

CS-BASED DEVICE-FREE LOCALIZATION IN THE PRESENCE OF MODEL ERRORS

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ABSTRACT

Compressive sensing (CS) has recently been applied for device-free localization (DFL) by exploiting spatial sparsity to reduce the number of measurements required by DFL systems while maintaining the high localization accuracy. However, few works considered model errors in CS-based DFL. This paper proposes an adaptive sparsity-based DFL approach to overcome the problem incurred by model errors. The novel feature of this method is to dynamically adjust the basis matrix (a.k.a. dictionary) based on a two-stage dictionary learning (DL) framework with non-negativity constraints. Compared to previous CS-based DFL methods, the proposed method can compensate the inaccuracy of the basis matrix and improve sparse reconstruction performance simultaneously. Experimental results verify the performance of the proposed approach on the location accuracy.

Index Terms—Device-free localization, compressive sensing, dictionary learning, non-negativity constraints

1. INTRODUCTION

In recent years, the low-cost DFL which only utilizes the received signal strength (RSS) measurements of wireless links in wireless networks has become an attractive technology and shown enormous promise in applications ranging from intrusion detection to elder care [1]. Compared with the existing device-free techniques such as infrared detector, video monitor and UWB radar detector, RSS-based DFL brings several advantages over other technologies by being able to work in obstructed environments, see through smoke, darkness, and walls. Several kinds of DFL methods have already been proposed to localize and track targets using the temporal variations of RSS. Youssef et al. [2-3] modeled the DFL problem as a machine learning problem and realized DFL with a fingerprint-matching method. Another approach to RSS-based DFL named radio tomographic imaging (RTI) [4-6], estimates the changes in the RF propagation field of the

monitored area and then forms an image of the changed field. This image is then used to infer the locations of targets within the deployed network. Zhang et al. [7-8] presented a signal dynamic model, and adopted the geometric method and the dynamic cluster-based algorithm to solve the DFL problem. Recently, Wang et al. [9] proposed to realize DFL based on multidimensional wireless link information, which significantly enriches wireless measurement information.

In recent years, the CS theory which receives a great deal of attentions has been successfully applied for wireless localization. To the best of our knowledge, Kanso and Rabbat carried out the first sparsity-based work to combine RF tomography and CS to solve the DFL problem [10]. In [11-12], the greedy algorithms were used to estimate targets' positions in DFL systems, which results in a substantial reduction of the amount of measurements. In fact, all these CS-based DFL approaches belong to the model-based DFL method, since these works must exploit the normalized ellipse shadowing (NES) model [5, 13] to construct the basis matrix for sparse models. A key problem in model-based DFL methods is to construct a reasonable shadowing model in order to accurately relate the shadowing experienced by a signal to attenuation at specific in space. Although the NES model has some physical justification for using an ellipse shape according to the ellipsoidal Fresnel zone, the decision to set the weights of all of the grids equally in each ellipse and invariably in all environments has no physical basis. In addition, it is not always reasonable that the weight is only reliant on the distance between two nodes in one wireless link. Moreover, the RSS is extremely sensitive to the variations of environments, and therefore the fixed dictionary based on the NES model may mismatch actual variations of RSS measurements, which will reduce DFL performance, especially in the multipath environment.

Unlike previous works that the predefined dictionary is invariable in the localization process, in this paper we propose an adaptive CS-based DFL (ADFL) method to dynamically adjust both the dictionary and the sparse

solution so that the dictionary can better match the actual scenario. The proposed method first performs supervised offline DL to obtain the practical initial dictionary. Then, the online DL stage uses the results from the offline stage as warm restart to handle the unseen online variation for enhancing its adaptability. Thus, the ADFL algorithm can utilize CS to tackle the space-domain sparse feature for locating device-free targets, and exploit the DL technique to deal with the time-domain gradually changed feature for error self-calibration.

2. SYSTEM MODEL

Consider P unknown-location targets located in an area of interest, which is divided into N grids. Suppose Q wireless nodes consist of a wireless network, and then the total number of wireless links with every pair of nodes is $M=Q \times (Q-1)/2$. Here, any pair of nodes is counted as a link, whether or not communication actually occurs between them. Generally, the number of targets P is considerably less than the number of grids N . Hence, the CS-based DFL model can be described in matrix form as [10-12]

$$\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{n} \quad (1)$$

where $\mathbf{y}=[\Delta y_1, \dots, \Delta y_M]^T$ is a $M \times 1$ vector that represents the changes of RSS measurements, $\mathbf{x}=[x_1, \dots, x_N]^T$ is a $N \times 1$ vector to be estimated, where $x_i (1 \leq i \leq N)$ represents the RSS attenuation at the grid i which corresponds to the fact that whether a target is located at the i th grid. \mathbf{W} is a $M \times N$ weighing dictionary that describes the shadowing effect of each grid on each wireless link, which can be calculated by the NES model. The $M \times 1$ vector \mathbf{n} represents noise terms.

Although the NES model is popularly used in DFL researches due to its simplicity, it is only approximate to the real radio propagation character and cannot accurately express actual relationship between shadowed links and RSS attenuations caused by targets. To overcome this problem, in this paper we exploit DL technology to automatically calibrate the dictionary. To avoid the difficulty of estimating all kinds of time-varying factors, we denote the perturbation matrix $\mathbf{\Gamma}$ to describe the difference between the approximate model and the actual dictionary. Thus, the sparse DFL model is correspondingly modified as:

$$\mathbf{y} = (\mathbf{W} + \mathbf{\Gamma})\mathbf{x} + \mathbf{n} = \mathbf{H}\mathbf{x} + \mathbf{n} \quad (2)$$

where $\mathbf{H}=(\mathbf{W}+\mathbf{\Gamma})$ denotes the practical dictionary. Note that the weighting values must be nonnegative, so the dictionary \mathbf{H} is also under non-negativity constraints.

3. THE TWO-STAGE DL ALGORITHM

Since the perturbation matrix $\mathbf{\Gamma}$ is time-varying and cannot be known in advance, we must estimate the sparse vector and weighing dictionary simultaneously to deal with the uncertainty of the dictionary. According to the CS theory

and DL technology, the above problem in (2) can be converted into the following problem

$$\min_{\substack{\mathbf{H}, \mathbf{X} \\ \mathbf{H} \geq 0}} \|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2 + \lambda \sum_{i=1}^L \|\mathbf{x}_i\|_1 \quad (3)$$

where $\mathbf{Y}=[\mathbf{y}_1, \dots, \mathbf{y}_L]$ is the training dataset, and $\mathbf{X}=[\mathbf{x}_1, \dots, \mathbf{x}_L]$ is the corresponding sparse representations. $\|\cdot\|_F$ and $\|\cdot\|_1$ are the Frobenius norm and l_1 norm respectively. λ is the parameter tuning the constraint on the sparsity.

Since the above problem is not convex with respect to the pair (\mathbf{H}, \mathbf{X}) , most DL algorithms deal with this problem by alternately performing a two-step procedure: Starting with an initial dictionary $\mathbf{H}_0=\mathbf{W}$, the following two steps are repeated several times.

3.1. Sparse recovery step

Let us first consider the sparse recovery step, where \mathbf{H} is fixed. The penalty term can be rewritten as

$$\|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2 = \sum_{i=1}^L \|\mathbf{y}_i - \mathbf{H}\mathbf{x}_i\|_2^2 \quad (4)$$

Thus, the sparse recovery problem posed in (3) can be decoupled to L distinct problems of the form

$$\mathbf{x}_i = \arg \min_{\mathbf{x}_i} \|\mathbf{y}_i - \mathbf{H}\mathbf{x}_i\|_2^2 + \lambda \|\mathbf{x}_i\|_1, i = 1, \dots, L \quad (5)$$

This problem is a normal sparse coding problem and many algorithms have been proposed. In this paper we employ the BGMP algorithm in [12] to calculate sparse vectors.

3.2. Dictionary calibration step

3.2.1. Offline DL stage

$$\mathbf{H} = \arg \min_{\mathbf{H} \geq 0} \|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2 \quad (6)$$

In this stage, the ideal initial dictionary is firstly trained by using the available training data to construct a practical initial dictionary according to the offline DL method. Since the sparse vectors are known in the dictionary update step, $\|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2$ can be converted into the following expression:

$$\begin{aligned} \|\mathbf{Y} - \mathbf{H}\mathbf{X}\|_F^2 &= \text{tr}[(\mathbf{Y} - \mathbf{H}\mathbf{X})^T (\mathbf{Y} - \mathbf{H}\mathbf{X})] \\ &= \text{tr}(\mathbf{H}\mathbf{X}\mathbf{X}^T \mathbf{H}^T) - 2\text{tr}(\mathbf{Y}\mathbf{X}^T \mathbf{H}^T) + \text{tr}(\mathbf{Y}\mathbf{Y}^T) \quad (7) \\ &= (\text{vec}(\mathbf{H}^T))^T (\mathbf{I} \otimes \mathbf{X}\mathbf{X}^T) \text{vec}(\mathbf{H}^T) \\ &\quad - 2(\text{vec}(\mathbf{X}\mathbf{Y}^T))^T \text{vec}(\mathbf{H}^T) + \text{tr}(\mathbf{Y}\mathbf{Y}^T) \end{aligned}$$

where $\text{tr}[\cdot]$ and $\text{vec}(\cdot)$ respectively represent the trace and the vertical concatenation of columns of a matrix. $(\cdot)^T$, \mathbf{I} and \otimes denote transpose, the identity matrix, and the Kronecker product, respectively. For clarity of notation, we denote $\mathbf{a}=\text{vec}(\mathbf{H}^T)$, $\mathbf{G}=\mathbf{I} \otimes \mathbf{X}\mathbf{X}^T$ and $\boldsymbol{\gamma}=\text{vec}(\mathbf{X}\mathbf{Y}^T)$. Omitting the terms that do not depend on \mathbf{H} , the objective function in (6) can be equivalent to

$$\mathbf{a} = \arg \min_{\mathbf{a} \geq 0} \mathbf{a}^T \mathbf{G} \mathbf{a} - 2\boldsymbol{\gamma}^T \mathbf{a} \quad (8)$$

Note that (8) is a quadratic programming problem which can be solved by many algorithms such as the active set

method in [14]. The cost function in (3) alternately descends between (5) and (8) until the absolute difference of cost function (3) is smaller than the convergence threshold, then obtaining the optimal offline pre-trained dictionary \mathbf{H}_{off} .

3.2.2. Online DL stage

Although the off-line DL stage has adjusted the basis matrix according to the training data, it is impossible to be fit for all kinds of time-varying RSS variation patterns. Moreover, its computation load is very large for real-time localization. To accommodate further the unseen dynamic variation when new samples arrive, the offline pre-trained dictionary needs to be updated according to the latest measurements. Therefore, we add the online DL stage to dynamically calibrate the pre-trained initial dictionary according to the past on-line measurements. Thus, the dictionary calibration procedure in this paper includes two stages: one for constructing the practical initial dictionary, and one for performing real-time calibration.

So far, most existing online DL methods do not use the robust function in the data fitting term and might be vulnerable to large outliers [15]. In fact, during the process of object tracking, there may be some outlier links due to the measurement noise and multi-path propagation. The RSS measurement is also sensitive to be affected by temperature, humidity, intrinsic motion, et al. These challenging factors are easy to induce outliers. In [15], l_1 norm fitting functions are found to make estimation more reliable than l_2 norm in robust statistics. Inspired by the previous work in [15], we propose a robust online DL method with non-negativity constraints. Different from l_2 norm constraints, the objective function of robust DL is defined as

$$\mathbf{H} = \arg \min_{\mathbf{H} \geq 0} \|\mathbf{Y} - \mathbf{H}\mathbf{X}\| \quad (9)$$

Since the sparse vectors and the initial dictionary \mathbf{H}_{off} are known, (9) can be regarded as a l_1 regression problem. As in [15], the iterative reweighted least squares (IRLS) algorithm can be used to solve (9):

$$\mathbf{H}(j,:) = \arg \min_{\mathbf{H}(j,:) \geq 0} \frac{1}{L} \sum_{i=1}^L \beta_i^j (\mathbf{y}_i(j) - \mathbf{H}(j,:) \mathbf{x}_i)^2, j=1, \dots, M \quad (10)$$

where $\mathbf{y}_i(j)$ is the j th element of \mathbf{y}_i , $\mathbf{H}(j,:)$ represents the j th row of \mathbf{H} , and $\beta_i^j = 1 / \sqrt{(\mathbf{y}_i(j) - \mathbf{H}(j,:) \mathbf{x}_i)^2 + \delta}$. δ is a small positive value to prevent the occurrence of the overlarge value. By taking derivatives for (10) and setting them to zeros, the optimum result can be reached by solving $\mathbf{H}(j,:)$ in the linear system as follows:

$$\mathbf{C}^j = \mathbf{H}(j,:) \mathbf{D}^j, \text{ s.t. } \mathbf{H}(j,:) \geq 0 \quad (11)$$

where $\mathbf{C}^j = \sum_{i=1}^L \beta_i^j \mathbf{y}_i(j) \mathbf{x}_i^T$ and $\mathbf{D}^j = \sum_{i=1}^L \beta_i^j \mathbf{x}_i \mathbf{x}_i^T$. The (11)

can be solved by the nonnegative least squares (NNLS) algorithm, which can be directly implemented in MATLAB as the function *lsqnonneg*.

To meet the requirement of real-time localization, we utilize the low-complexity incremental training method in the on-line DL stage. As the dictionary updates with the coming data, the online versions of \mathbf{C}^j and \mathbf{D}^j are as follows:

$$\mathbf{C}_t^j = \mathbf{C}_{t-1}^j + \beta_t^j \mathbf{y}_t(j) \mathbf{x}_t^T \quad (12)$$

$$\mathbf{D}_t^j = \mathbf{D}_{t-1}^j + \beta_t^j \mathbf{x}_t \mathbf{x}_t^T \quad (13)$$

For completeness, a full description of the algorithm is summarized in Algorithm 1.

Algorithm 1 Online Robust Nonnegative Dictionary Update

Input: the sample set $\mathbf{Y}=[\mathbf{y}_1, \dots, \mathbf{y}_L]$; regularization parameter λ
the initial dictionary obtained from the off-line stage;

$$\mathbf{C}_0^j \leftarrow \mathbf{0}, \mathbf{D}_0^j \leftarrow \mathbf{0}, j=1, \dots, M$$

1. **for** $t=1$ to L **do**
2. Sparse recovery by using BGMP:
 $\mathbf{x}_t = \arg \min_{\mathbf{x}_t} \|\mathbf{y}_t - \mathbf{H}_{t-1} \mathbf{x}_t\|_2^2 + \lambda \|\mathbf{x}_t\|_1$
3. Dictionary update: compute \mathbf{H}_t by using \mathbf{H}_{t-1} as warm restart;
4. **repeat**
5. **for** $j=1$ to M **do**
6. $\beta_t^j = 1 / \sqrt{(\mathbf{y}_t(j) - \mathbf{H}_{t-1}(j,:) \mathbf{x}_t)^2 + \delta}$
7. $\mathbf{C}_t^j = \mathbf{C}_{t-1}^j + \beta_t^j \mathbf{y}_t(j) \mathbf{x}_t^T$
8. $\mathbf{D}_t^j = \mathbf{D}_{t-1}^j + \beta_t^j \mathbf{x}_t \mathbf{x}_t^T$
9. solve linear system $\mathbf{C}_t^j = \mathbf{H}_t(j,:) \mathbf{D}_t^j$ by using NNLS
10. **end for**
11. **until convergence**
12. **end for**

Output: online trained dictionary \mathbf{H}_{on}

4. EXPERIMENTAL RESULTS

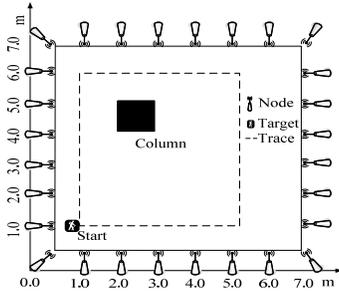
An experimental network (EN) containing 28 nodes was deployed in an indoor area which is bounded by glass windows on one side, and has a concrete column within the deployment area. Each node is placed 1.0m apart along the perimeter of $7 \times 7 \text{m}^2$ and 0.9m off the ground on a pedestal. A photograph and map of the experimental setup are shown in Fig.1. Each node operates in the 2.4G frequency band and runs the IEEE 802.15.4 protocol for communication. To avoid network transmission collisions, a simple token ring protocol is used to control transmission. A base-station node is used to gather signal strength information from each node, and saves them to a laptop with Intel i7 3.5GHz processor and 8GB memory for real-time processing.

To evaluate the performance of the proposed algorithm, we compare it with the CS-DLF method in [12] and the RTI technique [5]. In the experiment, a target (a person) moved clockwise along a rectangular trajectory and its location was estimated once per second. Before the target entered into the area, we recorded 0.5 minutes RSS scans for off-line training. The default parameters are as follows: grid size is

0.25 m× 0.25 m, the width of the ellipse in the NES model is 0.15m, and true speed of the target is about 0.55m/s.



(a)



(b)

Fig. 1 (a) Photograph of the EN. (b) Geometry of the EN.

The tracking error, which is denoted as the Euclidean distance between the true location and estimated one, is shown in Fig. 2. The results show that the proposed approach has the least tracking error. Moreover, it should be noted that the tracking errors of the CS-DFL and RTI methods are distinctly large for some instants, especially when the target walks around the concrete column. This is because the concrete column obstructs signal propagation between some links, which not only aggravates model mismatch, but also results in fewer links travelling through the target. On the contrary, the variation of the tracking errors in the ADFL algorithm is very small, so the tracking performance of the ADFL algorithm is relatively stable to the environmental variations. This advantage results from the fact that the weighting model in the ADFL algorithm is automatically calibrated by using the two-stage DL method.

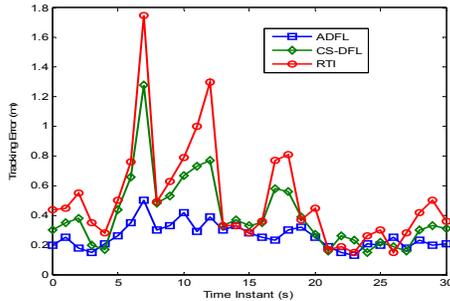


Fig. 2 Tracking errors in the experiments.

The detailed statistical character of the tracking errors are summarized in Table 1. We can see that the tracking performance of the ADFL algorithm is better when compared with the CS-DFL and RTI methods, with mean tracking error reduced by 36% and 49%, respectively. Meanwhile, we can see that although the mean values of the tracking errors in three schemes are all less than 0.51m, the ADFL approach has significantly better performance than the other two methods in terms of max error. These results reveal that the ADFL method can enhance location accuracy in time-varying environments. The complexity is also compared in terms of the CPU running time. From Table 1, it shows that the average running time of the proposed method is largest. However, most running time is spent at the offline training stage. Since offline training is performed before the tracking starts, the slight complexity increase in the on-line stage is acceptable.

Table 1: Comparison of localization error and running time

Algorithm	Mean (m)	Standard Deviation (m)	Max (m)	Average Running Time (ms)
CS-DFL	0.402	0.238	1.280	25.76
RTI	0.509	0.348	1.750	11.13
ADFL	0.259	0.083	0.500	388.11(offline) +37.29(online)

5. CONCLUSION

In this paper, we have exploited the inherent spatial sparsity to present a novel DFL method by combining the offline training and online learning into a unified DL framework, thereby overcoming the problem of model mismatch and better matching time-varying scenarios. Meanwhile, since outlier links are inevitable in the practical process of object tracking, a robust online DL algorithm with non-negativity constraints is proposed to overcome the impacts of outliers. The effectiveness of the proposed scheme has been verified by experimental results where substantial improvement for localization accuracy is achieved.

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