Transfer Regression Model for Indoor 3D Location Estimation

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Abstract. Wi-Fi based indoor 3D localization is becoming increasingly prevalent in today's pervasive computing applications. However, traditional methods can not provide accurate predicting result with sparse training data. This paper presented an approach of indoor mobile 3D location estimation based on TRM (Transfer Regression Model). TRM can reuse well the collected data from the other floor of the building, and transfer knowledge from the large amount of dataset to the sparse dataset. TRM also import large amount of unlabeled training data which contributes to reflect the manifold feature of wireless signals and is helpful to improve the predicting accuracy. The experimental results show that by TRM, we can achieve higher accuracy with sparse training dataset compared to the regression model without knowledge transfer.

Keywords: 3D Location, Transfer Regression Model, Semi-Supervised Learning, Manifold Regularization.

1 Introduction

Nowadays, location information is an important source of context for multimedia service systems, especially for mobile service systems. For instance, in a LBS (Location Based Services) system of video on demand, users in different location will receive different video program or same video with different qualities, and more accurate location will promise better video quality.

Wi-Fi based location systems are becoming more and more popular for some advantages of WLAN (Wireless Local Access Network). Today, GPS provides localization for users outdoors, but it can not provide precise indoor location because of the technical constraints. Historically, we have seen indoor location systems based on infra-red, ultrasound, narrowband radio, UWB, vision, and many others in 2D location [1]. But deployments of high precision indoor location systems have not involved large coverage areas due to the cost of equipping the environment, meanwhile, the accuracy or deployment cost is unsatisfactory. On the other hand, many systems which use the 802.11 WLAN as the fundamental infrastructure is more and more popular. Considering the expanding coverage of Wi-Fi signals and Wi-Fi modules are equipped in the mobile devices widely, existed WLAN usually is selected as the manner for indoor localization system to minimize the cost of deployment and infrastructure.

S. Boll et al. (Eds.): MMM 2010, LNCS 5916, pp. 603–613, 2010.

Most systems use RSS (Received Signal Strength) as Wi-Fi feature. Those methods employ machine learning or statistical analysis tools. The algorithms of those learning methods usually contain two phases: offline training phase and online localization phase. Ferris et al. in [2] proposed a framework using Gaussian process models for location estimation. Nguyen et al. [3] apply kernel methods and get more accurate result for location prediction. Pan et al. [4] realized a system based on manifold regularization as a semi-supervised algorithm to mobile-node location and tracking. This method can reduce greatly the calibration effort.

However, those works addressed 2D location problems. Today, indoor 3D location is becoming more and more important. As we all know, many public or proprietary services are always based on the geospatial locations and therefore named as Location Based Services (LBS). As the rapid developments of ubiquitous computing systems as well as wireless networking, location sensing techniques, LBS is increasingly considered as a very important service. However, most existing LBS can only deal with 2D geospatial data and offer related 2D geospatial services. They lack in supporting 3D datasets as well as 3D services. In the mean time, 3D information is rapidly increasing, partly due to the fast data acquisition techniques, which can bring people more vivid presentations of the real world .To use the existing and newly emerging 3D datasets, implement 3D LBS systems turn to be more and more necessary.

This paper presented TRM (Transfer Regression Model) and its application in indoor 3D location estimation. TRM is essential a regressive model which also learns the mapping function between signal space and location space. It has the advantage that can import the other dataset in training progress when the training dataset is rather sparse, which will refine the regressive model and improve the prediction accuracy.

The rest of this paper is organized as follows. We describe related research works in Section 2, and present in details the theory of TRM and TRM based 3D location in Section 3. Section 4 shows the experiments. Finally, we give our conclusions and future works in Section 5.

2 Related Works

Some systems on 3D location [5, 6, 7, 8] have been developed to realize 3D LBS, the most significant achievements in the 3D research area concerning key issues of 3D GIS, which is intensive and covers all aspects of the collecting, storing and analyzing real world phenomena. Chittaro et al. in [6] presented an approach to give evacuation instructions on mobile devices based on interactive location-aware 3D models of the building. This system uses RFID technology to determine user's position in the real building. It needs place RFID tags in needed part of the building. RFID tags have a range of about 4 meters and send their signal to the RFID reader every 500 milliseconds. But few systems can provide accurate and satisfactory 3D location and easily be implemented especially in indoor environment.

There are also some pure 3D location systems such as SpotON [9], an indoor 3D location sensing technology based on RF signal strength, can be used to locate indoor but it is too expensive compared with WLAN based systems and it alone is almost certainly not the ultimate solution in the problem space. Pedestrian Localization [10], a foot-mounted inertial unit, a detailed building model, and a particle filter be combined to provide absolute positioning in a 3D building, but the foot-mounted inertial unit is expensive and each building needs a detailed building model which is time-consuming.

From those documents described above, 3D location estimation is still an on going problem. Furthermore, the current systems always require changing the infrastructure which sequentially leads to high cost. Intuitively, we can train dedicated 2D location model in each floor, but it would bring huge human labors to collect the data and label the data.

In this case, we propose the method of 3D location based on TRM. TRM is designed to train effective regressive model for the target floor with sparse training data by reusing the large amount of data collected from the other floor.

3 TRM for 3D Location Estimation

In this section, we first demonstrate the 3D location problem. Then, TRM a regression model with the capability to import knowledge from the third party of dataset is introduced. Then, TRM based 3D location estimation is described.

3.1 Indoor 3D Location Problem

Let us define some parameters formally. Suppose there are totally r APs deployed in the wireless environment, and they can be detected both on the third and fourth floors. The RSS values can be represented as a row vector $x = (x_1, x_2, ..., x_r) \in R_r$, where x_i stands for the RSS value received from AP $_i$ and sometime we fill the value with -100db if no actual signal strength is detected. The value of -100db is the lowest signal strength that can be detected in our experiment.

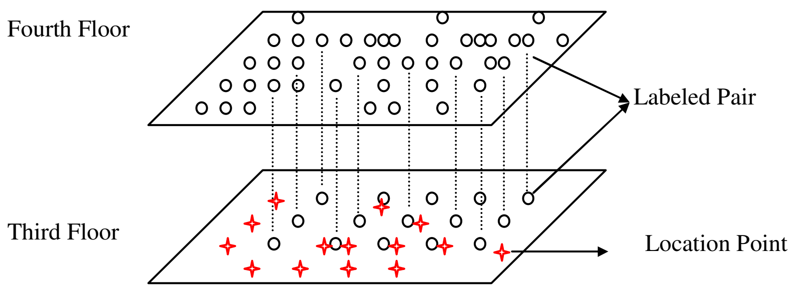

Fig. 1. The 3D location problem

We carry out the 3D location experiment on the third and fourth floor in a building. As shown in Fig. 1, the black circles represent the position with labeled coordinates while the red stars represent the position we want to know the coordinates. There are some labeled pairs, and each pair means two points with same physical coordinates but from different floors. In the case of 2D location estimation, we may train two prediction model $y = f_3(x)$ and $y = f_4(x)$ respectively for third floor and fourth floor. x is the Wi-Fi signal vector and y a two dimensional vector represents the coordinates of the location point. The problem is: If we just use the labeled data on the third floor to train the location estimation model f_3, the prediction accuracy is very limited for the training data is so sparse. So can we reuse the plentiful data of the fourth floor to improve the prediction accuracy for model f_3? If the old data can be reused well, the labeled data and human calibration effort would be reduced greatly. This is always a meaningful direction to build 3D location model with less manual cost.

Now, the 3D location problem is to train a regressive model f_3 with three datasets X, Y, Z, that is: $f_3 : X \rightarrow Y \mid Z$. X is the Wi-Fi signal set collected in third floor, Y is the coordinates of the location points, and Z is the Wi-Fi signal set collected in fourth floor. As we know, some regressive model such as SVR (Support Vector Regression) and BP (Back Propagation) network can not perform such learning task which is based on three datasets, so we propose the novel learning framework of Transfer Regression Model.

3.2 Transfer Regressive Model

This section proposes TRM (Transfer Regression Model), a kind of regression method for learning from sparse training data. Limited training data will lead to reduction of regression accuracy for traditional regression method. TRM can adopt large number of unlabeled data based on Manifold Regularization and transfer useful knowledge from third part of dataset when training the regression model. For TRM is original from MR (Manifold Regularization), we give a brief introduction of the theory of regularization and manifold regularization.

3.2.1 Regularization for Regression Problems

Regularization is a well built mathematical approach for solving ill-posed inverse problems. It is widely used in machine learning problem [11], and many popular algorithms such as SVM, splines and radial basis function can be broadly interpreted as the instance of regularization with different empirical cost functions and complexity measures.

Here we give a brief introduction of regularization on regression learning, whose detail can be referred in [11]. Given a set of data with labels $\{x_i, y_i\}_{i=1,2,\ldots,l}$, the standard regularization in $RKHS$ (Reproducing Kernel Hilbert Space) is to estimate the function f^* by a minimizing:

$$f^* = \underset{f \in \mathrm{H_K}}{\arg\min} \frac{1}{l} \sum_{i=1}^{l} V(x_i, y_i, f) + \gamma \|f\|_K^2 \tag{1}$$

Where V is some loss function, and $\|f\|_K^2$ is the penalizing on the $RKHS$ norm reflecting smoothness conditions on possible solutions. The classical Representer

Theorem states that the solution to this minimization problem exists in $RKHS$ and can be written as:

$$\boldsymbol{f}^*(\boldsymbol{x}) = \sum_{\boldsymbol{i}=1}^{\boldsymbol{l}} \alpha_{\boldsymbol{i}} \boldsymbol{K}(\boldsymbol{x}_{\boldsymbol{i}}, \boldsymbol{x}) \tag{2}$$

Substituting this form in the problem above, it is transformed to optimize α^*. In the case of the squared loss function of $V(x_i, y_i, f) = (y_i - f(x_i))^2$. We can get final RSL (Regularized Least Squares) solution:

$$\alpha^* = (\boldsymbol{K} + \gamma \boldsymbol{lI})^{-1} \boldsymbol{Y} \tag{3}$$

3.2.2 Manifold Regularization

M. Belkin, et al [12] extended the standard framework to manifold regularization, which is described as the following form:

$$f^* = \arg\min_{f \in \mathrm{H_K}} \frac{1}{l} \sum_{i=1}^{l} V(x_i, y_i, f) + \gamma_A \|f\|_K^2 + \gamma_I \|f\|_I^2 \tag{4}$$

The differences between manifold regularization and standard framework lie in two aspects. The first is the former incorporate geometric structure of the marginal distribution P_X in the minimizing, which is reflected by the third item $\|f\|_I^2$. While minimizing, the coefficient γ_I controls the complexity of the function in the intrinsic geometry of P_X and γ_A controls the complexity of the function in ambient space. M. Belkin, et al [12] employ Laplacian manifold to represent the geometric structure embedded in high dimensional data. The second difference is the importing of unlabeled data $\{X_i\}_{i=l+1}^{i=u}$ by manifold regularization. While the lost function is calculated only by the labeled samples as before, when calculating the third penalizing item $\|f\|_I^2$, manifold regularization imports large mount of unlabeled samples that reflect the manifold distribution structure. So the solution changed with a new form:

$$f^*(x) = \sum_{i=1}^{l+u} \alpha_i^* K(x, x_i) \tag{5}$$

And the corresponsive solution of α^* is in Equation (6). $J = diag(1,1,...,0,0)$ with the first l diagonal entries as 1 and the rest 0. $\mathbf{L}$ is the Laplacian graph. We can notice that if γ_I=0 which means there is no unlabeled data in training, the Equation (6) will be identical with Equation (3).

$$\alpha^* = \left(\boldsymbol{JK} + \gamma_A \boldsymbol{lI} + \frac{\gamma_I \boldsymbol{l}}{(\boldsymbol{u}+\boldsymbol{l})^2} \boldsymbol{LK} \right)^{-1} \boldsymbol{Y} \tag{6}$$

3.2.3 Transfer Regression Model

We extend framework of manifold regularization to TRM, which can transfer the knowledge of the third party of dataset to the training model while importing large amount of unlabeled data.

We first have a survey on our transfer problem in Fig.1. The target is to build the regressive relationship $y = f(x)$ between variables of X and Y. X and Y correspond to two sparse training data. There is another variable Z, and Y is the function of Z, that is $y = h(z)$. In the task of 3D location estimation, X means the signal vectors collected on the third floor and Z means the signal vectors collected on the fourth floor and Y means the physical coordinators of the corresponding location points. There are some data pairs in X and Z, and these data have same function value in Y, which represent the same physical coordinates in different floor. Our purpose is to find schedules to reuse the data Z to improve the regressive model of X and Y.What we can depend on is the data pairs in X and Z, and the relationship of Z and Y .

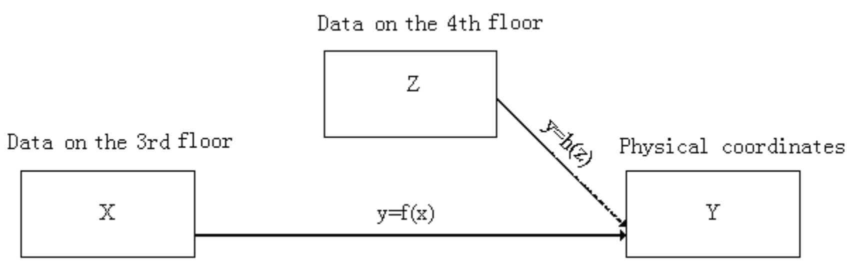

Fig. 2. Transfer problem in location estimation

Obviously, the traditional regression model such as BP (Back Propagation) network and SVM (Support Vector Machine) can not perform regressive training based on three datasets. In this paper, based on the framework of MR, we designed the schedule of TRM to improve $y = f(x)$ by importing data Z and optimize the regression model $y = f(x)$ and $y = h(z)$ at the same time. The strategy is to make the output of h and f have identical output while keep normal constraints of model h and f .

Now we construct the optimization problem:

$$
\begin{aligned}
(f^*, g^*, h^*) = \arg\min_{f\in \mathrm{H_K}} \frac{1}{l}\sum_{i=1}^{l} V\left(x_i, y_i, f\right) + \gamma_{A1}\|f\|_K^2 + \gamma_{I1}\|f\|_I^2 \\
+\frac{1}{l}\sum_{i=1}^{l} V\left(z_i, y_i, h\right) + \gamma_{A2}\|h\|_K^2 + \gamma_{I2}\|h\|_I^2 \\
+\frac{1}{l}\sum_{i=1}^{l} (h(z_i) - f(x_i))^2
\end{aligned} \tag{7}
$$

Sequentially, according to the classical Representer Theorem, the solution to this minimization problem exists in $RKHS$ (Reproducing Kernel Hilbert Space). We construct the regressive function as follows:

$$f^*(x) = \sum_{i=1}^{l} \alpha_i K_1(x_i, x) \tag{8}$$

$$h^*(z) = \sum_{i=1}^{l} \omega_i K_2(z_i, z) \tag{9}$$

Substitute them to (7), we can obtain the optimization problem of α and ω:

$$
\begin{aligned}
(\alpha^*, \omega^*) = \arg\min \frac{1}{l}(Y - J_1K_1\alpha)^T(Y - J_1K_1\alpha) + \gamma_{A1}\alpha^T K_1\alpha + \frac{\gamma_{I1}}{(u_1+l)^2}\alpha^T K_1 L_1 K_1\alpha \\
+\frac{1}{l}(Y - J_2K_2\omega)^T(Y - J_2K_2\omega) + \gamma_{A2}\omega^T K_2\omega + \frac{\gamma_{I2}}{(u_2+l)^2}\omega^T K_2 L_2 K_2\omega \\
+\frac{1}{l}(J_1K_1\alpha - J_2K_2\omega)^T(J_1K_1\alpha - J_2K_2\omega)
\end{aligned} \tag{10}
$$

For h and f are both based on the labeled pairs, which means the number of the labeled data is the same, so $J_1 = J_2 = J$, $u_1 = u_2 = u$.

After derivation, we can represent α and ω as:

$$\alpha = \left(2JK_1 + \gamma_{A1} lI + \frac{\gamma_{I1} l}{(u+l)^2} L_1 K_1\right)^{-1} (Y + JK_2\omega) \tag{11}$$

$$\omega = \left(2JK_2 + \gamma_{A2} lI + \frac{\gamma_{I2} l}{(u+l)^2} L_2 K_2\right)^{-1} (Y + JK_1\alpha) \tag{12}$$

Combine two formulations above, and let

$$A = \left(2JK_1 + \gamma_{A1} lI + \frac{\gamma_{I1} l}{(u+l)^2} L_1 K_1\right)^{-1} \tag{13}$$

$$B = \left(2JK_2 + \gamma_{A2} lI + \frac{\gamma_{I2} l}{(u+l)^2} L_2 K_2 \right)^{-1} \tag{14}$$

Then, the solutions are:

$$\alpha^* = (I - AJK_2BJK_1)^{-1}(AY + AJK_2BY) \tag{15}$$

$$\omega^* = (I - BJK_1AJK_2)^{-1}(BY + BJK_1AY) \tag{16}$$

We can observed from the Equation (15) that the solution of α^* is based on the parameters A, K_1, Y, B, K_2, the later two parameters is computed upon the dataset of Z, which means the third party data have contribution to the final regression model.

In addition, if the data Z have no contribution for the training, such as when $Z = X$, then $K_1 = K_2 = K$, $L_1 = L_2 = L$, $\alpha = \omega$. We can get:

$$\alpha^* = \omega^* = \left(JK + \gamma_{A1} lI + \frac{\gamma_{I1} l}{(u+l)^2} LK \right)^{-1} Y \tag{17}$$

The solution is identical as the solution of MR in Equation (6). It just means that MR (Manifold Regularization) is a special case of TRM, which can train regression model based on three dataset.

Once α^* is computed, the model f in Equation (8) is then obtained, and it can be applied as a regressive model to predict the physical coordinates for the new input point on the third floor. For the model contains location and Wi-Fi information of the fourth floor, it performs better than that without knowledge transfer. It can be observed in the followed experiment section.

4 Experiments

4.1 Experiment Setup

Our experiments are carried out based on real Wi-Fi data set. The data were collected within the building of ICT (Institute of Computing Technology). To test the ability of the transfer model, we collected Wi-Fi signal data in third and fourth floor in a 34.8*83.4m area respectively. The physical structures are same for the two floors as shown in Fig. 3.

We prepared a large amount of data in the third floor which is enough to provide high location accuracy, and just acquired a small dataset which can only provide low location accuracy, as shown in Table 1.

In the third floor, there are totally 23 APs are detected, and we choose 10 of them to pick up the RSS. There are 500 labeled data are selected as training data.

In the fourth floor, the same APs as in third floor are selected. There are also 500 labeled data are acquired corresponding to those of third floor. So total 500 labeled pairs are prepared and 12700 unlabeled data are prepared in the training data set.

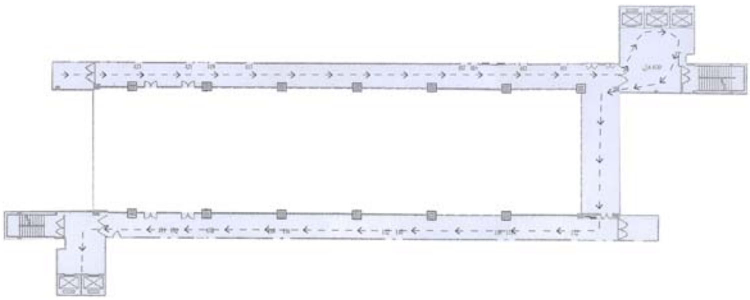

Fig. 3. The shared physical layout of third and fourth floor

4.2 TRM Based Location Estimation

Two experiments are carried out that train the prediction model with and without transferring knowledge from the data of the fourth floor.

- With transfer: In this case, three datasets are involved in the training procedure of TRM.
- Without transfer: In this case, just two datasets X, Y from third floor are involved, and the dataset Z of fourth floor is ignored. As mentioned before, if there is no contribution of dataset Z, TRM will be transformed into MR which is a regressive model without knowledge transfer.

For a given location, we use ED (Error Distance) parameter to evaluate the predicting result. In the experiment. If $y_0 = f(x_0)$ is the predicted position for the given input x_0, and y_t is the true position at that location, the prediction error will be the Euclidean distance between y_0 and y_t, that is $\mathrm{ED} = \| y_0 - y_t \|$. If ED is less than a threshold ED_0, the result is regarded as a correct one, or a wrong one. Three thresholds are selected to evaluate our prediction accuracy.

In the experiments, some parameters of TRM need to be specified first. We test them as in our previous work [13]. Finally, they are set as: the number of neighbors $k = 6$, and γ_A=0.014362, γ_I=0.2852，K is calculated using Gaussian Kernel function, and the kernel parameter is set as 0.935. Under such case of the parameters, we get better results than other configure case.

Table 1. Experiments of transfer knowledge

	Prediction Accuracy		
	ED_0 =1m	ED_0 =2m	ED_0 =3m
With Transfer	65.2%	78.3%	89.6%
Without Transfer	51.5%	66.7%	85.3%
Improved Percent	26.6%	17.4%	5%

The regression results are shown in Table 1. From Table 1, the prediction accuracy is improved in different degree corresponding to different error distance threshold.

We also compute the prediction accuracy under different AP selection, and the strategy to select the APs in our experiment is according to the average signal strength that collected at all points. Generally speaking, strong signal strength means the AP is detected well, which is beneficial for location estimation. Finally, we compare the result of TRM and other two regressive model SVR and BP neural network. For SVR and BP model, the data from fourth floor is ignored.

Fig. 4 gives the comparison under different AP selection. It can be concluded that, on the whole, TRM outperforms both SVR and BP.

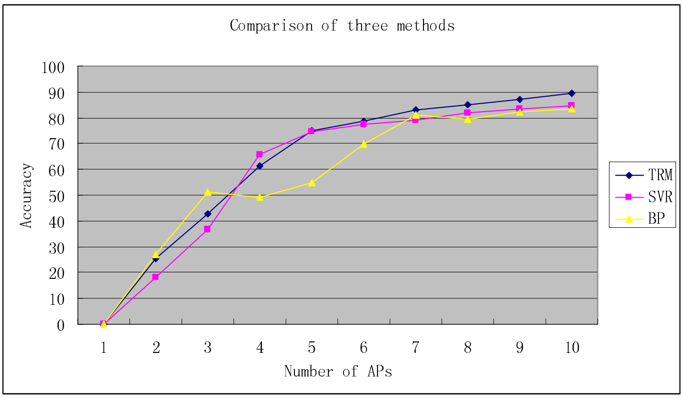

Fig. 4. Comparison of three methods under different AP selection

5 Conclusion and Future Works

In this paper, we present a novel transfer regressive model for indoor 3D location problem. TRM can effective import knowledge from the third party of dataset. The experiments of applying TRM to 3D location problem show that it is a good model to transfer the knowledge of location and Wi-Fi signal between various floors of the building. What's more, only a small labeled training data is needed for the target floor, which reduces calibration effort greatly.

In the future, we will consider the transfer learning on different devices, the situation that the well trained model can be transferred to a new type of wireless device. For instance, we use the notepad computer first to get a location model with high accuracy. Once we want to estimate location with a mobile cell phone, no large amount of data needed any more to train the new model, for our transfer model will utilize the previous data collected by the notebook computer.

Acknowledgements

This work is supported by National High-Technology Development '863' Program of China (2007AA01Z305) and Co-building Program of Beijing Municipal Education Commission. Thank Qiong Ning, Xiaoqing Tang for Wi-Fi data collection.

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