Practical Indoor Localization using Ambient RF

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***Abstract*—The article presents a simple, practical approach for indoor localization using Received Signal Strength fingerprints from the GSM network, including an analysis of the relationship between signal strength and location, and the evolution of localization performance over time. Support Vector Machine regression applied to very high dimensional fingerprints does not reveal any smooth functional relationship between fingerprints and position. Classification using Support Vector Machines however provides very good results on discriminating different rooms in an indoor environment, albeit with performance that degrades over time. Transductive inference, introduced as a means of updating models to overcome degradation over time, provides hints that accurate indoor localization can be achieved by applying classification methods to cellular Received Signal Strength fingerprints, performance robustness being maintained via model updating and refining.**

Keywords-localization; indoor; fingerprint; transductive support vector machine

I. INTRODUCTION

Indoor localization systems are an important extension to Location Based Services (LBSs), for assisted living scenarios, tracking of Alzheimer's patients, and in more general situations [1]. As GPS receivers are unable to function in indoor environments, a variety of indoor localization strategies have been proposed to try to tackle this challenging task [2-11]. Methods based on the measurement of Received Signal Strength (RSS) in RF networks such as Wi-Fi and Bluetooth networks, for example, have proven to be effective [2-6]. However, time and labor intensive deployment and maintenance of these networks is a drawback that reduces the impact of these techniques.

Aside from these specially deployed networks, indoor localization based on ambient radiotelephone networks, such as GSM and CDMA, has also been studied [8-10]. In the past few years, methods based on the use of RSS fingerprints acquired from large numbers of GSM channels have appeared promising [10, and references therein]. Recent results also suggest that an appropriately programmed standard cellular mobile phone can provide a simple, inexpensive solution for accurate room-level indoor localization [11].

The studies proposed in [10-11], however, were preliminary for two reasons. First, they did not attempt to explore the distribution of measured RSS values, or to discover a functional relationship between RSS and position in indoor environments. Secondly, no prescription was made for correcting for RSS drifts over time, which is a well-known challenge in RSS based systems, particularly for long-range signals [12]. Indeed, due to shadowing, multipath and environmental effects such as building geometry, network traffic, presence of people, and atmospheric conditions, RSS is expected to be nonlinear with distance, non-Gaussian, and time varying [2], which can lead to performance degradation over time.

In this article, after an initial description of the data collection procedures used (section II), we turn our attention to seeking a functional relationship between GSM RSS and position, using Support Vector Machine (SVM) regression. The results, in fact, presented in section III, show that no such relationship exists for the indoor environments tested, indicating that interpolation/extrapolation schemes based on RSS measurements at a small number of points as in [10] will not be viable for localization. .

On the other hand, because of the local nature of shadowing and multipath effects, RSS fingerprints acquired over entire rooms can potentially be useful for room-level classification, as proposed in [11]. The scheme is presented in section IV, using data collected during "random walks" that explore an entire area. This section also presents long term tests showing that the performance of our RSS based indoor localization method degrades over time. We introduce transductive inference, which uses new, incoming unlabeled data to update SVM classifiers as a means of reducing performance degradation caused by RSS drift. The use of small amounts of new labeled data as a model update scheme is also explored here. Overall conclusions and some perspectives appear in section V.

II. MEASUREMENT SITES AND DATASETS

Two types of datasets were collected, for regression and classification experiments, respectively, both recorded in a 4th floor laboratory building (steel frame, concrete and plaster walls) in central Paris, France (Fig. 1). The first set, which we shall call the regression set, was collected in a single room (office 7) using so-called machine-to-machine, or M2M, GSM/GPRS modules [13], which can be driven using standard and manufacturer-specific AT modem commands. We used 8 identical modules, with nominally identical specifications and technical parameters. During data collection, the M2M

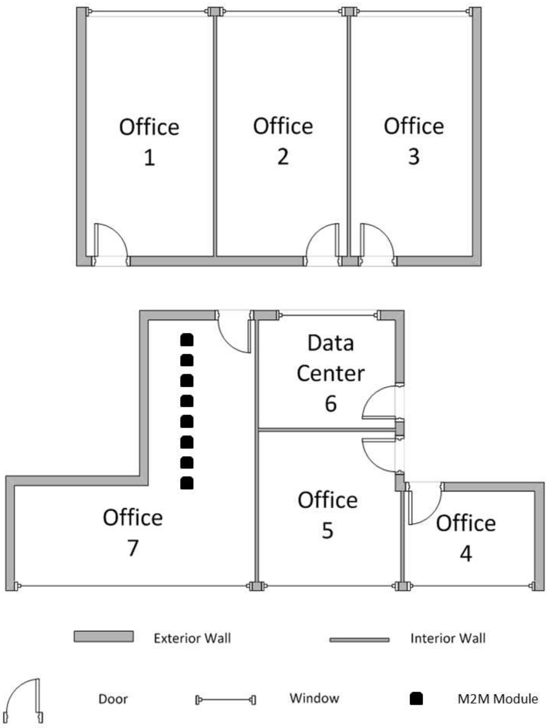

Figure 1. Layout of the laboratory where the datasets were recorded

modules were placed at fixed positions, in a line, spaced at an interval of 0.6m, as illustrated in Fig. 1. A total of 600 GSM scans for each module were recorded over 5 working days. Each scan contains the RSS of all 548 carriers in the GSM900 and GSM1800 bands, and consists of RSS values ranging in value from -108dBm to -40dBm. All the scans were labeled manually with location from 0m to 4.2m indicating where the scan was made.

The second dataset, which will be used for SVM classification, was collected in 7 rooms of the laboratory as described in [11]. The data acquisition device in this case is a Sony-Ericsson mobile phone with embedded scanning software, which is able to obtain a scan of the entire GSM900 and GSM 1800 bands in about 300 milliseconds. Scans were recorded in each of the 7 rooms and manually labeled with the corresponding room numbers during “random walks”. Four datasets were recorded during weekends over a period of six months in the same setting, hereafter called *S1* (5000 scans in each room), *S2* (2000 scans), *S3* (1000 scans) and *S4* (1000 scans).

III. Position From RSS

It was shown in [10] that the classification of RSS vectors recorded at fixed points works quite well. The objective here is to see if a regression method allows to measure locations at intermediate positions between the fixed points by finding a functional relationship between location and RSS in this indoor environment.

A. SVM Regression Algorithms

Since the number of variables is very large (548 carriers) and the size of the training set is relatively limited, SVM regression was deemed appropriate because of its built-in regularization mechanism [16].

Consider a given dataset $\{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_n, y_n)\}$, where $\mathbf{x}_i$ is the fingerprint vector at location i and y_i is the coordinate of the location (assuming that 1-D localization is performed as described above). There exists a variety of Support Vector Regression (SVR) techniques, serving different purposes. $\varepsilon - SVR$, which was used in our experiments, aims to find a parameterized function $f(\mathbf{x}, \Theta)$ such that prediction errors $\|y_i - f(\mathbf{x}_i, \Theta)\|$ do not exceed a given value ε for all elements of the training set, and, at the same time, is as regular as possible, i.e. does not wiggle unnecessarily [14]. Assume that we are looking for a linear relationship between the RSS fingerprint and the location. The function has the form:

$$f(\mathbf{x}, \Theta) = \mathbf{w} \cdot \mathbf{x} + b \tag{1}$$

where $\Theta = [\mathbf{w} \;\; b]^T$. The parameters are sought as solutions to the constrained optimization problem:

$$\begin{aligned} &\text{minimize} \;\; \frac{1}{2}\|\mathbf{w}^2\| \\ &\text{subject to} \;\; \|y_i - (\mathbf{w} \cdot \mathbf{x}_i - b)\| \le \varepsilon \end{aligned} \tag{2}$$

The optimal solution, if it exists, can be shown to be of the form

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i (\mathbf{x}_i \cdot \mathbf{x}) + \alpha_0 \tag{3}$$

where α_0 and all the α_i are solutions of a constrained quadratic optimization problem.

If such a solution does not exist, slack variables ζ_i and ζ_i^* can be introduced to relax the constraints, allowing some examples of the training set to be predicted with an error larger than ε. The problem becomes:

$$\begin{aligned} &\text{minimize} \;\; \frac{1}{2}\|\mathbf{w}^2\| + C\sum_{i=1}^{n}(\zeta_i + \zeta_i^*) \\ &\text{subject to} \;\; \begin{cases} y_i - \mathbf{w} \cdot \mathbf{x}_i - b \le \varepsilon + \zeta_i \\ \mathbf{w} \cdot \mathbf{x}_i + b - y_i \le \varepsilon + \zeta_i^* \quad \forall i \\ \zeta_i, \, \zeta_i^* \ge 0 \end{cases} \end{aligned} \tag{4}$$

where C is a hyperparameter called “regularization constant”.

If we want to look for a non-linear relationship between the RSS fingerprint and the location, non-linear regression can be realized by first performing a nonlinear transformation of the variables that defines a more suitable feature space, in which linear regression is performed. The final solution is in the form

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i K(\mathbf{x}_i, \mathbf{x}) + \alpha_0 \tag{5}$$

where *K*(**.**, **.**) is called the *kernel* function. In our experiments, linear and nonlinear regression (using Gaussian and Polynomial kernels) were performed, using the Spider toolbox [15].

B. Results

The results of SVRs are estimated through the mean squared localization error $\frac{1}{8}\sum_{k=1}^{8}\sqrt{\frac{1}{600}\sum_{i=1}^{600}\left[y_k - f\left(\mathbf{x}_{ik}, \boldsymbol{\theta}^{-k}\right)\right]^2}$,

TABLE I. REGRESSION RESULTS

Regression Method	Mean Squared Localization Error
Linear LS-Regression	2.3m
Linear SVM Regression	1.8m
Polynomial SVM Regression (d = 5)	1.3m
Gaussian SVM Regression	2.4m

where y_k is the position of measuring device k, $\mathbf{x}_{ik}$ is the RSS vector measured during scan i taken at location k, and $\boldsymbol{\theta}^{-k}$ is the parameter vector found by training from the data pertaining to all locations except location k.

The results for linear and non-linear regressions are shown in Table I. The soft margin parameter C, polynomial degree d and Gaussian kernel parameter σ were selected through cross-validation. Results from linear least squares regression (LS-Regression) are also given for comparison.

As shown in the table, the mean positioning error of all the regression methods is so large as to be unexploitable. The regression error is approximately equal to the average distance between the 8 locations, meaning that no linear or non-linear relationship between RSS and the position in a small indoor environment is evident. This appears to rule out using full-band RSS GSM vectors obtained in this way to interpolate between fixed positions in an indoor localization method.

IV. ROOM LEVEL CLASSIFICATION AND RSS DRIFT

An alternative scheme, first introduced in [11], is to perform room-level classification based on RSS measurements made during "random walks". In this case, we use classifiers to perform room-level indoor localization, where each room is a class. Data-driven classification problems are often solved in two stages: off-line training; and on-line testing. In the off-line training stage, discriminant functions are determined using training data and known labels, while in the on-line testing stage, a new test fingerprint is presented to the classifier and given a label based on the discriminant functions.

The RSS-based room level SVM classifiers in [10] gave good results when training and test data were obtained over the same one-month period. Here, we explore the time dependence of the "random walk" approach, proposing transductive inference to continuously adjust a discriminant function with newly collected unlabeled data, in order obtain an updated classifier.

A. SVM Classifier

SVM classifiers were used in our experiments, since they are deemed appropriate to deal with the high dimensional RSS fingerprints for the same reasons as described above for SVRs.

Consider a set of n examples of items belonging either to class A or class B, each example being described by a p-dimensional vector $\mathbf{x}_i$. Further assume that the examples are linearly separable, i.e. that there exists a hyperplane of equation $f(\mathbf{x}) = 0$ that separate all examples without error: $f(\mathbf{x}_i) > 0$ for all examples i belonging to class A and $f(\mathbf{x}_i) < 0$ otherwise. It can be proved that $f(\mathbf{x})$ can be written under the form

$$f(\mathbf{x}) = \sum_{i=1}^{n} \alpha_i y_i (\mathbf{x}_i \cdot \mathbf{x}) + \alpha_0 \qquad (6)$$

where the α_i (i = $0 \cdots n$) are parameters whose values are estimated from the examples; $y_i = +1$ if example i belongs to class A and $y_i = -1$ otherwise.

If the examples are not linearly separable, a "soft-margin" approach can be used to reduce the complexity of the classifier by introducing slack variables ζ_i and performing a tradeoff between accuracy of classification of the training examples and ability to generalize; the price to pay is the introduction of a "regularization" constant C whose value must be chosen appropriately.

B. Transductive SVM Classifier

Transductive SVMs take unlabeled test examples into account and adjust the separating surface to separate both training examples and test examples with maximum margin. For a linearly separable data case, this leads to the following optimization problem [17]:

$$\begin{aligned} &\text{minimize} \quad \frac{1}{2}\left\|\mathbf{w}^2\right\| \\ &\text{subject to} \begin{cases} y_i\left(\mathbf{w}\cdot\mathbf{x}_i + b\right) \geq 1 \\ y_j^*\left(\mathbf{w}\cdot\mathbf{x}_j^* + b\right) \geq 1 \end{cases} \quad \forall i, j \end{aligned} \qquad (7)$$

where x_j^* is the unlabeled data and y_j^* is the label corresponding to x_j^* given by TSVMs. Therefore, minimization must be performed with respect to $\mathbf{w}$, b, $\mathbf{x}_j^*$ and y_j^*, $j = 1 \ldots N$, by contrast to standard SVMs where minimization must be performed with respect to $\mathbf{w}$ and b only. To be able to handle non-separable data, slack variables ζ_i are introduced as in standard SVM classifiers. Algorithms for solving this optimization problem are described in [17, 18].

The transductive SVMs used in our study, were implemented using $\text{SVM}^{\text{light}}$ [19].

C. Results, and Comparison to "Re-Training"

Experimental results are shown in Table II. The performance is presented as the percentage of correctly classified test examples. The results shown on the first row were published in [11] and reproduced here for comparison. The first 100 unlabeled test examples of each room in *S1*, *S2* and *S3* sets were used for TSVM training to adjust the model, the remaining examples were used for testing. In SVM classifiers, we use the model trained on set *S1* to test the test data in sets *S2*, *S3* and *S4*. Only linear one-vs-all multi-class scheme was used because this method gave the best performance when testing on set *S1*.

As can be seen in Table II, when building the classifier with set *S1* and testing it on sets *S2*, *S3* and *S4* taken in different time periods, the performance varies dramatically, from about 94% for "fresh" data (*S1* set), down to as low as 32% (*S4* set). However, by using only 100 new unlabeled test examples of each room with the TSVM, a substantial amount of the lost performance can be recovered, with accuracies up to 78.4%.

TABLE II. COMPARISON OF SVM AND TSVM

Test Set	Training Set	SVM	TSVM
S1	*S1*	94.2%	—
S2	*S1*	60.4%	78.4%
S3	*S1*	39.7%	58.8%
S4	*S1*	32.3%	49.6%

TABLE III. RESULTS OF RE-TRAINING THE MODEL

Training Data	Test Data	Algorithm	Result
The first 100 scans of *S3*	The last 900 scans of *S3*	Linear one-vs-all	83.3%
The first 100 scans of *S4*	The last 900 scans of *S4*	Linear one-vs-all	77.4%

The TSVM approach is interesting because it presents a way of recovering some of the performance loss due to RSS drift, at the cost only of obtaining some recent *unlabeled* RSS measurements. In practice, such data might be obtained from scans performed on the handsets of users of the localization system, but without the need to manually label the data. Though the improvement obtained with the TSVM is still not sufficient, the results nevertheless suggest that any scheme that keeps the classifier model "current", by tracking the evolution of the RSS values, should be of interest to us.

This hypothesis is supported by Table III, which presents the results of training a new classifier "from scratch" based on a small number of new *labeled* scans of each room. In this scenario, "hand" labeling of the update data is necessary, but could perhaps be performed by specially designated employees, or by volunteers in exchange for some "reward" (i.e., *crowdsourcing*). The table shows that even if the current model is too outdated to give good performance, the *S3* and *S4* sets for example, it can be trained using only a small amount of labeled data and give substantially improved performance.

V. CONCLUSIONS AND PERSPECTIVES

In a study of ambient RSS distribution in an indoor environment using SVM regression, no smooth functional relationship could be discovered between GSM RSS and position for the indoor environment tested, implying that interpolation-based techniques are not likely to be successful. The use of ambient GSM RSS-based classifiers trained with data collected throughout the areas of rooms, however, presents a viable alternative, and experimental results show that the percentage of correct room labeling can be up to 94% if the model is used before significant RSS drift sets in. In order to cope with performance degradation caused by RSS drift over time, transductive inference was introduced to update the SVM classifiers with new unlabeled data. When tested on data sets collected over 6 months, this approach proved capable of restoring a significant part of the lost performance. The use of small amounts of current labeled data to create "current" room classifiers also appears to be a promising approach, even if performance still needs to be improved.

In future work, we will continue to strive for a continuously updatable, high-performance indoor room classifier. We also intend to investigate the use of W-CDMA network data in our measurements.

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