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INDOOR LOCALIZATION IN THE PRESENCE OF RSS VARIATIONS VIA SPARSE SOLUTION FINDING AND DICTIONARY LEARNING

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Abstract—In the received signal strength (RSS) based indoor wireless localization system, RSS measurements are very susceptible to the complex structures and dynamic nature of indoor environments, which will result in the system failure to achieve a high location accuracy. In this paper, we investigate the indoor positioning problem in the existence of RSS variations without prior knowledge about the localization area and without time-consuming off-line surveys. An adaptive sparsity-based localization algorithm is proposed to mitigate the effects of RSS variations. The novel feature of this method is to adjust both the overcomplete basis (a.k.a. dictionary) and the sparse solution using a dictionary learning (DL) technology based on the quadratic programming approach so that the location solution can better match the actual RSS scenario. Moreover, we extend this algorithm to deal with the problem of positioning targets from multiple categories, a novel problem that few works have ever concerned before. Simulation results demonstrate the superiority of the proposed algorithm over some state-of-art environmental-adaptive indoor localization methods.

1. INTRODUCTION

Nowadays, with the rapid development of wireless local area network (WLAN) technology, indoor positioning based on WLAN is especially

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favored because of no requirement for extra infrastructure investments. Indoor localization systems based on angle of arrival (AOA) or time of arrival (TOA) have been proposed and have reportedly achieved up to 1 m localization granularity [1–3]. However, the measurements of AOA or TOA necessitate special hardware at either the server side or the client side. Since RSS can be easily obtained by a WiFi-integrated mobile device without any additional hardware modification, many WLAN-based positioning systems rely on the location dependency of RSS. Generally, there are two kinds of mainstream methods for the RSS-based indoor positioning, which are the propagation model based method and the fingerprinting based method [4–6]. Existing model-based positioning approaches mainly depend on the specific path loss model that converts RSS measurements into corresponding distances. The main difficulty of this method is to establish a reliable signal propagation model and estimate its path loss parameters in an indoor environment due to the unpredictable nature of indoor radio channel. In order to obtain accurate localization results, the fingerprinting method need record RSSs at every possible location through off-line training process and compare the RSS of each target to be localized with the recorded RSSs to find the best matching RSS pattern. However, this method is also environment dependent and any significant change on the topology implies a costly new recalibration.

In recent years, compressive sensing (CS) which receives a great deal of attention, has been successfully applied for indoor localization, which results in higher localization accuracy and reduces the dimensions of measurement vectors [7–9]. Since targets generally lie at a few points in the discrete spatial domain, we can exploit this inherent sparsity to convert the localization problem into a sparse recovery problem. In [7, 8], it has been realized that the localization problem can be formulated as a distributed sparse approximation problem, by which inter-sensor communication costs can be reduced significantly. However, a localization dictionary has to be locally estimated at each sensor node. Feng et al. proposed a server-based sparse multiple target localization algorithm in [9], where the localization dictionary is constructed at the location center (i.e., the server) and each sensor only transmits a small number of compressive measurements to the location center. However, the above methods neglected a number of factors that affect the RF signal propagation in an indoor environment including multi-path, channel fading, temperature and humidity variations, opening and closing of doors, and shadowing, etc., which will cause the system failure to achieve a high location accuracy. An affinitybased CS localization scheme (ACS) is proposed by exploiting affinity propagation and cluster matching to reduce the effects of RSS variations in [10]. But this method may result in large positioning bias for the reason that the false cluster matching can take place due to noisy measurements and environmental variations. In addition, the neural network (NN) localization method in [11] proposed a learning-based approach utilizing training samples to calibrate RSS variations. However, the assumption that the indoor space remains consistent from the training phase to the localization phase thus does not hold true in practice.

In this paper, we continue to investigate the CS-based indoor positioning problem in the existence of RSS variations and an adaptive RSS-based sparse localization algorithm (ARSL) is proposed to adjust both the overcomplete basis and the sparse solution so that the solution can better adapt to dynamic nature of indoor environments. Different from the previous work, we use DL techniques to combine the location estimating and RSS modifying into a unified CS framework based on current APs observations. Since DL techniques can learn dictionaries to better fit the actual RSS model, the effects of RSS variations due to channel impediments can be effectively mitigated. We also extend this algorithm to tackle the problem of positioning targets from multiple categories, which few works have ever concerned before. Furthermore, we provide the comprehensive simulations to justify the validity of our algorithm.

The notation used in this paper is according to the convention. Symbols for matrices (upper case) and vectors (lower case) are in boldface. $(\cdot)^T$, $(\cdot)^H$, $\|\boldsymbol{\theta}\|_0$, $\|\boldsymbol{\theta}\|_1$, $\|\boldsymbol{\theta}\|_2$, $\|\boldsymbol{\theta}\|_F$, $\mathbf{I}_N$, and $\otimes$ denote transpose, conjugate transpose (Hermitian), 0-norm, 1-norm, 2-norm, Frobenius norm, identity matrix with the dimension N, and the Kronecker product, respectively. For any matrix $\mathbf{Y}$, $\mathrm{vec}(\mathbf{Y})$ is denoted as the vertical concatenation of the columns of $\mathbf{Y}$, and $\mathrm{tr}(\mathbf{Y})$ is the trace of $\mathbf{Y}$. Finally, $\hat{\mathbf{x}}$ denotes the estimate of the parameter of interest $\mathbf{x}$. The remainder of the paper is organized as follows. Section 2 describes the system model assumed throughout this paper and formulates as a sparse recovery problem. In Section 3, we introduce a scheme calibrating the overcomplete basis dynamically and estimating the sparse solution adaptively. The extension of the ARSL algorithm for positioning targets from multiple categories is investigated in Section 4. Simulation results are given in Section 5. Finally, Section 6 concludes the paper.

2. SIGNAL MODEL AND PROBLEM FORMULATION

Consider K unknown-location targets are located in an area of interest which is divided into N grids. Assume M access points (APs) in the targeted localization area which take RSS measurements from these targets at the grid. In general, $N \gg M > K$, and the localization problem can be modeled as a sparse problem since at each time instance the user is located at a specific point in space. The goal is to determine the locations of these targets simultaneously and accurately, using only a small number of noisy RSS measurements.

Assume that the locations of the targets over the grid is denoted by $\boldsymbol{\theta} = [\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_N]$, which is a sparse vector that having in total K nonzero entries, where the indices of nonzero entries in $\boldsymbol{\theta}$ represent the actual locations. When L $(< M)$ available APs are selected to locate the targets, we let $\mathbf{y}$ be a $L \times 1$ column vector recording the measurements of the L APs. Then, we formulate the location problem as a following CS problem

$$\mathbf{y} = \mathbf{\Phi}\mathbf{\Psi}\boldsymbol{\theta} + \mathbf{V} \overset{\Delta}{=} \mathbf{H}\boldsymbol{\theta} + \mathbf{V} \tag{1}$$

with $\mathbf{\Psi}$ being a $M \times N$ energy decay matrix defined by

$$\mathbf{\Psi} = \begin{bmatrix} S_{1,1} & S_{1,2} & \ldots & S_{1,N} \\ S_{2,1} & S_{2,2} & \ldots & S_{2,N} \\ \vdots & \vdots & \vdots & \vdots \\ S_{M,1} & S_{M,2} & \ldots & S_{M,N} \end{bmatrix} \tag{2}$$

where $S_{i,j}$, $1 \leq i \leq M$, $1 \leq j \leq N$ represents the RSS value transmitted from the jth grid and received by the ith AP. The $L \times M$ matrix $\mathbf{\Phi}$ is AP selection operator as defined in the following section. The matrix $\mathbf{V}$ represents noise terms, which is assumed as the independent and identically distributed (i.i.d.) Gaussian process, uncorrelated with the signals.

CS provides a novel framework for recovering signals, which are sparse or compressible under a certain basis, with far fewer noisy measurements than the traditional methods. To make this possible, the overcomplete basis $\mathbf{\Psi}$ must be obtained in advance. There are generally two methods to construct the basis matrix $\mathbf{\Psi}$ for RSS-based indoor localization problem, i.e., path loss model and fingerprinting. Although the fingerprinting method can achieve higher accuracy, its off-line stage is obviously time-consuming process especially inside large buildings and dynamic environments. Additionally, due to dynamic environments changes and the possibility of moving some APs to new locations, the whole off-line site survey needs to be repeated from time to time which is impractical and time-consuming as well. On the contrary, although a simple parameterized path loss formula is only approximate to model signal power changes indoors, it is commonly used for target localization due to its simplicity. Therefore, we use the path loss model method to construct the basis matrix $\mathbf{\Psi}$ in this paper.

The traditional log-distance path loss model is as follows [12]:

$$PL = PL(d_0) + 10\alpha \log_{10}(d/d_0) \tag{3}$$

where $PL(d_0)$ is the path loss at a close-in reference distance d_0 and α is the path loss exponent. For simplicity, we assume there is 30 dB attenuation at $d_0 = 1\,\text{m}$. The path-loss exponent is usually set between 2 and 5 according to reference [12], and $\alpha = 2.6$ is suggested to be used in an indoor environment with hard partitions in [12]. Then, we can calculate $S_{i,j}$ using the Eq. (3) and the initial overcomplete dictionary can be constructed according to (2). It should be noted that $\mathbf{H}$ can be known using the above overcomplete dictionary, which means that we can estimate the actual coordinates of targets as long as we find the positions of nonzero values in $\boldsymbol{\theta}$. That is, the problem of localization is converted into one of sparse signal recovery from (1). Moreover, the number of these dominant nonzero values gives K.

However, the above path loss model is very coarse where a number of factors that affect the signal propagation are neglected and the non-ideal factors are inevitable in a practical localization system. When these happen, the predefined dictionary can not effectively express the actual signal, which will cause performance degradation in the sparse recovery process. For avoiding the difficulty of estimating all kinds of time-varying factors, we assume the error dictionary matrix $\boldsymbol{\Gamma}$ which describes the difference between the predefined dictionary and the practical received signals. Note that the error matrix $\boldsymbol{\Gamma}$ is time-varying and can not be known in advance. In this scenario, the sparse positioning model is correspondingly modified as:

$$\mathbf{y} = (\mathbf{H} + \boldsymbol{\Gamma})\boldsymbol{\theta} + \mathbf{V} \stackrel{\Delta}{=} \mathbf{D}\boldsymbol{\theta} + \mathbf{V} \tag{4}$$

where $\mathbf{D} = (\mathbf{H} + \boldsymbol{\Gamma})$ denotes the actual overcomplete basis with time-varying interferences. To prevent $\mathbf{D}$ from having arbitrarily large values (which would lead to arbitrarily small values of $\boldsymbol{\theta}$), it is common to constrain its columns $\mathbf{d}_1, \ldots, \mathbf{d}_N$ to have a 2-norm less than or equal to one. Since the mismatch exists between the columns of $\mathbf{D}$ and the corresponding columns of the ideal basis $\mathbf{H}$, the performance degradation is inevitable in the sparse recovery process. In order to obtain accurate localization results, we will exploit a DL technology to calibrate RSS variations according to current measurements automatically.

3. ARSL ALGORITHM BASED ON DICTIONARY LEARNING

Focused on the above problem, an adaptive sparse recovery algorithm based on DL is proposed in this paper, which calibrates the overcomplete basis automatically so that the sparse solution can better fit the actual scenario. Firstly we describe the ARSL algorithm for targets from single category, and then extend this algorithm to locate multiclass targets in the next section.

3.1. Access Point Selection

Due to the wide deployment of APs, the total number of detectable APs is generally much greater than that required for positioning, which will lead to redundant computations. Therefore, choosing only a subset of detectable APs for positioning is an intuitive way to reduce the computational burden on and storage requirement of the device [13]. This motivates the use of AP selection techniques to select a subset of available APs used for positioning. According to (2), the set of APs can be denoted as M, with the number of APs in M is M. At the same time, the number of RSS measurements should be equal or more than $O(K \log(N/K))$ to make sparse recover successful according to the CS theory [14]. Therefore, the objective of AP selection is to determine a set $L \subseteq M$ such that the number of APs in L should obey $O(K \log(N/K)) \leq L \leq M$. This process is carried out by using the AP selection matrix $\mathbf{\Phi}$. Each row of $\mathbf{\Phi}$ is a $1 \times M$ vector with all elements equal to zero except $\Phi(l) = 1$, where l is the index of the AP that is selected for positioning. Here we investigate the strongest AP selection method [15] to select $\mathbf{\Phi}$. In this approach, the set of APs with the highest RSS readings is selected, arguing that the strongest APs provide the highest probability of coverage over time. Therefore, we can sort the measurement vector into the decreasing order of RSS readings, and the APs corresponding to the least indices are used. Since $\mathbf{\Phi}$ is created based on the current measurement vector $\mathbf{y}$, this criterion may create different $\mathbf{\Phi}$ at different runs.

3.2. Dictionary Learning Method

The key feature of adaptive sparse recovery in this paper is to adaptively adjust the overcomplete basis according to the current RSS readings, and thus the positions of unknown targets can be better recovered from measurements with the presence of environment variations. This process generally learns the uncertainty of the dictionary, which is not available from the prior knowledge, but rather has to be estimated using a given set of samples. Several different DL algorithms have been presented recently [16], however, these methods generally can not effectively handle training data changing over time. To overcome this shortcoming, we propose a simple DL approach by using the quadratic programming approach. So far, most DL methods are generally based on alternating minimization. In one step, a sparse recovery algorithm finds sparse representations of the training samples with a fixed dictionary. In the other step, the dictionary is updated to decrease the average approximation error while the sparse coefficients remain fixed. The proposed method in this paper also uses this formulation of alternating minimization.

3.2.1. Sparse Recovery Phase

According to the CS theory, the above problem of noisy sparse signal recovery in (4) can then be converted into a following optimization problem

$$\min \|\mathbf{y} - \mathbf{D}\boldsymbol{\theta}\|_F^2 /2 + \lambda \|\boldsymbol{\theta}\|_0 \tag{5}$$

where λ is the regularization parameter and typically $\lambda = \sigma\sqrt{2\log(N)}$ where σ is the noise level [17]. Note that (5) is NP-hard to solve. An alternative is to use 1-norm instead of 0-norm to enforce sparsity, which leads to

$$\min \|\mathbf{y} - \mathbf{D}\boldsymbol{\theta}\|_F^2 /2 + \lambda \|\boldsymbol{\theta}\|_1 \tag{6}$$

However, it should be emphasized that larger coefficients in $\boldsymbol{\theta}$ are penalized more heavily in the 1-norm than smaller coefficients, unlike the more democratic penalization of the 0-norm [18]. In practice, large coefficients are usually the entries corresponding to the actual positions of targets, while small coefficients commonly represent the noise entries. The imbalance of the 1-norm penalty will seriously influence the recovery accuracy, which may result in many false targets. Therefore, in this paper we choose the reweighted 1-norm minimization algorithm in [18] as our sparse recovery method, which can overcome the mismatch between 0-norm minimization and 1-norm minimization while keeping the problem solvable with convex estimation tools.

3.2.2. Dictionary Learning Phase

In this phase, the dictionary is optimized to better represent the data of the current samples. Since the sparse coefficients are fixed in the DL stage, the resulting optimization problem becomes:

$$\min \|\mathbf{y} - \mathbf{D}\boldsymbol{\theta}\|_F^2 /2, \quad s.t.\ \mathbf{d}_i^H \mathbf{d}_i \leq 1, \quad i = 1, \dots, N \tag{7}$$

in which $\|\mathbf{y} - \mathbf{D}\boldsymbol{\theta}\|_F^2$ can be written as

$$\begin{aligned} \|\mathbf{y}-\mathbf{D}\boldsymbol{\theta}\|_F^2 &= \mathrm{tr}\left[(\mathbf{y}-\mathbf{D}\boldsymbol{\theta})^H (\mathbf{y}-\mathbf{D}\boldsymbol{\theta})\right] \\ &= \mathrm{tr}\left(\mathbf{D}\boldsymbol{\theta}\boldsymbol{\theta}^H\mathbf{D}^H\right) - 2\mathrm{tr}\left(\mathbf{y}\boldsymbol{\theta}^H\mathbf{D}^H\right) + \mathrm{tr}\left(\mathbf{y}\mathbf{y}^H\right) \\ &= \mathrm{vec}\left(\mathbf{D}^H\right)^H \left(\mathbf{I}\otimes\boldsymbol{\theta}\boldsymbol{\theta}^H\right)\mathrm{vec}\left(\mathbf{D}^H\right) - 2\mathrm{vec}\left(\boldsymbol{\theta}\mathbf{y}^H\right)^H \mathrm{vec}\left(\mathbf{D}^H\right) + \mathrm{tr}\left(\mathbf{y}\mathbf{y}^H\right) \end{aligned} \tag{8}$$

Let's introduce several new expressions for clarity of notation

$$\alpha \triangleq \mathrm{vec}\left(\mathbf{D}^H\right)$$
$$\mathbf{G} \triangleq \mathbf{I} \otimes \theta\theta^H$$
$$\gamma \triangleq \mathrm{vec}\left(\theta\mathbf{y}^H\right)$$

Omitting the terms that do not depend on $\mathbf{D}$, the objective function in (7) can be equivalent to

$$\min \frac{1}{2}\alpha^H \mathbf{G}\alpha - \gamma^H \alpha, \quad s.t.\ \mathbf{d}_i^H \mathbf{d}_i \leq 1, \quad i = 1, \ldots, N \tag{9}$$

Note that (9) is a standard form of constrained quadratic programming problem which can be solved by any standard optimization method, such as the gradient projection algorithm in [19]. Moreover, the matrix $\mathbf{G}$ is obviously a positively definite matrix, and thus (9) is convex function and can be guaranteed to find a global optimum [20] in the DL phase. This alternating minimization continues until the algorithm attains a specified maximum number of iterations. For completeness, a full description of the algorithm is given in Algorithm 1.

Algorithm 1:

1. **Initialization:** collect RSS readings at APs and send to the location server; set the dictionary $\mathbf{\Psi}$ according to (2) and (3);
2. **AP Selection**: obtain measurement matrix $\mathbf{\Phi}$ according to the strongest AP selection method;
3. **DL Stage:**
   input $\hat{\mathbf{D}}^{(0)} = \mathbf{\Phi\Psi}$ and set the number of iterations T;
   $j = 1$;
   while $j < T$
   1) use the reweighted 1-norm algorithm to compute the sparse vector $\hat{\boldsymbol{\theta}}^{(j)}$ with $\hat{\mathbf{D}}^{(j-1)}$ fixed for each sample;
   2) use the gradient projection algorithm to minimize the objective function in (9) with respect to $\hat{\mathbf{D}}^{(j)}$ keeping $\hat{\boldsymbol{\theta}}^{(j)}$ fixed;

   $j = j + 1$;
   end while
4. **Output**: $\hat{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}}^{(T)}$.

4. POSITIONING ALGORITHM FOR MULTICLASS TARGETS

Although the CS theory has been applied to the indoor positioning systems [7–9], most of the existing work assumes that targets in the location area belong to the same category. In fact, the category of targets may be usually different due to the device heterogeneity. A realistic wireless network consists of wireless devices of dramatically different characteristics, e.g., laptops, PDAs, smart phones, and Wi-Fi location tags, etc.. Thus, the different categories of targets could have different path decay models, based on which different energy decay matrix $\mathbf{\Psi}$ can be formulated. Even when the targets follow the same path decay model as Eq. (3), the transmitted power and the path loss exponent α could be different, producing different categories of targets. Considering the dissimilarity in the training examples, in this paper we divide a complete DL task into several different subtasks, and each task is defined as learning a dictionary from a certain type of examples, which is obtained by K-mean clustering algorithm [21].

Assume there are Q categories of targets, with each having its own overcomplete matrix characterizing the category-specific target energy decay features. Denote these matrices by $\mathbf{\Psi}_i$ for $i = 1, 2, \ldots, Q$, which can be obtained using the same method in Section 2. Then the matrix $\mathbf{\Psi}_{multi}$ for positioning targets from multiple categories can be defined by

$$\mathbf{\Psi}_{multi} = \begin{bmatrix} \mathbf{\Psi}_1 & 0 & \ldots & 0 \\ 0 & \mathbf{\Psi}_2 & \ldots & 0 \\ \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \ldots & \mathbf{\Psi}_Q \end{bmatrix} \tag{10}$$

Similarly we can obtain AP selection operator $\mathbf{\Phi}_{multi}$

$$\mathbf{\Phi}_{multi} = [\mathbf{\Phi}_1\ \mathbf{\Phi}_2 \ldots \mathbf{\Phi}_Q] \tag{11}$$

where $\mathbf{\Phi}_i$ for $i = 1, 2, \ldots, Q$ is the $L \times M$ measurement matrix defined in Section 3.1, which contains exactly one 1 at each row, with all other entries filled by 0's. The unknown vector containing the positioning information is denoted by $\boldsymbol{\theta}_{multi}$ and we have

$$\boldsymbol{\theta}_{multi} = \left[\boldsymbol{\theta}_1^T\ \boldsymbol{\theta}_2^T \ldots \boldsymbol{\theta}_Q^T\right]^T \tag{12}$$

where $\boldsymbol{\theta}_i$ is a $N \times 1$ vector that denotes the location of targets from category i in N grids. Let $\mathbf{H}_{multi} = \mathbf{\Phi}_{multi}\mathbf{\Psi}_{multi}$, we can obtain

$$\mathbf{y}_{multi} = \mathbf{\Phi}_{multi}\mathbf{\Psi}_{multi}\boldsymbol{\theta}_{multi} + \mathbf{V}_{multi} = \mathbf{H}_{multi}\boldsymbol{\theta}_{multi} + \mathbf{V}_{multi} \tag{13}$$

where $\mathbf{V}_{multi}$ still represents Gaussian noise terms. To reflect dynamic RSS changes in indoor environments, we also define the error dictionary matrix $\mathbf{\Gamma}_{multi}$ to describe the difference between the predefined dictionary and the practical received signals. Then, the sparse positioning model is correspondingly modified as:

$$\mathbf{y}_{multi} = (\mathbf{H}_{multi}+\mathbf{\Gamma}_{multi})\boldsymbol{\theta}_{multi}+\mathbf{V}_{multi} \triangleq \mathbf{D}_{multi}\boldsymbol{\theta}_{multi}+\mathbf{V}_{multi} \quad (14)$$

where $\mathbf{D}_{multi} = [\mathbf{D}_1\ \mathbf{D}_2 \ldots \mathbf{D}_Q]$ denotes the actual basis with time-varying interferences for multiclass targets. Similar to the single-class target localization, here we do not estimate the changeable path loss exponent dynamically to adapt to dynamic nature of indoor environments, while we use DL techniques to learn dictionaries to better fit the actual RSS model.

Once RSS samples from multiclass targets are categorized by K-means clustering method all sub-dictionaries are learned simultaneously by the server using the same method as Algorithm 1. Thus, a big DL task is divided into several subtasks which can make the individual sub-dictionary represent the model of samples more accurately. At the same time, multiple DL also enhances the speed of DL on each tasks and the final reconstruction accuracy. Once multiple DL procedures are finished, the eventual results about the sparse vector $\boldsymbol{\theta}_{multi}$ can be obtained simultaneously whose indices of nonzero entries represent the estimated positions.

5. SIMULATION RESULTS

In order to evaluate the performance of the proposed ARSL method and compare it with the ACS approach in [10] and the NN approach in [11], we performed extensive simulations. The localization area of the scene (which is the part of the third floor plane in the electrical engineering department of Nanjing Normal University) is shown in Fig. 1, which is divided into $N = 30 \times 23$ grids in simulations. This means yielding a 1 m resolution along both x and y axes. A total of 17 APs are used to measure RSS values in the localization area. The target locations are selected at random, uniformly, within the measurement area. The experiments have been run on an Intel Core i5 CPU at 3.1 GHz processor with 8 GB memory. In the following sections, the performance of the localization system is evaluated by the average localization error (ALE), which is calculated by averaging the Euclidean distance between the estimated locations of the targets and their actual locations over the testing points by 100 simulations.

5.1. Simulation Results for Targets from Single Category

In this section, we assume that the transmitted signal power from each target is set the same value as 20 mW (13 dBm), and the

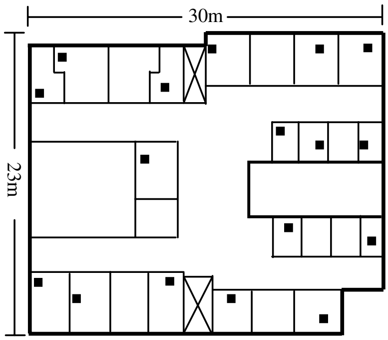

Figure 1. The configuration of localization area. The black dots show the locations of the APs.

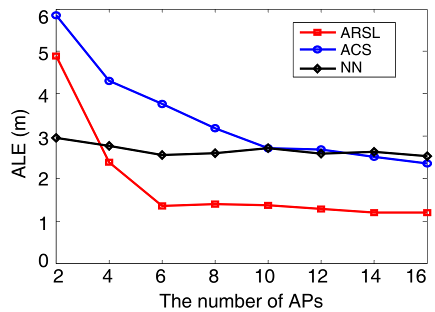

Figure 2. Effects of the number of APs on the localization error.

path-loss exponent α is set 2.6 to construct the initial energy decay overcomplete basis. To investigate the effects of RSS variations, a random perturbation matrix $\mathbf{\Gamma}$ is added on the overcomplete basis $\mathbf{\Psi}$. Since the variation of RSS measurements is wide (from 5 dBm to 20 dBm) in typical 802.11 infrastructure according to the experimental results in [22], each element in the matrix $\mathbf{\Gamma}$ is assumed to subject to the uniform distribution with zero mean and its standard deviation is $b \in [5\,\text{dBm} \;\; 20\,\text{dBm}]$. The measurement noise is assumed to be a white Gaussian random variable with zero mean and standard deviation 1 mW.

In the first test case, the localization errors versus the number of APs used in three different algorithms are studied when b is set to 13 dBm and the number of targets is fixed at 2. As the simulation results shown in Fig. 2, it is noticed that as an overall trend, the larger number of APs, the smaller the error for all algorithms. However, even though the number of APs is sufficient, the localization error of the ACS and NN methods is still more than 2 m due to the effects of RSS fluctuations. By comparison, the localization error of the ARSL algorithm is small since the proposed method performs the DL technique to mitigate the effects of RSS variations. When the number of APs used for the ARSL algorithm comes to 6, which is just more than $O(K \log(N/K)) \approx 5.1$, the localization error becomes below 1.5 m. Moreover, with the number of APs increasing, the ALE of the ARSL algorithm will not apparently decrease after convergence. This result shows that the ARSL algorithm based on DL can obtain the location estimates by using only a small number of noisy measurements, even if the fluctuation of RSS variations is serious.

The second simulation investigates the performance of three different algorithms as a function of the number of targets when b is also equal to 13 dBm. The number of targets changes from 1 to 7, and the number of APs is fixed at 16. Fig. 3 illustrates the location error with respect to the number of targets. With the increase in the number of targets, the ALE of the NN algorithm increases quickly due to the high sensitivity to the estimated number of targets. On the contrary, the variations of ALE for two CS-based algorithms are very small. Although the ACS method can achieve better accuracy than the NN method, it is clearly outperformed by the proposed algorithm under the same parameter settings. This is because the fluctuation of RSSs may result in cluster mismatch in the ACS method while the ARSL algorithm exploits the DL technique to correct the effects of RSS variations. The importance of the low sensitivity of our algorithm to the number of targets is twofold. First, the number of sources is usually unknown, and low sensitivity provides robustness against mistakes in estimating the number of targets.

In the third simulation, the localization errors with respect to standard deviation b are studied. The number of targets is fixed at 3, and the number of APs is set as 16. Here, b changes from 5 dBm to 20 dBm. From Fig. 4, both ACS and NN algorithms perform poorly as b increases. The average error is increased approximately from 1.9 m to 3.7 m and 2.0 m to 4.0 m, respectively. By contrast, the ALE of our algorithm remains almost constant with b changes from 5 dBm to 20 dBm. These results reveal that the ARSL method is very robust to large fluctuation of RSS variations and can effectively enhance location accuracy.

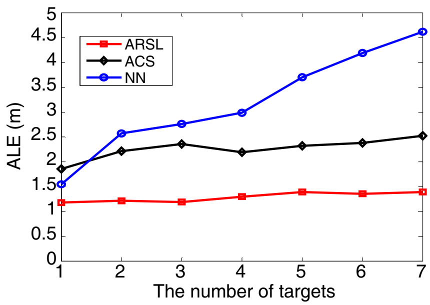

Figure 3. The localization errors with respect to the number of targets.

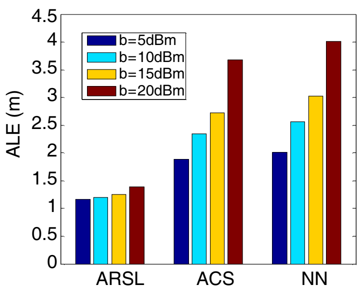

Figure 4. Robustness comparisons when RSS values are interfered by different fluctuation levels.

5.2. Simulation Results for Targets from Multiple Categories

We now report our simulation results when there are targets from multiple categories. Here we assume that all targets follow the same energy decay model defined by Eq. (3) but with different transmitted power P_t and α value. Let Q be the total number of target categories. In our simulation, Q varies from 1 to 3, and the corresponding number of each category is the same value as two. The parameter settings for the three categories of targets are specified as follows.

$$\text{Category 1: } P_t = 10\,\text{dBm}, \quad \alpha = 2.0; \tag{15}$$

$$\text{Category 2: } P_t = 15\,\text{dBm}, \quad \alpha = 3.0; \tag{16}$$

$$\text{Category 3: } P_t = 20\,\text{dBm}, \quad \alpha = 2.6; \tag{17}$$

The simulation setup is similar to that of single category target localization except that RSS samples are firstly classed by the K-mean clustering algorithm, and all sub-dictionaries are learned simultaneously by the server using the same DL method in Algorithm 1.

Figure 5 shows the implementation result about the localization errors versus the number of APs, when b is also set to 13 dBm. As noticed that once the number of measurements exceeds the minimum bound as required by the CS theory, our proposed positioning system achieves the best performance among the three approaches. As shown in Fig. 5, the ARSL algorithm leads to the location estimate error improvement of about 1 m and 1.5 m over that of the ACS and NN methods, respectively, when 12 APs are used.

Accordingly, it can be seen from the localization errors in Fig. 6 that the proposed algorithm can provide much better performance over the other two schemes, when the number of APs is set as 16. The ALE of the proposed algorithm is still improved 2 m to 3 m when the b varies from 15 dBm to 20 dBm, compared with the ACS and NN algorithms. However, it can be observed that the localization performance of all of three algorithms for multiclass targets decline obviously comparing with the case of single category targets under the same standard deviation in Fig. 4. Besides the influence of clustering matching, this is attributed to the fact that Q actually increases the sparsity level. As indicated in Section 4, when the targets in a grid belong to Q different categories, they actually occupy Q entries in the vector $\boldsymbol{\theta}_i$ and therefore markedly increases the sparsity level from k to roughly Qk.

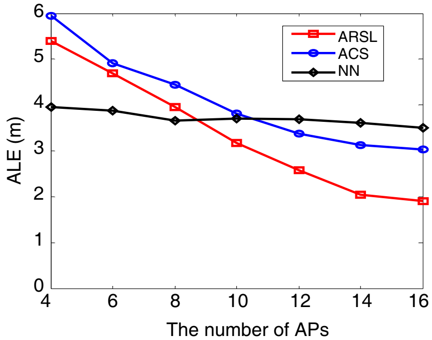

Figure 5. Effects of the number of APs on the localization error for targets from multiple categories.

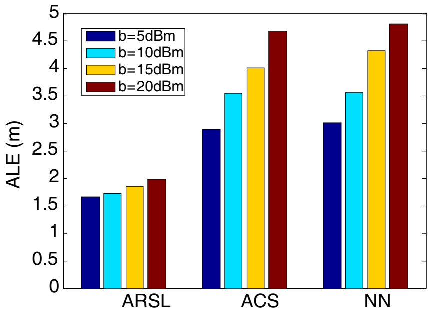

Figure 6. Robustness comparisons when RSS values are interfered by different fluctuation levels for targets from multiple categories.

6. CONCLUSION

RSS-based localizations have attracted considerable attention due to their simplicity and low cost. However, one of the most important issues is still the lack of the automated calibration mechanism that captures the relationship between the RSS measurements and the geographical positions. In this paper, we exploit the inherent spatial sparsity to investigate the indoor positioning problem in the existence of RSS variations without extra network hardware. To mitigate the effects of RSS variations, we present a novel sparsity-based indoor localization algorithm which makes use of the DL technology to design dictionaries for fitting the actual RSS scenario, and thus the proposed method has environmental-adaptation capabilities. At the same time, this algorithm can perform well without prior knowledge about the targeted environments and without time-consuming off-line surveys. Therefore, the ARSL method can improve the location accuracy compared with the ACS and NN algorithms. This study also investigates the applicability of the ARSL algorithm for locating targets from multiple categories. The effectiveness of the proposed scheme has been demonstrated by simulation results where substantial improvement for localization performance is achieved. Further research will emphasize on the off-grid error analysis and the theoretic bound on the location estimation precision.

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