Decentralized Indoor Wireless Localization Using Compressed Sensing of Signal-Strength Fingerprints

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ABSTRACT

This paper combines recent developments in sparse approximation and distributed consensus theory to efficiently perform decentralized localization in wireless networks. To this goal, we exploit the Compressed Sensing (CS) framework, which provides a new paradigm for recovering signals being sparse in some basis by means of a limited amount of random incoherent projections. In particular, we propose a novel decentralized technique that considers the spatial correlations among the received measurements at the base stations (BSs) to provide global accurate position estimation, while reducing significantly the amount of measurements exchanged among the BSs and required for accurate positioning. We exploit the common structure of the received measurements to design a gossip-based algorithm in order to alleviate the effects of radio channel-induced signal variations on the estimation accuracy. Experimental evaluation with real data demonstrates the superiority of the proposed decentralized CS-based localization technique over traditional fingerprinting methods in terms of the achieved positioning accuracy.

Categories and Subject Descriptors

C.3 [**Special-Purposed and Application-Based Systems**]: Signal Processing Systems

General Terms

Algorithms, Measurement, Performance

Keywords

Average consensus, Compressed Sensing, Fingerprinting, Indoor Localization, Received Signal Strength Indicator

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1. INTRODUCTION

Location and mobility management are major functions that rapidly become essential to the seamless and ubiquitous computing environment for mobile devices. Health care monitoring, emergency management, personal tracking, context dependent information services, and advertisement are some of the potential applications, which benefit from such features.

Wireless technologies have entered the realms of indoor location based services. Particularly, IEEE 802.11 is currently the dominant local wireless networking standard as access points are installed in a large number of buildings. Although this extensive deployment and the availability of infrastructure make IEEE 802.11 appealing for localization as well, it is currently not used for positioning purposes. Furthermore, there is a growing interest in leveraging the close proximity of access point nodes in an area in order to reduce installation costs by eliminating time-consuming wiring between offices, walls, floors, and buildings [1].

A typical localization scenario consists of a set of base stations (BSs) placed at known positions and a mobile station (MS) carried by a person that needs to be located. Certain positioning systems are based on the signal strength transmitted from the BSs and require the MS to compute its own position. On the other hand, since the BSs are aware of the presence of a user, some systems utilize the data packets transmitted from the MS to compute the location of the user remotely at the BSs.

The majority of signal-strength based systems can be classified into two categories, namely the *distance-prediction based* and the *map-* or *fingerprinting-based*. Distance- prediction based systems estimate the position of the MS by calculating its distances from at least three reference points (*e.g.*, access points (APs), anchor nodes) using a known RF propagation loss model [2–5]. The main challenge arising in these localization systems is the difficulty to formulate a reliable radio propagation model due to multipath fading, shadowing, the low probability of line-of-sight (LOS) path, and specific parameters such as floor layout and moving objects.

To address these difficulties, map- or fingerprinting-based systems create signature maps in order to represent the physical space by capturing the variations of the dynamic nature of indoor radio propagation [6–10]. The localization process typically includes two phases: an *offline/training* phase and an *online/runtime* phase. In the offline phase, location fingerprints are collected with respect to different locations in the target region. During the online phase, the runtime signal strength measurements of the MS are accumulated and compared with the fingerprints obtained during the offline phase to perform localization. Although the accuracy of these systems is high, the time required for the calibration phase remains a disadvantage.

Compressed Sensing (CS) provides a novel framework that allows the recovery of a signal that is sparse in a suitable transform basis, while enabling an important reduction in the sampling costs compared to traditional methods [11,12]. CS is based on the observation that a small collection of linear projections of a sparse signal contains enough information for reconstruction [11]. A signal is called sparse when its elements are mostly zero in a specific domain. In positioning problems, a significant observation is that the localization process presents an inherent sparsity in the spatial domain. We consider a grid representation of the physical space where each cell of the grid indicates a possible position of the user. Thus, the mobile location is sparse over the ground plane as it can be modelled as a sparse vector where the index of the non-zero component indicates the presence of the MS in the corresponding cell.

Recently in [13] we explored the CS theory to reformulate the location estimation as a sparse-approximation problem. Following this reformulation, we introduced in [14] a centralized CS signal strength based localization scheme that considers the measurements received at the BSs and offers accurate position estimation at a fraction of the measurements needed by current state of the art methods. According to our centralized localization protocol, all local samples are sent to a central unit to perform sparse signal recovery via joint CS.

However, centralized approaches exhibit several potential drawbacks. Specifically, they cannot handle the problem of single point failure, that is, if the central unit fails, the system becomes inoperative and location sensing impossible. Indeed, in a dynamic wireless scenario one can expect the possibility of a breakdown or the inaccessibility of the existing infrastructure and subsequently the inability of a centralized algorithm to adapt to a collapse (*e.g.*, power or network outage). Moreover, traditional fault tolerance techniques, such as server failover, are still sensitive to large-scale outages of electrical power or the wired network infrastructure. Hence, to prevent extra cost of using additional backup servers, we propose to exploit the available infrastructure by performing localization at the BSs which form the wireless backbone of the network (wireless mesh routers, wireless APs, sensor nodes). A decentralized localization protocol provides flexibility to the network administration since position estimations are distributed over the network and thus are accessible from each individual BS.

Considering the above observations, in this work we develop a novel *decentralized fingerprint-based CS signal strength localization* scheme that makes use of the signal correlation structures among the received measurements. In contrast to existing fingerprint based approaches, we consider both intra- and inter- signal correlation structures among the received signal strength measurements. An accurate positioning is therefore provided using only a limited amount of runtime measurements. Exploiting the joint sparsity of the signal ensemble, the proposed method builds on *gossip consensus* based approaches to distribute decision estimations in the network. Recently, gossip algorithms have received a great deal of attention in wireless networks because they possess certain desired operational attributes, such as simplicity, scalability, and robustness [15].

The proposed localization algorithm can be applied to the infrastructure network of a building, *e.g.*, a wireless distribution system (WDS) or a wireless mesh network (WMN) [1], where indoor navigation is mandatory. Our approach will be beneficial to environments where wired networks are not applicable or not easily set up, as for example in military or emergency (fire/safety/rescue) fields. On the other hand, in cases where the robustness of the location infrastructure is at stake, the decentralized version of the proposed localization protocol will allow each BS to estimate the position of the mobile user locally. Furthermore, by performing the localization task at each BS, we reduce the computational complexity and the energy consumption at the MS. This is important since, in spite of constant improvements in energy consumption, battery capacity grows slowly and power management is still a challenge in mobile computing.

The organization of this paper is as follows. Section 2 discusses related work concerning fingerprinting-based systems. In Section 3 we present the necessary CS background. Section 4 sets up the problem and reviews preliminary concepts. Section 5 introduces the proposed decentralized localization protocol. In Section 6, the performance of the proposed approach is studied and compared to other state of the art map-based algorithms. Finally, we conclude and give directions for future work in Section 7.

2. RELATED WORK

Current literature shows a growing interest for location-sensing systems that use RF signals. In the following, we briefly describe some of the existing indoor positioning techniques. Most of them are centralized and perform the localization task at the mobile device. The more recent ones employ the notions of compressed sensing.

Radar [9] is an indoor position tracking system that exploits the existing WLAN technology. Particularly, it combines signal strength measurements with specific signal propagation modeling to provide accurate positioning. The Compass system [16] is based on the IEEE 802.11 infrastructure and digital compasses to achieve low cost localization services. Compass uses signal strength fingerprints and a probabilistic approach to determine the position of the user. Moreover, Horus [17] is a map-based system, which considers different causes for the wireless channel variations and uses them for location sensing. Horus employs a stochastic description of the signature map and performs localization via a maximum likelihood based approach.

A common approach for position estimation is the k-nearest neighbor algorithm (kNN) which employs signature maps that combine signal strength measurements acquired during the training phase at different positions of the mobile device [9, 18]. The signal-strength measurements received during the runtime phase are compared with the reference map to acquire the k positions of the nearest neighbors, *i.e.*, the ones with the lower distances in the signal space. The estimated position is given by the average of the coordinates of the k closest neighbors.

A Bayesian classification method was also adopted to address the localization problem [19]. The Bayesian estimator is a probabilistic approach that computes the conditional distribution of a certain possible position of the user given the runtime signal strength measurements. This method searches for the maximum likelihood estimator of the position.

Recently, a sparse approximation approach to mobile localization has been introduced. The authors in [20] proposed a two-phase localization algorithm, performed at the MS, which differs from our method from the way the CS measurements are acquired to the way the location estimation is performed. The main goal in [20] is to minimize the number of the APs needed for accurate position estimation. Therefore, a measurement matrix was defined as an AP selection operator that considers a subset of available APs. On the other hand, our proposed decentralized algorithm aims to reduce the total number of measurements transmitted throughout the network.

In another recent work [21], indoor localization was also approached via the CS framework. The algorithm is based on the measurements transmitted from the APs, while it requires the MS to interact with a central unit that estimates its position. In contrast to [21], the proposed method is completely decentralized. The approach introduced in [21] exploits the inter-signal correlation structures of the received measurements, while it ignores intra-signal correlation structures. To the best of our knowledge, our work is the first CS-based approach that rests on the concept of joint sparsity in order to represent the physical characteristics of location sensing.

Moreover, distance-based gossip algorithms that consider a propagation model, have been proposed for distributed localization of energy sources in sensor networks. In [22], the estimated position is computed by averaging the locations of the BSs that are closest to the target, while providing lower weights to the base stations that are further from the target. While, in [22] the positions of the BSs are considered known, the authors in [23] propose a distributed gossip localization algorithm that aims to reduce the number of BSs with known locations. The authors in [24] propose a distributed distance-based signal strength localization protocol for wireless mesh networks. The two-phase localization algorithm builds a relative coordinate system and applies a mass-spring approach for the optimization of the MS location in the second phase. Finally, the commercial Mesh-Network Positioning system (MPS) leverages the patented position location methods built into mesh network quadrature division multiple access (QDMA) radio technology [25].

3. COMPRESSED SENSING BACKGROUND

Compressed Sensing builds on the observation that a signal which has a sparse representation in a transform domain can be reconstructed from far fewer measurements than the number of Nyquist samples [11], [12]. Consider the discrete-time signal $\boldsymbol{x} \in \mathbb{R}^D$ that can be represented in terms of a sparsifying basis (dictionary) $\boldsymbol{\Psi}$ of $D \times 1$ vectors $\{\boldsymbol{\psi}\}_{i=1}^{D}$ such that:

$$\boldsymbol{x} = \boldsymbol{\Psi} \boldsymbol{b} \tag{1}$$

where $\boldsymbol{b} \in \mathbb{R}^D$ is a K-sparse vector ($\|b\|_0 = K$).

According to CS theory, the sparse signal $\boldsymbol{x}$ can be reconstructed by considering M linear projections $y(m) = \langle \boldsymbol{x}, \boldsymbol{\phi}_m^T \rangle$ of the signal $\boldsymbol{x}$ into M measurement basis vectors $\{\boldsymbol{\phi}_m\}_{m=1}^{M}$. The symbol T denotes the transpose of the vector and $\langle \cdot, \cdot \rangle$ denotes the inner product. Considering the vector $\boldsymbol{y} \in \mathbb{R}^M$ that gathers the $y(m)$ measurements and the measurement matrix $\boldsymbol{\Phi} \in \mathbb{R}^{M \times D}$ with rows the basis vectors $\boldsymbol{\phi}_m^T$, the measurement model can be written as:

$$\boldsymbol{y} = \boldsymbol{\Phi} \boldsymbol{x} = \boldsymbol{\Phi} \boldsymbol{\Psi} \boldsymbol{b} = \boldsymbol{\Theta} \boldsymbol{b} \tag{2}$$

An essential property for the reconstruction of the original signal $\boldsymbol{x}$ is that the matrix $\boldsymbol{\Theta} = \boldsymbol{\Phi}\boldsymbol{\Psi}$ must hold the so-called restricted isometry property (RIP). RIP implies that the rows $\{\phi_m\}$ of $\boldsymbol{\Phi}$ cannot sparsely represent the columns $\{\psi_i\}$ of $\boldsymbol{\Psi}$. Particularly, incoherent matrices satisfy the RIP with very high probability. It has been proved that both RIP and incoherence could be achieved by selecting the measurement matrix $\boldsymbol{\Phi}$ as a random matrix, *e.g.* the elements of vectors $\boldsymbol{\phi}_j$ are independent and identically distributed (i.i.d.) random Gaussian or Bernoulli variables [12].

When the above conditions hold, the sparse signal $\boldsymbol{x}$ can be accurately recovered from $M \geq K \log(D/K)$ compressive measurements with high probability by solving the following convex optimization problem

$$\hat{\boldsymbol{b}} = \arg\min \|\boldsymbol{b}\|_1 \quad s.t. \;\; \boldsymbol{y} = \boldsymbol{\Theta} \boldsymbol{b}. \tag{3}$$

Considering the M CS measurements and the sparsifying basis $\boldsymbol{\Psi}$, the original vector $\boldsymbol{b}$, and thus the signal $\boldsymbol{x}$, (cf. 1), can be recovered by a number of different reconstruction algorithms. Greedy sparse recovery algorithms compute the support (sparsity pattern) of the signal iteratively and can be very efficient and computationally flexible when the signal of interest is highly sparse. The Basis Pursuit (BP) [26] algorithm formulates the reconstruction problem with equality constrains and solves it through an interior-point method. BP is precise but slow in general and thus not applicable in real-world scenarios. Additionally, algorithms such as the Orthogonal Matching Pursuit (OMP) [27, 28], identify the basis vectors that are most correlated with the signal, in a greedy way. Compared to BP, OMP is faster but it converges with lower probability [29]. Simultaneous Orthogonal Matching Pursuit (SOMP) [30] gives simultaneous sparse approximations by identifying one coefficient of the sparse vector at a time.

The principles of the CS theory have been applied for signal reconstruction, detection and classification by exploiting the intra-signal structures at a single collection point (*e.g.*, a sensor, base station). Nevertheless, multiple collection points usually capture related phenomena and a joint structure is expected for the signals ensemble, in addition to the intra-signal correlation between the individual measurements. Recently, the authors in [31] introduced a theory for *distributed compressed sensing* (DCS) that exploits both intra- and inter-signal correlation structures. DCS considers the joint sparsity of a signal ensemble to obtain accurate signal reconstruction. DCS adopts the SOMP algorithm to recover an ensemble of signals which share a common sparse structure.

4. PROBLEM FORMULATION

Consider the network of J wirelessly connected BSs modeled by a network graph $\mathcal{G}(\mathcal{J}, \mathcal{I})$ where $\mathcal{J} =: \{1, \ldots, J\}$ is the set of BSs and $\mathcal{I} = \{(j,k) : j,k \in \mathcal{J}\}$ is the set comprising the bi-directional links between the BSs. Graph $\mathcal{G}$ is assumed connected, meaning that data at any BS can become available to any other BS generally through a multi-hop path of $\mathcal{G}$.

Suppose that there is a MS equipped with an active wireless adapter card. A BS that listens to a channel, collects the packets transmitted from the MS, at that channel and

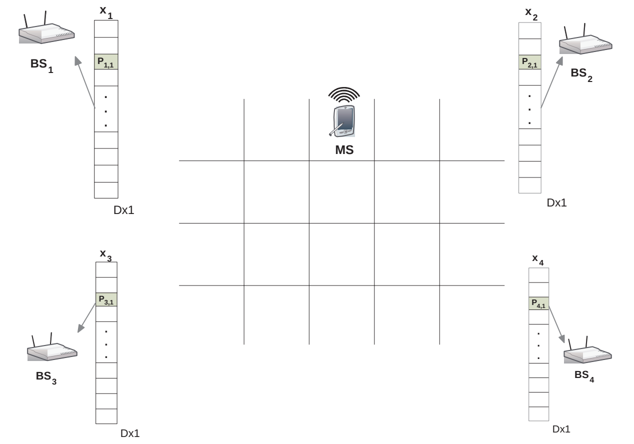

Figure 1: Common sparse support set in an indoor environment. Each BS receives signal-strength vectors $\boldsymbol{x}$ on its local grid. Each vector has non-zero coefficient at the position occupied by the MS.

Algorithm 1 Distributed Localization via CS

Offline phase

- Each BS collects RSSI fingerprints in order to capture the physical space via the $\boldsymbol{\Psi}_j$ basis matrix.
- Each BS creates a measurement matrix $\boldsymbol{\Phi}_j$.

Online phase

- Each BS samples locally RSSI measurements to collect $\boldsymbol{y}_j$.

1. Each BS computes the correlations among the runtime measurements and the basis matrix $\boldsymbol{\Psi}_j$.
2. Update the estimations of the BSs via average consensus.
3. Upon convergence, each BS obtains the global estimation of mobile user's location.

records its *received signal strength information* (RSSI) values. Details concerning the characteristics of RSSI can be found in [32]. Given that the BS vendor provides the appropriate API, the RSSI information on the BS's hardware can be retrieved with high level programming.

The CS-based fingerprint method consists of two phases, the offline (training) phase and the online (runtime) phase. During the offline phase, a calibration procedure is adopted in order to create a signature map for each BS. Specifically, each BS j receives signal strength measurements from a MS that moves to various sample grids, the so-called Reference Points (RPs). The signature basis matrix $\boldsymbol{\Psi}_j$ is represented as:

$$\boldsymbol{\Psi}_j = \begin{pmatrix} P_{1,1,j} & P_{1,2,j} & \cdots & P_{1,D,j} \\ P_{2,1,j} & P_{2,2,j} & \cdots & P_{2,D,j} \\ \vdots & \vdots & \ddots & \vdots \\ P_{D,1,j} & P_{D,2,j} & \cdots & P_{D,D,j} \end{pmatrix}. \tag{4}$$

Particularly, each column of $\boldsymbol{\Psi}_j$ corresponds to the RSSI from a MS at the corresponding RP. We denote the t-th RSSI sample the j-th BS receives from a node at location k as $P_{t,k,j}$.

To perform localization, we discretize the spatial space and therefore, we consider the finite set of cells $\mathcal{C} = \{p_1, p_2, \ldots, p_D\}$, where D is the number of RPs. The sparse vector $\boldsymbol{b} \in \mathbb{R}^D$ selects elements from $\mathcal{C}$. Particularly, a non-zero component in $\boldsymbol{b}$ at the i-th position indicates the presence of a mobile node at cell p_i. For instance, the vector

$$\boldsymbol{b} \;=\; [0, 0, 1, \ldots, 0]^T, \tag{5}$$

indicates that the node is located at cell p_3. Using the above notation, we can express the received signal strength measurements $\boldsymbol{x}_j$ received at the j-th BS as:

$$\boldsymbol{x}_j \;=\; \boldsymbol{\Psi}_j \boldsymbol{b}, \tag{6}$$

where $\boldsymbol{b}$ is supported on the same $\mathcal{C}' \subset \mathcal{C}$ and $|\mathcal{C}'| \;=\; 1$.

Compressed Sensing exploits sparsity in the spatial domain to acquire a signal representation without collecting D samples [11]. The main goal to efficiently perform location sensing, translates to the accurate detection of the non-zero coefficient of sparse vector $\boldsymbol{b}$. In this work, we exploit the joint sparsity structure of the received signals $\boldsymbol{x}_j$ at the BSs (cf. Fig. 1) to provide accurate location estimations. The key observation is that the BSs share a common sparse support set, as each received signal $\boldsymbol{x}_j$ has non-zero coefficient at the position occupied by the MS.

5. DECENTRALIZED LOCALIZATION

The new localization scheme that we introduce in this Section, exploits the spatial correlations among the measurements received at the J BSs and efficiently disseminates them throughout the network using a gossip algorithm. The goal is to allow *every BS* to have an estimation of the sparse coefficient vector when the algorithm terminates. Thus at convergence, all BSs should have knowledge of the mobile device position.

The fingerprinting-based system is characterized by two phases (Algorithm 1). During the offline phase, each BS collects RSSI measurements for a period of time to create the signature map of the physical space $\boldsymbol{\Psi}_j \in \mathbb{R}^{D\times D}$, as it was described in (4). Moreover the construction of a measurement matrix $\boldsymbol{\Phi}_j \in \mathbb{R}^{M\times D}$ is essential in order to effectively implement the CS methodology. Each BS constructs a random measurement matrix $\boldsymbol{\Phi}_j \in \mathbb{R}^{M_j\times D}$, where $M_j = rD$ is the number of CS measurements, $M_j \ll D$, and r is the sampling factor. For simplicity and without loss of generality, we choose $M_j = M$, $\forall j \in \mathcal{J}$. The measurement matrix $\boldsymbol{\Phi}_j$ contains i.i.d. random variables from a Gaussian probability density function with mean zero and variance 1/D in order to satisfy the property required by the CS theory. We recall that D is the number of the RPs.

During the online phase, the location estimation procedure is executed. Particularly, each BS receives M runtime RSSI measurements $\boldsymbol{y}_j = [P^R_{j,1}, \ldots, P^R_{j,M}]^T_{(1\times M)}$ from the mobile device, where $P^R_{j,i}$ indicates the i-th sample received at the j-th BS. The runtime measurements can be expressed as:

$$\boldsymbol{y}_j \;=\; \boldsymbol{\Phi}_j \boldsymbol{x}_j \;=\; \boldsymbol{\Theta}_j \boldsymbol{b}, \quad \forall j \in \mathcal{J}, \tag{7}$$

where $\boldsymbol{\Theta}_j \;=\; \boldsymbol{\Phi}_j \boldsymbol{\Psi}_j$. Then, distributed localization is performed in three stages, namely, *initial estimation*, *decision fusion*, and *fine localization*.

5.1 Initial estimation

In the first stage, the joint sparsity structure of the signal ensemble is observed independently at each BS to perform an initial estimation of the sparse vector $\boldsymbol{b}$. Each BS estimates its own sparse vector $\boldsymbol{b}_j$ in order to obtain locally a first guess of the atom that contributes the most energy to the runtime signal $\boldsymbol{y}_j$, according to:

$$b_{j,i} = \frac{<\boldsymbol{y}_j, \boldsymbol{\theta}_{j,i}>}{\|\boldsymbol{\theta}_{j,i}\|_2} \quad , \quad \forall i = 1, \ldots, D \quad and \quad \forall j = 1, \ldots, J, \tag{8}$$

where $b_{j,i}$ are the coefficients of the vectors $\boldsymbol{b}_j$ and $\boldsymbol{\theta}_{j,i}$ are the columns of the matrix $\boldsymbol{\Theta}_j = [\boldsymbol{\theta}_{j,1}, \ldots, \boldsymbol{\theta}_{1,D}]$.

5.2 Decision Fusion

In our physical set-up, the collected sparse signals $\boldsymbol{y}_j$ are constructed from the same basis elements of the signature map $\boldsymbol{\Psi}_j$ but with arbitrarily different coefficients. By taking advantage of this property, in the second stage, an *average consensus* algorithm is adopted to iteratively update the estimations at each BS.

At each iteration t, a BS j is chosen uniformly at random from the set $\mathcal{J}$, using the asynchronous time model described in [33], and randomly selects a BS k such that $(k, j) \in \mathcal{I}$. By executing a gossip algorithm, the estimations described in (8) are carried out locally to obtain a global decision. Here, we propose two different gossip variants to distribute the estimations $\boldsymbol{b}_j$ in the network.

First, consider the matrix $\boldsymbol{B}(0) = [\boldsymbol{b}_1(0), \boldsymbol{b}_2(0), \ldots, \boldsymbol{b}_J(0)]^T$ that gathers the initial values of each BS. Let $\boldsymbol{B}(t)$ denote the matrix that collects the current values of the averaged estimations. Gossip algorithms update their estimates linearly at each iteration t according to an averaging matrix $\boldsymbol{W}(t)$ such that:

$$\boldsymbol{B}(t) = \boldsymbol{W}(t)\boldsymbol{B}(t-1). \tag{9}$$

Pairwise Gossip considers random pairs of nodes that iteratively and locally average their estimations until convergence to the global estimate. Particularly, in each gossip round only the values of two BSs j, k are averaged. Consequently, the averaging matrix $\boldsymbol{W}(t)$ is

$$\boldsymbol{W}(t) = \boldsymbol{I} - \frac{(\boldsymbol{e}_j - \boldsymbol{e}_k)(\boldsymbol{e}_j - \boldsymbol{e}_k)^T}{2}, \tag{10}$$

where $\boldsymbol{e}_j = [0, \ldots, 1, \ldots, 0]^T$ is the $J \times 1$ unit vector that has the j-th component equal to 1 [15, 34]. $\boldsymbol{I}$ indicates the identity matrix. It is straightforward to observe that in Pairwise Gossip, the averaging matrix $\boldsymbol{W}(t)$ is doubly stochastic as it satisfies the following properties:

$$\boldsymbol{W}(t)\mathbf{1} = \mathbf{1} \tag{11a}$$

$$\mathbf{1}^T\boldsymbol{W}(t) = \mathbf{1}^T, \tag{11b}$$

where property (11a) ensures that the global average is acquired and property (11b) ensures stability. $\mathbf{1}$ represents a vector of ones. The distributed linear iteration (9) converges to the average, for any initial vector $\boldsymbol{b}_j(0) \in \mathbb{R}$ if and only if

$$\lim_{t\to\infty} \boldsymbol{W}(t) = \frac{\mathbf{1}\mathbf{1}^T}{J}. \tag{12}$$

Pairwise gossip fulfils the requirements of the decentralized localization estimation and it is a simple algorithm which does not require global knowledge.

Selective Gossip solves the average consensus problem iteratively by adaptively determining which elements are significant and which are insignificant while gossiping [35]. In order to preserve bandwidth, the algorithm computes only the entries of a vector which are above a defined threshold. Specifically, two one-hop neighbors exchange information concerning only the components that at least one of them believes to be significant, resulting in fewer transmissions of the insignificant ones. In practice, the two-neighboring nodes exchange three transmissions as to inform each other about the components that they consider significant. Let $b_{j,i}$ denote the i-th component for the j-th BS. Then BS j and k update the significant components i for which either $|b_{j,i}(t-1)| \geq \tau$ or $|b_{k,i}(t-1)| \geq \tau$ by setting

$$b_{j,i}(t) = b_{k,i}(t) = \frac{1}{2}(b_{j,i}(t-1) + b_{k,i}(t-1)). \tag{13}$$

For values for which $|b_{j,i}(t-1)| < \tau$ and $|b_{k,i}(t-1)| < \tau$, no changes are performed. The threshold τ is defined as the d-th value of the vector $\boldsymbol{b}_j = [b_{j,max}, \ldots, b_{j,min}]$, where $b_{j,max}$ and $b_{j,min}$ is the maximum and minimum value of the vector $\boldsymbol{b}_j$, respectively. The d-th value is defined as $d = qD$, where q indicates the percentage of the decisions that will be exchanged at each gossip round.

Selective gossip converges in a global consensus [35]. The nature of the localization problem makes selective gossiping an appropriate technique for estimating the most significant coefficients in the sparse vector $\boldsymbol{b}$. Specifically, location sensing is based on the detection of the largest coefficient of the sparse vector $\boldsymbol{b}$, as it was described in Section 4. Thus, although all coefficients contain significant information, selective gossip gives more importance to the largest coefficients of the vector $\boldsymbol{b}$ and distributes them efficiently through the network.

5.3 Fine Localization

Upon convergence of the average consensus protocol, each column of the matrix $\boldsymbol{B}(t)$ (cf. 9) contains the averaged estimations $\boldsymbol{b}_{ave}$ such that:

$$\lim_{t\to\infty} \boldsymbol{b}_{ave} = \frac{1}{|\mathcal{J}|}\sum_{j=1}^{J} \boldsymbol{b}_j(0). \tag{14}$$

Thus, the global estimation vectors $\boldsymbol{b}_{ave}$ have been distributed in the network to efficiently allow each BS to identify the coefficients with the largest magnitude. In the fine localization stage, each BS detects the position p_i of the mobile device as the index that corresponds to the largest coefficient of vector $\boldsymbol{b}_{ave}$.

$$p_i = \arg\max_{i=1,\ldots,D} \boldsymbol{b}_{ave}. \tag{15}$$

6. EXPERIMENTS

In this Section, we evaluate the performance of the proposed decentralized localization system. Real RSSI data were collected at the long hallway and the Telecommunications and Networks Lab (TNL) of FORTH, an area of $8.5m \times 14m$. For this area, a grid-based structure was considered with cells of size $55cm \times 55cm$. TNL is partitioned by 1.60m-height cubicle walls with hard-partioned offices and

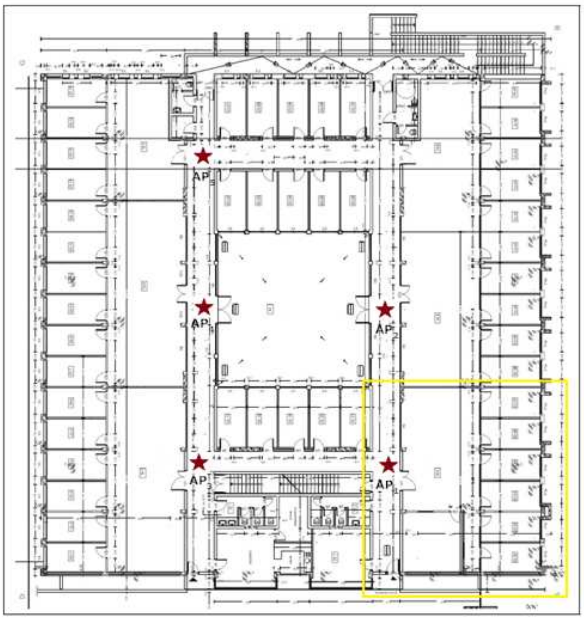

Figure 2: Experiment set up at FORTH. The stars indicate the position of the APs. The yellow block indicates the experimental area.

glass windows. The experiment involved a total of 5 APs (Cisco Aironet 1200 series APs, 802.11 b/g) placed on the same floor where TNL is located (Fig. 2).

The AP operating system, Cisco IOS, possess a special command that enters the device in *scanner*/*monitor* mode. When the AP is in monitor mode, it receives packets that contain the RSSI information. In a real environment where the device is not transmitting enough packets per time unit, we trigger the device with the assistance of the infrastructure (*i.e.*, ping) to produce packet transmissions more frequently. Each AP uses the unique MAC address of the mobile device as a distinctive feature to recognize the packets of the transmitter that wants to be located. The signature maps were constructed during the training phase at various cells of the grid. Specifically, the RSSI observations were collected for a period of 20 seconds over 135 reference points ($D = 135$). The online observations were collected at a different period of time by the APs from the device at 30 unknown distinct cells in order to evaluate the performance of the system in a time-varying environment. The number of RPs and online observations is comparable to those reported in [20] and [36]. The performance is evaluated in terms of the location error. The location error is defined as the Euclidean distance between the center of the estimated cell of the user location and the true cell where the mobile user was located during the runtime phase.

To evaluate the convergence of the proposed decentralized CS-based localization scheme, in Figure 3 we illustrate the median location error with respect to the number of iterations for the two gossip variants during decision fusion, for different number of CS measurements. It is reminded that the first iteration demonstrates the accuracy during the initial estimation while the last iteration shows the accuracy in fine localization. Figure 3 shows that the algorithm converges faster as the number of CS measurements increases.

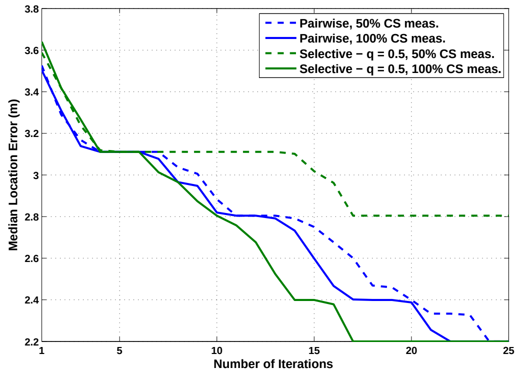

Figure 3: Median location error vs. the number of iterations for different gossip variants during decision fusion.

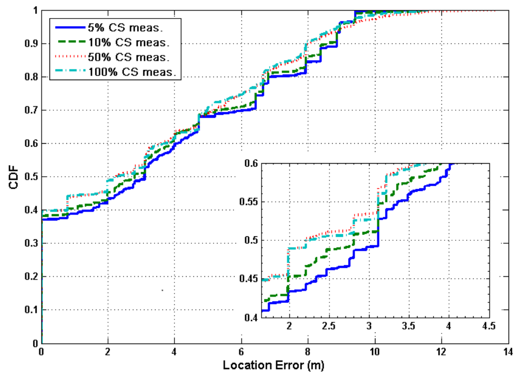

Figure 4: Empirical CDF curves of the Pairwise Gossip algorithm during the fine localization stage as a function of CS measurements.

Selective Gossip algorithm transmits only a fraction of the decisions acquired during the initial estimation procedure, thus as the number of the exchanged values decreases the convergence time increases.

The effect of the number of CS measurements in the estimated accuracy is further examined for the Pairwise Gossip variant in terms of the location error. Figure 4 depicts the empirical CDf curve ($P(|X| \leq x)$) as a fraction of the number of the RSSI runtime measurements used during the fine localization phase ($M = rD$ with $r \in \{5\%, 10\%, 50\%, 100\%\}$). We observe that the location error of the decentralized scheme decreases as the number of measurements increases. This behavior is consistent with CS theory, as the accuracy of the recovery algorithm is affected by the number of CS measurements. Particularly, the 36^{th} percentile of the location error for the CS Pairwise Gossip algorithm is almost zero with only 5% of the RSSI measurements. We note that 5% of the measurements corresponds to $M \approx 7$ which is above the minimum bound of $\log(D) \approx 7.08$, as required by the CS theory.

Figure 5 depicts the median location error of the decentralized selective localization scheme as a function of q, the percentage of decisions exchanged at each gossip round. Vary-

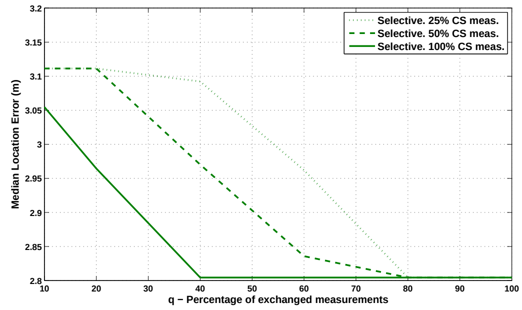

Figure 5: Median location error of the Selective Gossip algorithm during the fine localization stage as a function of transmitted estimations and for different CS measurements.

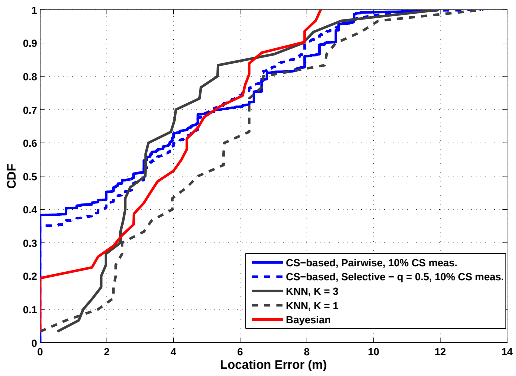

Figure 6: CDF curves for the fingerprint-based localization methods.

ing q changes the localization accuracy. Specifically, as the number of exchanged decisions among the BSs decreases the location error increases. However, fewer transmitted values result in less energy consumption and bandwidth. Moreover, we observe that as the number of CS measurements increases the percentage of exchanged measurements among the BSs decreases.

Figure 6 compares the effectiveness of the proposed decentralized gossip based localization framework with two well-known localization algorithms, the KNN and the Bayesian classification methods. Only 10% of the total runtime RSSI measurements were employed by the proposed CS localization algorithm while both the KNN and the Bayesian classification methods used all the available RSSI measurements for location sensing. Figure 6 illustrates the empirical CDF curve for the different fingerprinting-based localization schemes. We notice that the proposed CS pairwise gossip-based algorithm leads to improvements in terms of median location error (*i.e.*, the value bellow which 50% of location errors fall) in the order of 9.8% and 40% for KNN, $K = 3$ and $K = 1$ respectively and 30% for the Bayesian algorithm. It is shown that the decentralized selective-gossip algorithm provides effective location estimation, compared with the pairwise-gossip algorithm, while exchanging only 50% of the initial decisions.

7. CONCLUSIONS - FUTURE WORK

In this work, we proposed a novel fully decentralized cooperative CS localization scheme based on signal strength fingerprints. The localization procedure is performed at the BSs to eliminate the need for a central unit and requires a limited amount of signal-strength measurements for accurate positioning. The decentralized protocol exploits the signal correlation structures among the individual runtime measurements. Based on the joint sparsity of the signal ensemble among the BSs, it builds a gossip consensus approach to distribute decision estimations within the network. Upon convergence, all BSs have knowledge of the mobile device position. We performed an evaluation of the decentralized localization scheme under two gossip based variants to effectively distribute the decisions in the network. The implementation results in the premises of FORTH reveal a superior performance of the proposed decentralized CS-based localization scheme when compared with traditional localization schemes.

Intense research work by the scientific community is carried today to develop completely decentralized algorithms for consensus computation in networked systems. Adaptive gossip based algorithms can be applied to address the issues caused by the transient phenomena appearing in indoor environments. The wireless channel is highly time varying resulting in unexpected behaviors of the received signal strength measurements. Thus, future work will investigate novel adaptive gossip based algorithms that will consider the constant transmitted signals of the mobile device to update efficiently the estimations at each base station.

At the same time, there exists a growing interest in applying different modalities to improve the location estimation. To mention one example, the ambient sound and the light sensed by the mobile device provide complementary information for the indoor environment. Thus, our interest is to incorporate different modalities in the CS-localization framework for more accurate positioning.

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