Adaptive Temporal Radio Maps for Indoor Location Estimation

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Abstract

In this paper, we present a novel method to adapt the temporal radio maps for indoor location estimation by off-setting the variational environmental factors using data mining techniques and reference points. Environmental variations, which cause the signals to change from time to time even at the same location, present a challenging task for indoor location estimation in the IEEE 802.11b infrastructure. In such a dynamic environment, the radio maps obtained in one time period may not be applicable in other time periods. To solve this problem, we apply a regression analysis to learn the temporal predictive relationship between the signal-strength values received by sparsely located reference points and that received by the mobile device. This temporal prediction model can then be used for online localization based on the newly observed signal-strength values at the client side and the reference points. We show that this technique can effectively accommodate the variations of signal-strength values over different time periods without the need to rebuild the radio maps repeatedly. We also show that the location of mobile device can be accurately determined using this technique with lower density in the distribution of the reference points.

1 Introduction

Location estimation is an important task in today's pervasive computing applications that range from context-dependent content delivery to people monitoring [4, 16]. In an indoor environment, increasing attention is paid to location estimation using the inexpensive and popular IEEE 802.11b wireless networks as the fundamental infrastructure. Many systems utilize the signal-strength values received from the access points to infer the location of mobile device, based on deterministic or probabilistic techniques [1, 6, 10, 11, 17].

In general, location-estimation systems using radio frequency (RF) signal strength function in two phases: an *offline training phase* and an *online localization phase*. In the offline phase, a *radio map* is built by tabulating the signal-strength values received from the access points at selected locations in the area of interest. These values comprise a radio map of the physical region, which is compiled into a deterministic or statistical prediction model for the online phase. In the online localization phase, the real-time signal-strength samples received from the access points are used to search the radio map to estimate the current location based on the learned model.

In most of the previous work, the radio maps are assumed to be static, which means that once learned in the offline phase, a radio map is applied thereafter to estimate the various locations in later time periods without adaptation. This simplistic approach poses a serious problem. In a dynamic environment caused by the unpredictable movements of people, layout changes, radio interference and signal propagation, the signal-strength samples measured in the online phase may significantly deviate from those stored in the radio map. As a result, location estimation based on a static radio map may be grossly inaccurate. Even if we attempt to deal with the variations of signal strength using additional reference points, as is done in [11] with RFID networks, the accuracy can be guaranteed only when the reference points are densely distributed, which drives up the cost of hardware and increases the potential computational time of location estimation. Conversely, a sparse distribution may not solve the problem satisfactorily. Therefore, it is a challenging task to design a location-estimation system which is both accurate and robust with respect to dynamic environmental changes.

In this paper, we present a novel method to adapt the radio map along the time dimension by offsetting the environmental dynamics using a regression analysis. Figure 1 illustrates the idea behind our proposed method. As in previous work, we start by collecting data to construct a static radio map in time period t_0. In any later time period t_i, where $i \geq 1$, instead of rebuilding the radio maps re-
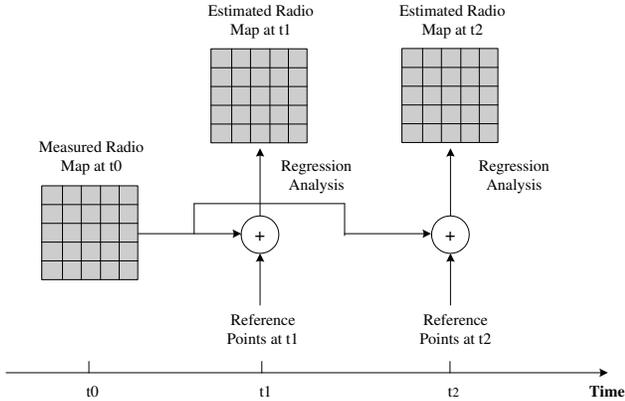
Figure 1. Illustration of the proposed method using adaptive temporal radio maps

peatedly, we place radio frequency (RF) receivers which act as dynamic reference points in the environment. Based on the signal-strength values received by the reference points, we apply a regression analysis to obtain the estimated radio maps which comprise the corrections we need to make to the static radio map. In our approach, the static radio map is compiled into regression models that predict the client locations using both the signal-strength values collected by the mobile client and those collected by the reference points. During the localization phase, the regression models are used to predict the most likely location of the mobile client. To the best of our knowledge, the Maximum Likelihood (ML) method is one of the best approaches to location estimation [10, 19]. We show that, using adaptive temporal maps through reference points, our approach can gain a higher average accuracy of localization over different time periods, which is 15% higher than the ML method (within 1.5 meters). In addition, our approach does not require that the physical positions of the reference points are known. Therefore, the location of mobile device can be accurately determined even with a lower density of reference points as compared with previous reference-point based methods such as the LANDMARC system [11].

The novelty of our work can be summarized as follows:

- Compared with previous static radio map-based techniques, our proposed method can adapt well to the variations of signal-strength values caused by the environmental dynamics.

- By capturing the dynamic relationship between signal-strength values received by the reference points and that received by the mobile device using regression models, the reference points can be sparsely distributed in the environment.

The rest of the paper is organized as follows. Section

2 discusses related work on location-determination systems using RF signal strength. Section 3 provides an overview of the problem domain. Section 4 presents the algorithms used in our analysis. Section 5 describes the experimental results. Section 6 concludes the paper and discusses directions for future work.

2 Related Work

Significant work has been done in the area of location estimation using RF signal strength. Most of the previous work are based on the techniques of using radio map, which can be classified into two broad categories: *deterministic techniques* and *probabilistic techniques*. Deterministic techniques [1, 2, 3, 14] apply deterministic inference methods to estimate a client's location. For example, the RADAR system by Microsoft Research [1, 2] uses nearest neighbor heuristics and triangulation methods to infer a user's location. Each signal-strength sample is compared against the radio map and the coordinates of the best matches are averaged to give the location estimation. The accuracy of RADAR is about three meters with fifty percent probability. In [3], an online procedure based on feedback from users was employed to correct the location estimation of the system.

Probabilistic techniques [4, 10, 13, 17, 18, 19] construct the signal-strength distributions over different locations in the radio map and use probabilistic inference methods for localization. The robotics-based location sensing system in [10] applies Bayesian inference to compute the conditional probabilities over locations based on received signal-strength samples from various access points. Then a post-processing step, which utilizes the spatial constraints of a user's movement trajectories, is used to refine the location estimation and to reject the estimates showing significant changes in the location space. Depending on whether the postprocessing step is used or not, the accuracy of this method is 83% or 77% within 1.5 meters respectively. Likewise, Youssef et al. [19] used a joint clustering technique to group locations together to reduce the computational cost of the system. The method first determines a most likely cluster within which to search for the most probable location, then applies a Maximum Likelihood (ML) method to estimate the most probable location within the cluster. A time-series analysis technique is introduced in [17] to study the correlation among consecutive samples received from the same access point over time. In this way, higher accuracy is obtained by taking the information about sample sequences into account. Most of the above work are all based on a common assumption that the radio map collected in the offline phase does not change much later in the online phase. A major limitation with this assumption stems from the dynamic characteristics of signal propagation and the

environment, where the signal-strength values measured in the online phase can significantly deviate from those that are stored in the radio map, thereby limiting the accuracy of such systems.

Another related work is the LANDMARC system which is based on the RFID technology [11]. LANDMARC utilizes the concept of reference tags to alleviate the effects caused by the fluctuation in RF signal strength. The method first computes the distance between the signal-strength vector received from the tracking tag and those from different reference tags respectively. It then uses k nearest reference tags' coordinates to calculate the approximate coordinate of the tracking tag. However, the accuracy of LANDMARC can be guaranteed only when the reference tags are densely distributed. The authors report that one reference tag is needed for each square meter to accurately locate the objects within the error distance between one and two meters. However, in many location-based applications, the deployment of a dense infrastructure for location estimation is not feasible. Moveover, the RFID readers are expensive, making them cost-prohibitive for localization in a large area. In contrast, our adaptive system utilizes the IEEE 802.11b wireless network which is already widely available and are relatively inexpensive. More importantly, the location of mobile devices can be determined even with a lower density of the reference points. In addition, our work is related to the LEASE system [9], which employs a few stationary emitters and sniffers to assist location estimation for indoor RF wireless networks. In this work, a synthetic model is generated for each sniffer, which estimates the signal-strength value at each grid point based on the coordinates of the stationary emitters and the signal-strength values received from them. The authors evaluate the performance of LEASE in two different experimental test-beds. However, the focus of our work is mainly to demonstrate the adaptivity of our proposed method to dynamic environmental changes over different time periods. Moreover, our approach, as compared with [9], does not require that the physical positions of reference points are known.

3 Wireless Environment

In this section, we describe our experimental setup and the noisy characteristics of wireless channel which makes the problem of location determination a challenging task.

3.1 Experimental Setup

Our experiments were conducted in a real environment which is equipped with an IEEE 802.11b wireless Ethernet network. We will discuss the experimental test-bed in detail in Section 5.1. The conditions of our experimental setup are as follows: (1) The number of reference points is known while the physical positions of reference points are not necessarily given. (2) The number of access points that can be detected in the environment is known, but we need not know the layout of the access points. (3) We performed the experiment in a two-dimensional location space, but it can be easily extended to a three-dimensional location space.

We developed a wireless API under the Window XP operating system to record the signal-strength values from all detectable access points along with their MAC addresses using the mode of active scanning. Using this API, the mobile client and reference points can receive the signal-strength values from the access points simultaneously. As the mobile client and reference points have the capabilities of communicating with the Internet using IEEE 802.11b wireless network, all the information received from the access points is first sent over to a specific program running on the location server. After the information is received by the server, the signal-strength values received by each reference point are packaged and transmitted to the mobile client via a wireless network socket. The location computation is done in an online manner by the mobile client.

3.2 Noisy Characteristics

The IEEE 802.11b standard uses radio frequencies in the 2.4 GHz band, which is attractive because it is license-free in most places around the world. However, it does suffer from inherent disadvantages. In the 2.4 GHz band, microwave ovens, BlueTooth devices, 2.4 GHz cordless phones and other devices can be sources of interference. Moreover, 2.4 GHz is the resonant frequency of water and human bodies can absorb RF signal strength.

Subject to reflection, refraction, diffraction and absorption by structures and humans, signal propagation suffers from severe multi-path fading effects in an indoor environment [8]. As a result, a transmitted signal can reach the receiver through different paths, each having its own amplitude and phase. These different components are combined to reproduce a distorted version of the original signal. Moreover, changes in the environmental conditions such as the change in temperature and humidity affect the signals to a large extent. As a result, the signal-strength values received from an access point at a fixed location varies with different time periods as well as physical surroundings.

Figure 2 gives a typical example of three normalized histograms of the signal-strength values received from an access point at a fixed location over different time periods. To build each particular histogram, 450 samples were taken in about 45 seconds over different time periods. It is clear that the signal-strength values received from the same access point varies with time even at a fixed location. Previous work [10, 18, 19] showed that it would be better to directly use these histograms rather than reduce the data into
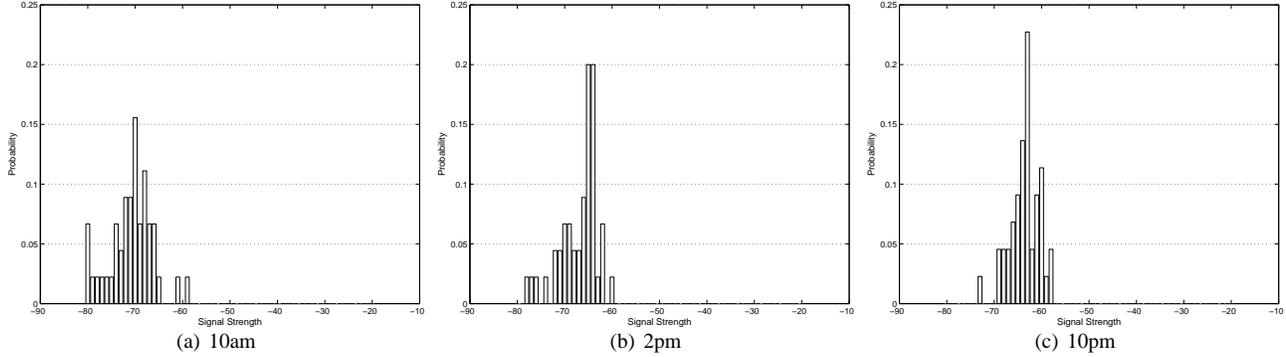
Figure 2. The variations of signal-strength histograms over different time periods at a fixed location

average values. By doing this, the essential assumption is that the histograms constructed in the training phase does not change much over time. However, in reality, as shown in Figure 2, the signal-strength histograms vary noticeably over different time periods, with significantly higher noise levels when more people are moving in the building. These variations suggest that, depending on the signal-strength histograms trained in the offline phase, the results of location estimation might be inaccurate if the signal-strength samples measured in the online phase deviate significantly from those collected in the offline phase. This motivates us to make use of reference points to adaptively offset the environmental dynamics that cause the variations in signal strength.

4 Methodology

We first define the location-state space $\mathbb{L}$ as a set of n physical grid points on the floor map. $\mathbb{L}$ is denoted as

$$\mathbb{L} = \{l_1 = (x_1, y_1, \theta_1), \ldots, l_n = (x_n, y_n, \theta_n)\},$$

where each tuple $(x_i, y_i, \theta_i), 1 \leq i \leq n$, represents a mobile user's location and orientation. Note that we describe the algorithm in a two-dimensional location space, but our algorithms can be easily extended for three-dimensional localization.

Suppose that there are p access points that can be detected in the environment. The signal-strength vector received by a mobile device is defined as $\mathbf{s} = (s_1, \ldots, s_p)$, where $s_j, 1 \leq j \leq p$, represents the signal-strength value received from the jth access point. Note that if the signal-strength value of an access point is too weak to be detected by the mobile device, we assign s_j with a small signal-strength value, e.g., -95 dBm. Suppose that there are m reference points placed in the environment. We define the signal-strength vector received by the kth reference point as

$\mathbf{r}_k = (r_{k1}, \ldots, r_{kp})$, where $r_{kj}, 1 \leq k \leq m, 1 \leq j \leq p$, represents the signal-strength value received by the kth reference point from the jth access point. As described in Section 3.1, for each location l_i, we can obtain the signal-strength vector $\mathbf{s}$ received by a mobile user at this location, along with m signal-strength vectors $\mathbf{r}$ received by m reference points in the same time period.

Since our objective is to determine the location of a mobile user using reference points in an adaptive way, the vital issue is how to correlate the signal-strength values received by the reference points with that of the mobile device over different time periods. For this purpose, our proposed approach works in two phases:

(1) During the offline phase, which corresponds to time period t_0, we apply a regression analysis to learn the predictive relationship of signal-strength values between the reference points and the mobile device which is tracked at each selected location. First, if we consider a location to be $l_i, 1 \leq i \leq n$, where for the jth access point, $1 \leq j \leq p$, we learn the corresponding relationship f_{ij}. Here f_{ij} indicates the relationship between the signal-strength values $(r_{kj}(t_0))$ received by each of the k reference points, $1 \leq k \leq m$, and the value received by the mobile device $(s_j(t_0))$. In particular, we build a regression relationship using the following function, which we will discuss in detail in the next two subsections:

$$s_j(t_0) = f_{ij}(r_{1j}(t_0), r_{2j}(t_0), \ldots, r_{mj}(t_0)),$$
$$1 \leq i \leq n, 1 \leq j \leq p.$$

While this function is learned in time period t_0, the functional relationship inherent in f captures the dynamic relationship between the signal-strength values received by reference points and the predicted signal-strength value received by the mobile device at each location.

(2) During the online phase in time period t, based on the signal-strength vectors received from the reference points, we compute the estimated signal-strength vector $\mathbf{s}_{est}(t) = (s_1(t), \ldots, s_p(t))$ that may be received at each location using the corresponding function f_{ij}. We refer to the signal-strength vector that is computed using the function f_{ij} as an *estimated signal-strength vector* $\mathbf{s}_{est}(t)$ and the signal-strength vector that is actually received by the mobile device as an *actual signal-strength vector* as $\mathbf{ss}_{act}(t)$. Then for each location $l_i, 1 \leq i \leq n$, we compute the Euclidian distance D_i between its corresponding estimated signal-strength vector $\mathbf{s}_{est}(t) = (s_1(t), \ldots, s_p(t))$ and the actual signal-strength vector $\mathbf{ss}_{act}(t) = (ss_1(t), \ldots, ss_p(t))$ as follows:

$$D_i(t) = \sqrt{\sum_{j=1}^{p}(s_j(t) - ss_j(t))^2}.$$

Finally, a location l_i is predicted to be the most probable location if its corresponding distance $D_i(t)$ is minimized.

Since the reference points are subject to the same effect in the environment as the tracked mobile device, the newly observed signal-strength values received by the reference points can be used to dynamically update the information for localization in real time. Therefore, this approach is more flexible and adaptive to the environmental dynamics. However, to achieve high accuracy, the critical issue is how to model the relationship between the signal-strength values received by the reference points and that received by the tracked mobile device during the offline phase. In the next two subsections, we will discuss two different algorithms to learn the function f_{ij}.

4.1 Multiple Regression

Our first attempt is to apply multiple regression to model the relationship of signal-strength values between reference points and the mobile device. Multiple regression is a generalization of simple linear regression which allows for the modelling of the relationship between a dependent variable and more than one independent variable [5, 7].

Based on the multiple regression model, at each location, for each access point, we compute the signal-strength value received by the mobile device as a linear aggregate of the signal-strength values received by m reference points, as follows:

$$s_j = \alpha_{0j} + \alpha_{1j}r_{1j} + \cdots + \alpha_{mj}r_{mj} + \varepsilon_j.$$

In this equation, s_j represents the signal-strength value received by the mobile device from the jth access point and $r_{kj}, 1 \leq k \leq m$, represents the corresponding signal-strength value received by the kth reference point from the jth access point. The regression coefficients $\alpha_{kj}, 1 \leq k \leq m$, represent the independent contributions of each reference point to the prediction of signal-strength value received by the mobile device. When all the r's are equal to 0, α_{0j} is called the intercept. In addition, ε_j is the random error, which is usually assumed to be normally distributed with mean zeros and variance σ^2.

1. *Offline Learning of Multiple Regression Model:* During the offline phase, we perform the *least square estimation* method to compute the regression coefficients $\boldsymbol{\alpha}_j = (\alpha_{0j}, \alpha_{1j}, \ldots, \alpha_{mj})^T$ for p access points respectively. [5, 7]. Specifically, we collected a series of q signal-strength samples received by the mobile device and m reference points simultaneously at each location. Note that we assume $q > m + 1$ so that for the jth access point, we have q linear equations, which are more than $(m + 1)$ parameters to be estimated, $\alpha_{0j}, \alpha_{1j}, \ldots, \alpha_{mj}$. Then the solutions to these linear equations provide the least squares estimates of the coefficients. Therefore, at each location, we can obtain a set of regression coefficients, $\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_p$, where $\boldsymbol{\alpha}_j$ corresponds to the jth access point.

2. *Online Application of Multiple Regression Model:* During the online phase, based on the signal-strength values received by the reference points, the regression coefficients can be used to calculate the estimated signal-strength vectors $\mathbf{s}_{est}$ for each location. Finally, the location with the smallest distance between $\mathbf{s}_{est}$ and $\mathbf{ss}_{act}$ is selected as the final predicted location.

3. *Analysis on Online Time Complexity:* When we apply multiple regression model during the online phase, the time complexity is $O(pmn)$, which is linear with the number of locations n, the number of reference points m and the number of access points p. However, in most cases m and p are small integers. In our experiment, $1 \leq m \leq 8, 1 \leq p \leq 9$, therefore, the location estimation can be done efficiently.

The multiple-regression based algorithm is simple and straightforward, however, it assumes that the relationship of signal-strength values between the mobile device and reference points can be well approximated by a linear model. In an indoor environment where the signal propagation is quite complex, this assumption may not hold and more effective approaches are therefore desired.

4.2 Model Tree

In this section, we propose a general nonlinear approximation approach based on a model tree [12, 15]. A model

tree is a binary decision tree with linear regression functions at the leaf nodes. Thus it can represent any piecewise linear approximation to an unknown function. Figure 3 illustrates the difference between a multiple regression and a model tree. As shown in the figure, a multiple regression uses a single linear model to fit the whole reference-point value space while a model tree divides the whole state space into several regions, in each of which a different linear model is used for relating the signal-strength values received by reference points with the value received by the mobile client.

(a) Multiple regression
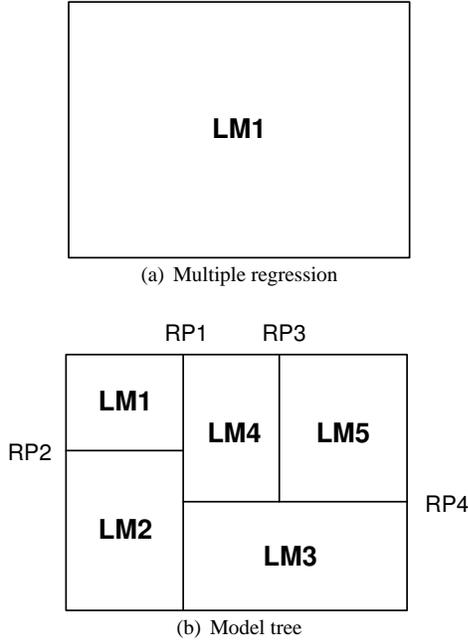
(b) Model tree

Figure 3. Illustration of multiple regression and model tree for an access point

For each access point, we build a model tree to learn the predictive relationship of signal-strength values between reference points and the mobile device. As an example, Figure 4 shows a model tree which is built over four reference points $(RP_1 \sim RP_4)$ to predict the signal-strength value received by the mobile device. Note that this tree structure is equivalent to the state-space structure in Figure 3(b). In the figure, each internal node corresponds to a test on the signal-strength value received by a particular reference point. Two subtrees are branched from an internal node, each corresponding to a binary range of values. Starting from the root node, a test sample will be asked a sequence of questions until it reaches a leaf node. Each leaf node at the lowest level is attached with a linear regression function from which the estimated signal-strength value received by the mobile device can be calculated.
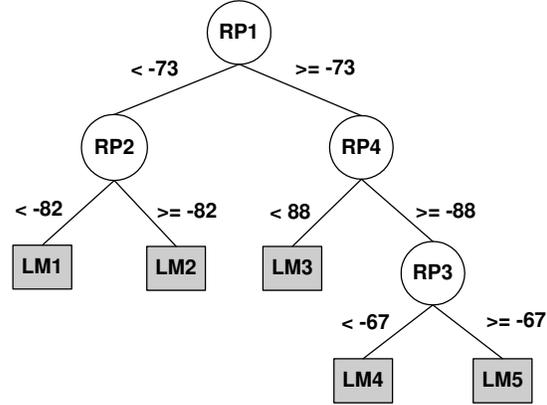
Figure 4. An example of model tree

Now let us explain the construction process of a model tree. A model tree is built through a process known as *binary recursive partitioning*. This is an iterative process of splitting the samples into two partitions and then splitting each partition further into subtrees. The vital part of the algorithm is the splitting criterion, derived from the measure of the impurity of a sample set. Since the class value to be predicted is continuous, the estimated variance of the class values is used as the impurity measure. The best splitting point of the samples in a node is chosen as the one that minimizes the expected variance V_{exp}, given by

$$V_{exp} = \frac{1}{N_L + N_R}(N_L \hat{\sigma}_L^2 + N_R \hat{\sigma}_R^2),$$

where N_L, N_R denote the number of samples falling into the left child node and the right child node. Accordingly, $\hat{\sigma}_L^2, \hat{\sigma}_R^2$ are the variances of predicted values at two children nodes respectively, computed by:

$$\hat{\sigma}_L^2 = \frac{1}{N_L}\sum_{n \in L}(y_n - \hat{\mu}_L)^2, \quad \hat{\sigma}_R^2 = \frac{1}{N_R}\sum_{n \in R}(y_n - \hat{\mu}_R)^2,$$

where y_n is the class value of each training sample, and $\hat{\mu}_L, \hat{\mu}_R$ are the means of the class values at the left child node and the right child node.

Based on the definition of the best splitting point, the algorithm of building a model tree works as follows: Initially, all of the training samples are placed together in the root node. The algorithm then tries breaking up the samples, using every possible binary split on every reference point. The algorithm chooses the splitting point that partitions the samples into two parts such that it minimizes the expected variances for each part. This splitting is then applied to each of the new branches. The process continues until each node reaches a user-specified minimum node size and becomes a leaf node. If the expected variance in a node is zero, then that node is considered a leaf node even if it has not reached

the minimum size. Then the algorithm prunes the tree by replacing subtrees with linear regression functions whenever this seems appropriate.

1. *Offline Learning of Model Tree:* During the offline phase, at each location, we use a series of q signal-strength samples received by the mobile device and m reference points simultaneously to learn p different model trees, one for each access point.

2. *Online Application of Model Tree:* During the online phase, for each access point, we walk along the corresponding model tree until a leaf node is reached, based on the signal-strength received by reference points. Through the linear model attached to that leaf node, we calculate the estimated signal-strength received by the mobile device. In this way, for each location we obtain an estimated signal-strength vector s_{est}. Finally, the location with the smallest distance is predicted.

3. *Analysis on Online Time Complexity:* When we apply model tree for localization during the online phase, The Time complexity is $O(p'mn)$, where $p' \leq p$ because the model-tree based algorithm, instead of using all the reference points, always chooses an optimal subset of reference points to build the tree. Similarly, since m and p' are small integers, the location estimation can be done efficiently in our experiment.

5 Experimental Results

In this section, we first discuss our experimental test-bed and the procedure for data collection. Then we evaluate the performance of our proposed algorithms and compare them with previous methods for indoor WLAN-based location estimation.

5.1 Experimental Test-bed

We conducted our experiment in a section of the third floor of the Academic Building where the Computer Science Department at Hong Kong University of Science and Technology is located. The layout of the experimental test-bed is shown in Figure 5. In our experiments, we chose eight available PC machines along the horizontal hallway, each of which is equipped with a Linksys Wireless-B USB Network adapter, as the reference points. The placement of reference points is marked with solid circles in the figure. In this environment, there are nine access points that can be detected, of which five access points distributed within this areas are marked with blank triangles in the figure. The other four access points are located either on the same floor outside this area or on the different floors. On average, the number of access points covering a location varies from five

to seven. In addition, an IBM laptop computer with the same wireless adapter served as the tracked mobile client in our experiment.
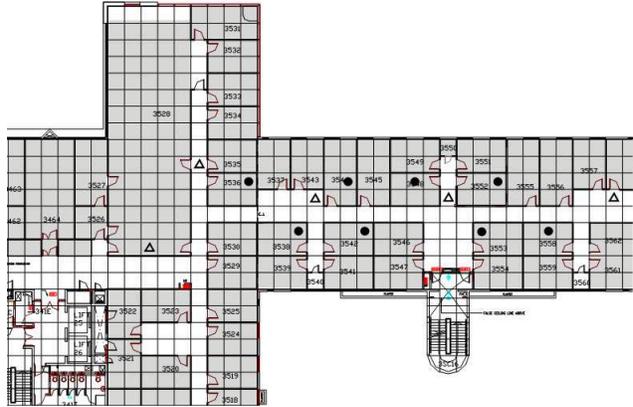
Figure 5. The layout of the experimental test-bed

With the placement of the reference points shown in the figure, we repeatedly collected signal-strength samples received by the eight reference points from the access points on every other hour from early morning to midnight (8:00 AM – 12:00 AM). Within each hour in which data are continuously collected, we simultaneously used an IBM laptop computer to collect signal-strength samples at various positions in the horizontal hallway, along which reference points are placed. More specifically, we collected samples at the positions every 1.5 meters apart from one end of the hallway to the other facing both directions (each grid cell is 1.5 meters). At each position, we took 450 samples at ten samples per second. Thus we obtained nine groups of one-hour data. The objective of our experiment is to test the adaptive abilities of our proposed algorithms. Therefore, we used one group of data collected at midnight 12:00 AM for training and other independent groups of data for testing.

5.2 Impact of Environmental Factors

In this section, we evaluate the performance of the multiple regression algorithm and the model-tree based algorithm discussed in Section 4. In particular, we compare the two algorithms with the Maximum Likelihood (ML) method in [10, 19] with respect to their ability to adapt to the environmental factors.

Table 1 shows the overall accuracy using the three approaches over different time periods. As shown in the table, we compare the accuracy of three approaches within different distances: 0.5, 1.5 and 3 meters. In this experiment, for the ML method, we used 450 samples collected

Table 1. Comparison of accuracy over different time periods

Different Times	Maximum Likelihood			Multiple Regression			Model Tree		
	0.5m	1.5m	3m	0.5m	1.5m	3m	0.5m	1.5m	3m
8am	35%	59%	77%	35%	76%	90%	41%	78%	91%
10am	26%	60%	76%	38%	72%	90%	40%	74%	92%
12pm	39%	72%	79%	32%	73%	89%	40%	75%	92%
2pm	27%	72%	81%	31%	74%	92%	38%	77%	93%
4pm	29%	60%	73%	28%	68%	86%	36%	72%	89%
10pm	54%	81%	89%	53%	80%	90%	56%	82%	90%

at each location at midnight 12:00 AM to train the radio map which was later used for testing over different time periods, as described in [10, 19]. In contrast, for the multiple regression and the model-tree based algorithms, we used signal-strength samples received by both the mobile device and reference points at the same time to learn the predictive relationships among them. The testing was also performed over different time periods. We can see from the table that the three approaches perform approximately the same at 10:00 PM, a quiet time in the department. For example, the accuracy within 1.5 meters is nearly 80%. This is because the environmental conditions at night are relatively static. For the ML method, the radio map built in the training phase can accurately model the signal-strength samples observed in the localization phase in these quiet time periods. Therefore, in this part of the experiments, there is not much difference in accuracy between the ML method with the two algorithms using reference points.
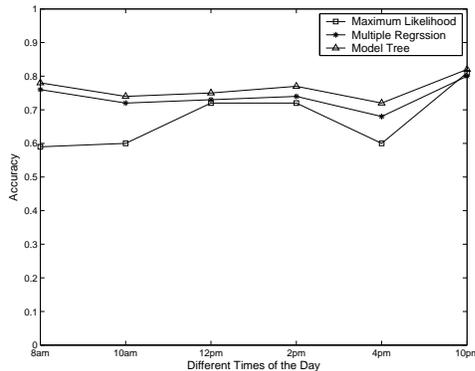
Figure 6. Comparison of accuracy within 1.5 meters over different daytime periods

The situation is quite different during the daytime, when the multiple-regression and the model-tree based algorithms can be seen to outperform the ML method by a large margin. Part of the results with respect to the accuracy within 1.5 meters in the daytime periods are shown in Figure 6 for illustration. In the figure, the accuracy of the ML method varies a lot over different daytime periods, while the accuracy of multiple-regression and model-tree based algorithms are relatively stable. More specifically, for the ML method, the variance of accuracy over different daytime periods is 0.0081. For the other two algorithms using reference points, the variances of accuracy are 0.0016 and 0.0012 respectively, which are much lower than that of the ML method. This is because the environment during the daytime is much more complex than at night due to people moving, door opening and closing. This causes the signal-strength samples measured during the daytime to significantly deviate from those in the radio map. Therefore, the performance of the ML method may decrease dramatically depending on the environmental dynamics. In contrast, by using reference points, both of our proposed algorithms can better adapt to the dynamics of environmental conditions. Moreover, we can see from the figure that the accuracy of the model-tree based algorithm is higher than that of the multiple-regression based algorithm. This shows that the linear assumption made by the multiple-regression algorithm may not hold in a complex indoor environment. The average accuracy of the model-tree based algorithm over different times is about 76% within 1.5 meters, which is increased by 15% as compared with the ML method.

5.3 Impact of Reference Points

In this section, we investigate the effect of the placement and number of reference points on the performance of our proposed algorithms. Intuitively, the placement and number of reference points are related to the technique used to build the model. For the multiple-regression based algorithm, the model is built using a linear function as described in Section 4.1; therefore, at least two points are needed for reasonable smoothing. This implies that a mobile device at any position should see at least two reference points. For the model-tree based algorithm, as described in Section 4.2, the model is built by first dividing the whole reference-point value space into sub regions and then fitting a different linear function to each sub region. Similarly for each sub region, at least two reference points are needed. Therefore, we use an engi-

neering solution to place the reference points in this paper. In our case, we divide the horizontal hallway into four sub squares with approximately equal area, in each of which at least two reference points are placed on two sides respectively along the hallway.
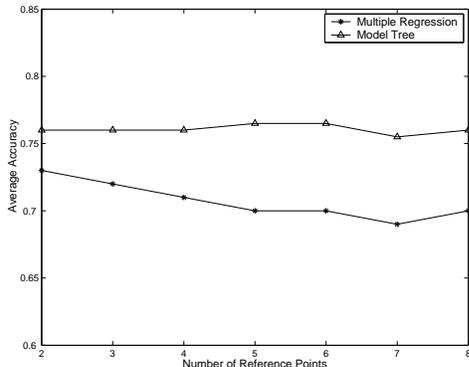
Figure 7. Comparison of average accuracy with respect to the number of reference points at 8:00 AM

Figure 7 compares average accuracy within 1.5 meters using the two approaches with respect to different numbers of reference points. For a specific number of reference points m, we define average accuracy as the accuracy averaged on all the possible subsets of reference points corresponding to m. We can see from the figure that, the accuracy of the model-tree based algorithm is not very sensitive to the number of reference points. This is because the model-tree based algorithm always chooses an optimal subset of reference points to build the tree according to their capability in predicting the signal-strength value received by the mobile device, even if more reference points are provided. However, the accuracy of the multiple-regression based algorithm depends on the number of reference points to a large extent. An interesting observation is that, the best accuracy of the multiple-regression based algorithm is usually obtained when the number of reference points is two. This is because the multiple-regression based algorithm always finds a linear model to approximately fit the relationships between signal-strength values received by reference points and that received by the mobile device. However, in reality, such relationships are nonlinear. As a result, the multiple-regression based algorithm tends to select as few reference points as possible to construct an optimal linear model. In contrast, the best accuracy of the model-tree based algorithm is achieved when five or six reference points are evenly distributed on two sides along the hallway. From the perspective of system design, it is difficult to specify the appropriate number of reference points before the system starts to work, therefore, the model-tree based algo-

rithm is more feasible than the multiple-regression based algorithm since its performance is less sensitive to the placement and number of reference points.

In addition, as shown in Figure 5, we roughly place one reference point at about five square meters to locate the mobile device. The average accuracy is 76% within 1.5 meters using the model-tree based algorithm. However, in the LANDMARC system [11], one reference tag is needed per square meter such that the worst error is two meters and the average is about one meter. Therefore, it is more feasible to implement our proposed algorithm in many location-based applications.

5.4 Impact of Access Points

In this section, we study the effect of the number of access points p on the performance of the multiple-regression based algorithm, the model-tree based algorithm and the ML method.
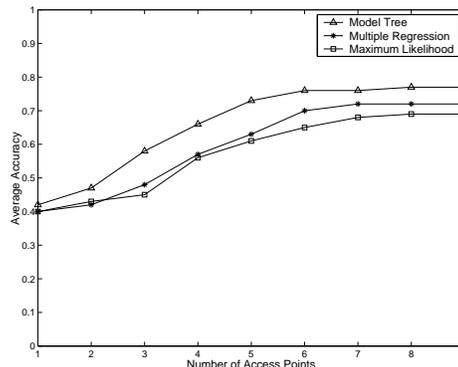
Figure 8. Comparison of average accuracy with respect to the number of access points at 12:00 PM

Figure 8 shows the average accuracy within 1.5 meters using three approaches with respect to different numbers of access points at 12:00 PM. Similarly, for a specific number of access points p, we define average accuracy as the accuracy averaged on all the possible subsets of access points corresponding to p. We can see from the figure that, initially, the accuracy of three approaches increases as the number of access points increases. This is because when more access points are used, we have more information for localization. However, when the number of access points increases to six or seven, for a particular approach, the accuracy remains approximately the same. This shows that when we have enough information to distinguish different locations, the added access points do not contribute to an increase in accuracy but to an increase in the computational complexity. Therefore, we roughly need six access points

to locate a mobile device in our environment. However, the model-tree based algorithm outperforms the other two approaches at different numbers of access points since it can adapt better to dynamic environmental changes.

6 Conclusions and Future Work

In this paper we have proposed a novel RF-based indoor location-estimation system which can adapt to dynamic environmental changes. We proposed a multiple-regression based algorithm and a model-tree based algorithm. While the former is based on a simple linear relationship between the signal-strength values received by the reference points and that received by the client device, the latter represents an improvement using a nonlinear function. Our experiments show that the proposed algorithms achieve a large advantage over the Maximum Likelihood method in terms of estimation accuracy by using adaptive temporal maps through reference points. Furthermore, we show that the model-tree based algorithm is much more robust with respect to reduction in the number of reference points. For the proposed algorithms, the number of reference points and the number of access points are known, but we need not know the physical positions of reference points and access points. In addition, the proposed algorithms can determine the locations of mobile devices even with a lower density of reference points.

Our work can be extended in several directions. First, we will consider applying more effective probabilistic methods to build the radio map at each grid point using the signal-strength values received by the reference points. Second, we wish to incorporate the user's movement trajectories to further improve the accuracy of location estimation. In addition, we also wish to test the validity of our proposed algorithms in a larger-scale environment.

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