{W_r^{ul}(i, j)\}_{T_p \times N_t}$ is the transposition of $W_{loc}^{lu}$. Then, the mixed neighbor weight matrices with respect to labeled and unlabeled data are constructed in (8) and (9) respectively.

$$W_l = \begin{bmatrix} W_l(i, j) \end{bmatrix}_{N_t \times N_t} = a W_r^l + (1-a) W_{loc}^{lu} \tag{8}$$

where $\alpha$ is the relative weight for mixed neighbor weight matrix.

$$W_u = \begin{bmatrix} W_u(i, j) \end{bmatrix}_{T_p \times T_p} = a W_r^u + (1-a) W_r^{ul} \tag{9}$$

Second, we construct the Laplacian operators with respect to labeled and unlabeled data, $L_l^l$ and $L_u^u$, and the one between them, $L_r^{lu}$, in (10).

$$\begin{bmatrix} L_l^l & 0 \\ 0 & L_u^u \end{bmatrix} = \begin{bmatrix} D^l & -W_r^{lu} \\ -W_r^{ul} & D_r^{lu} \end{bmatrix}. \tag{10}$$

where the diagonal matrices $D_l = \{D_l(i, i)\}_{N_t \times N_t}$, $D_u = \{D_u(i, i)\}_{T_p \times T_p}$, $D_r^{lu} = \{D_r^{lu}(i, i)\}_{N_t \times T_p}$, and $D_r^{ul} = \{D_r^{ul}(i, i)\}_{T_p \times N_t}$.

Third, we construct the graph Laplacian operator as

$$L = \begin{bmatrix} L_l^l & 0 \\ 0 & L_u^u \end{bmatrix} + \mu L_r^{lu} \tag{12}$$

where $\mu$ is the relative weight for graph Laplacian operator. Finally, after the graph Laplacian operator is obtained, we use (3) to physically label the unlabeled RSS data on user traces. To illustrate this process clearer, the pseudo code of the proposed GrassMA for the cost-efficient radio map construction is shown in Fig. 2.

VI. EXPERIMENTAL RESULTS

A. Environmental Setup

The practical test bed with the dimensions of 65 m by 18.5 m (see Fig. 3) is setup in a building, and some photos of the experimental environment are shown in Fig. 4. Five D-Link DAP 2310 APs are selected as the signal transmitters operating at 2.4 GHz frequency, which are labeled as AP1, AP2, AP3, AP4, and AP5 respectively. Fig. 5 shows the interface of our developed APP, which provides a convenient way to scan and record the RSS data from each AP. The recorded RSS data are exported and saved in “.txt” format into a security digital card, and then extracted by MATLAB to construct the database matrix. For the testing, we collect 100 RSS data (with the sampling rate of 1 Hz) at each RP (with the total number of 327) and 1210 unlabeled RSS data on 10 user traces. In addition, we set the three kernel parameters as $\theta_i = 0.1,$
B. Parameters Discussion

1) Number of Neighbors: The experiments are firstly carried out to study the impact of parameters $k_i$ and $k_e$ on localization performance. Fig. 6 plots the mean of localization errors as a function of $k_i/k_e$ under different value $k_e$. It can be found that the localization error generally decreases with the increase of values $k_e$ and $k_i/k_e$. The irregular change of localization error under $k_e = 10$ is due to the fact that the too small value $k_e$ (e.g., $k_e = 10$) fails to well characterize the neighborhood relations of different RSS data. At the same time, the time cost by the GrassMA for radio map construction under different value $k_e$ is compared in Fig. 7. From this figure, we can find that the time cost increases with the increase of values $k_e$ and $k_i/k_e$ as expected. Considering both the neighborhood relations preservation and time cost saving, we set $k_e = 40$ and $k_i = 4$ (which indicates that $k_i/k_e = 0.1$) in our system.
2) Relative Weights: In Fig. 8, we present a quantitative analysis towards the impact of different parameters $\alpha$, $\mu$, and $\gamma$ on the mean of localization errors. In Fig. 8(a), for a given value $\gamma = 0.1$, the localization error increases with the increase of value $\mu$ in the overwhelming majority of cases, but it exhibits an opposite variation trend when $\mu < 5$. Thus, for the sake of achieving high localization accuracy, we set $\mu = 5$ in our system. Furthermore, Fig. 8(b) and 8(c) show that the increase of values $\gamma$ and $\alpha$ results in the increase of localization error, and thereby the three relative weights are set as $\mu = 5$, $\gamma = 0.1$, and $\alpha = 0.1$.

3) Timestamps: Fig. 9 compares the Cumulative Distribution Functions (CDFs) of errors by the proposed GrassMA (with timestamps) and the existing Bray-Curtis Distance and A-star Algorithm based Laplacian Eigenmap (BCD+AA-LE) (with timestamps) [45] and LE (without timestamps) [38]. From this figure, we can find that with the help of the timestamps of unlabeled RSS data on user traces, both the GrassMA and BCD+AA-LE perform better than the LE without timestamps in localization accuracy. This result can be interpreted by the fact that the timestamps help a lot in preserving the neighborhood relations of the RSS data on each user trace, which is much beneficial for the physical labeling of unlabeled RSS data.

C. Localization Performance

In this section, we will illustrate the localization performance by using the proposed radio map and other seven existing ones constructed by the RADAR [21], Cubic Spline Interpolation (CSI) [48], Locally Linear Embedding (LLE) [49], LE [40], Semi-supervised Laplacian Regularized Least Squares (S2LapRLS) [50], L1-Graph-algorithm-based Semi-supervised Learning (LG-SSL) [34], and BCD+AA-LE [47].

Fig. 10 presents the estimated locations by using different radio maps, and the corresponding CDFs of errors are shown in Fig. 11. From these results, we can find that the proposed radio map performs best in localization accuracy. For example, compared with the radio map constructed by the BCD+AA-LE which has the closest localization performance to the proposed one, the confidence probability of errors within 3 m by the GrassMA is 80.78%, which is 4.83 percentages higher than the one by the BCD+AA-LE. In addition, the performance of the S2LapRLS and LG-SSL is not good since they do not take the timestamp information into account during the Laplacian graph construction.

We further illustrate the mean of errors under different ratios of labeled RPs in Fig. 12. As expected, the localization error generally decreases with the increase of the ratio of labeled RPs. Among them, the GrassMA exhibits the strongest robustness to the decrease of the ratio of labeled RPs. For example, when the ratio of labeled RPs decreases from 1 to 0.2, the mean of errors by the GrassMA increases from 2.16 m to 2.21 m (by 2.31%), while the one by the RADAR, CSI, LLE, LE, S2LapRLS, LG-SSL, and BCD+AA-LE increases from 2.32 m to 5.09 m (by 119.40%), from 2.30 m to 3.21 m (by 39.57%), from 2.30 m to 3.56 m (by 54.78%), from 2.30 m to 3.01 m (by 30.87%), from 2.32 m to 2.77 m (by 19.40%), from 2.28 m to 2.60 m (by 14.04%), and from 2.23 m to 2.30 m (by 3.14%) respectively.
Fig. 10. Estimated locations by using different radio maps. (a) RADAR. (b) CSI. (c) LLE. (d) LE. (e) S2LapRLS. (f) LG-SSL. (g) BCD+AA-LE. (h) GrassMA.

Fig. 11. CDFs of errors by using different radio maps.

D. Construction Cost

Finally, Fig. 13 compares the time cost required by different radio maps construction as the ratio of labeled RPs increases from 0.2 to 1. From this figure, we can find that the time cost by the GrassMA equals to the one by the LLE, LE, S2LapRLS, LG-SSL, and BCD+AA-LE, while it is much lower than the one by the RADAR and CSI especially under the large ratio of labeled RPs. This result can be interpreted by the fact that the former five radio maps are constructed by using the semi-supervised manifold learning, which is much beneficial for the calibration cost reduction.

For example, when the ratio of labeled RPs is 1, the GrassMA requires collecting 20 RSS data at each of the 327 RPs as well as 1210 unlabeled RSS data on 10 user traces for radio map construction, which spends 7750(= 20 × 327 + 1210)s in total, while the RADAR requires
72700 (≈ 100 × 327) s to collect labeled fingerprints, which is about 7 hours more than the one by the GrassMA.

VII. CONCLUSION

In this paper, we have investigated a new approach of reducing the effort of fingerprint database construction for indoor WLAN localization by decreasing both the number of labeled RPs and RSS sample capacity. The proposed semi-supervised manifold alignment approach is verified to be able to label the unlabeled data with physical locations, which can help a lot in enriching the raw sparse radio map, and consequently save the time and labor cost for fingerprints calibration. In future, we will continue to study the effectiveness and efficiency of the proposed system to be applied in a more complicated indoor environment, such as the multi-floor environment, and meanwhile explore the unsupervised manifold alignment approach to further reduce the fingerprints calibration cost for indoor WLAN localization.

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