Transferring Localization Models Across Space

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abstract

Machine learning approaches to indoor WiFi localization involve an offline phase and an online phase. In the offline phase, data are collected from an environment to build a localization model, which will be applied to new data collected in the online phase for location estimation. However, collecting the labeled data across an entire building would be too time consuming. In this paper, we present a novel approach to transferring the learning model trained on data from one area of a building to another. We learn a mapping function between the signal space and the location space by solving an optimization problem based on manifold learning techniques. A low-dimensional manifold is shared between data collected in different areas in an environment as a bridge to propagate the knowledge across the whole environment. With the help of the transferred knowledge, we can significantly reduce the amount of labeled data which are required for building the localization model. We test the effectiveness of our proposed solution in a real indoor WiFi environment.

Introduction

Many location based applications rely on our ability to accurately locate a mobile device in an indoor environment. There are many applications of location estimation, including activity recognition, robotics etc. Localization through WiFi signals is a major technique in indoor localization (Letchner, Fox, and LaMarca 2005). To enable localization, we can collect the received-signal-strength (RSS) values and their corresponding locations as the training data and build a localization model in an offline mode, and then apply the model on newly received data for estimation in an online mode. In order to collect the RSS training data, we have to carry a mobile device and walk around in a building to record values of signal strength at various locations. However, this process is very expensive, especially when the indoor building is large. Our work is aimed at developing a novel solution to this problem. In particular, we only collect the labeled data from a subarea of a building and unlabeled data from the remaining area. We then transfer the localization model from subarea to the rest of the building with the help of a few labeled data in the interested areas. As a result, calibration effort is greatly reduced.

In the past, a few approaches have been proposed to reduce the calibration effort, but none has addressed the problem of adapting the models learned in one spatial area to fit another spatial area across an environment. (Ferris, Fox, and Lawrence 2007) applied a Gaussian-Process-Latent-Variable model (GP-LVM) to construct a RSS mapping function under an unsupervised learning framework. In their model, an appropriate motion-dynamics model needs to be given. (Pan et al.) proposed to a manifold regularization model based on manifold regularization (Belkin, Niyogi, and Sindhwani 2006), which is under a semi-supervised learning framework. In this model, the labeled training data still need to be uniformly collected over the whole building. A challenging problem is to label the locations of only *a small part of a building* while learning a model that can be applied to all parts of the building.

Our problem can be considered as a transfer learning problem across space. To be sure, this is a very challenging problem, because the marginal probability distributions between the labeled data and the unlabeled data may be very different. This makes the same-distribution assumption of many semi-supervised learning techniques do not hold. We address this problem as a transfer learning problem (Caruana 1997), in which we derive some implicit domain knowledge from the labeled data in one area and propagate the knowledge to the rest of the environment to learn an accurate complete mapping function.

More specifically, we denote the WiFi signal data collected in an area **A** as S^a and denote WiFi signal data collected in an area **B** as S^b. We assume S^a to be fully labeled whereas S^b to have only a few labeled examples and some unlabeled ones that can be easily obtained by quickly walking through the area. Our key observation is that there must be some latent knowledge or common structure between S^a and S^b, which can be used for propagating the label information across space, when the area **A** and the area **B** are in a same indoor WiFi environment.

Our solution consists of two subtasks. Firstly, we auto-

matically extract the domain knowledge of an indoor environment from the labeled data collected in an area. We formulate a quadratically constrained quadratic program (QCQP) optimization problem (Boyd and Vandenberghe 2004) to solve this problem via a manifold of the WiFi signal data. This manifold acts as a bridge that propagates the common knowledge across different areas. Secondly, we incorporate the extracted domain knowledge into a model to propagate the label information to unlabeled data collected in the rest of the environment. We exploit the common knowledge learned in the previous step as constraints and incorporate them to another QCQP optimization problem to estimate labels of the unlabeled data collected in the rest of the environment. We empirically evaluate our proposed solution by conducting experiments in a real office WiFi environment. The experimental results show that our solution is quite effective in learning a high performance localization model while reducing the calibration effort.

WiFi Localization in Indoor Environments

Received-signal-strength (RSS) based indoor localization and tracking methods have been increasingly popular for WiFi networks (Bahl, Balachandran, and Padmanabhan 2000). The problem of RSS based indoor localization is to estimate locations of a mobile device based on its RSS values. Consider a two-dimensional indoor localization problem. [1] A location is represented by $\boldsymbol{\ell} = (x, y)$, where x and y correspond to a value of x-coordinate and a value of y-coordinate, respectively. Assume that there are m transmitters, such as Access Points (APs), in an indoor environment, which periodically send out wireless signals. A mobile device can receive signals sent by each of the m APs. Thus, the signals received by a mobile device at a certain location can be represented by a vector $\mathbf{s} = (\mathbf{s}_1, \mathbf{s}_2, ..., \mathbf{s}_m)^T \in \mathbb{R}^m$. The goal of a localization system is to estimate the location $\boldsymbol{\ell}_i$ of a mobile device based the RSS vector $\mathbf{s}_i = (\mathbf{s}_{i_1}, \mathbf{s}_{i_2}, ..., \mathbf{s}_{i_m})^T$ received by the mobile device. In an *offline* or *training phase*, a mapping function is learned from a large amount of location-labeled RSS vectors collected at various areas in a building. In an *online* phase, the learned mapping function is used to locate the mobile device using its real-time signal vectors. Here the locations of APs are not necessarily known.

Existing approaches of RSS based localization fall into two main categories: propagation-model based methods and learning-based methods. Propagation-model based methods rely on indoor radio-signal propagation models. These methods are poor in handling the uncertainty (Bahl, Balachandran, and Padmanabhan 2000). Learning-based methods apply machine learning techniques, such as Gaussian processes (Ferris, Hähnel, and Fox 2006) and kernel methods (Nguyen, Jordan, and Sinopoli 2005), to handle the uncertainty in localization problems. A major drawback of these methods is that they all require a large amount of labeled data to train the models. In order to reduce the calibration effort or the size of labeled data, (Ferris, Fox, and Lawrence 2007) applied Gaussian-Process-Latent-Variable models (GP-LVMs) to exploit the latent-space locations under an unsupervised framework. An assumption of this model is that an accurate motion dynamics model is given, which can benefit building a localization mapping function. (Pan and Yang 2007) proposed to apply a semi-supervised manifold technique for mobile device tracking in wireless sensor networks. However, their model still needs to collect labeled data through the whole indoor environment, which cannot reduce the calibration effort dramatically. Our solution can derive implicit knowledge from the labeled data collected in an area. By using the extracted knowledge, we can reduce the labeled data collected in the rest of the building area dramatically while keeping the localization performance at a high level.

[1] The localization problem can be seen as a dimensionality reduction problem. Thus an extension to the three-dimensional case is straight-forward.

Transfer Learning for WiFi Localization

Problem Statement

Consider a transfer learning problem for two-dimensional WiFi indoor localization. Suppose that we have n_1 signal data collected in an area **A**. These data are denoted by $S^a = \{\mathbf{s}_i^a\}$, where $\mathbf{s}_i^a = [\mathbf{s}_{i_1}^a, \mathbf{s}_{i_2}^a, \ldots, \mathbf{s}_{i_m}^a]$, $i = 1, 2, \ldots, n_1$, and m is the number of APs. For simplicity, we assume that all the n_1 signal vectors in S^a are labeled, which means that the locations corresponding to all the signal vectors are known[2]. In addition, we have n_2 signal vectors collected in the remaining area **B** of the indoor environment. These data are denoted by $S^b = \{\mathbf{s}_i^b\}$, where $\mathbf{s}_i^b = [\mathbf{s}_{i_1}^b, \mathbf{s}_{i_2}^b, \ldots, \mathbf{s}_{i_m}^b]$, and $i = 1, 2, \ldots, n_2$. We assume that the first l_2 signal vectors (where $l_2 \ll n_2$ and $l_2 \ll n_1$) in S^b are labeled. Now, we have two signal strength matrices $S^a_{n_1 \times m}$ and $S^b_{n_2 \times m}$, and their label vectors $\mathcal{L}^a = [\boldsymbol{\ell}_1^a, ..., \boldsymbol{\ell}_{n_1}^a]$ and $\mathcal{L}^b = [\boldsymbol{\ell}_1^b, ..., \boldsymbol{\ell}_{n_2}^b]$, where $\boldsymbol{\ell}_i^a$ is the labeled location of $\mathbf{s}_i^a$, for all $i \leq n_1$. Similarly, $\boldsymbol{\ell}_i^b$ is the labeled location of $\mathbf{s}_i^b$, if $i \leq l_2$, otherwise, 0[3]. Our goal is to automatically discover some shared knowledge (KB) in the indoor localization domain. Then we incorporate the KB and the data S^a and S^b to construct a accurate mapping function for the whole environment, including both areas **A** and **B**.

Motivation

To achieve our goal of deriving implicit knowledge from the training data collected in a certain subarea and then transferring it to the remaining area, we need to answer two questions. The first question is what knowledge can be extracted from the signal strength data. As we know, once a wireless communication system is set up in an indoor environment, many APs are fixed at certain locations. Hence, unlike other dynamic environmental factors such as the movement of furniture, these APs are often fixed at their original locations. Intuitively, we can learn a more accurate mapping function from the RSS values to locations once we have knowledge

[2] In general, some locations of S^a can be unknown.

[3] We use 0 to denote an unknown location.

of the APs' locations, or at least their relative locations. We can learn this important domain knowledge from the labeled signal data collected in an area of the environment.

Our second question is how to make the best use of the domain knowledge that we extract based on the labeled examples. As mentioned in the previous subsection, we have two signal strength matrices S^a and S^b in hand. Let us take S^a as an example for explaining our idea. The signal strength vector received by a mobile device in a certain location corresponds to an m-dimensional row in S^a. In contrast, each AP is represented by a particular n_1-dimensional column. Underlying the m-dimensional signal strength data is a two-dimensional manifold, because these signal strength data are collected by a mobile device moving around a two-dimensional physical space. Likewise, underlying the n_1-dimensional AP data is also a two-dimensional manifold, because all the APs are placed on a two-dimensional physical floor[4]. With the above observations, we come to three important domain characteristics implied by the signal strength matrix: (1) If two rows in the signal strength matrix are similar to each other, it implies that the corresponding locations where a mobile device receives the signals are close to each other. (2) If two columns are similar to each other, it implies that the locations of the two corresponding APs are close to each other. (3) Each element $\mathbf{s}^a_{ij}$ reflects the signal strength received by a mobile device at a certain location $\boldsymbol{\ell}$ from the jth AP. If the signal strength is strong, it implies that the location $\boldsymbol{\ell}$ is close to the location of the jth AP. Considering these characteristics, if the location information of the APs is known, we can propagate the label information from a data set S^a to another data set S^b, and then build a accurate localization mapping function with S^a and S^b.

However, in reality, we cannot obtain the location information of all the APs in advance. For example, it is common that an office building is taken by different companies and these companies may set up their own APs. Due to privacy reasons, people from one company may not know the positions of the APs set up by another company. Our transfer learning approach for indoor localization aims at exploiting data collected in a limited area to learn a mapping function for the whole area. Therefore, we can first derive knowledge of the APs' location information from the abundant signal data S^a collected in area **A**. After that, we formalize the estimation of location labels of signal data S^b (collected in an area **B**) as an optimization problem and incorporate the derived knowledge as constraints. In this way, we can obtain an accurate mapping function with S^a, S^b and their labels.

Discovering Domain Knowledge

We now discuss how to extract the location information of the APs from the data S^a collected in area **A**. In order to estimate the locations (physical coordinates) of the APs, a straightforward way is to apply manifold embedding techniques to the columns in S^a, whose intrinsic dimensionality is two. If some APs' locations are known, we can apply semi-supervised techniques to make the estimation more accurate (Ham, Lee, and Saul 2005). However, using only the column data is not enough since the APs are usually far from each other, which violates the basic assumption of manifold methods. Furthermore, it is important to construct the mapping function simultaneously so that we can estimate the locations of the mobile devices at the same time. Fortunately, recall the third domain characteristic mentioned in the previous subsection, namely that there should be certain relations between the rows and the columns. This makes it possible to incorporate the similarities among the rows, the similarities among the columns and the similarities among the rows and columns together to estimate the locations of APs and building the mapping function. We call this process co-localization. In the following subsections, we first introduce a preliminary implementation of co-localization in (Pan and Yang 2007) and then present our important extension, which addresses a major limitation of their model.

Initial Solution for Co-Localization The problem of co-localization described above can be solved through an the optimization process outlined in the optimization problem in (1) in an offline phrase. Note that our goal is to derive knowledge of the APs' locations from the labeled data collected in area **A**, thus the notations used in the optimization problem in (1) are consistent with those related to S^a given in the *Problem Statement* section.

$$f^*_x = \arg\min_{f_x \in \mathbb{R}^{(n_1+m)}} \sum_{i=1}^{n_1} |f_{x_i} - \boldsymbol{\ell}_{x_i}|^2 + \sum_{i=n_1+1}^{n_1+l} |f_{x_i} - \boldsymbol{\ell}_{x_i}|^2 + \gamma_1 f_x^T L f_x. \quad (1)$$

where $f^*_{x_i}$ is the estimated value of x-coordinate of a physical location corresponding to x_i. Similarly, we can estimate f^*_y by replacing x by y. Thus, $\mathbf{f} = [f^*_x, f^*_y] \in \mathbb{R}^{(n_1+m)\times 2}$ is the location coordinate matrix of the mobile device and APs. The first n_1 rows of $\mathbf{f}$ are the location coordinates of the mobile device, and the last m rows are location coordinates of APs. l is the number of labeled columns (corresponding to APs whose locations are known), γ_1 is a parameter to control the smoothness of coordinates along the manifold, and $L \in \mathbb{R}^{(n_1+m)\times(n_1+m)}$ is the graph Laplacian matrix.

L should reflect three types of similarities: the similarities between signal strength vectors $\mathbf{s}_i$ and $\mathbf{s}_j$ (rows of S^a), the similarities between APs and the similarities between APs and signal strength vectors. For the first type of similarities, we can use the rows of S^a to compute the weight matrix $W_s = [w_{ij}]_{n_1\times n_1}$, where $w_{ij} = \exp(-\|\mathbf{s}^a_i - \mathbf{s}^a_j\|^2/2\sigma_s^2)$ if $\mathbf{s}^a_i$ is one of the k nearest neighbors of $\mathbf{s}^a_j$, or vice versa. The corresponding graph Laplacian matrix is $L_s = D_s - W_s$, where $D_s = \text{diag}(d_1, d_2, \ldots, d_{n_1})$ and $d_i = \sum_{j=1}^{n} w_{ij}$. Similarly, we can construct the graph Laplacian matrix corresponding to the similarities between APs: $L_a = D_a - W_a$. We expand L_s and L_a as $L_1 = \begin{bmatrix} L_s & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \end{bmatrix}_{(n_1+m)\times(n_1+m)}$ and $L_2 = \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{0} & L_a \end{bmatrix}_{(n_1+m)\times(n_1+m)}$. The graph Laplacian matrix corresponding to the correlation between

[4]For simplicity, we do not consider the height of the APs since the factor will not affect the localization performance.

APs and signal strength vectors can be constructed as $L_3 = \begin{bmatrix} D_1 & -S^o \\ -S^{oT} & D_2 \end{bmatrix}_{(n_1+m)\times(n_1+m)}$, where S^o is the original signal strength matrix, D_1 and D_2 are diagonal matrices which make the row sums zero (Hendrichson 2006). Note that we use the Gaussian kernel to compute the weight matrix and then construct L_1 and L_2, while we use the original signal strength values in L_3. In order to make L_3 comparable to L_1 and L_2, we can transform $S^o = [s^o_{ij}]_{n_1\times m}$ to a new matrix $S' = [s'_{ij}]_{n_1\times m}$ by the Gaussian kernel $s'_{ij} = \exp(-|s^o_{ij} - s_{max}|^2/2\sigma^2_{ss})$, where s_{max} is the maximal signal strength detected by a mobile device. Thus, L_3 is rewritten as $L_3 = \begin{bmatrix} D'_1 & -S' \\ -S'^T & D'_2 \end{bmatrix}$, where D'_1 and D'_2 are still diagonal matrices which make the row sums zero. One way to construct L from L_1, L_2 and L_3 is to combine them linearly, as: $L = \mu_1 L_1 + \mu_2 L_2 + \mu_3 L_3$, where $\mu_i \geq 0$ for $i = 1, 2, 3$.

In the online phase, the corresponding location of a query $\mathbf{s}_i = [\mathbf{s}_{i_1}, \mathbf{s}_{i_2}, \ldots, \mathbf{s}_{i_m}]$ is estimated using the method of harmonic functions (Zhu, Ghahramani, and Lafferty 2003), which is defined in Equation (2), as:

$$\mathbf{f}_i = \frac{\sum_{j\in\mathcal{N}} w_{ij}\mathbf{f}_j}{\sum_{j\in\mathcal{N}} w_{ij}}, \tag{2}$$

where $\mathcal{N}$ is the set of k nearest neighbors of $\mathbf{s}_i$ in S^a, w_{ij} is the weight between $\mathbf{s}_i$ and $\mathbf{s}^a_j$ which can be obtained as described above, and $\mathbf{f}_j$ is the location of $\mathbf{s}^a_j$ solved from the optimization problem in (1).

Extended Co-Localization The parameters μ_1, μ_2 and μ_3 for combining L_1, L_2, L_3 are not easy to be tuned. We now develop a method to automatically determine the parameters. In our method, we take the parameters as variables and construct some constraints using these variables. By imposing these constraints and reformulating the optimization problem in (1), we can obtain the optimal solution of $\mathbf{f}$ without explicitly setting the parameter values. In practice, we use $\tilde{L} = L^T L$ instead of L (Ham, Lee, and Saul 2005). Similarly, we use $\tilde{L_1}$, $\tilde{L_2}$ and $\tilde{L_3}$, which are positive semidefinite, to replace L_1, L_2 and L_3. We view this problem as a kernel matrix learning problem where the target kernel matrix is a linear combination of some semidefinite positive kernel matrices (Lanckriet et al. 2004). Thus the optimization problem in (1) can be rewritten as:

$$\begin{aligned} \min_{f_x} \quad & (f_{x_i} - \boldsymbol{\ell}_{x_i})^T J (f_{x_i} - \boldsymbol{\ell}_{x_i}) + \gamma_1 f_x^T L f_x \\ \text{subject to} \quad & trace(L) = c, \\ & L \succeq 0, \\ & L = \textstyle\sum_{i=1}^3 \mu_i L_i, \\ & u = [u_1, u_2, u_3] \geq 0, \end{aligned} \tag{3}$$

where $J_{(n_1+m)\times(n_1+m)}$ is a diagonal matrix and $J(i,i) = 1$ for $1 \leq i \leq n_1$, if the corresponding location of $\mathbf{s}^o_i$ is known; $J(i,i) = 1$ for $n_1 + 1 \leq i \leq n_1 + m$, if the location of the corresponding AP is known; otherwise, $J(i,i) = 0$.

After several steps of derivation (we leave out the details because a similar derivation can be found in (Lanckriet et al. 2004)), the optimization problem in (3) can be rewritten as the following QCQP problem:

$$\begin{aligned} \min_{f_x, t} \quad & (f_{x_i} - \boldsymbol{\ell}_{x_i})^T J (f_{x_i} - \boldsymbol{\ell}_{x_i}) + \gamma_1 ct \\ \text{subject to} \quad & \tfrac{1}{\mu_i} f_x^T L_i f_x \leq t,\ i = 1, 2, 3. \end{aligned} \tag{4}$$

This problem can be solved using standard software toolboxes such as SeDuMi (Sturm 1999). Similarly, we can find the optimal solution of f_y by replacing x by y. Finally, we get the location coordinate matrix $f = [f^*_x, f^*_y]$ of the signal strength vectors and APs. The first n_1 coordinates are used in the mapping function. The last m coordinates are the estimated locations of the APs. We denote it as $P = [P_x, P_y]_{m\times 2}$. P is the knowledge we want to incorporate into the estimating labels of the data S^b collected in area **B**. We describe this procedure in detail in the next section.

Encoding Domain Knowledge for Building Radio Mapping

In the previous subsections, we have described what domain knowledge can be extracted in the indoor localization problem and how to extract it automatically. In this subsection, we present how to incorporate the extracted domain knowledge into the estimation of labels of the unlabel data collected in another area, and then construct the mapping function for the whole environment. Since the amount of labeled data in S^b is small, we cannot expect to obtain accurate location estimations of the unlabeled part in S^b by solving the optimization problem in (3) with S^b or S^a directly. However, since we have the extracted domain knowledge in terms of the APs' location information, we can reformulate the optimization problem in (3) so that we can take the knowledge into consideration and consequently result in better location estimation. The reformulated optimization problem is given as follows:

$$\begin{aligned} \min_{f_x} \quad & \{(f_{x_i} - \boldsymbol{\ell}_{x_i})^T J (f_{x_i} - \boldsymbol{\ell}_{x_i}) + \gamma_1 f_x^T L f_x + \\ & \gamma_2 (J_2 f_{x_i} - P_x)^T (J_2 f_{x_i} - P_x)\} \\ \text{subject to} \quad & trace(L) = c, \\ & L \succeq 0, \\ & L = \textstyle\sum_{i=1}^3 \mu_i L_i, \\ & u = [u_1, u_2, u_3] \geq 0, \end{aligned} \tag{5}$$

where $J_2 = [\mathbf{0}_{m\times n_2}\ \mathbf{I}_{m\times m}]$, and γ_2 can be seen as a confidence coefficient controlling the impact of the prior knowledge on the optimization problem. The extra item in the objective function in (5), in comparison to the objective function in (3), is $\gamma_2(J_2 f_{xi} - P_x)^T(J_2 f_{xi} - P_x)$, which imposes an additional constraint requiring that the estimated locations (values of the x-coordinate) of the APs through S^b should be consistent with those obtained through S^a. Based on our assumption that S^a is much larger than S^b, the estimated location of APs using S^a is more accurate than those estimated with S^b only. As a result, the extra item in the objective function in (5) will lead to better estimation of APs' location, which can further result in a better estimation of

the locations corresponding to the rows of S^b. Therefore, location estimation of data S^b may be more accurate.

The optimization problem in (5) is also a QCQP problem, which is equivalent to the following optimization problem:

$$\begin{aligned} \min_{f_x,t} \quad & \{(f_{x_i} - \boldsymbol{\ell}_{x_i})^T J (f_{x_i} - \boldsymbol{\ell}_{x_i}) + \gamma_1 ct + \\ & \gamma_2 (J_2 f_{x_i} - P_x)^T (J_2 f_{x_i} - P_x)\} \qquad (6) \\ \text{subject to} \quad & \tfrac{1}{\mu_i} f_x^T L_i f_x \le t,\ i = 1, 2, 3. \end{aligned}$$

Similarly, we can derive the optimization problem for the optimal estimation of f_y by replacing x by y in (6).

Finally, with the n_2 estimated location coordinates $f = [f_x, f_y]$ of S^b and the labeled data S^a, we can construct a mapping function using harmonic functions as defined in 2) for the whole environment.

Experimental Results

In this section, we verify our proposed solution in a real indoor 802.11 WiFi environment. As shown in Figure 1(a), we collect two groups of data in areas **A** and **B**, and conduct three experiments on these two groups of data. The experimental results demonstrate that our proposed solution is quite effective in exploiting the data collected in an area so as to reduce the calibration efforts for training a localization mapping function for the whole indoor environment.

To collect the experimental data, we carried an $\mathbf{IBM}^{©}$ T60 laptop and walked on the floor of an office building, whose size is about $35 \times 120\ m^2$. The laptop is equipped with an $\mathbf{Intel}^{©}$ Pro/3945ABG internal wireless card and installed with a software to record values of WiFi signal strength every 0.5 seconds. We collected the first data set (denoted by S^a) with a total of 665 examples in area **A**. We collected another data set (denoted by S^b) in area **B**, which consists of 486 examples. S^a is split into training data S^a_{tr} (60%) and test data S^a_{tst} (40%), and S^b is also randomly split into training data S^b_{tr} (50%) and test data S^b_{tst} (50%). [5] We repeat this three times. The results reported in the following are averaged results of these three experiments. All the collected examples are labeled manually. When collecting the data, we detect a total of 150 access points (APs), among which we only know the locations of 17 of them. In the following experiments, S^a_{tr} are always fully labeled while a lot of labels of S^b_{tr} are hidden. In all the experiments, we set $\gamma_1 = \gamma_2 = 0.0001$ and use 10 nearest neighbors to construct the Laplacian matrices in (4) and (6).

The first experiment is to qualitatively show the fact that the performance of a brute-force use of the training data S^a_{tr} and S^b_{tr} is much worse than the performance of our proposed solution, which can effectively leverage the knowledge in the training data S^a_{tr}. In this experiment, S^a_{tst} and S^b_{tst} are used as the test data. We randomly select k (k = 0, 3, 5, 7, 9, 20, 40) examples from S^b_{tr} and combine them with S^a_{tr} as the labeled training data. The labels of all the remaining examples in S^b_{tr} except the k selected examples are hidden and they are used to augment the training procedure. In this experiment, the baselines are *LeMan*, *Colocalization1* and *Colocalization2*. LeMan (Pan et al.) is a localization algorithm that is based on a graph-based semi-supervised learning technique. *Colocalization1* denotes that we apply the extended co-localization method presented in (4) on S^b_{tr} to estimate the labels F^b_{tr} of S^b_{tr}, and then apply harmonic functions as defined in (2) to estimate location labels of S^a_{tst} and S^b_{tst}. *Colocalization2* denotes that we apply extended co-localization method to the combination of S^a_{tr} and S^b_{tr} to estimate the labels F^b_{tr} of S^b_{tr}, and use harmonic functions to estimate location labels of S^a_{tst} and S^b_{tst}. Our proposed solution is denoted by $TransMapping$, in which we first apply the extended co-localization method to S^a_{tr} to extract the knowledge of APs's location information, and then apply (6) on S^b_{tr} to estimate F^b_{tr}. Finally, we also use the harmonic function as the final mapping function. Figure 1(b) shows a comparison of the average error distances of the test data when the number of labeled data collected in area **B** changes. We can see that our solution achieves high performance with only a few labeled data. More specifically, our proposed solution reduces the average error distance in the whole area to around 2 meters with only 7 labeled data collected in area **B**. That means we only need to collect one labeled data every 15 meters in a building, which can reduce the calibration effort dramatically.

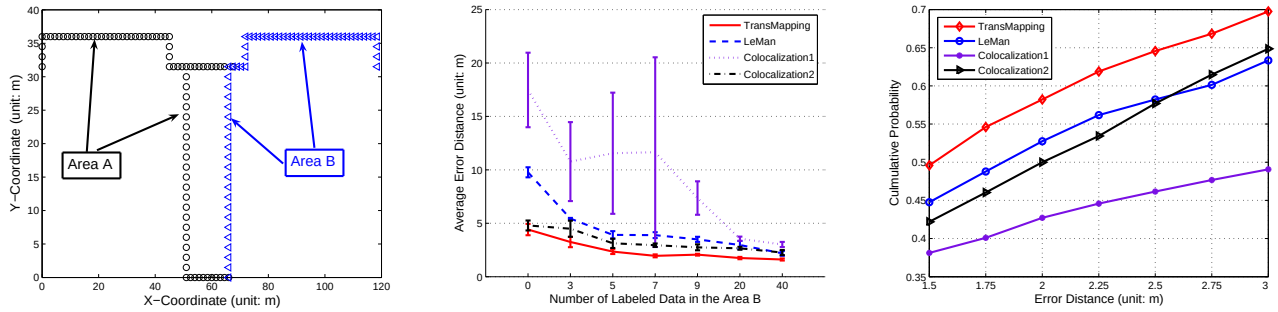
In the second experiment, we fix the number of labeled data in area **B** to 5 and compare the performance of our proposed solution with the baseline methods. Figure 1(c) shows the culmulative probabilities of our solution and the baseline methods at different acceptable error distances. Here, culmulative probability means the estimation accuracy at different acceptable error distances. From Figure 1(c), we can see that the culmulative probabilities of our solution are much higher than all baseline methods at acceptable error distances from 1.5 meters to 3 meters.

The above two experiments are designed to verify localization performance over the whole area (both areas **A** and **B**) of our solution. However, we also want to know the performance of our solution in area **B**, in which only a few labeled data are collected. Thus, we conduct the third experiment to compare our solution with the baseline methods in area **B**. Results are shown in Table 1. We can see that all the three solutions can accurately estimate locations of a mobile device in area **A**. However, traditional semi-supervised learning based approaches, *LeMan* and *Colocalizaiton2*, fail

Areas	*TransMapping*	*LeMan*	*Colocalization2*
A	1.25 (0.078)	1.19 (0.124)	1.27 (0.104)
B	3.45 (0.393)	6.64 (0.627)	4.97 (0.880)

Table 1: Comparing the Average Error Distance (unit:m) of different solutions in Area **A** and Area **B**. A value outside a parenthesis represents average error distance and a value inside a parenthesis represents standard deviation of three round results (the number of labeled data in the area **B** is 5).

[5] Here, we just want to ensure the sizes between the test data in area **A** and the test data in area **B** are comparable.



(a) Ground Truth Environment (b) Comparison of Error Distance (c) Comparison of Accuracy

Figure 1: Results of Location Estimation

to estimate locations in area **B**, while our proposed solution can can still get an average error distance of around 3.5 meters in area **B**, which is acceptable in a large-scale indoor building [6].

Conclusion and Future Work

In this paper, we have presented a novel solution to transferring the learned model from one spatial area to another for indoor WiFi localization. Our contribution amounts to solving two fundamental problems: what to transfer and how to transfer. For the first problem, we developed a manifold learning based approach to discover the hidden structure and knowledge in terms of APs' location information. For the second problem, we proposed an approach to encode the extracted knowledge to propagate label information from one area to another area, which is formalized as a new optimization problem. Our experimental results give strong evidence for the above solutions. In our future work, we plan to explore more techniques for domain adaptation for indoor localization. We also wish to develop an online solution for our problem.

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