Localization in Wireless Networks via Laser Scanning and Bayesian Compressed Sensing

Sofia Nikitaki[1,2]*, Philipp M.Scholl*[3]*, Kristof Van Laerhoven*[3] *and Panagiotis Tsakalides*[1,2]

[1] Institute of Computer Science, Foundation for Research and Technology - Hellas (FORTH-ICS),
[2] Department of Computer Science, University of Crete, Heraklion, Crete, Greece
[3] Embedded Sensing Systems, Technische Universität Darmstadt
email:{nikitaki,tsakalid}@ics.forth.gr, {scholl,kristof}@ess.tu-darmstadt.de

ABSTRACT

WiFi indoor localization has seen a renaissance with the introduction of RSSI-based approaches. However, manual fingerprinting techniques that split the indoor environment into predefined grids are implicitly bounding the maximum achievable localization accuracy. WoLF, our proposed Wireless localization and Laser-scanner assisted Fingerprinting system, solves this problem by automating the way indoor fingerprint maps are generated. We furthermore show that WiFi localization on the generated high resolution maps can be performed by sparse reconstruction which exploits the peculiarities imposed by the physical characteristics of indoor environments. Particularly, we propose a Bayesian Compressed Sensing (BCS) approach in order to find the position of the mobile user and dynamically determine the sufficient number of APs required for accurate positioning. BCS employs a Bayesian formalism in order to reconstruct a sparse signal using an undetermined system of equations. Experimental results with data collected in a university building validate WoLF in terms of localization accuracy under actual environmental conditions.

Index Terms— fingerprint-based positioning, Bayesian compressed sensing, laser-scanning, received signal strength

1. INTRODUCTION

Navigation and localization support in indoor environments is gradually becoming available in our everyday lives. The technical challenges associated with the hardly predictable signal propagation paths posed by dynamic indoor environments, render signal fingerprinting approaches most necessary. The application domains range from entertainment and medicine to commerce and security environments [1]. For example, the recent Google Indoor Maps project starts to provide indoor navigation support in shopping malls and airports throughout Japan and the USA via WiFi and GSM fingerprinting.

IEEE 802.11 is currently the dominant local wireless networking standard as access points are installed in a large number of buildings. Thus, its low cost and wide availability makes it appealing to be used for localization. Received Signal Strength Indicator (RSSI), i.e. a metric of the power level of the received signal, is the basic measured quantity for WiFi localization. In indoor environments, this metric is subject to multipath fading and attenuation by static and dynamic objects like walls or moving people. These factors make it hard to model the signal propagation in order to predict a given signal at a certain position. Fingerprinting approaches solve this problem by sampling the WiFi RSSI signal during the so called *training phase* which generates a mapping from position to RSSI measurements, called the *fingerprint* map. During the *runtime phase*, this mapping is reversed in order to estimate the user's position from the collected RSSI data [1, 2]. User positioning presents an inherent sparsity in the spatial domain. Particularly, employing a grid-representation of the physical space, the location of a user is unique over the ground plane and it can be represented as an 1-sparse vector. The above observation has motivated the use of Compressed Sensing (CS) for positioning problems. CS theory provides a new framework that allows the recovery of signals that are sparse in a specific domain, while it significantly reduces the sampling costs. Recently, in [3] we explored the CS theory in order to reformulate the location problem as a sparse approximation problem and we showed that CS-based techniques outperform traditional localization methods in terms of localization accuracy.

Fingerprint-based systems achieve high accuracy, however their major problem is the exhaustive training phase, as it requires substantial cost and labour [4–7]. Effective location sensing requires the collection of a large number of

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Corresponding author: nikitaki@ics.forth.gr

representative training data to increase the localization accuracy. Consequently, a recalibration is mandatory every time the number of APs or the physical environment changes. The manual nature of georeferencing the various locations during training delays the actual use of fingerprint-based localization and can reduce the accuracy due to possible human error. Recently *crowdsourcing* approaches to the training phase have been proposed. They promise to significantly decrease the inherent training effort [8], however they still face the problem of manual fingerprint map building.

To address the aforementioned issues we propose WoLF, the *Wireless localization and Laser-scanner assisted Fingerprinting* system. It combines recent developments of sparse approximation theory with an innovative georeferencing system. WoLF provides an *automatic training phase* by employing a handheld laser-scanner based simultaneous localization and mapping (SLAM) system [9] combined with consumer-grade WiFi cards. During training, WoLF automatically gathers a map of the physical environment, localizes the user on this map and scans the WiFi channels in parallel. Based on the gathered fingerprint map, WoLF employs a Bayesian Compressed Sensing WiFi localization algorithm to localize a user during runtime. WoLF is also adaptive as it introduces a novel dynamic access point selection algorithm that determines the optimum number of APs required for localization. The automated training phase diminishes the practical barriers of state-of-art fingerprint based systems, while the sparse approximation approach to estimate the user location ensures an improved position detection accuracy.

2. RELATED WORK

RSSI-fingerprint based localization algorithms can be broadly classified into three categories. *Deterministic* methods, such as k-Nearest Neighbors and voting techniques [10] estimate location by considering received measurements only by their value. *Probabilistic* methods, such as Bayesian inference [7, 11] estimate location by modelling measurements as a random process. The recently introduced *spatial sparsity* techniques reformulate the localization problem by advances in sparse approximation and compressed sensing (CS) theory. Considering that the position of the user is sparse in the space domain, they provide accurate location estimation while reducing the communication and computational cost. Feng et. al. [12] proposed a two-phase localization technique during runtime where CS is applied in order to identify the optimum number of APs. Authors in [13] perform location sensing via a Bayesian Compressend Sensing (BCS) approach that minimizes the number of measurements transmitted in the network. In this work, we extend the BCS framework by introducing a dynamic AP selection algorithm that determines the required number of APs for accurate positioning.

Radar [5] was one of the first RSSI-fingerprint based systems for WiFi indoor localization. In order to construct the fingerprint map, Radar combines signal strength measurements with signal propagation models which take obstacles, like walls, into account. During the runtime phase a k-Nearest Neighbour (KNN) algorithm is used to compare the fingerprints of the training phase with the ones obtained during runtime in order to retrieve the positions of the k neighbours with the lowest distances in the signal space. The final location of the user is the centroid of the neighbour's coordinates. The Horus [7] system in contrast presented a probabilistic approach, where the signal space is approximated with histograms.

Both of the aforementioned systems, as well as a large number of other techniques, are manually calibrated. Their training phase is carried out by splitting the area into a predefined grid and measuring RSSI-values in each cell by hand. To date the most extensive training phase was performed by Haeberlen et. al. [14]; 28 man-hours of work spanning an area of $12558m^2$, with an average cell size of $24.6m^2$. Ocana et. al. [15] tried to automate the measurement collection process with the help of a mobile robot, which however did not simulate the natural movement pattern of a human user. Recent works, like Zee [8], try to decrease the training effort by crowdsourcing. Zee employs the inertial sensor of a mobile phone to get a rough movement pattern by step counting and compares these measurements to prior information about the environment. However, all existing systems assume that a map of the indoor environment is readily available. WoLF in contrast simultaneously builds an indoor physical map, a signal strength map, and localizes the user.

3. COMPRESSED SENSING

Compressed Sensing asserts that a signal which has a sparse representation in a certain basis can be reconstructed from a limited number of measurements. Denote the sparse signal $\boldsymbol{b} \in \mathbb{R}^D$, with K non-zero components ($K \ll D$) and M measurements collected in the vector $\boldsymbol{y} \in \mathbb{R}^M$, where $M \ll D$. The relationship between the measurement vector $\boldsymbol{y}$ and the sparse vector $\boldsymbol{b}$ is given by

$$\boldsymbol{y} = \boldsymbol{\Phi}\boldsymbol{b}, \tag{1}$$

where $\boldsymbol{\Phi} \in \mathbb{R}^{M\times D}$ is the measurement matrix. When the matrix $\boldsymbol{\Phi}$ satisfies the so-called Restricted Isometry Property (RIP), the sparse vector can be recovered from the undetermined system of equations by solving the following ℓ_1 minimization problem:

$$\hat{\boldsymbol{b}} = \arg\min \|\boldsymbol{b}\|_1 \;\; s.t. \;\; \|\boldsymbol{y} - \boldsymbol{\Phi}\boldsymbol{b}\|_2 < .pdfilon, \tag{2}$$

where $.pdfilon$ is the noise level. Commonly used approaches to solve (2) include convex relaxation and greedy strategies such as Orthogonal Matching Pursuit (OMP) [16].

Bayesian Compressed Sensing provides a Bayesian framework for solving the inverse problem of compressed sensing [17]. Compared to the CS, BCS estimates *error bars* that provide a measure of confidence of the estimated sparse vector. The error bars benefit the construction of stopping criteria that define the optimum number of measurements for accurate detection of non-zero components of the sparse vector $\boldsymbol{b}$.

Specifically, BCS defines a zero-mean Gaussian prior with variance a_i on each element of the sparse vector $\boldsymbol{b}$, $p(\boldsymbol{b}|\boldsymbol{\alpha}) = \prod_{i=1}^{D} \mathcal{N}(b_i|0, a_i^{-1})$. Moreover, the measurement vector $\boldsymbol{y}$ is expressed as a Gaussian distribution with with variance a_0, $p(\boldsymbol{y}|\boldsymbol{b}, a_0)$.

By employing Bayes' rule and the Gaussian likelihood model, the posterior probability is defined as:

$$p(\boldsymbol{b}|\boldsymbol{y}, \boldsymbol{a}, a_0) = (2\pi)^{-\frac{D}{2}}|\boldsymbol{\Sigma}|^{-\frac{1}{2}}\exp(-\frac{1}{2}(\boldsymbol{b}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{b}-\boldsymbol{\mu})), \tag{3}$$

where the mean $\boldsymbol{\mu}$ and the covariance matrix $\boldsymbol{\Sigma}$ are

$$\boldsymbol{\mu} = a_0\boldsymbol{\Sigma}\boldsymbol{\Phi}^T\boldsymbol{b} \tag{4}$$

$$\boldsymbol{\Sigma} = (\boldsymbol{A} + a_0\boldsymbol{\Phi}^T\boldsymbol{\Phi})^{-1} \tag{5}$$

and $\boldsymbol{A} = diag(a_1, \ldots, a_D)$. $\boldsymbol{a}$ and a_0 are the hyperparameters over each component of the estimated sparse vector given the prior [17]. The diagonal elements of the covariance matrix (eq. 5) provide confidence intervals (*i.e.* error bars) on the accuracy of the estimated components of the sparse vector $\boldsymbol{b}$. As the number of measurements increases the variance of the estimated components decreases.

4. SYSTEM OVERVIEW

We consider a typical WLAN positioning scenario of J connected APs and one mobile station (MS), equipped with a wireless adapter card, which is carried by a person to be located. WoLF is based on the RSSI measurements transmitted from the APs and consists of two distinct phases.

Fig. 1. The handheld laser-scanner hardware comprising a low-cost MEMS Inertial Measurement Unit (IMU), an UTM-30LX LIDAR system and four consumer WiFi cards.

4.1. Training phase

The goal of the training phase is to establish a mapping between the current user's position and the RSSI measurements on the wireless channel. To establish this mapping we used the hardware shown in Fig. 1. This hardware runs a SLAM-approach [9], in which the laser scans are stabilized with the included IMU. This returns the position and the map of the current environment at $40Hz$. The consumer-grade WiFi modules passively scan the surrounding WiFi networks, i.e. they constantly listen for beacon frames sent by the APs on a specified channel. This allows to gather a fingerprint map in a fine-grained spatial resolution ($5cm$), in the user's most natural movement patterns.

However the sampling rate of the user's position is much higher than the achievable sampling rate of the WiFi networks, which is why we decided for a passive scanning approach. An active WiFi scan works by sending a beacon request on one of the 35 WiFi channels on the 2.4 and $5GHz$ bands and then listening on this channel for roughly $100 - 200ms$. It should be noted that, due to security reasons, most APs are not reacting to this beacon request and only send out beacon frames periodically. A full spectrum scan then takes between $3.5 - 7sec$. An average human has walked almost $11m$ in such a timespan, which would result in a low spatial resolution for the WiFi scans. To counteract this problem, we simply set the WiFi cards into passive mode on four fixed channels and only report the RSSI values of the periodically sent beacons of the APs. The period of these beacons is typically between $200ms$ and $1sec$ and we achieved sampling rates in our environment of $60 - 100Hz$ by passively scanning the WiFi network.

Even though the sampling rate is increased by the passive scanning approach, we still face the problem of incomplete RSSI measurement vectors. This is due to the fact that our position estimation is not synchronized with the WiFi scanning, i.e. the RSSI measurement vectors do not include all reachable APs at a certain location. To solve this problem the area is discretized into a finite set of cells of equivalent size and all measurement vectors in the same cell are gathered into vector $\boldsymbol{\phi}_i = [P_{i,1}^t, \ldots, P_{i,J}^t]^T \in \mathbb{R}^J$. $P_{i,j}^t$ corresponds to the mean value of RSSI samples received from the j-th AP at grid point i during training. This reduces the spatial resolution of the fingerprint map, but allows for systems that assume a complete RSSI measurement vector at each position. The fingerprint map is represented by the matrix $\boldsymbol{\Phi} = [\boldsymbol{\phi}_1 \ldots \boldsymbol{\phi}_D]_{J\times D}$ where D is the number of the grid points. The localization server collects the fingerprint map in order to perform location sensing.

4.2. Runtime phase

During the runtime the MS scans the available channels to collect the runtime RSSI measurements. The MS creates the runtime measurement vector $\boldsymbol{y} = [P_1^r, \ldots, P_J^r]^T \in \mathbb{R}^{J\times 1}$, where P_j^r is the mean value of the RSSI measurements from the j-th AP during runtime.

The main goal is to determine the location of the user by identifying the cell in which he is located. We define the sparse vector $\boldsymbol{b} \in \mathbb{R}^D$ that has the dimensions of the physical

Algorithm 1 Dynamic Access Point Selection via BCS

Input: fingerprint map $\mathbf{\Phi}$, runtime measurements $\boldsymbol{y}$, minimum number of APs k, threshold h.

Output: Optimum number of APs J_{opt}, estimated cell c

1. Apply the BCS reconstruction method to estimate $\hat{\boldsymbol{b}}$ via (7)

if $|\sqrt{diag(\mathbf{\Sigma})} - h| \leq \eta$ **then**
  $J_{opt} \leftarrow k$; $c = \arg\max \hat{\mathrm{b}}$;
else
  $k = k + 1$; go to 1;
end if
return J_{opt}, c;

space and a non-zero component in the corresponding occupied location. Consequently, we can express the set of the runtime measurements $\boldsymbol{y}$ as:

$$\boldsymbol{y} = \mathbf{\Phi}\boldsymbol{b} + .pdfilon \tag{6}$$

where $.pdfilon$ is the noise level, $\mathbf{\Phi} \in \mathbb{R}^{J \times D}$. Indoor radio propagation is affected by multipath effects, a fact that results in differences between the training and runtime fingerprints corresponding to the same grid point.

The server employs the proposed iterative Dynamic AP selection via BCS algorithm (Algorithm 1) in order to estimate the location of the MS and dynamically determine the sufficient number of APs required for localization. Particularly, it collects the runtime measurements $\boldsymbol{y}$ from the MS and estimates the sparsity pattern of the vector $\boldsymbol{b}$ from the fingerprint map $\mathbf{\Phi}$ by solving the following ℓ_1 minimization problem

$$\hat{\boldsymbol{b}} = \arg\min_{\boldsymbol{b}}(\|\boldsymbol{b}\|_1 + \rho\|\boldsymbol{y} - \mathbf{\Phi}\boldsymbol{b}\|_2^2) \tag{7}$$

where the factor ρ controls the sparseness of the signal (first term) and the relative importance of the reconstruction error (second term). The Bayesian framework described in Section 3 is adopted in order to solve the optimization problem (7). The BCS approach provides confidence intervals that benefit the construction of stopping criteria that determine the optimum number of APs, *i.e.* the number of measurements. Particularly, the optimum number of APs is defined dynamically when the absolute difference of the variance of the recovered vector $\hat{\boldsymbol{b}}$ from the predefined threshold h does not exceed a positive constant η. The variance of the recovered vector is defined as the square root of the diagonal elements of the covariance matrix (eq. 5). The estimated cell is detected as the index that corresponds to the largest coefficient of vector $\boldsymbol{b}$.

5. EXPERIMENTS

The effectiveness of proposed WoLF localization system employing the BCS approach is studied via real time experiments performed at the floor of TU Darmstadt, spanning an area of $100m \times 12m$. The purpose of the experiment is to evaluate the accuracy of the proposed system under different environmental parameters. During the training phase, we performed two random walks in order to collect RSSI observations via the laser mapping (cf. Fig 1). From the 10755 measurement points, we extracted 206 different location cells. In total 64 APs were involved. We compare our proposed approach with the KNN localization method under different parameters, and define the location error as the Euclidean distance between the center of the estimated cell and the position measured by the laser mapping system.

The laser mapping utilized during the training phase provides a dense training map. We validated the accuracy of the proposed BCS localization method under various cells sizes. Figure 2 demonstrates the mean location error for the BCS and KNN techniques as a function of the grid size. We observe that as the grid spacing increases, the localization accuracy decreases. This behaviour is expected since by increasing the discretization of the physical space, the distance between the center of the estimated cell and the real location of the user decreases, given that the localization system has high accuracy. We observe the robustness of the proposed BCS localization approach under the different resolution levels for the physical space. One should keep in mind that high space resolution increases the computational complexity as the dimension of space increases.

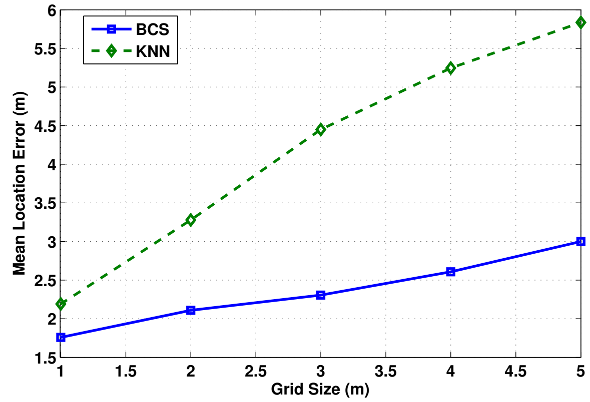

Fig. 2. Location error for the BCS and the KNN localization techniques as a function of the grid size.

Figure 3 indicates the mean localization error for the BCS and the KNN algorithms as a function of the number of APs and for grid space equal to one meter. The localization error decreases as the number of APs increases. Interestingly, the localization performance is not affected after a certain number of APs (6 in our experiment). The proposed BCS algorithm identifies the optimum number of APs by adopting the dynamic AP selection algorithm. Particularly, when the average error bars reach the required threshold, the number of APs is enough in order to achieve the desired accuracy. Table 1 indicates the average error bars as a function of the number of

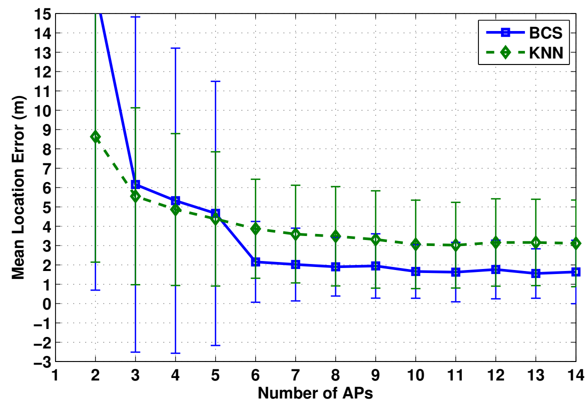

Fig. 3. Impact of the number of APs on the localization error for the BCS and the KNN localization algorithms.

APs. As the number of APs increases, the variance decreases.

Number of APs	3	4	5	6	7
Mean error bars	0.073	0.064	0.062	**0.0523**	0.0521

Table 1. Mean error bars vs. the number of APs

Figure 4 presents the performance in terms of localization error CDF curve $(P|X| \leq x)$ for the two positioning techniques. The proposed BCS dynamic AP selection algorithm stops at the iteration when the average error bar reaches as low as the threshold $h = 0.052$. On the contrary, the KNN algorithm utilizes all the available APs. The average number of detectable APs per cell is 24. The proposed dynamic AP selection algorithm utilizes on average 25% of the available APs. We observe that the median location error (*i.e.* the value below which 50% of the location errors fall) is $1.4m$ for the BCS algorithm vs. $2.7m$ for the KNN approach.

6. CONCLUSIONS

In this paper we proposed WoLF, a combination of a handheld laser-based simultaneous localization, mapping (SLAM), and WiFi localization system based on Bayesian Compressed Sensing. WoLF allows to accelerate the cumbersome procedure of spatially sampling the WiFi RSSI signal (i.e. building fingerprint maps) while also retaining a high spatial resolution concerning the user's position. We argued that discretizing an indoor environment into predefined grids, as usually done for evaluating RSSI localization systems, bounds the maximum achievable localization accuracy.

To overcome the problem of strongly different sampling rates of the user's position $(40Hz)$ and the RSSI WiFi channel $(1-20Hz)$, we proposed a BCS approach for RSSI-based localization. By assuming a Gaussian localization error distribution this approach is able to select the most significant APs, thus decreasing the overall localization error. The results revealed the superiority of the proposed technique over the KNN localization method in an experimental setup.

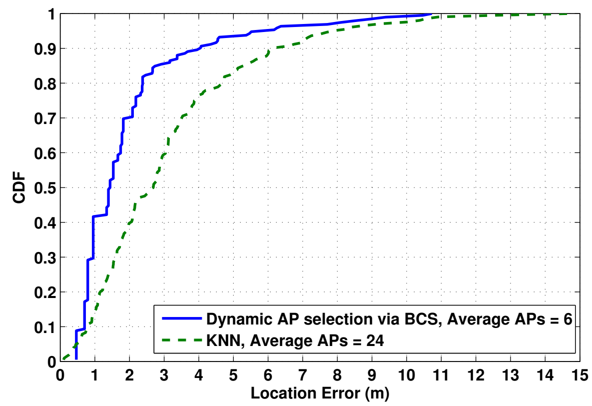

Fig. 4. CDF of localization error for the BCS and KNN algorithms. The proposed Dynamic Access Point selection algorithm utilizes on average 25% of the APs.

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