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Unsupervised Deep Feature Learning to Reduce the Collection of Fingerprints for Indoor Localization using Deep Belief Networks

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***Abstract*—One of the most practical localization techniques is WLAN-based fingerprinting for location-based services because of the availability of WLAN Access Points (APs). This technique measures the Received Signal Strength (RSS) from APs at each indicated location to construct fingerprints. However, the collection of fingerprints is notoriously laborious and needs to be repeatedly updated due to the changes of environments. To reduce the workload of fingerprinting, we apply Deep Belief Networks to unlabeled RSS measurements to extract hidden features of the fingerprints, and thereby minimize the collection of fingerprints. These features are used as inputs for conventional regression techniques such as Support Vector Machine and K-Nearest Neighbors. The experiment results show that our feature representations learned from unlabeled fingerprints provide better performance for indoor localization than baseline approaches with a small fraction of labeled fingerprints traditionally used. In the experiment, our approach already improves the localization accuracy by $1.9\,\mathrm{m}$ when using only 10% of labeled fingerprints, compared to the closest baseline approach which used 100% of labeled fingerprints.**

***Index Terms*—WLAN-fingerprint based localization, unsupervised deep feature learning, indoor localization, fingerprint reduction, deep belief network**

I. Introduction

Indoor localization is an essential task for a wide range of mobile computing applications, such as logistics, crowd monitoring, network allocation, and marketing. Although the Global Positioning System (GPS) is undoubtedly the most popular positioning technology, it commonly fails to localize targets in indoor environments due to signal attenuation and scattering [1], [2]. Among alternative localization technologies for indoor environments such as acoustics, magnetic fields, accelerometers, and Received Signal Strength (RSS), RSS is the most popular one because of the proliferation of WiFi WiFi Access Points (APs) and mobile devices. Therefore, using the measurements of radio signals such as RSS between smartphones and APs become one of the most practical solutions for indoor localization. The same fingerprinting techniques also can be used with Bluetooth Low Energy (BLE) devices.

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Accurate indoor localization using WiFi infrastructure, however, remains elusive. Although fingerprinting algorithms such as [3]–[6] can provide acceptable localization accuracy, they require an enormous amount of measurements, the so-called fingerprints, to build a fingerprint database for an off-line training phase before real-time position estimation. Such an essential requirement imposes restraints on autonomous deployments of a localization system in practice, especially for large and complex spaces. Using fingerprinting localization systems in large areas also requires that significantly large amounts of data from the fingerprint database have to be acquired and stored in the mobile device for location estimation. Even if the laborious fingerprinting can be done, the environment may later change frequently, and thus the accuracy of fingerprinting systems will significantly decrease. Hence, the fingerprinting approach needs to update the fingerprint database regularly to maintain high accuracy. These problems severely affect the application of indoor localization systems based on fingerprinting.

Many approaches have been proposed [7]–[9] to alleviate the tedious collection of location-labeled signatures. However, these approaches use dimension-reduction schemes which cannot learn the hidden features of the localization fingerprint as well as deep learning schemes can. The main reason is that the proposed methods are relatively shallow as they can infer only one-layer representations. Deep learning approaches such as Deep Belief Network (DBN) [10], on the other hand, use a generative probabilistic model that can represent hierarchically hidden features at different hidden layers. Each hidden layer unit learns a statistical relationship between the units in the lower layer; the higher layer representations tend to become more complex. Training a DBN consists of two phases: pre-training and fine-tuning. We observed that the pre-training can learn a probability distribution from unlabeled samples in an unsupervised manner. To the best of our knowledge, deep feature learning using the pre-training phase of DBN has not been extensively applied to fingerprinting localization to reduce the efforts of the location annotation of RSS fingerprints.

In this paper, we aim at reducing the labeled fingerprints while maintain the localization accuracy as high as possible by employing the unsupervised pre-training phase of DBN.

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Our work builds on the principle that only a small number of fingerprint measurements have known location (are labeled), while a large number of fingerprint measurements have unknown locations (are unlabeled). The reason is that the unlabeled fingerprints are easier to be collected, especially with the crowdsourcing concept, in which mobile phones simply take a snapshot of observed RSS values. Our hypothesis is that even though an unlabeled fingerprint measurement is less informative than a labeled fingerprint measure, a large number of unlabeled fingerprints may be equally informative if their hidden representations can be effectively exploited.

We evaluate our unsupervised feature learning based approach on a real-world dataset, i.e., the UJIIndoorLoc [11], which contains thousands of fingerprint measurements with thousands of fingerprints. The fingerprints are collected in large buildings by 25 of smartphones. The experimental results show that a combination of Support Vector Regression (SVR) and deep feature learning can estimate quite accurately unknown locations of smartphones, even when only 1% (52 over 5249) of the labeled fingerprints in the dataset is used. Conversely, the baseline approach with shallow feature learning, from one-layer of units, mostly fails under such a low number of labeled fingerprints.

The rest of this paper is organized as follows. Section II reviews the related techniques of WiFi-based localization, especially for indoor environments. Section III presents a brief of unsupervised feature learning and Deep Belief Networks, followed by our solution based on unsupervised deep feature learning in Section IV. The performance evaluation and important observations presented in Section V. Finally, we conclude our paper in Section VI.

II. Related Work

Although GPS is definitely the most popular positioning technology, it does not work well in GPS-blocked environments due to signal attenuation and scattering. As alternative technologies, short-range radio communications such as WiFi and BLE are widely used for indoor environments. Most WiFi-based indoor localization systems are mainly categorized into either location-based fingerprinting techniques or ranging based on radio signal propagation models. When accuracy is crucial, fingerprinting is preferred. Otherwise, range-based localization with a multilateration method is used due to its simplicity.

For simplicity, range-based approaches with multilateration are the most used in mobile computing [12]–[15]. Range-based approaches demand an offline phase to calibrate the parameters for the pass-loss model. The path-loss model typically consists of a number of environmental parameters. For example, the Radio Frequency (RF) signal is generally considered to follow the Log-Normal Shadowing Model (LNSM) in indoor environments [16], which defines the decay of the signal over a distance. To calculate the distance using such RSS model, the environmental parameters of the LNSM needs to be known or calculated. There are also more complicated LNSM models such as those presented in [17], [18] that consider the effects of fading channels caused by obstacles such as walls and the unpredictable multipath effects. Usually, a simple LNSM model such as the one presented in [16] is used in many works including [12]–[15] since it is simpler and still valid for many indoor environments [16].

However, the majority of proposed range-based approaches generally give a relatively poor accuracy due to the intrinsic phenomenon of the radio signal propagation and fundamental limit of the current estimation methods. On the other hand, most indoor environments cause severe multipath effects that lead to a high variability over time for the same location. Such high variability results in a large error even for a stationary device.

Fingerprinting techniques build a fingerprint database that can be used to approximate a location. The database, a so-called radio map, is constructed by measuring RSS at a number of known locations – *labeled fingerprints*. The test location is then estimated by comparing the new RSS values to the fingerprint database.

RADAR [3], [19] is a naive fingerprinting technique that determines smartphone's location by finding a known signature that is most similar to the actual RSS measurement of the location. In RADAR, it is shown that the highest accuracy is obtained by computing the mean coordinates of three nearest neighboring signatures. The k-Nearest Neighbors (KNN) technique, in addition to its simplicity, turned out to be among the most accurate ones. This technique is later improved to LWR-WKNN [4] (a data interpolation technique). More advanced techniques based on shallow supervised neuron networks such as Radial Basis Function (RBF) [5] and Support Vector Machine (SVM) [20] also have been used for fingerprinting localization.

However, building such a fingerprint database is a laborious task as it requires to collect fingerprints from numerous positions. The built fingerprint database generally stays valid only for a short time as the environment may change due to objects and human mobility, among others. And also the APs may be changed.

To tackle the problem of labeled fingerprint collection, many researchers have proposed techniques to reduce the required labeled fingerprints [7]–[9]. These works aim at making use of unlabeled data. In fact, with the abundance of smartphones in crowds, the collection of unlabeled fingerprints is much more convenient and less privacy-intrusive, compared to the labeled ones. However, the main techniques used in these existing studies are shallow mechanisms which are either (i) data interpolation, in which data interpolation is used to semi-automatically label unknown fingerprints, or (ii) dimension reduction which is used to extract the shallow hidden features of the fingerprints in an unsupervised manner. Conversely, in this paper we focus on deep hidden feature learning.

The work which is most related to our approach is [6]. This work uses deep learning techniques including DBN to predict smartphone locations. The authors use DBN as a supervised regression for location estimation, whereas we employ DBN as an unsupervised manner for feature learning.

In fact, DBN [10] has been subsumed in deep learning

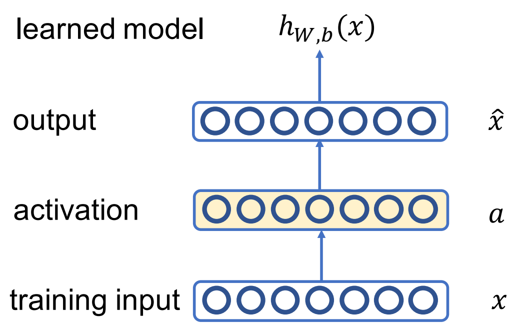

Fig. 1: Unsupervised feature training architecture with autoencoder.

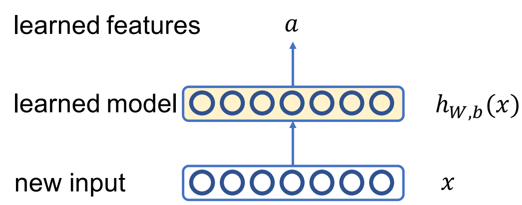

Fig. 2: Unsupervised feature transforming with learned activations.

approaches, and excelled in pushing the state-of-the-art all relevant benchmark tasks in machine learning and computer visions. Much of these works have been motivated by the human neural networks of cortexs hierarchical organization and indeed many researchers frequently compared their algorithm results to the receptive fields of oriented nerve cells found in frontal cortex. Despite the success of deep learning on efficient performance of unsupervised layer-by-layer, supervised learning and inference [21] in many applications, the typical problems of overfitting and premature convergence within error backpropagation have not been completely feasible yet in traditional deep networks. Therefore, DBN was becoming significantly increase for computing power of numbers of big data applications proved by the success of works in computer vision [22], [23], machine transcription and translation [24], classification tasks [25], [26] and voice recognition [27].

To the best of our knowledge, deep feature learning using the pre-training phase of DBN has not been extensively applied to fingerprinting localization to reduce the efforts of the location annotation of RSS fingerprints.

III. Preliminary Background

In this section, we will introduce briefly the concept of unsupervised feature learning and the DBN architecture. Through this section, we clarify between *shallow feature learning* and *deep feature learing*.

A. Unsupervised Feature Learning

Suppose we have unlabeled training data x. The key idea of unsupervised feature learning is applying *backpropagation*. In other words, input x can be used as both the input and the output of a training network as illustrated in Fig. 1, so-called an *autoencoder* neural network. By doing so, we can train the network to obtain a function $h_{W,b}(x) \approx x$, so as to approximate output $\hat{x}$ that is similar to x.

Having trained the parameters W of this model, given any new example of input x, we can compute the corresponding unsupervised features which are the activations a of the hidden units as illustrated in Fig. 2.

Conventionally, Principal Component Analysis (PCA) [28] with the core is Singular Value Decomposition (SVD) [29] is used to generate the unsupervised features as studied in [9]. PCA is a linear feature learning approach since it rotates the original axes to a new coordinate system aligning with the orientation of maximum variability in the input. Rotation is a linear transformation. Hence, PCA is considered as a *shallow feature learing* since it exploits only the shallow representation of the data, the first-order and the second-order moments of the input data. Moreover, PCA can only reduce but extend the dimension. In other words, the number of the learned features (activations) cannot be greater than the dimension of the input. These limitations make PCA may not well characterize the hidden features of complex and unstructured data such as the radio map.

B. Deep Belief Networks

In [10], Hinton et. al. showed that DBNs can be built by stacking Restricted Boltzmann Machiness (RBMs) [10]. Such RBMs-stacked model can be trained in a greedy manner to extract a deep hierarchical representation of the training data. The joint distribution between the vector $\mathbf{x}$ of observations and the l hidden layers $\mathbf{h}^k$ is modeled as follows.

$$P(x, h^1, \ldots, h^k) = \left(\prod_{k=1}^{l-2} P(h^k | h^{k+1}) \right) P(h^{l-1}, h^l), \quad (1)$$

where $x = h^0$, $P(h^{k-1}|h^k)$ is a conditional distribution for the visible units conditioned on the hidden units of the RBM at level k, and $P(h^{l-1}, h^l)$ is the visible-hidden joint distribution in the top-level RBM. The DBN can be visualized as in Fig. 3 as a stack of RBMs.

To train a DBN network we first pre-train the network with unlabeled data. The dash arrows in Fig. 3 indicate the pre-training path. Similar to the autoencoder described in Section III-A, we feed unlabeled examples of x as the inputs of the pre-training DBN to approximate the outputs which are the approximation $\hat{x}$. By doing so, we obtain the corresponding trained RBM model which can be used to compute the feature vector. Since this autoencoder comprises stacks of deep learning models, RBMs, it may provide better insights into hidden features. This RBM-based approach is so-called *deep feature learning*.

IV. Unsupervised Feature Learning based Approach

We assume that we can obtain limited labeled fingerprints and abundant unlabeled fingerprints. We will present our

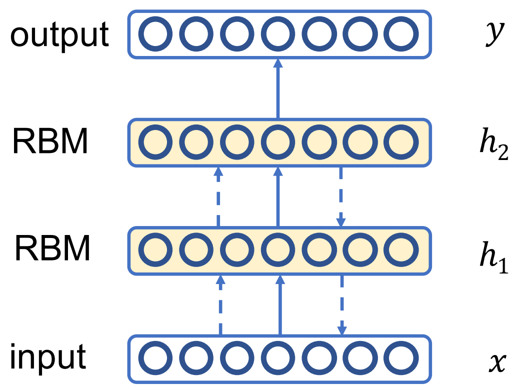

Fig. 3: The network architecture of Deep Belief Network. Dash arrows illustrate pre-training with unlabeled data. Solic arrows illustrate fine-tuning with labeled data.

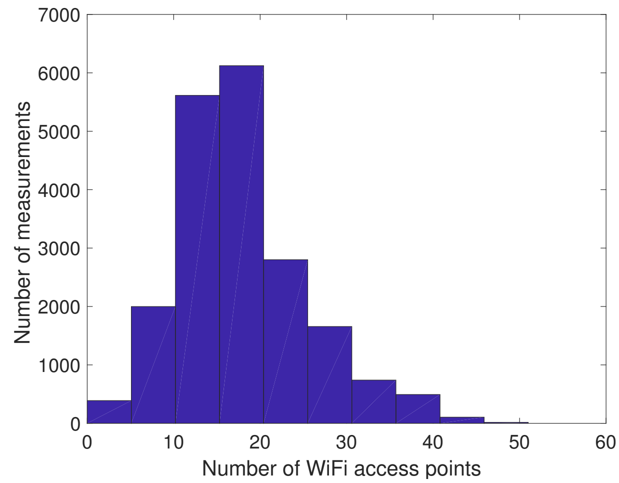

Fig. 4: The histogram of APs scanned by smartphones in the first building of the UJIIndoorLoc dataset [11].

fingerprinting localization using unsupervised feature learning with DBN through two phases: the offline phase and the online phase.

In the offline phase, firstly, both labeled and unlabeled fingerprints are used for unsupervised shallow feature learning, and then the trained shallow feature learning model is used to transform the fingerprints to shallow features. Secondly, the shallow features are used for unsupervised deep feature learning. Finally, both the shallow and deep feature learning models are used to transform the labeled fingerprints into labeled deep features, and then these deep features, together with their location labels, are used to train a supervised location estimation model.

In the online phase, the fingerprints of unknown/test locations will first be transformed to the deep features using the trained unsupervised feature learning models in the offline phase. Then the deep features of the test data will be used to infer the unknown location using the trained supervised location estimation model.

The above steps are presented in more details in the following subsections.

A. *Shallow Feature Learning (Offline)*

In large buildings there are typically numerous APs; however, not all of them can be scanned by a smartphone from a specific location due to the limits of WiFi's communication range. For example, Fig. 4 shows the histogram of the APs scanned by smartphones according to the UJIIndoorLoc dataset [11]. The average number of APs each smartphone could scan was 18, whereas, there are 520 APs in total. The dataset was collected by means of more than 20 different users and 25 different Android devices.

Since the number of APs scanned in each measurement is too small compared to the number of available APs, a lot of the RSS values of the measurements will not be available. Thus, the input will be somewhat redundant. Moreover, the adjacent APs are highly correlated since they would give very similar RSS values. Because of the redundancy and correlation, we use PCA [28] with the core is SVD [29] to reduce effectively the dimension. Note that PCA and SVD also allow us to extract the shallow hidden features in an unsupervised manner as studied in [9].

In addition, the WiFi radio signal is extremely sensitive to objects and environments, especially the human body. In other words, the RSS measurements are noisy. Hence, we use PCA whitening to reduce the noise effects.

These shallow features, which are processed by noise whitening and dimension reduction, will be used as the input for deep feature learning in the next step. Note that such shallow features also can be used as input to train fingerprinting models as studied in previous works.

B. *Deep Feature Learning (Offline)*

In highly dynamic indoor environments, localization systems using only the shallow features learned in the previous steps cannot maintain their high performance for a long time due to the poor level of generalization of the shallow architectures. However deep architectures such as DBN can learn high levels of features that represent the dynamic indoor environment.

In this work, we employ the pre-train phase of DBN for unsupervised training of the DBN model, using the shallow features of the unlabeled RSS measurements of the training set. The hidden layers are pre-trained using the Greedy Layer-wise algorithm, which ensures a fast way to performing approximate inference training each RBM bottom up.

The trained deep feature learning model is then used to transform shallow features into deep features, when using the validation set and test set.

C. *Fingerprinting Model Training (Offline)*

To train the fingerprinting model that can be used in the online phase for location estimation, we use shallow supervised regression/classification algorithms such as SVM. Regression is used when we want to estimate the location at the coordinate level, whereas, classification is used when we want to estimate the location at the room and floor level. We train the supervised fingerprinting model with the labeled fingerprints. In particular, the labeled fingerprints are first transformed to shallow features. The shallow features are then transformed to the deep features. These deep features are used as the input of the regression/classification algorithms.

The trained regression/classification model is stored at the server for location estimation in the online phase.

D. Location Estimation (Online)

New locations of users' smartphones are estimated using the models trained during the offline phase: the shallow feature learning, the deep feature learning, and the location regression or classification. The raw RSS values from the APs measured by the smartphones at unknown locations will be used to extract first the shallow features and then the deep features. These deep-learned features of the unknown locations will be used as the input for the regression/classification model to estimate the unknown locations.

V. Experiment

A. Dataset

To verify our approach, we use the UJIIndoorLoc dataset [11], which has been considered as a benchmark for indoor localization. The dataset was collected in 3 buildings with a total surface of $108\,703\,\mathrm{m}^2$. The dataset consists of 19937 training measurements and 1111 test measurements. The test set was taken 4 months after the training one to assure the independence of the dataset. In the dataset, there are 520 APs which are scanned by smartphones. The experiments were done by more than 20 users carrying 25 different smartphones with different models.

In this paper, we will present only the localization results in the first building from the dataset since the results of the two other buildings are similar. For the first building, there are 5249 measurements in the training set and 536 measurements in the test set. Each measurement comprises 520 RSS values corresponding to the 520 APs. In other words, the input examples have 520 dimensions. All of them were labeled with the actual location. In order to validate the unsupervised feature learning approaches, we split randomly the training set into two parts. One part is considered as labeled dataset, and the other part is considered as unlabeled dataset. This division is repeated with different ratios, ranging between 1% to 99%.

B. Algorithm Setup

To investigate the performance of localization with unsupervised deep feature learning, we implemented the SVM as a regression model, the so-called SVR. Previous work such as [20] has shown that SVM outperforms other techniques. The implemented SVR is combined with either our deep feature learning or the shallow feature learning. In fact, SVR with shallow feature learning PCA is one of the best approaches for the conventional fingerprinting.

Given the UJIIndoorLoc dataset, we first set up parameters for the shallow feature learning based on PCA with the SVD solver. Since the average number of APs scanned by each smartphone was 16 in the training set of the building, we set the number of lower dimension is $2 \times 16 = 32$ to assure it covers sufficiently the informative channels. Setting with a value higher than 32 would result in redundant dimensions and increasing computation.

For the deep feature learning based on the pre-training phase of DBN, we set the network architecture as 2 hidden layers of 260 nodes. The number of epoch for RBM is set to 300. The learning rate of RBM is set to 0.01. The Rectified Linear Unit (ReLU) is used to speed up the training process. This setting is based only our heuristic tries with various architectures of the DBN using the training dataset, with regards to the performance in terms of accuracy and running time.

For the location supervised training and estimation based on SVM. The kernel of SVR is set as RBF of which coefficient is 0.1 as default. A neuron network with RBF kernel has been shown to be effective for location estimation in [5].

With these settings, we implemented the algorithms using in Python with the TensorFlow framework.

C. Experimental Results

Fig. 5 shows the overall performance RMSE of the SVM algorithm when using with the shallow feature learning and the deep feature learning. In the figure we vary the number of labeled measurements, from 52 (corresponding to 1% of the measurements) to 5249 (corresponding to 100% of the measurements). When used with deep feature learning, SVM provides significantly better location estimation. Note that the SVM perform poorly when paired with raw values of RSS measurements, thus we exclude the results from the figures.

In addition, we observed from the figure that the performance of both approaches are improved when there are more labeled measurements. However, the improvement only increases significantly when the number of unlabeled measurements is below 524. This means keeping increasing the labeled measurement does not always improve the localization performance, while it increases significantly the cost of data collection and annotation.

Furthermore, Fig. 5 shows that deep feature learning can help the SVM algorithm maintain its localization performance when the number of labeled measurements are low. Despite using only 52 labeled measurements, the SVM with deep feature learning can still provide relatively good results. This is shown by the fact that RMSE increases only about $1.9\,\mathrm{m}$ (from $6.2\,\mathrm{m}$ to $8.1\,\mathrm{m}$) compared with when using 5249 labeled measurements. Furthermore, our approach improves the localization accuracy by $2.1\,\mathrm{m}$ when using only 10% of labeled fingerprints, compared to the most closest baseline approach which used 100% of labeled fingerprints.

Since Fig. 5 only shows the overall performance in terms of RMSE, we investigate the performance in detail using the Cumulative Distribution Function (CDF) plot as shown in Fig. 6 and Fig. 7. In particular, Fig. 6 and Fig. 7 show the distribution

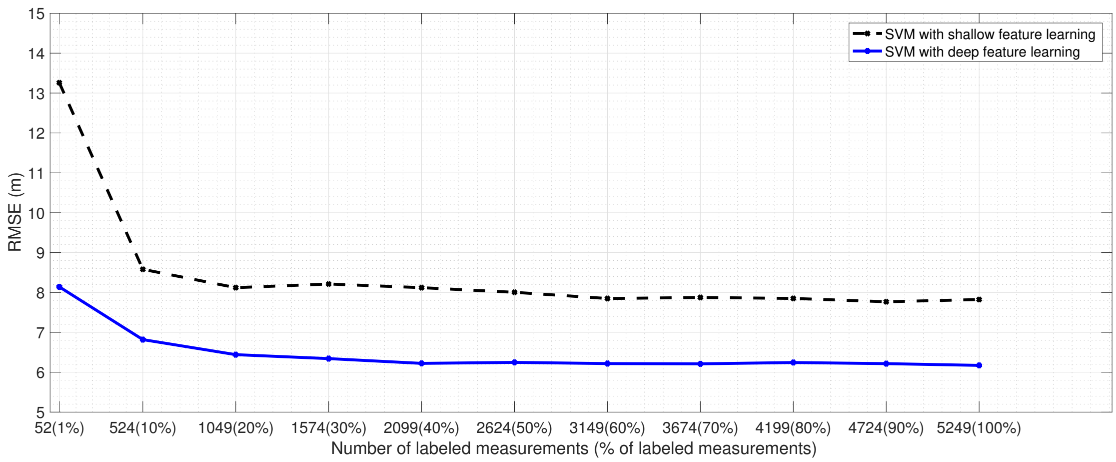

Fig. 5: The Root Mean Square Error (RMSE) when varying the number of labeled fingerprints.

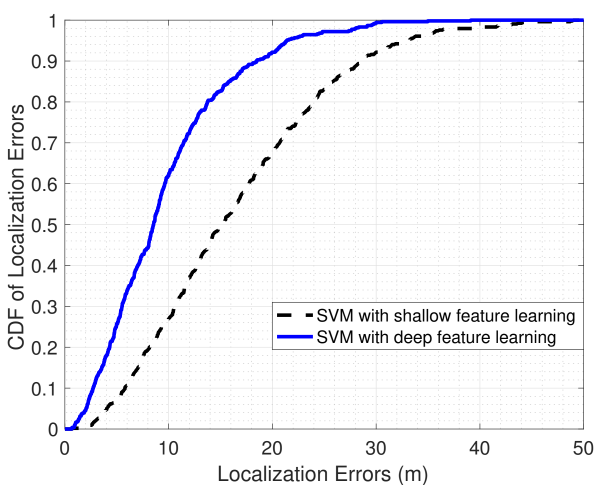

Fig. 6: The Cumulative Distribution Function (CDF) of smartphone localization errors when using 52 labeled fingerprints.

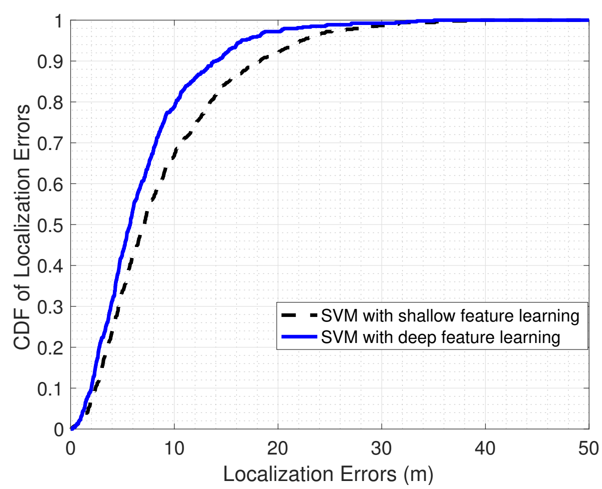

Fig. 7: The Cumulative Distribution Function (CDF) of smartphone localization errors when using 5249 labeled fingerprints.

of localization errors when 52 and 5249 labeled measurements are used, respectively.

As it can be seen from Fig. 6, using only 52 labeled, SVM combined with deep feature learning still performs very well, where 90% of test positions have an error smaller than $18.0\,\mathrm{m}$. It can also been seen from Fig. 6 that performance of SVM combined with shallow feature learning performs are significantly affected by the lack of labeled measurements, where 90% of test positions have an error smaller than $28.0\,\mathrm{m}$

The above difference of localization performance between the shallow feature learning and deep feature learning is much less when the labeled measurements are abundant as shown in Fig. 7, which is the case of using 100% of labeled fingerprints. In this case, the performance of SVM when combined with the shallow feature learning and deep feature learning are both better and quite similar. The performance of SVM combined with the shallow feature learning is closely behind that of SVM combined with the deep feature learning.

VI. Conclusion

In this paper we have presented a new fingerprint localization approach that can perform well even with a limited number of labeled fingerprints. The bottom line of our approach is the Greedy-wise pre-training phase of Deep Belief Network (DBN) which is typically used to pre-train data for a supervised classification or regression problem. However, in this paper, we employed the pre-training phase to train an unsupervised deep feature learning model. The model is then used to extract the deep features of the labeled fingerprints for localization estimation. By doing so, we can take the advantage of unlabeled data which are much more convenient to be collected since they do not require location annotation and are less sensitive to users' privacy. Moreover, deep feature learning from large numbers of unlabeled fingerprints even provide better localization accuracy than traditional approaches with labeled fingerprints such as using raw Received Signal Strength (RSS) values and shallow features.

We validated our approach using Support Vector Regression (SVR) and one of the most popular real-world datasets which contains thousands of examples. The validation results show that the new approach based on Support Vector Machine (SVM) combined with deep feature learning surpassed the conventional approaches SVM combined with shallow feature learning or raw data. Furthermore, even when using our deep feature learning with only 1% of the available labeled fingerprints, the Root Mean Square Error (RMSE) is still as good as when using conventional shallow feature learning with 100% of available labeled fingerprints. We hope that our work will inspire more research on indoor localization to exploit unsupervised feature learning for fingerprint reduction and mapping.

In our future work, we will verify our approach with more WLAN-based fingerprint data sets and develop deep transfer feature learning techniques to extract hidden features from different data domains. Concretely, the hidden features of an indoor environment can be extracted from unlabeled fingerprints collected in other different indoor environments. If we can get our algorithm to perform the transfer feature learning, it will be much more practical as it reduces significantly the cost of fingerprint collection.

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