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Transferring Localization Models Over Time*

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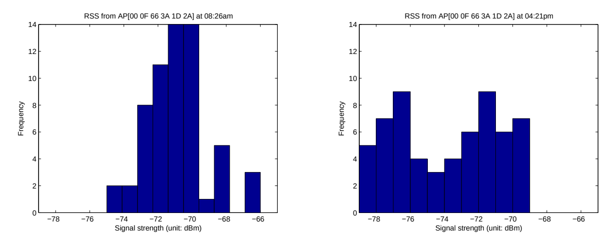
Abstract

Learning-based localization methods typically consist of an offline phase to collect the wireless signal data to build a statistical model, and an online phase to apply the model on new data. Many of these methods treat the training data as if their distributions are fixed across time. However, due to complex environmental changes such as temperature changes and multi-path fading effect, the signals can significantly vary from time to time, causing the localization accuracy to drop. We address this problem by introducing a novel semi-supervised Hidden Markov Model (HMM) to *transfer* the learned model from one time period to another. This adaptive model is referred to as transferred HMM (TrHMM), in which we aim to transfer as much knowledge from the old model as possible to reduce the calibration effort for the current time period. Our contribution is that we can successfully transfer out-of-date model to fit a current model through learning, even though the training data have very different distributions. Experimental results show that the TrHMM method can greatly improve the localization accuracy while saving a great amount of the calibration effort.

Introduction

Recently, indoor localization have attracted more and more attention in artificial intelligence (AI) research community (Nguyen, Jordan, and Sinopoli 2005; Ferris, Haehnel, and Fox 2006; Ferris, Fox, and Lawrence 2007). In general, learning-based indoor localization systems use Radio Frequency (RF) signal strength for location estimation in two phases. In the *offline training* phase, a mobile device moving around the wireless environment collects multiple wireless signals from various access points. Then, these received signal strength values are used as the training data to build a mapping function from a signal space to a location space. In the *online testing* phase, real-time received signal strength (RSS) values collected by a mobile device are tested through the learned mapping function for location estimation.

Most of the previous works assume that the data distributions keep unchanged over time. However, this assumption does not hold in a real, complex indoor wireless environment. For example, subject to reflection, refraction, diffraction and absorption by obstacles and humans, the signal propagation may suffer from multi-path fading effect, and the received signal strength distribution may vary significantly from time to time. Figure 1 shows the variation of RSS distributions at the same location over different time periods at a day. As a result, the location estimation performance can be grossly inaccurate as time elapses.



(a) RSS at 08:26am (b) RSS at 04:21pm

Figure 1: RSS variations over time at a fixed location.

However, it is impractical to collect new calibrated data entirely at each new time period. This implies the need to design a transfer learning algorithm that can adapt trained models smoothly under different data distributions from time to time. In this paper, we propose a semi-supervised HMM framework for such a transfer learning task. Specifically, we are trying to adapt an out-of-date localization model while requiring only a small amount of additional calibration effort for collecting new data.

Figure 2 illustrates our idea. We model the prediction problem as a classification problem of discrete location grids. In our experiments we have over 100 grids in the environment. At time 0, we collect RSS data with location labels over the whole area. This step is time consuming, but is done only once. This dataset consists of both the RSS samples at each location and some unlabelled user traces collected as the user walks around the environment in arbitrary trajectories. Based on this data, we train an HMM $\theta_0 = (\lambda_0, A_0, \pi_0)$ for localization at time 0. As we will explain in detail later, λ_0 is the radio map that connects the RSS values to the locations, A_0 is the transition matrix that reflects the way the user moves, and π_0 is the prior knowl-

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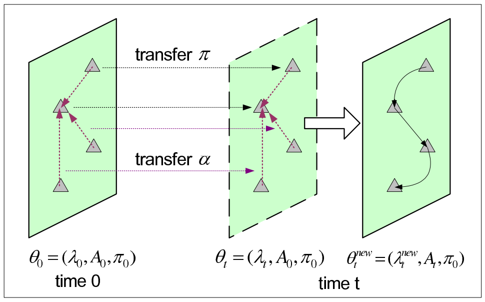

Figure 2: Adapting a localization model from time 0 to time t using TrHMM. The triangles denote reference point locations in the area.

edge on the likelihood of where the user is. Note that λ_0 is changing over time because signal strength varies. A_0 can also be changing over time because at different time periods, people may have different activities. For example, at noon, people are more likely to go to carteen for lunch; and during working hours, people are more likely to move within the office area. Therefore, both λ_0 and A_0 need to be adapted to λ_t and A_t for a new time period t. π_0 is kept unchanged over time[1], since in reality, the basic human behavior does not change dramatically. For example, a professor usually stays at his office longer than his walking in a corridor.

In TrHMM, we carry out three steps for transferring with respect to the three HMM model parameters (λ_0, A_0, π_0):

- At time 0, we select some locations to place sniffing sensors to collect up-to-date RSS values. We call such set of selected locations as "reference points". We then learn the *regression weights* $\boldsymbol{\alpha}$ among the RSS data from the few reference points and the remaining non-reference points, in order to transfer the radio map from time 0 to time t.
- We note that even though the data distributions change, the relationship between neighboring locations do not change much. This relationship can be used as a bridge for transferring the knowledge over radio map change. Therefore, by introducing a constraint that the regression weights remain static, we build a radio map λ_t at each non-reference point location at time t by collecting up-to-date data on the few referent points (shown as Triangles in Figure 2) with known locations.
- At time *t*, some unlabeled user traces are collected by simply walking around the environment. Since these traces data encode the knowledge of current time period data distribution and also the user transition behaviors, they are further used to transfer the localization model to λ_t^{new} and A_t by an expectation-maximization (EM) algorithm.

Note that our choice of using HMM model is motivated by the following considerations. Compared with other localization models, HMM can utilize both single RSS samples and user trajectories in the form of sequential knowledge. Therefore, we may be able to transfer more information for the new time periods. In the experimental section, we verify our algorithm through some real-world data and show that, compared with state-of-art methods, our TrHMM algorithm can greatly improve the localization accuracy under different data distributions while saving a large amount of calibration efforts.

[1] However, a changing π_0 can be addressed in an extension of this work.

Related work

Generally, localization methods fall into two categories: propagation-model based and machine-learning based. Propagation-model based techniques rely on radio propagation models which use triangulation techniques for location estimation (Savvides, Han, and Strivastava 2001). Learning-based techniques try to handle the uncertainty in wireless environments and use statistical learning such as KNN (Bahl and Padmanabhan 2000), kernel learning (Nguyen, Jordan, and Sinopoli 2005) and Gaussian process (Ferris, Haehnel, and Fox 2006; Ferris, Fox, and Lawrence 2007). There are few works on studying the data distribution variations in wireless indoor localization. *LANDMARC* (Ni et al. 2003) and *LEASE* (Krishnan et al. 2004) utilized a large number of hardware equipments, including stationary emitters and sniffers, to obtain up-to-date RSS values for updating the radio maps. (Pan et al. 2007) used multi-view manifold learning to constrain the agreements between different distributions. However, in practice, many of these works cannot work well due to different model constraints.

Recently, there has been a growing interest in transfer learning. Several researchers have explored specific aspects of transfer learning in natural language and image processing areas (Thrun and Mitchell 1995; Ben-David and Schuller 2003). (DauméIII and Marcu 2006) investigated how to train a general model with data from both a source domain and a target domain for a natural language mention-type classification task. (Daumé III 2007) applied redundant copies of features to facilitate the transfer of knowledge. In the area of machine learning based localization, few work on transfer learning has been done before.

Preliminaries of Hidden Markov Models

Hidden Markov Model is a well known technique in pattern recognition and has a wide range of applications (Rabiner 1990; Bui, Venkatesh, and West 2002). In indoor localization, HMM can be used to model the user traces by treating user's locations as hidden states and the signal strength measurements as observations (Ladd et al. 2002). As shown in Figure 3, an HMM for user-trace modeling is defined as a quintuple (L, O, λ, A, π), where L is a location-state space $\{l_1, l_2, ..., l_n\}$, and each l_i is explained as a discrete grid cell of the physical locations with $x-$ and $y-$ coordinates: $l_i = (x_i, y_i)$. O is an observation space $\{\mathbf{o}_1, \mathbf{o}_2, ..., \mathbf{o}_m\}$, and each $\mathbf{o}_j$ is a set of k signal strength measurements received from k different Access Points (APs): $\mathbf{o}_j = (s_1, s_2, ..., s_k)$. λ is a radio map $\{P(\mathbf{o}_j|l_i) : \mathbf{o}_j \in O, l_i \in L\}$ that gives the conditional probability of obtaining a signal strength measurement $\mathbf{o}_j$ at location l_i. A is a location-state transition matrix $\{P(l_j|l_i) : l_i, l_j \in L\}$; it encodes the probability for a user moving from one location l_i to another location l_j. π

is an initial location-state distribution $\{P(l_i), l_i \in L\}$ with each $P(l_i)$ encoding the prior knowledge about where a user initially may be.

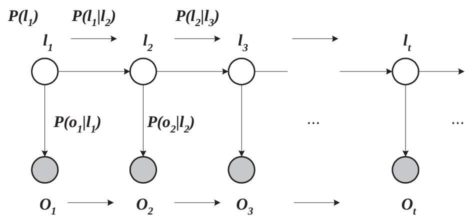

Figure 3: Hidden Markov Model.

In the offline training phase, a set of labeled traces $T = \{(tr_i, q_i) : i = 1, ..., N\}$ is collected, with each user trace $tr_i = (\mathbf{o}^1, \mathbf{o}^2, ..., \mathbf{o}^{|t|})$ and the corresponding location sequence $q_i = (l^1, l^2, ..., l^{|t|})$. Here, $\mathbf{o}^j \in O$ and $l^j \in L$. Then, these labeled traces are used to train an HMM. We denote an HMM's parameters as $\theta = (\lambda, A, \pi)$. The radio map λ can be obtained by modeling the conditional probability $P(\mathbf{o}_j|l_i)$ as a Gaussian distribution:

$$P(\mathbf{o}_j|l_i) = \frac{1}{(2\pi)^{k/2}|\mathbf{\Sigma}|^{1/2}} e^{-\frac{1}{2}(\mathbf{o}_j - \boldsymbol{\mu})^T \mathbf{\Sigma}(\mathbf{o}_j - \boldsymbol{\mu})}, \quad (1)$$

where $\boldsymbol{\mu}$ is the mean vector of the observations, and $\mathbf{\Sigma}$ is the covariance matrix. By assuming the independence among the APs (Ladd et al. 2002), we can simplify $\mathbf{\Sigma}$ as a diagonal matrix. The transition matrix $A = \{P(l_{i+1}|l_i)\}$ encodes the probability for a mobile device to move from one location l_i to another location l_{i+1}. It can be easily obtained from the labeled traces by counting the transition statistics of each location to all possible next locations. In an indoor environment, a mobile device carried by a human being usually does not move too fast, which allows us to constrain the transition probability $P(l_{i+1}|l_i)$ to be zero if l_{i+1} is more than a few meters away from l_i; in our experiments we set the threshold as three meters. The initial location-state distribution π can be derived by our prior knowledge. Generally, it is set by a uniform distribution over all the locations, since a user can start at will from any location. This assumption can be revised easily if we have more prior knowledge about user location patterns.

In the online test phase, given a model parameter θ and an observed user trace $tr = (\mathbf{o}^1, \mathbf{o}^2, ..., \mathbf{o}^{|tr|})$, the well-known *Viterbi algorithm* (Rabiner 1990) can then be used to infer the most probable hidden state sequence q.

TrHMM: Transferred Hidden Markov Model

As mentioned above, we use three steps to transfer the HMM for the new time period.

Applying regression analysis at time 0

Our first step is to transfer the collected radio map λ_0 at time 0 to another time t. To do this, we propose to model the signal variation with time. Note that in a wireless indoor environment, signals over different locations are correlated, *e.g.,* when the signal on a location l_1 increases with time, the signal on its neighboring location l_2 is also likely to increase. Motivated by this observation, we apply a regression model to learn the temporal predictive correlations between the RSS values by sparsely located reference points and that by the mobile device. Specifically, we apply a *Multiple Linear Regression* model on the data at time 0 over all the location grids, and derive the regression coefficients $\boldsymbol{\alpha}^k = \{\alpha_{ij}^k\}$, which encode the signal correlations between reference point locations $\{l_c\}$ and one non-reference point location k. In more detail, we have:

$$s_j^k = \alpha_{0j}^k + \alpha_{1j}^k r_{1j} + ... + \alpha_{nj}^k r_{nj} + \epsilon_j \quad (2)$$

where s_j^k is the signal strength received by the mobile device at location k from j^{th} AP, $\alpha_{ij}^k : 1 \le i \le n$ is the regression weights for j^{th} AP signal at location k, and $r_{ij} : 1 \le i \le n$ is the signal strength received by i^{th} reference point location from j^{th} AP.

Rebuilding the radio map at time t

After learning the regression weight $\boldsymbol{\alpha}^k$ for each non-reference point location k, we can use them to rebuild the radio map at time t. This is done by updating non-reference point locations' signal strengths with the newly collected signal strengths on the reference point locations $\{l_c\}$, whose locations are known beforehand. Considering that there may be a possible shift for the regression parameters over time, we add a tradeoff constraint to derive the new λ_t:

$$\boldsymbol{\mu}_t = \beta \cdot \boldsymbol{\mu}_0 + (1 - \beta) \cdot \boldsymbol{\mu}_t^{reg} \quad (3)$$

$$\begin{aligned} \mathbf{\Sigma}_t = \beta \cdot \left[\mathbf{\Sigma}_0 + (\boldsymbol{\mu}_t - \boldsymbol{\mu}_0)(\boldsymbol{\mu}_t - \boldsymbol{\mu}_0)^T\right] \\ +(1-\beta) \cdot \left[\mathbf{\Sigma}_t^{reg} + (\boldsymbol{\mu}_t - \boldsymbol{\mu}_t^{reg})(\boldsymbol{\mu}_t - \boldsymbol{\mu}_t^{reg})^T\right] \end{aligned} \quad (4)$$

where $\boldsymbol{\mu}$ is the mean vector of Gaussian output for each location, $\mathbf{\Sigma}$ is the covariance matrix. We balance the regressed radio map $\lambda_t^{reg} = (\boldsymbol{\mu}_t^{reg}, \mathbf{\Sigma}_t^{reg})$ and the base radio map $\lambda_0 = (\boldsymbol{\mu}_0, \mathbf{\Sigma}_0)$ by introducing a parameter $\beta \in [0, 1]$.

Using EM on unlabeled traces at time t

In previous steps, we first trained an HMM $\theta_0 = (\lambda_0, A_0, \pi_0)$ at time 0 as the base model. Then, in another time t, we improve λ_0 by applying the regression analysis, and obtain a new HMM $\theta_t = (\lambda_t, A_0, \pi_0)$. Now we will try to further incorporate some unlabeled trace data to improve the derived θ_t. We achieve this by applying the *expectation-maximization* (EM) algorithm.

Given a set of unlabeled traces $T = \{(tr_i, q_i)\}$, EM is used to adjust the model parameters $\theta_t = (\lambda_t, A_0, \pi_0)$ iteratively to find a θ^* such that the likelihood $P(T|\theta^*)$ is maximized. Recall that here tr_i is a sequence of RSS observations on a trace i, and q_i are its corresponding locations. Therefore, maximizing the likelihood $P(T|\theta^*)$ is to adapt the model θ_t to best fit the up-to-date unlabeled traces data. By using such adaptation, the HMM can be more accurate in location estimation for the new time period t's data. The EM algorithm has two steps in each iteration: an Expectation step (E-step) and a Maximization step (M-step). For the k-iteration, in E-step, we calculate the conditional probability $P(q|tr, \theta^k)$, *i.e.* location estimations q given the RSS observations tr, from the unlabeled trace data T by using the θ^k from last iteration's M-step:

$$P(q|tr, \theta^k) = \frac{P(tr, q|\theta^k)}{P(tr|\theta^k)} = \frac{P(tr|q, \theta^k)P(q|\theta^k)}{\sum_q P(tr|q, \theta^k)P(q|\theta^k)} \tag{5}$$

where $P(tr|q, \theta^k) = \prod_{n=1}^{|tr|} P(\mathbf{o}^n|l^n, \theta^k)$ is the likelihood of observing a trace tr given the mobile device's location sequence is q. Notice that this term can be calculated from the last M-step k's radio map λ^k, since λ^k already encodes the conditional probability of $P(\mathbf{o}^n|l^n)$. The term $P(q|\theta^k) = P(l^1|\theta^k) \times \prod_{n=1}^{|tr|} P(l^n|l^{n-1}, \theta^k)$ is the probability of q being location sequence in a user trace. This can be calculated from prior knowledge π_0 and transition matrix A^k, because π_0 encodes the probabilities of $P(l^n)$ and A^k encodes the conditional probabilities $P(l^n|l^{n-1})$ for different n's. In the M-step, an expected loglikelihood (*i.e. Q-function*) is maximized over the parameter θ based on the E-step. The parameter θ^k is then updated to obtain θ^{k+1}:

$$\begin{aligned}\theta^{k+1} &= \arg\max_\theta Q(\theta, \theta^k) \\ &= \arg\max_\theta \sum_{tr \in T} \sum_q P(q|tr, \theta^k) \log P(tr, q|\theta)\end{aligned} \tag{6}$$

In particular, by following the derivation of (Bilmes 1997), we show the update for each parameter in $\theta^{k+1} = (\lambda^{k+1}, A^{k+1}, \pi)$. Note that since π is the prior knowledge of the user locations, it's set to be fixed and not involved in EM. Specifically, the radio map $\lambda^{k+1} = \{P(\mathbf{o}_j|l_i)^{(k+1)} : \mathbf{o}_j \in O, l_i \in L\}$ is shown to be updated by:

$$\boldsymbol{\mu}_{l_i}^{(k+1)} = \frac{\sum_{tr \in T} \sum_{n=1}^{|tr|} \mathbf{o}^n P(l^n = l_i|tr, \theta^k)}{\sum_{tr \in T} \sum_{n=1}^{|tr|} P(l^n = l_i|tr, \theta^k)}$$

$$\boldsymbol{\Sigma}_{l_i}^{(k+1)} = \frac{\sum\limits_{tr \in T} \sum\limits_{n=1}^{|tr|} (\mathbf{o}^n - \boldsymbol{\mu}_{l_i})(\mathbf{o}^n - \boldsymbol{\mu}_{l_i})^T P(l^n = l_i|tr, \theta^k)}{\sum_{tr \in T} \sum_{n=1}^{|tr|} P(l^n = l_i|tr, \theta^k)} \tag{7}$$

And the transition matrix $A^{k+1} = \{P(l_j|l_i)^{(k+1)} : l_i, l_j \in L\}$ is updated as:

$$P(l_j|l_i)^{(k+1)} = \frac{\sum_{tr \in T} \sum_{n=1}^{|tr|-1} P(l^n = l_i, l^{n+1} = l_j|tr, \theta^k)}{\sum_{tr \in T} \sum_{n=1}^{|tr|-1} P(l^n = l_i|tr, \theta^k)} \tag{8}$$

The EM algorithm guarantees the likelihood $P(T|\theta^{k+1}) \geq P(T|\theta^k)$ and the parameter θ eventually converges to a stable θ^*. The new HMM is finally updated as $\theta_t^{new} = (\lambda_t^{new}, A_t^{new}, \pi_0)$. In the online phase at time t, the derived parameters in θ_t^{new} are used to infer the most probable location sequence for the queried trace based on Viterbi algorithm (Bilmes 1997), given the obtained RSS values. We summarize our TrHMM in Algorithm 1.

Experiments

In this section, we empirically study the benefits of transferring HMM for adapting indoor localization. Our experiments were set up in an academic building equipped with

Algorithm 1 Transferred Hidden Markov Model (TrHMM)

Input: Labeled traces at time 0, labeled RSS samples collected from reference points and unlabeled traces at time t
Output: Adapted model $\theta_t^{new} = (\lambda_t^{new}, A_t^{new}, \pi_0)$
At time 0,

1. Build an HMM base model $\theta_0 = (\lambda_0, A_0, \pi_0)$ using labeled traces from time 0;
2. Learn the signal regression weights α^k among referent points and the rest, using labeled trace data from time 0;

At time t,

1. Rebuild the radio map using the labeled RSS samples collected from reference points at time t, and update the model to $\theta_t = (\lambda_t, A_0, \pi_0)$;
2. Apply EM to improve θ_t as $\theta_t^{new} = (\lambda_t^{new}, A_t^{new}, \pi_0)$, by using unlabeled traces from time *t*;
3. Return the HMM model $\theta_t^{new} = (\lambda_t^{new}, A_t^{new}, \pi_0)$.

802.11g wireless network. The area is $64m \times 50m$, including five hallways. It's discretized into a space of 118 grids, each measuring $1.5m \times 1.5m$. Our experimental evaluation method is based on classification accuracy, which is calculated as the percentage of correct predictions over all predictions. The problem is difficult because a random guess would result in less than 1% in accuracy.

We collected calibration data over three time periods: 08:26am, 04:21pm and 07:10pm. We use 08:26am data to build the base model and carry out adaptation on other time periods. 60 samples were collected at each grid. We randomly splitted 2/3 of the data as training and 1/3 as testing. Traces for building HMM were also collected at each time period. For training, we have 30 labeled traces for 08:26am data, each having 20 samples on average. In the remaining time periods, we obtained 30 unlabeled traces, each having 250 samples for training. For testing, we have 20 traces for each time period, each having 250 samples on average. In the experiments, β is set as 0.4. We tested different β-values[2], and found that for different time periods, the performances with different β-values are similar, and $\beta = 0.4$ gives roughly the best results. This coincides with our intuition of allocating around half the weight to the regressed radio map and old radio map in Equation (3).

Impact of distribution variation

We test the localization accuracy over different data distributions without adaptation. We use the 08:26am dataset to build the base model θ_0, and then apply θ_0 to predict the labels for test data traces of the three time periods. We use 10% of locations as reference points and 5 unlabeled traces for adaptation. As shown in Figure 4, the localization accuracy of 08:26am data is the highest, at 92%[3]. This high

[2]We do not provide the results here due to space limit.

[3]The error distance is set to be 3 meters, which means the predictions within 3 meters of the true location are all counted as correct predictions.

accuracy is due to the fact that the test data follow the same distribution with the training data. As time goes by, the signals become more noisy and changing, and the performance drops. At 04:21pm, the busiest time in the work area, the noise level reaches the highest because of many people walking around at that time. During this period, the accuracy thus drops to the lowest point to about 68%, which is unsatisfactory. This observation implies a need for transferring the localization model over different data distributions.

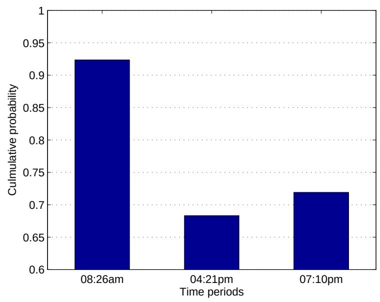

Figure 4: Use 08:26am model to predict others.

Impact of reference points

We next study the impact of using different number of reference points, *i.e.* different amount of labeled data, for adaptation. We compare TrHMM with three baselines using reference points for adaptation, including RADAR (Bahl and Padmanabhan 2000), LANDMARC (Ni et al. 2003) and an recent adaptation method, LeManCoR (Pan et al. 2007). RADAR is a K-nearest-neighbor method. The number of nearest neighbors is set to be five, as tested in (Bahl and Padmanabhan 2000). LANDMARC is a nearest-neighbor weighting based method. In this experiment, the number of nearest neighbors is set to two, since only few reference points are sparsely deployed in the environment. LeManCoR is a semi-supervised manifold method. It treats different time as multiple views and uses a multi-view learning framework to constraint the predictions on reference points to be consistent. In this experiment, we use 5 unlabeled traces for both TrHMM and LeManCoR. We run the experiments for 5 times and report the error bar charts. As shown in Figures 5(a) and 5(b), our TrHMM consistently outperforms the other methods over time, especially when the number of reference points is small. For RADAR and LANDMARC, they can only work when the environment is densely installed with reference points. For LeManCoR, as discussed in (Pan et al. 2007), it cannot benefit from either the increasing number of reference points or the trace sequential information, so our TrHMM method can outperform it consistently.

Impact of unlabeled data

We also study the impact of using different number of unlabeled traces for adaptation. We compare TrHMM with two baseline methods. The first method is unsupervised HMM (UnHMM) (Chai and Yang 2005), which only uses unlabeled traces. UnHMM builds a base model θ_0, and then directly use EM to iteratively update the model θ_0 using the unlabeled traces. The second method is LeManCoR, which uses unlabeled data for manifold regularization in adaptation. We use 10% of locations as reference points for both TrHMM and LeManCoR. We run the experiments for 5 times and report the error bar chart. As shown in Figures 5(c) and 5(d), our TrHMM consistently outperforms the baselines. Our TrHMM can outperform UnHMM because TrHMM carefully models the signal variation over time while UnHMM not. Our method also outperforms LeManCoR because TrHMM better models the signal variations and also uses the sequential information in traces.

Sensitivity to error distance

We study the sensitivity of TrHMM to different error distances. In experiment, 10% locations were used as reference points for collecting labeled data and 5 traces were used for unlabeled data. We run the experiments for 5 times and report the error bar charts. As shown in Figures 5(e) and 5(f), our TrHMM method is insensitive to the error distance in calculating the localization accuracy[4]. In addition, compared to other localization methods, our TrHMM can work much better even when the error distance is small. Both of these observations testifies our TrHMM method can provide accurate location estimation with small calibration effort.

Conclusions and Future Work

In this paper, we study the problem of transfer learning using a semi-supervised HMM for adaptive localization in a dynamic indoor environment. We carefully model the signal variation with time and employ a semi-supervised HMM framework, which appropriately combine both labeled data and unlabeled data together for model adaptation. By applying it to the real-world indoor localization, we show our TrHMM algorithm can greatly improve the accuracy while saving a great amount of the calibration efforts, even when the data distribution is a function of time. Our experiments confirm that our TrHMM can successfully transfer the out-of-date model to current time periods.

In the future, we plan to extend this algorithm to online setting such that the system can make predictions while it collects new trace data. Besides, we would consider how to optimally place the reference points for adaptation. We are also interested in incorporating transfer learning with Gaussian process for localization.

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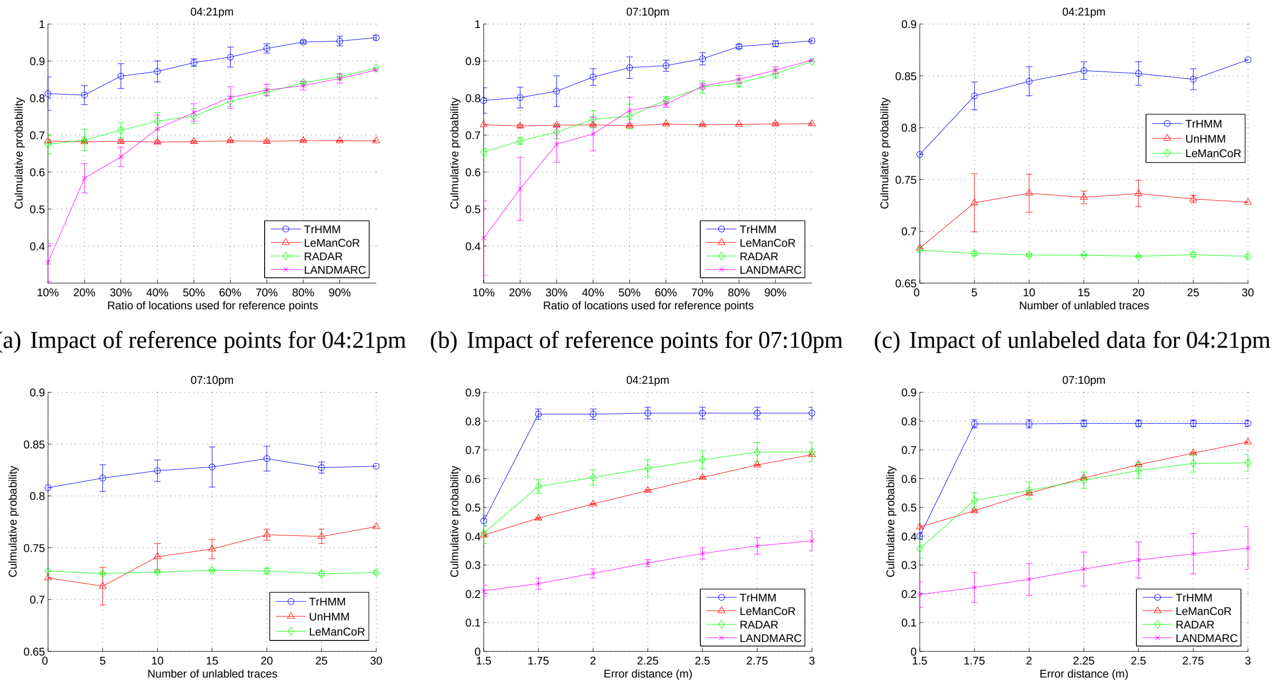
[4]Note that the predictions of HMM are discrete hidden variables, which in our case are $1.5m \times 1.5m$ grids, so the accuracy is stable from 1.75m to 3m.



(a) Impact of reference points for 04:21pm (b) Impact of reference points for 07:10pm (c) Impact of unlabeled data for 04:21pm

(d) Impact of unlabeled data for 07:10pm (e) Sensitivity to error distance for 04:21pm (f) Sensitivity to error distance for 07:10pm

Figure 5: Experimental results

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