WLAN-BASED INDOOR PATH TRACKING USING COMPRESSIVE RSS MEASUREMENTS

Dimitris Milioris[1,2], *George Tzagkarakis*[3,5], *Philippe Jacquet*[1,2] *and Panagiotis Tsakalides*[4,5]

[1]Bell Laboratories, Alcatel-Lucent, France
[2]Département d'Informatique, École Polytechnique ParisTech, France
[3]EONOS Investment Technologies, Paris, France
[4]Computer Science Department, University of Crete
[5]Institute of Computer Science - FORTH, Crete, Greece

E-mail: {dimitrios.milioris, philippe.jacquet}@alcatel-lucent.com,
geotzag@gmail.com, tsakalid@ics.forth.gr

ABSTRACT

In this paper, a hybrid path-tracking system is introduced, which exploits the power of compressive sensing (CS) to recover accurately sparse signals, in conjunction with the efficiency of a Kalman filter to update the states of a dynamical system. The proposed method first employs a hierarchical region-based approach to constrain the area of interest, by modeling the signal-strength values received from a set of wireless access points using the statistics of multivariate Gaussian models. Then, based on the inherent spatial sparsity of indoor localization, CS is applied as a refinement of the estimated position by recovering an appropriate sparse position-indicator vector. The experimental evaluation with real data reveals that the proposed approach achieves increased localization accuracy when compared with previous methods, while maintaining a low computational complexity, thus, satisfying the constraints of mobile devices with limited resources.

***Index Terms*—** Compressive sensing, sparse representations, multivariate Gaussian model, Kalman filter, fingerprinting, indoor localization.

1. INTRODUCTION

During the last decade, location estimation and navigation systems emerged as important areas of research in the fields of pervasive and mobile computing. Transportation, security, entertainment, and medicine are just a few examples where accurate location estimation is a key ingredient. Focusing on the problem of *indoor localization*, numerous solutions have been proposed based on distinct technologies, such as IEEE802.11 [1], infrared [2], ultrasonic [3], bluetooth [4], or even a combination of optical, acoustic, and received signal-strength (RSS) information along with motion attributes [5].

Based on the wide deployment of wireless local area networks (WLANs) using IEEE802.11 infrastructures, most indoor positioning systems employ the RSS values obtained directly from a set of access points (APs) by any mobile device which is connected to the network. However, the nature and structure of indoor environments pose significant challenges, since phenomena, such as shadowing and multipath fading, result in radio channel obstructions and variations of the RSS values. This makes the design of accurate positioning systems a difficult and challenging task.

On the other hand, the inherent spatial sparsity, which characterizes a location estimation problem, motivates naturally the use of the novel mathematical framework of *compressive sensing* (CS) [6]. CS states that signals that are sparse or compressible in a suitable transform basis can be recovered from a highly reduced number of incoherent linear random projections, in contrast to the traditional signal processing methods, which are dominated by the well-established Nyquist-Shannon sampling theorem.

Motivated by the need to locate and track accurately a mobile user who holds a device with potentially limited power, processing, and bandwidth resources, in this paper we introduce a hybrid path-tracking method, which extents our recently introduced fingerpint-based positioning approach [7], which was tailored to the localization of static users. More specifically, we propose a two-step path-tracking method: First, we employ a region-based multivariate Gaussian model to restrict the search space of candidate cells; then, for each region, we perform CS reconstruction of an appropriate sparse position-indicator vector, combined with a Kalman filter, as a refinement step for the update of the mobile user's estimated position.

The rest of the paper is organized as follows: Section 2 overviews the current state-of-the-art on indoor path-tracking methods, while Section 3 describes in brief our recent CS-based localization method for static users, introduced in [7]. Section 4 analyzes in detail the proposed algorithm for tracking the location of a mobile user in an indoor environment, while Section 5 evaluates experimentally and compares the performance of our approach with previous state-of-the-art localization methods. Finally, Section 6 summarizes the main conclusions and gives directions for future work.

2. PRIOR WORK ON RSS-BASED PATH TRACKING

RSS-based location estimation methods can be classified roughly in two categories, namely, the fingerprint- and prediction-based ones. Fingerprint-based methods consist of two individual phases, that is, the *training* and the *runtime* phase. During the training phase, a wireless device records the RSS values at known predefined positions on a discretized grid partition of the physical space and constructs the training signature map [1, 8]. During the runtime phase, the system also records the RSS values at an unknown position to construct a runtime signature, which is then compared with the training signature map to estimate the user's location.

On the other hand, prediction-based techniques use the RSS values and radio propagation models to predict the distance of a wireless device from an AP [9]. The main challenge of these techniques is the difficulty to formulate a reliable radio propagation model due to multipath fading, shadowing, floor layout, and moving objects.

In the following, we focus on fingerprint-based localization techniques. Current state-of-the-art methods are reviewed in brief, which were shown to be efficient in several indoor environments, and with which we compare the performance of the proposed path-tracking architecture.

A common approach in location estimation problems is the use of the k-Nearest Neighbor algorithm (kNN) [10], where an RSS map is constructed by averaging separately the RSS values received from each AP. It computes a signature vector of the unknown runtime cell and a signature vector of the cell extracted during the training phase. Then, the algorithm calculates the Euclidean distance between the runtime and all the training cells, and reports the k closest neighbors by sorting the distances in increasing order. The final estimated position is given by computing the centroid of these k closest neighbors.

In [11], the problem of indoor path tracking is also treated in a probabilistic framework. In particular, a reduced number of locations is sampled to construct a radio map, in conjunction with an interpolation method, which is developed to patch effectively the radio map. Furthermore, a Hidden Markov Model (HMM) that exploits the user traces to compensate for the loss of accuracy is employed to achieve further improvement of the radio map due to motion constraints, which could confine possible location changes. The HMM-based localization technique requires several iterations to converge, while in each iteration several model parameters have to be estimated. The major benefit of our proposed algorithm, when compared with the HMM-based approach, is the significantly reduced computational complexity and implementation simplicity, as well as the high accuracy in several specific environments (obstacle-free, robust measurements) as it was revealed by the experimental evaluation. On the other hand, the HMM-based approach can be proven to be more robust in case of system failures, but at the cost of requiring increased computational resources.

In another work introduced by Guvenc *et al.* [12], the Kalman filter is used without considering the time complexity of the algorithm, especially in case of runtime performance, which introduces large delays in estimating the location. This is also a major drawback of the path-tracking methods proposed in [13, 14].

In a recent work [15], Au *et al.* introduced a tracking system analyzed in two stages. During the coarse localization stage the appropriate cells are chosen, while during the second stage the Kalman filter is used to refine the location estimates. In particular, the localization algorithm is carried out on the mobile device by using the average RSS values in order to construct the transform basis. Our proposed work differs from the previous one in several aspects, from the way we acquire the compressed set of measurements to the way we perform the location estimation. For instance, in contrast to [15], where the estimation is performed onboard by the wireless device with the potentially limited resources, in our system the computational burden is put on the server, where increased storage and processing resources are available. Besides, in the proposed localization technique the CS approach is applied directly on the raw RSS measurements and not on their average as in [15], and thus exploiting their time-varying behavior. Moreover, in [15], the lack of a random measurement matrix required when working in the framework of CS may decrease the system's performance under unpredictable environmental conditions, while also the communication of the projected measurements from the wireless device to the APs, where the localization takes place, could pose undesired security issues. In our work, there is no insight of the physical space during runtime experiments where in [15] a map information of the area is provided.

Except for the Kalman filter, particle filters [16] have been also very popular in the design of positioning systems. However, the main disadvantage of a particle filter lies in its high computational cost [17]. For instance, for an indoor space of 70 m^2 we need almost 5000 particles for each filter update. This is against the power constraints of mobile devices, such as, cell phones, making particle filters unsuitable for indoor localization in case of lightweight mobile devices with limited resources.

In [18], a localization via random field differentiation is applied in order to track a continuous trajectory between sampling points. Our approach is complementary to this, since the field differentiation is used as a refinement after the CS algorithm identifies the best candidate cell as if the tracking node were static. The field differentiation uses the variation in the random field and is more appropriate to track motion trajectory between cells.

One of the main advantages of our proposed approach, is that it succeeds to run in real time with a significantly reduced computational complexity, and thus, satisfying the constraints of devices with limited power, memory, and bandwidth resources, which was not addressed completely in these earlier studies.

3. CS-BASED LOCATION ESTIMATION

In this section, we review briefly the main concepts of our previous work on localization of static users, based on the statistical modeling of the RSS values using multivariate Gaussian (MvG) models [19], in conjunction with a spatial sparsity assumption exploited in the framework of CS [20].

3.1. Statistical modeling of RSS values using MvG models

We start by considering that the physical space is discretized as a grid consisting of cells with known coordinates. Then, during the training phase, a statistical signature is extracted for each cell by modeling the RSS values received from a set of APs using a multivariate Gaussian (MvG) distribution. During the runtime phase, a statistical signature is generated at the unknown position in a similar way, which is then compared with the training signatures by means of a statistical similarity measure, namely, the *Kullback-Leibler divergence* (KLD). The estimated location is found by minimizing the following KLD ($D(\cdot\|\cdot)$) between two MvGs,

$$j^* = \arg\min_{j=1,\ldots,C} D(f_R \| f_{j,T}) \;, \tag{1}$$

where C is the number of cells in the grid representing the physical space, f_R denotes the estimated MvG for the runtime cell, and $f_{j,T}$ is the estimated MvG for the j-th training cell.

A hierarchical region-based approach [19] is applied as an initial step to restrict the space of candidate cells, as follows: First, the space is divided into regions (groups of cells) and then, the process is repeated iteratively by dividing the selected region into sub-regions and applying the algorithm on them, until we end up with the final estimated cell. This process reduces the likelihood of selecting a single false region/cell over the correct one. The closest region is found by minimizing the following KLD between two MvGs,

$$s^* = \arg\min_{s=1,\ldots,S} D(f_R \| G_{s,T}) \;, \tag{2}$$

where S is the number of regions and $G_{s,T}$ denotes the MvG whose parameters are estimated from the RSS values over all cells of the s-th region during the training phase.

3.2. Exploiting inherent spatial sparsity using CS

The spatial sparsity, which is inherent in a localization problem, motivated us to extend our previous statistical-based localization scheme in the framework of CS [20]. More specifically, the problem of estimating the unknown position is reduced to a problem of recovering a sparse position-indicator vector, with all of its components being zero except for the component corresponding to the unknown cell where the user is placed.

Let $\mathbf{\Psi} \in \mathbb{R}^{P\times N}$ $(P \geq N)$ be a matrix whose columns correspond to a, possibly overcomplete, transform basis. In terms of signal approximation it has been demonstrated [6] that if a signal $\mathbf{x} \in \mathbb{R}^N$ is K-sparse in basis $\mathbf{\Psi}$ (meaning that the signal is exactly or approximately represented by K elements of this basis), then it can be reconstructed from $M = rK \ll N$ non-adaptive linear projections onto a second measurement basis, which is incoherent with the sparsity basis, and where $r > 1$ is a small overmeasuring constant. The measurement model generating these projections in the original space-domain is written as $\mathbf{g} = \mathbf{\Phi x}$, or via its equivalent transform-domain representation,

$$\mathbf{g} = \mathbf{\Phi \Psi w}\ , \tag{3}$$

where $\mathbf{g} \in \mathbb{R}^M$ is the vector of compressed measurements, $\mathbf{\Phi} \in \mathbb{R}^{M\times N}$ denotes the measurement matrix, and $\mathbf{w}$ is the sparse vector of transform coefficients.

In our indoor positioning application, the training measurement model associated with the $i-$th AP is given by

$$\mathbf{g_i} = \mathbf{\Phi}^{\boldsymbol{i}}_{\boldsymbol{T}} \mathbf{\Psi}^{\boldsymbol{i}}_{\boldsymbol{T}} \mathbf{w}, \tag{4}$$

and the runtime measurement model for cell c is expressed as

$$\mathbf{g_{c,i}} = \mathbf{\Phi}^{\boldsymbol{i}}_{\boldsymbol{R}} \boldsymbol{\psi}^{\boldsymbol{i}}_{\boldsymbol{R,c}}\ , \tag{5}$$

where the subscripts T and R are used to denote the variables (matrices and vectors) generated in the training and runtime phase, respectively, and $\boldsymbol{\psi}^{\boldsymbol{i}}_{\boldsymbol{R,c}}$ is the vector of runtime RSS values collected at cell c from AP i.

For the localization problem, let $\mathbf{w} = [0\, 0\, \cdots\ 0\, 1\, 0\, \cdots\ 0]^T \in \mathbb{R}^C$ be a *position-indicator vector* whose j-th component is equal to "1" if the mobile device is located in the j-th cell. The inherent sparsity in the problem of location estimation comes from the fact that the device to be localized can be placed in exactly one of these cells. Thus, in the framework of CS, the problem of localization is reduced to a problem of recovering the 1-sparse vector $\mathbf{w}$.

4. CS-KALMAN FILTER

Kalman filtering is a well-established method for estimating and tracking the position of mobile targets. A typical Kalman filter [21] is applied recursively on a given dataset in two steps: i) the *prediction* and ii) the *updating*. The main advantage of this algorithm is that it can be executed in real time, since it is only based on the currently available information and the previously estimated position.

Focusing on the problem of indoor localization, the device collects periodically the RSS values from each AP at a specific time interval Δt. Then, the indoor tracking system estimates the user's position at time t, which is denoted by $p^*(t) = [x^*(t), y^*(t)]^T$. Following a Kalman filtering approach, we assume that the process and observation noises are Gaussian, and also that the motion dynamics model is linear. The process and observation equations of a Kalman filter-based tracking model are given by

$$\mathbf{x}(t) = \mathbf{F}\mathbf{x}(t-1) + \boldsymbol{\theta}(t) \tag{6}$$
$$\mathbf{z}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t) \tag{7}$$

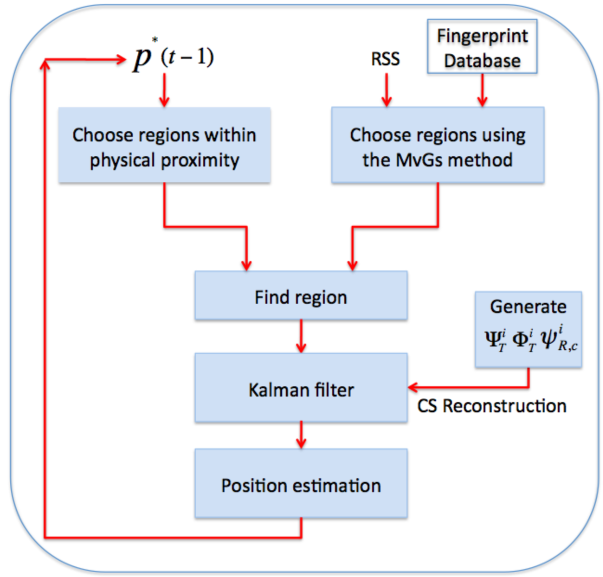

Fig. 1. Flow diagram of the proposed path-tracking system.

where $\mathbf{x}(t) = [x(t), y(t), v_x(t), v_y(t)]^T$ is the state vector, with x and y being the coordinates in the physical space (user's location) and $v_x(t), v_y(t)$ the velocity across the axes x and y, respectively, $\mathbf{z}(t)$ is the observation vector, while matrices $\mathbf{F}$ and $\mathbf{H}$ define the linear motion model. The process noise $\boldsymbol{\theta}(t) \sim N(\mathbf{0}, \mathbf{S})$ and the observation noise $\mathbf{v}(t) \sim N(\mathbf{0}, \mathbf{U})$ are assumed to be independent zero-mean Gaussian vectors with covariance matrices $\mathbf{S}$ and $\mathbf{U}$, respectively. The current location of the mobile user is assumed to be the previous one plus the distance travelled, which is computed as the time interval Δt multiplied by the current velocity.

The steps to update the current estimate of the state vector $\mathbf{x}^*(t)$, as well as its error covariance $\mathbf{P}(t)$, during the prediction and the updating phase are given by the following equations:

$$\mathbf{x}^{*-}(t) = \mathbf{F}\mathbf{x}^*(t-1) \tag{8}$$
$$\mathbf{P}^-(t) = \mathbf{F}\mathbf{P}(t-1)\mathbf{F}^{\mathbf{T}} + \mathbf{S} \tag{9}$$
$$\mathbf{K}(t) = \mathbf{P}^-(t)\mathbf{H}^T(\mathbf{H}\mathbf{P}^-(t)\mathbf{H}^T + \mathbf{U})^{-1} \tag{10}$$
$$\mathbf{x}^*(t) = \mathbf{x}^{*-}(t) + \mathbf{K}(t)(\mathbf{z}(t) - \mathbf{H}\mathbf{x}^{*-}(t)) \tag{11}$$
$$\mathbf{P}(t) = (\mathbf{I} - \mathbf{K}(t)\mathbf{H})\mathbf{P}^-(t) \tag{12}$$

where the superscript "$-$" denotes the prediction at time t, and $\mathbf{K}(t)$ is the optimal Kalman gain at time t.

The proposed CS-Kalman tracking system exploits not only the highly reduced set of compressed RSS measurements, but also the previous user's position estimate to restrict the set of candidate training regions based on physical proximity. The Kalman filter is applied on the CS-based positioning system [22], described briefly in Section 3.2, to improve the estimation accuracy of the mobile user's path. More specifically, let $\mathbf{w}^*$ be the reconstructed position-indicator vector. Of course in practice $\mathbf{w}^*$ will be not truly sparse, thus the current estimated position $[x_{CS}, y_{CS}]$, or equivalently, cell c_{CS}, corresponds to the highest-amplitude index of $\mathbf{w}^*$. Then, this estimate is given as an input to the Kalman filter by assuming that it corresponds to the previous time $t-1$, that is, $\mathbf{x}^*(t-1) = [x_{CS}, y_{CS}, v_x(t-1), v_y(t-1)]^T$, and the current position is updated using (8). At this point, we would like to emphasize the computational efficiency of the proposed approach, since it is solely based on the use of the very low-dimensional set of compressed RSS measurements given by (3), which are obtained via a simple matrix-vector multiplication with the original high-dimensional RSS vector. Given the limited memory and bandwidth capabilities of a small mobile device, the proposed approach can be an effective candidate to achieve accurate location estimation, while increasing the device's lifetime. Fig. 1 summarizes the proposed indoor path-tracking system.

5. EXPERIMENTAL RESULTS

The efficiency of the proposed tracking system is evaluated on sets of real data acquired in INRIA at Rocquencourt campus[1] and Bell Labs, in Murray Hill, NJ[2]. The estimation accuracy of the tested methods is evaluated in terms of the localization error, which is defined as the Euclidean distance between the centers of the estimated and the true cell at time t, where the mobile user is located at runtime.

5.1. Evaluation in INRIA, Paris

A detailed description of the physical space can be found in the experimentations section of [18]. The wireless coverage is achieved by using an infrastructure consisting of five IEEE802.11 APs. The physical space is discretized in cells of equal dimensions $0.76\ \mathrm{m} \times 0.76\ \mathrm{m}$, while the RSS map consists of measurements from different cells and for an average number of five APs per cell.

The reconstruction performance is compared for two widely-used CS algorithms, thus working with the much lower-dimensional compressed RSS measurements, as well as with methods working directly with the original full-dimensional RSS vectors. In the *CS domain* we employ and test: 1) ℓ_1-norm minimization using the primal-dual interior point method (L1EQ-PD)[3]and 2) BCS-GSM [23]. In the *original RSS domain* we evaluate: 3) a kNN-based approached [10], 4) our previous method based on MvGs [19], 5) a typical Kalman filter, and 6) a method employing a particle filter.

Fig. 2 shows the cumulative distribution functions (CDFs, $P(X < x)$) of the localization error of the kNN and MvG fingerprint-based methods working in the original RSS domain, together with the CDFs corresponding to the L1EQ-PD and BCS-GSM implementations of the proposed CS-Kalman approach. As it can be seen, the CS-based methods obtain an improved position estimation accuracy compared to standard fingerprint-based methods achieving median errors of 1.71 m (L1EQ-PD) and 1.36 m (BCS-GSM), as opposed to a median error of 1.90 m for the kNN and 1.69 m for the MvG. We emphasize that in this experimental setup the compression ratio r (ref. Section 3.2) of the runtime RSS measurements vectors employed by the CS-Kalman methods is equal to $r = \frac{M}{N} = 0.25$. In other words, the CS-based approach achieves better positioning results with a significantly reduced amount of data by exploiting the inherent spatial sparsity property of the localization problem.

Fig. 3 compares the localization error of the proposed CS-Kalman filter approach using BCS-GSM to solve the sparse reconstruction problem, with the typical Kalman and particle filters. Again, we observe that our proposed approach achieves a higher estimation accuracy with a significantly reduced computational complexity, when compared to the Kalman and particle filters.

[1]The data were collected during the first and third's authors affiliation with Hipercom team at INRIA, for which it is highly acknowledged.

[2]The Statistics and Learning Research department of Bell Labs in Murray Hill, NJ, and P. Mirowski are highly acknowledged for sharing the dataset.

[3]`http://sparselab.stanford.edu/`

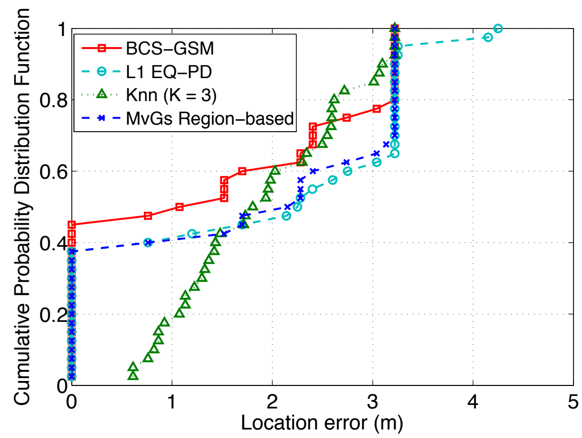

Fig. 2. Performance evaluation of the proposed path-tracking method (L1EQ-PD and BCS-GSM), compared with methods based on kNN and MvGs.

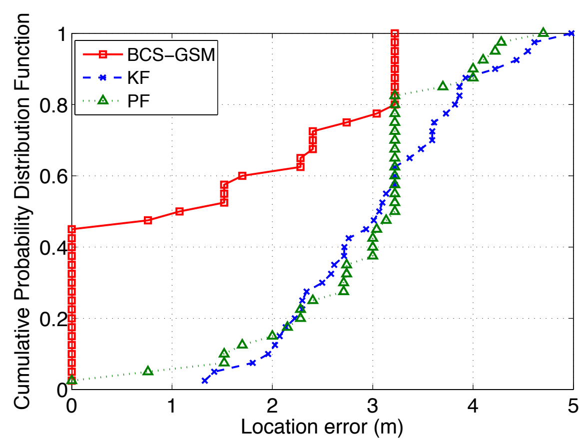

Fig. 3. Performance evaluation of the proposed path-tracking method (BCS-GSM), compared with the typical Kalman and particle filters.

5.2. Evaluation in Bell Labs, Murray Hill, NJ

Table 1 illustrates three different trajectories acquired both in an office space, in a large corridor with a high, slanted ceiling and in the 5-story atrium. The signal-strength was captured by a robot which covered an area of about $40\ \mathrm{m} \times 50\ \mathrm{m}$, on a single floor, with an installed mobile phone on it. Every channel of an AP is considered as a different AP, and we have 72 channels. One of the trajectories, with multiple small loops, is used for defining the fingerprints. Three other trajectories (so-called Track 1, Track 2 and Track 3) were acquired later the same day, towards the end of the business day when there were occasional people moving around the robot, which was a challenge. In order to define fingerprint cells, we simply subdivide the trajectory of the robot according to a regular grid defined using the building coordinates, which was $1\ \mathrm{m} \times 1\ \mathrm{m}$. In order to assess the impact of the fingerprint grid size and the trade-off between a denser fingerprint grid (with fewer RF samples) and a coarser fingerprint grid (with more RF samples in each cell), we have explored various resolutions for the fingerprint grid size in the Bell Labs atrium dataset: $1\ \mathrm{m}, 2\ \mathrm{m}, 3\ \mathrm{m}, 4\ \mathrm{m}, 5\ \mathrm{m}, 7.5\ \mathrm{m}$ and $10\ \mathrm{m}$. We expect that richer fingerprints containing more received signal strength (RSSI) samples per cell would enable better discrimination between RSSI distributions in different fingerprint cells.

The MvG algorithm takes advantage of correlations of the RSSI at certain positions from various APs. Due to the non-visibility of many APs (some of them are not frequently heard) in the positions during training and runtime, the MvG algorithm computes only the correlation between the common APs which are visible in both training and runtime cell. The proposed framework in Section 3 performs better in general, with best results for grid size of $2\ \mathrm{m} \times 2\ \mathrm{m}$.

Table 1. Results in Bell Labs, Murray Hill, NJ

Grid size (m)	1	2	3	4	5	7.5	10
Track 1 MvG	2.09	1.85	2.11	3.10	3.78	3.87	4.32
CS	1.73	1.57	1.92	2.23	2.32	3.30	3.80
Track 2 MvG	1.81	2.04	2.60	3.31	3.89	4.06	4.86
CS	1.33	1.23	1.46	2.61	2.45	2.59	3.74
Track 3 MvG	2.12	2.42	2.59	3.11	3.28	3.77	4.09
CS	1.92	1.61	1.63	2.51	2.79	3.01	3.47

6. CONCLUSION

In this paper, we proposed a path-tracking method for indoor localization by exploiting the efficiency of a CS framework with the accuracy of a Kalman filter. Using our previous method of MvG-based modeling as an initial step to constrain the area of interest, CS was applied then as a refinement step by recovering an appropriate sparse position-indicator vector. The experimental evaluation with a set of real datasets revealed an increased localization accuracy, when compared with previous state-of-the-art methods, while operating at a significantly reduced computational cost by using only a small number of compressed RSS measurements.

As a future work, we intend to exploit the joint sparsity structure of the position-indicator vector $\mathbf{w}$ among the several APs, improving the reconstruction accuracy. A further investigation could be also conducted on the inherent encryption properties of the proposed CS-based method for potential employment in secure localization.

7. REFERENCES

[1] P. Bahl and V. Radmanabhan, "An in-building RF-based user location and tracking system", in *19th IEEE Int. Conf. on Computer Com. (INFOCOM'00)*, Tel-Aviv, Israel, Mar. 2000.

[2] R. Want *et al.*, "The active badge location system", *ACM Trans. on Information Systems*, Vol. 10, No. 1, pp. 91–102, Jan. 1992.

[3] N. Priyantha, A. Chakraborty and H. Balakrishnan, "The cricket location-support system", in *6th ACM Int. Conf. on Mob. Comp. and Net. (MOBICOM'00)*, Boston, MA, Aug. 2000.

[4] U. Bandara *et al.*, "Design and implementation of a bluetooth signal strength based location sensing system", in *IEEE Radio and Wireless Conf. (RAWCON'04)*, Atlanta, GA, Sep. 2004.

[5] M. Azizyan, I. Constandache and R. Choudhury, "Surround-Sense: Mobile phone localization via ambience fingerprinting", in *15th ACM Int. Conf. on Mob. Comp. and Net. (MOBICOM'09)*, Beijing, China, Sep. 2009.

[6] D. Donoho, "Compressive sensing", *IEEE Transactions on Information Theory*, Vol. 52, No. 4, pp. 1289–1306, Apr. 2006.

[7] D. Milioris *et al.*, "Low-dimensional signal-strength fingerprint-based positioning in wireless LANs", *Ad Hoc Networks Journal, Elsevier*, (doi:10.1016/j.adhoc.2011.12.006).

[8] A. Ladd *et al.*, "Robotics-based location sensing using wireless ethernet", in *8th ACM Int. Conf. on Mob. Comp. and Net. (MOBICOM'02)*, Atlanta, GA, Sep. 2002.

[9] C. Fretzagias and M. Papadopouli, "Cooperative location sensing for wireless networks", in *IEEE Conf. on Pervasive Comp. and Com. (PERCOM'04)*, Orlando, FL, Mar. 2004.

[10] B. Li *et al.*, "Indoor positioning techniques based on wireless LAN", in *Int. Conf. on Wireless Broadband and Ultra Wideband Com. (AUSWIRELESS'06)*, Sydney, Australia, Mar. 2006.

[11] X. Chai and Q. Yang, "Reducing the calibration effort for probabilistic indoor location estimation", in *IEEE Transactions on Mobile Computing*, Vol. 6 , No. 6, pp. 649–662, June 2007.

[12] I. Guvenc *et al.*, "Enhancements to RSS based indoor tracking systems using Kalman filters", in *Proc. Global Signal Processing Exposition (GSPx)*, Dallas, TX, Apr. 2003.

[13] A. Bekkali, H. Sanson and M. Matsumoto, "RFID indoor positioning based on probabilistic RFID map and Kalman filtering", in *3rd IEEE Int. Conf. on Wireless and Mob. Comp., Net. and Com. (WIMOB'07)*, New York, NY, Oct. 2007.

[14] A. Paul and E. Wan, "RSSI-based indoor localization and tracking using sigma-point Kalman smoothers", in *Journal on Selected Topics in Sig. Proc.*, Vol. 3, No. 5, pp. 860–873, 2009.

[15] A. Au *et al.*, "Indoor tracking and navigation using received signal strength and compressive sensing on a mobile device", in *IEEE Transactions on Mobile Computing*, Is. 99, Aug. 2012 (DOI: 10.1109/TMC.2012.175).

[16] C. H. Chao *et al.*, "Location-constrained particle filter human positioning and tracking system", in *3rd IEEE Workshop on Sig. Proc. Syst. (SiPS'08)*, Washington, DC, Oct. 2008.

[17] H. Wang *et al.*, "WLAN-based pedestrian tracking using particle filters and low-cost MEMS sensors", in *4th Work. on Posit., Nav. and Com. (WPNC'07)*, Hanover, Germany, Mar. 2007.

[18] Y. Mezali, P. Jacquet and G. Rodolakis, "A path tracking algorithm using the IEEE 802.11 Infrastructure", in *14th Int. Symp. on Wireless Personal Multimedia Communications (WPMC'11)*, Brest, France, Oct. 2011.

[19] D. Milioris *et al.*, "Empirical evaluation of signal-strength fingerprint positioning in wireless LANs", in *13th ACM Int. Conf. on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM'10)*, Bodrum, Turkey, Oct. 2010.

[20] D. Milioris, G. Tzagkarakis, P. Jacquet and P. Tsakalides, "Indoor positioning in wireless LANs using compressive sensing signal-strength fingerprints", in *19th Europ. Sig. Proc. Conf. (EUSIPCO'11)*, Barcelona, Spain, Aug. 2011.

[21] M. Grewal and A. Andrews, "Kalman filtering: Theory and practice using MATLAB", 2nd Edition, 2001.

[22] C. Feng *et al.*, "Indoor navigation system on handheld devices for the visually impaired ", in *Canadian National Institute Conference for the Blind (CNIB'11)*, Canada, 2011.

[23] G. Tzagkarakis and P. Tsakalides, "Bayesian compressed sensing imaging using a Gaussian scale mixture", in *35th Int. Conf. on Acoustics, Speech, and Sig. Proc. (ICASSP'10)*, Dallas, TX, Mar. 2010.