

Robust Sparsity-Based Device-Free Passive Localization in Wireless Networks

Wei Ke*, Gang Liu, and Tongchangjian Fu

Abstract—As an emerging technique with a promising application prospect, the device-free passive localization (DFPL) technique has drawn considerable research efforts due to its ability of realizing wireless localization without the need of carrying any device and participating actively in the localization process. Recent technological achievements of the DFPL technique have made it feasible to realize location estimation using the received signal strength (RSS) information of wireless links. However, one major disadvantage of the RSS-based DFPL technique is that the RSS measurement is too sensitive to noise and environmental variations, which incur the misjudgment of shadowed links and degradation of localization performance. Based on the natural sparsity of location finding in the spatial domain, this paper proposes an environmental-adaptive sparsity-based localization method for the DFPL problem in the existence of model mismatch. 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) technique based on the quadratic programming approach so that the location solution can better match the changes of the RSS measurements between the node pairs to the spatial location of the target. Moreover, we propose a modified re-weighting l_1 norm minimization algorithm to improve reconstruction performance for sparse signals. The effectiveness of the proposed scheme is demonstrated by experimental results where the proposed algorithm yields substantial improvement for localization performance.

1. INTRODUCTION

Because of the requirement of location-aware services and potential promising commercial and military application, wireless localization has gained considerable attention over the past decade. Although Global Positioning System (GPS) has been in service for many years, it is only available in GPS-enabled devices and may encounter problems in certain urban settings and indoor environments where there are no direct visibilities to satellites [1]. Thus, the location estimation based on existing wireless infrastructures such as wireless local area network (WLAN), cellular network, and radio frequency identification (RFID) has advanced rapidly in recent years [2–6]. Most of these technologies have a common requirement that the target must be equipped with a wireless device like a smartphone or a RFID tag, since these technologies realize localization by utilizing the wireless measurements between the target and the anchor nodes whose locations are known a priori. However, in some applications such as battlefield surveillance, emergency rescue, and security safeguard, it is impractical to equip the target with a wireless device. In addition, important applications also exist in other settings like hospitals, residences and places of entertainment. For example, health care providers in hospital need to grasp the distribution of positions of the wandered patients associated without a device and quickly expand the relief operations. Therefore the DFPL technique capable of detecting and positioning entities which neither carry any devices nor participate actively in the localization process will be greatly helpful. Compared with the existing techniques such as passive infrared detector, photo-electric beam, video

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monitor and heat detector, the DFPL technique can monitor a larger deployment area, can work in the dark conditions, and can utilize the existing wireless infrastructure to realize the localization task. As an emerging wireless localization technique, the DFPL has drawn extensive attentions in recent years [7, 8].

However, the above works require that there should be sufficient number of wireless links to guarantee the localization performance, and these techniques will be infeasible when few wireless links are available. Owing to the recent advances in sparse signal reconstruction for compressive sensing (CS), in this paper we consider the target locations as a sparse signal and reconstruct the signal using the CS technique. Different from the previous works, we use DL techniques to combine the location estimating and overcomplete basis modifying into a unified CS framework based on current observations. We also propose an improved re-weighting l_1 norm reconstruction algorithm to improve reconstruction performance for sparse signals.

The notation used in this paper is according to the convention. Symbols for matrices (upper case) and vectors (lower case) are in boldface. $(\cdot)^T$, $|\theta|$, $\|\theta\|_0$, $\|\theta\|_1$, $\|\theta\|_2$, $\|\theta\|_F$, \mathbf{I}_N , and \otimes denote transpose, absolute value, l_0 norm, l_1 norm, l_2 norm, Frobenius norm, identity matrix with the dimension N , and the Kronecker product, respectively. The vector \mathbf{e}_N represents the all-one vector of the dimension N . For any matrix \mathbf{Y} , $\text{vec}(\mathbf{Y})$ is denoted as the vertical concatenation of the columns of \mathbf{Y} , and $\text{tr}(\mathbf{Y})$ is the trace of \mathbf{Y} . The remainder of the paper is organized as follows. Section 2 presents the related works. Section 3 describes the system model assumed throughout this paper and formulates as a sparse recovery problem. In Section 4, we introduce a scheme calibrating the overcomplete basis dynamically and estimating the sparse solution adaptively. Experimental results are given in Section 5. Finally, Section 6 concludes the paper.

2. RELATED WORKS

With the rapid spread and popularity of wireless communications, nowadays, wireless networks are ubiquitous. Wherever we are, it is unavoidable that wireless signals are in the environment around us and we are interacting with radio-frequency (RF) electromagnetic waves, and thus these link measurements offer fundamental measurement information for DFPL systems. Since DFPL is a promising technique, lots of research works have been carried out to realize DFPL. In this section, we summarize the most relevant research on the DFPL and the CS-based localization.

Motivated by the success of the computed tomography method in medical and radar systems, references [9, 10] formulated the DFPL model as a radio tomography imaging problem. They carried out in-depth research on the design of the statistical model for relating the temporal link signature with the target's location. Imaging-based RSS-DFPL systems need first estimate attenuation or motion image and then estimate the target's coordinate from that image, but information can be lost in the two-step process [11]. In [12], Moussa and Youssef modelled the DFPL problem as a fingerprint-matching question and realized DFPL with a machine learning method. As the fingerprinting method used in the device-dependent localization system, this method need build an offline radio map by placing the target at every possible location and store the wireless link measurements. However, the training measurements increase exponentially with the increase of the number of wireless links and targets. In addition, this method is also environment dependent and any significant change on the topology implies a costly new recalibration. A signal dynamic model in [13] was proposed to describe the character of the wireless links, and they adopted the geometric method and the dynamic cluster-based probabilistic algorithm to solve the DFPL problem. Recently, Chen et al. adopted the expectation maximum algorithm and an auxiliary particle filter to realize nodes localization and DFPL simultaneously [14]. However, these works require that there should be sufficient number of wireless links to guarantee the localization performance, and the localization performance will drop significantly when few wireless links are available.

In recent years, the CS theory which receives a great deal of attentions has been successfully applied for wireless localization, which results in higher localization accuracy and reduces the dimensions of measurement vectors. However, so far most CS-based localization methods concentrate on device-dependent methods, and few works adopt the CS method to realize DFPL [15–17]. 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 DFPL problem [15]. They used the l_1 norm minimization scheme to estimate

the location of the target and achieved better performance than the traditional regularization method. References [16] exploited the elliptical weight model in [18–20] to construct sparse model and used the greedy algorithm to estimate target locations, but elliptical weight model is approximate and may be inaccurate in the multipath environment. Wang et al. [17] modelled the DFPL problem as a sparse signal reconstruction problem and proposed a Bayesian greedy matching pursuit (BGMP) algorithm to efficiently realize sparse signal reconstruction. Although the above CS-based efforts are easy to be implemented in the sparse deployment scenario, most methods are extremely sensitive to the variations of environmental dynamic factors, and thus they can not achieve stable performance under complex circumstances.

In this paper, we continue to investigate the CS-based DFPL problem with the existence of model mismatch, which is commonly neglected by the published DFPL methods. An adaptive device-free sparse localization algorithm is proposed to adjust both the overcomplete basis and the sparse solution so that the solution can better adapt to dynamic nature of wireless environments.

3. SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we first present a linear model for relating the change of the RSS measurements between the node pairs to the spatial location of the target, and then formulate the localization problem as a sparse signal reconstruction question in the presence of model mismatch.

3.1. System Model

Consider C unknown-location targets located in an area of interest, which is divided into N grids. Suppose M wireless nodes consist of the wireless network as shown in Figure 1, and then the total number of wireless links with every pair of nodes is $K = M \times (M - 1)/2$. Here, any pair of nodes is counted as a link, whether or not communication actually occurs between them. When wireless nodes communicate, the radio signals pass through the physical area of the network. Objects within the area absorb, reflect, diffract, or scatter some of the transmitted power. Since grid locations are known, DFPL allows one to know where attenuation in a network is occurring, and therefore, where objects are located.

In theory, the propagation of electromagnetic waves is regulated by certain principle. The shadowing model is the most widely adopted model to approximate the signal propagation character [18–20]. With the shadowing model, the measurements $y_i(t)$ of link i is described as

$$y_i(t) = P_i - L_i - S_i(t) - F_i(t) - v_i(t) \tag{1}$$

where P_i is the transmitted power in dBm, $S_i(t)$ the shadowing loss in decibels due to objects that attenuate the signal, $F_i(t)$ the fading loss in decibels, and L_i the static losses in decibels due to distance,

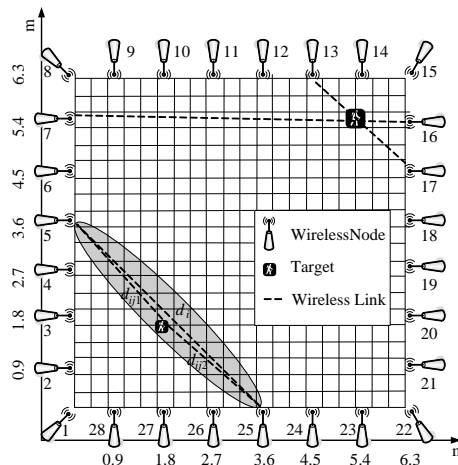


Figure 1. Illustration of the device-free localization.

antenna patterns, device inconsistencies, etc.. $v_i(t)$ represents noise and interference, which is assumed as wide-sense stationary, zero mean, complex Gaussian process, uncorrelated with the signals. Since the radio propagation parameters and the transceiver parameters are almost the same in the adjacent two time instants, all static losses can be removed over time [7, 8]. For two time instant t_1 and t_2 , the change of the RSS measurement $\Delta y_i(t)$ is

$$\Delta y_i(t) = y_i(t_2) - y_i(t_1) = S_i(t_1) - S_i(t_2) + F_i(t_1) - F_i(t_2) + v_i(t_1) - v_i(t_2) = S_i(t_1) - S_i(t_2) + n_i \quad (2)$$

where the noise n_i is the grouping of fading and measurement noise, i.e., $n_i = F_i(t_1) - F_i(t_2) + v_i(t_1) - v_i(t_2)$. From (2), we can see that $\Delta y_i(t)$ is primarily determined by the shadowing loss difference of the two time instants. The shadowing loss can be approximated as the sum of attenuation that occurs in each grid [18], hence, $\Delta y_i(t)$ can be written as

$$\Delta y_i(t) = \sum_{j=1}^N w_{ij} x_j + n_i \quad (3)$$

where x_j is the difference of attenuation at grid j which corresponds to the fact that whether a target is located at the grid. w_{ij} is the weight that represents the contribution of grid j for link i . If the knowledge of an environment were available, one could estimate the weight w_{ij} for link i which reflected the spatial extent of multiple paths between transmitter and receiver. However, without site-specific information, we require a statistical model that describes the linear effect of the attenuation field on the path loss for each link. According to the past studies, the ellipsoid model with foci at each node location can be used as a method for determining the approximate weighting for each link in the network [18]. Hence, the weighting can be described as

$$w_{ij} = \frac{1}{\sqrt{d_i}} \begin{cases} 1, & \text{if } d_{ij1} + d_{ij2} < d_i + \rho \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

where d_{ij1} and d_{ij2} are the distances from the center of grid j to the two nodes of link i , d_i is the distance between two nodes of link i , and ρ is a tunable parameter defining the width of the ellipse.

When all links in the network are considered simultaneously, the system of RSS measurements can be described in matrix form as

$$\mathbf{y} = \mathbf{W}\mathbf{x} + \mathbf{n} \quad (5)$$

where $\mathbf{y} = [\Delta y_1, \dots, \Delta y_K]^T$ is a $K \times 1$ vector that represents the change of the RSS measurements vector, $\mathbf{x} = [x_1, \dots, x_N]^T$ a $N \times 1$ vector to be estimated, and \mathbf{W} the weighting matrix of the dimension $K \times N$, with each column corresponding to a single grid, and each row describing the weighting of each grid for that particular link. The $K \times 1$ vector \mathbf{n} represents noise terms.

3.2. Formulation with Compressive Sensing

In the well-known Shannon/Nyquist theorem, a bandlimited signal should be sampled at no less than two times of its bandwidth for perfect reconstruction. CS provides a novel framework for reconstructing signals from a much lower sampling rate, when signals are sparse or compressible under a certain basis. Since only C targets are within the deployment area, after sufficient dense gridding, each target can be guaranteed to have a unique location in one grid. As long as $C \ll N$, the vector \mathbf{x} will be a sparse signal, and it will be possible to reconstruct \mathbf{x} from a few measurements. This assumption may hold for most of the DFPL applications. When a target moves into a grid j , the x_j will be a non-zero value, otherwise, the x_j will be zero, and hence the number of targets C equals to the number of nonzero components in \mathbf{x} . Since grid locations and node locations are known, the overcomplete basis \mathbf{W} can be known according to the above ellipsoid model. Thus, we can estimate the actual coordinates of targets as long as we find the positions of nonzero values in \mathbf{x} . That is, the problem of localization is converted into one of sparse signal recovery from (5).

However, in the real environment there are a number of factors that affect the RF signal propagation including multi-path, temperature and humidity variations, opening and closing of doors, etc, besides channel fading, shadowing, and noise. These non-ideal factors are inevitable in a practical localization system and result in best \mathbf{W} being unknown. When these happen, the predefined dictionary can not

effectively express the actual weight for each wireless link, and 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 $\mathbf{\Gamma}$ which describes the difference between the predefined dictionary and the practical weights. Note that the error matrix $\mathbf{\Gamma}$ is time-varying and can not be known in advance. In this scenario, the sparse positioning model is correspondingly modified as:

$$\mathbf{y} = (\mathbf{W} + \mathbf{\Gamma})\mathbf{x} + \mathbf{n} = \mathbf{H}\mathbf{x} + \mathbf{n} \quad (6)$$

where $\mathbf{H} = (\mathbf{W} + \mathbf{\Gamma})$ denotes the actual overcomplete basis with time-varying interferences. To prevent \mathbf{H} from having arbitrarily large values (which would lead to arbitrarily small values of \mathbf{x}), it is common to constrain its columns $\mathbf{h}_1, \dots, \mathbf{h}_N$ to have a l_2 norm less than or equal to one. Since the mismatch exists between the columns of \mathbf{H} and the corresponding columns of the ideal basis \mathbf{W} , the performance degradation is inevitable in the sparse recovery process. However, all the CS-based DFPL methods presented so far almost ignore the effects of environmental variations. In order to obtain accurate localization results, therefore, we will exploit DL technique to calibrate time-varying factors according to current measurements automatically.

4. DFPL ALGORITHM BASED ON DICTIONARY LEARNING

Focused on the above problem, an adaptive sparse recovery algorithm based on DL is proposed in this section, which calibrates the overcomplete basis automatically so that the sparse solution can better fit the actual scenario. 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 [21]. Although many different DL algorithms have been presented recently [21], these methods generally can not obtain the global optimum results. To overcome this shortcoming and effectively handle training data changing over time, 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 (SR) 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.

4.1. Sparse Recovery Algorithm via Improved Re-Weighting l_1 Norm Minimization

According to the CS theory, the above problem of noisy sparse signal recovery in (6) can then be converted into a following optimization problem

$$\min \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2 / 2 + \lambda \|\mathbf{x}\|_0 \quad (7)$$

where λ is the regularization parameter and typically $\lambda = \sigma\sqrt{2\log(N)}$ where σ is the noise level [22]. Note that (7) is NP-hard to solve. An alternative is to use l_1 norm instead of l_0 norm to enforce sparsity, which leads to

$$\min \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2 / 2 + \lambda \|\mathbf{x}\|_1 \quad (8)$$

Up to now, sparse recovery algorithms for l_1 norm minimization problems have two major groups, namely Basis Pursuit (BP) [22] and greedy algorithms such as Orthogonal Matching Pursuit (OMP) algorithm [23]. However, it should be emphasized that in these algorithms larger coefficients in \mathbf{x} are penalized more heavily in the l_1 norm than smaller coefficients, unlike the more democratic penalization of the l_0 norm [24]. 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 l_1 norm penalty will seriously influence the recovery accuracy, which may result in many false targets. Therefore, in this paper we propose an improved re-weighting l_1 norm minimization algorithm as our sparse recovery method, which is called IRL1 in the following sections.

In order to overcome the mismatch between l_0 norm minimization and l_1 norm minimization while keeping the problem solvable with convex estimation tools, the reweighted l_1 norm minimization problem [24] is given by

$$\min \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2 / 2 + \lambda \|\mathbf{Q}\mathbf{x}\|_1 \quad (9)$$

where $\mathbf{Q} = [q_1, \dots, q_N]$ is the weight vector. Starting with an initial $\mathbf{Q}^{(0)} = \mathbf{e}_N$, in the $(k+1)$ th iteration the weight vector is updated to $\mathbf{Q}^{(k+1)}$ with its i th component given by

$$q_i^{(k+1)} = \begin{cases} 1 / (|x_i^{(k)}| + \eta), & |x_i^{(k)}| > \delta \\ \beta\eta / (|x_i^{(k)}| + \eta), & |x_i^{(k)}| < \delta \end{cases} \quad (10)$$

where $x_i^{(k)}$ denotes the i th component of vector $\mathbf{x}^{(k)}$ obtained in the k th iteration, δ the threshold value, and η a small positive scalar to prevent numerical instability when $|x_i^{(k)}|$ approaches zero. β is the calibrating parameter for small coefficients. Obviously, for a small coefficient this re-weighting strategy yields a large weight and vice versa. Hence, this re-weighting l_1 norm minimization method can solve the problem in (9) with the approximate l_0 norm penalty, and result in forcing a sparser solution.

It should be noted that this re-weighting strategy is different from the canonical re-weighting method in [24], where the i th component in the weight vector is directly given by $q_i^{(k+1)} = 1/(|x_i^{(k)}| + \eta)$. Although this re-weighting method is easier than our method, the location results will be unstable in many experiments if the parameter η is not selected suitably. Especially, for small coefficients the weight values will evidently decrease with the parameter η increasing. This will alleviate the penalty for small coefficients, which commonly represent the noise entries. On the contrary, in our method the weight values for small coefficients (which are below threshold δ) are guaranteed to be close to β , while the re-weighting approach for large coefficients is the same one as in [24]. And thus, the improved re-weighting l_1 norm minimization algorithm can equally penalize the large and small coefficients, and allow large coefficients to be easily identified with significantly decreasing iterative times, especially in low SNR conditions. The remaining part of the IRL1 algorithm is the same as the canonical re-weighting l_1 norm minimization (CRL1) algorithm in [24].

4.2. Dictionary Learning Method

In this phase, the dictionary is optimized to better represent the data of the current sample sets. Since the sparse vector \mathbf{x} is fixed in the DL stage, the resulting optimization problem becomes:

$$\min \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2 / 2, \quad \text{s.t. } \mathbf{h}_i^T \mathbf{h}_i \leq 1, \quad i = 1, \dots, N \quad (11)$$

in which $\|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2$ can be written as

$$\begin{aligned} \|\mathbf{y} - \mathbf{H}\mathbf{x}\|_F^2 &= \text{tr} \left[(\mathbf{y} - \mathbf{H}\mathbf{x})^T (\mathbf{y} - \mathbf{H}\mathbf{x}) \right] = \text{tr} (\mathbf{H}\mathbf{x}\mathbf{x}^T \mathbf{H}^T) - 2\text{tr} (\mathbf{y}\mathbf{x}^T \mathbf{H}^T) + \text{tr} (\mathbf{y}\mathbf{y}^T) \\ &= \text{vec} (\mathbf{H}^T)^T (\mathbf{I} \otimes \mathbf{x}\mathbf{x}^T) \text{vec} (\mathbf{H}^T) - 2\text{vec} (\mathbf{y}\mathbf{x}^T)^T \text{vec} (\mathbf{H}^T) + \text{tr} (\mathbf{y}\mathbf{y}^T) \end{aligned} \quad (12)$$

Table 1. The proposed DFPL algorithm.

1.	Initialization:
2.	Collect RSS readings at nodes and send to the location server;
3.	Set the dictionary $\mathbf{H}^{(0)} = \mathbf{W}$ according to (4);
4.	Input the number of iterations P ; set $j=1$;
5.	while $j < P$
6.	SR Stage: use the IRL1 algorithm to compute the sparse vector $\mathbf{x}^{(j)}$ with $\mathbf{H}^{(j-1)}$ fixed for each sample;
7.	DL Stage: use the gradient projection algorithm to minimize the objective function in (13) with respect to $\mathbf{H}^{(j)}$ keeping $\mathbf{x}^{(j-1)}$ fixed;
8.	$j = j + 1$;
9.	end while
10.	Output: $\mathbf{x} = \mathbf{x}^{(P)}$.

For clarity of notation, several new expressions are denoted by $\alpha \triangleq \text{vec}(\mathbf{H}^T)$, $\mathbf{G} \triangleq \mathbf{I} \otimes \mathbf{x}\mathbf{x}^T$ and $\gamma \triangleq \text{vec}(\mathbf{x}\mathbf{y}^T)$. Omitting the terms that do not depend on \mathbf{H} , the objective function in (11) can be equivalent to

$$\min \frac{1}{2} \alpha^T \mathbf{G} \alpha - \gamma^T \alpha, \quad \text{s.t. } \mathbf{h}_i^T \mathbf{h}_i \leq 1, \quad i = 1, \dots, N \quad (13)$$

Note that (13) 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 [25]. Moreover, the matrix \mathbf{G} is obviously a positively definite matrix, and thus (13) is a convex function and can be guaranteed to find a global optimum [26] 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 Table 1.

5. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed algorithm, we performed some experiments based on the measurement data from a wireless peer-to-peer network comprised of 28 nodes in an ordinary office environment in the electrical engineering department of Nanjing normal university. The transceivers of the nodes are system-on-chip (SoC) CC2430 devices; each node has a monopole antenna and uses the 2.4 GHz IEEE 802.15.4 standard for communications. To avoid network transmission collisions, a simple token ring protocol is used to control transmission. Each node is assigned an ID number and programmed with a known order of transmission. When a node transmits, each node that receives the transmission, examines the sender identification number and reserves the RSS from the transmitting node. The receiving nodes check to see if it is their turn to transmit, and if not, they wait for the next node to transmit. If the next node does transmit, or the packet is corrupted, a timeout cause each receiver to move to the next node in the schedule so that cycle is not halted. A base-station node that receives all broadcasts is used to gather signal strength information from each node, and saves it to a computer for real-time processing. These wireless nodes are deployed 0.9 m apart along the perimeter of a 6.3 m × 6.3 m square, with two humans standing inside the area at coordinates (3, 1) m and (5, 5) m. The default parameters are as follows: grid size is 0.9 m × 0.9 m, total number of links is 378, link measurements adopted by the signal reconstruction algorithms is 60, the width of the ellipse $\rho = 0.15$ m, the threshold value $\delta = 0.1$, the small positive scalar $\eta = 0.05$ and the calibrating parameter β is 10.

To evaluate the performance of the proposed method, we compare it with the CRL1 algorithm in [24] and the OMP algorithms in [23] under the same condition. The performance of the localization system is evaluated by the root mean square error (RMSE) based on 40 times repeating with the

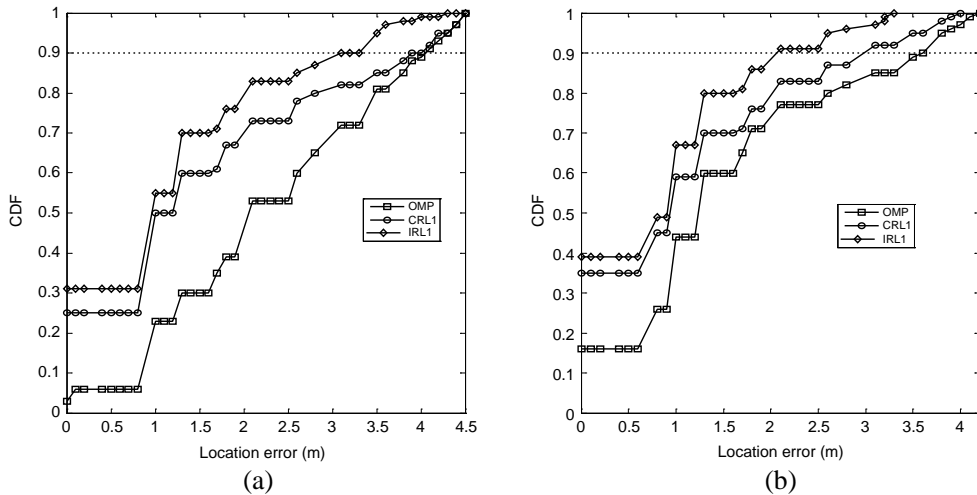


Figure 2. CDF of the location error: (a) without DL and (b) with DL.

same parameters. The cumulative distribution function (CDF) of the localization errors are shown in Figure 2. As the grid size is 0.9 m and the estimated target is assumed locating at the centre of grid at each time instant, hence, the CDF of the algorithms demonstrate a ladder form. It can be seen from the experimental results that the proposed method achieves the least RMSE among all the three methods, whether the overcomplete basis is learned or not. The result confirms that the proposed IRL1 algorithm is a robust and effective sparse signal reconstruction algorithm. From Figure 2, we also can see the great improvement in the accuracies on the location estimation obtained after the dictionary is corrected. For example, the proposed IRL1 method achieves an excellent performance with 90% location error at 2.1 m after DL, while the same percent location error is about 3 m without DL. This advantage results from the fact that the proposed DL method can make use of the alternating minimization to correct the model mismatch and the effects of environmental variations iteratively. The detailed statistical character of the localization errors is summarized in Table 2. In Table 2, we also can see that the performance of the proposed IRL1 algorithm outperforms the others significantly.

Table 2. Comparison of location error for three algorithms.

Algorithm	Average (m)	Standard Deviation (m)	90% (m)	Max (m)
IRL1+DL	1.31	0.95	2.10	3.31
CRL1+DL	1.81	1.07	3.09	4.01
OMP+DL	2.23	1.18	3.61	4.23
IRL1	1.72	1.10	3.05	4.01
CRL1	2.25	1.27	3.83	4.49
OMP	2.83	1.32	4.04	4.51

Figure 3 illustrates the comparative results in terms of RMSE between the IRL1 and CRL1 algorithms with respect to different threshold δ . From Figure 3, the performance of the IRL1 algorithm clearly outperforms that of the IRL1 algorithm under the condition of $\delta < 0.5$, whether the DL technique is used or not. We also can see that the RMSE of the IRL1 algorithm is almost steady when δ is less than 0.3. However, the location performance decreases as the value of δ increases, once the value of δ exceeds 0.3. This is because that when the value of δ is too large, some large coefficients may be incorrectly ascribed to the small coefficients family and be penalized more heavily.

Figure 4 shows how the RMSE varies as more link measurements are available. As the figure shows, the IRL1 algorithm could achieve a RMSE of 0.9 m when the value of link measurements is bigger than 100, however, it requires more than 200 link measurements for the other algorithms to achieve the same level of accuracy. That is to say, the proposed IRL1 algorithm could achieve the same localization performance as other algorithms with only half number of link measurements. This

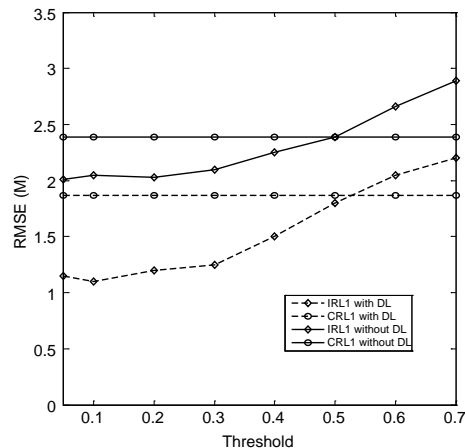


Figure 3. Effects of the threshold δ .

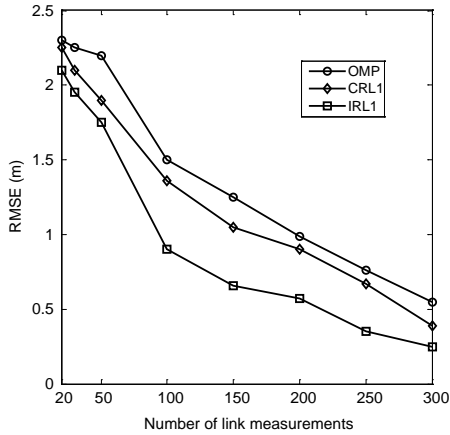


Figure 4. Performance under different number of link measurements.

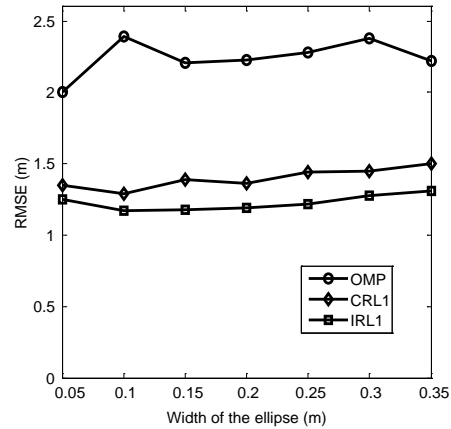


Figure 5. Effects of the width of the ellipse.

confirms that the IRL1 algorithm is suitable for the applications where a small set of measurements are available. Meantime, it should be pointed out that in large scale wireless networks, if all the nodes wake up and perform wireless measuring, the battery of the wireless nodes will run out soon. To make the algorithm applicable in large scale wireless networks, the wireless nodes must be in the sleep mode as much as possible. Since the IRL1 algorithm could reconstruct location information from a small set of link measurements, one can wake up a subset of nodes whose links travel around the target to participate in the measure and the subsequent sparse signal reconstruction for large scale DFPL.

Furthermore, Figure 5 illustrates the RMSE with respect to the different widths of the ellipse. From the figure, we can see that the IRL1 algorithm is robust and achieves stable results under different conditions. As for the ρ , it should be set a proper value that not only large enough to guarantee the effective area of the link, but also not so large that the target could not block the LOS path anymore. Therefore, the value of ρ must be comparable with the size of the target. As the effective region of a person is about 0.2 m \times 0.1 m, hence, a value of about 0.1 m or 0.15 m will be a proper value for ρ .

6. CONCLUSION

DFPL is a new and exciting localization method for physical objects, and may provide a low-cost and flexible alternative to exciting localization techniques. To achieve robust DFPL under the complex environment, an adaptive DFPL scheme which utilizes the DL technique was proposed. The effectiveness of the proposed scheme has been demonstrated by experimental results where substantial improvement for localization performance is achieved with a few measurements. This advantage comes from the fact that the proposed method can exploit the inherent spatial sparsity and the alternating minimization to correct the model mismatch and the effects of environmental variations iteratively, and thus the positions of unknown targets can be better recovered from measurements even in the existence of model mismatch.

It should be noted that although the CS-based DFPL technique has been proposed, previous studies focused on using the simple and coarse ellipsoid model, which can not always represent the relationship between the shadowed links and the location of the target quite well. On the contrary, since our method can learn dictionaries to compensate for the inaccuracy of the measurement matrix, the novel DFPL scheme can better develop the reasonable weight model for relating the changes of the RSS measurements between the node pairs to the spatial location of the target. And then, we proposed the IRL1 algorithm to realize signal reconstruction and location estimation. The algorithm can make use of a few measurements to estimate the possible location of the target, and adopts an iterative method to realize signal reconstruction.

Further research will emphasize on the off-grid error analysis and the theoretic bound on the location estimation precision.

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REFERENCES

1. Gonzalo, S. G., A. L. Jose, J. B. David, and L. R. Gustavo, "Challenges in indoor global navigation satellite systems," *IEEE Signal Processing Magazine*, Vol. 29, No. 2, 108–131, 2012.
2. Lee, J. H., Y. S. Jeong, and S. W. Cho, "Application of the Newton method to improve the accuracy of TOA estimation with the beamforming algorithm and the MUSIC algorithm," *Progress In Electromagnetics Research*, Vol. 116, 475–515, 2011.
3. Jamlos, M. F., T. A. Rahman, and M. R. Kamarudin, "A novel adaptive Wi-Fi system with RFID technology," *Progress In Electromagnetics Research*, Vol. 108, 417–432, 2010.
4. Mitilineos, S. A. and S. C. A. Thomopoulos, "Positioning accuracy enhancement using error modeling via a polynomial approximation approach," *Progress In Electromagnetics Research*, Vol. 102, 49–64, 2010.
5. Liu, H., H. Darabi, H. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics — Part C*, Vol. 37, No. 6, 1067–1080, 2007.
6. Mitilineos, S. A., D. M. Kyriazanos, and O. E. Segou, "Indoor localization with wireless sensor networks," *Progress In Electromagnetics Research*, Vol. 109, 441–474, 2010.
7. Patwari, N. and J. Wilson, "RF sensor networks for device-free localization: Measurements, models, and algorithms," *Proceeding of the IEEE*, Vol. 98, No. 11, 1961–1973, 2010.
8. Youssef, M., M. Mah, and A. Agrawala, "Challenges: Device-free passive localization for wireless environments," *13th ACM MobiCom*, 222–229, 2007.
9. Wilson, J. and N. Patwari, "Radio tomographic imaging with wireless networks," *IEEE Transactions on Mobile Computing*, Vol. 9, No. 5, 621–632, 2010.
10. Wilson, J. and N. Patwari, "See through walls: Motion tracking using variance-based radio tomography networks," *IEEE Transactions on Mobile Computing*, Vol. 10, No. 5, 612–621, 2011.
11. Wilson, J. and N. Patwari, "A fade-level skew-Laplace signal strength model for device-free localization with wireless networks," *IEEE Transactions on Mobile Computing*, Vol. 11, No. 6, 947–957, 2012.
12. Moussa, M. and M. Youssef, "Smart devices for smart environments: Device-free passive detection in real environments," *7th IEEE PerCom*, 1–6, 2009.
13. Zhang, D., Y. Liu, X. Guo, and L. M. Ni, "RASS: A real-time, accurate and scalable system for tracking transceiver-free objects," *IEEE Transactions on Mobile Computing*, Vol. 24, No. 5, 996–1008, 2013.
14. Chen, X., A. Edelstein, Y. Li, M. Coates, M. Rabbat, and A. Men, "Sequential Monte Carlo for simultaneous passive device-free tracking and sensor localization using received signal strength measurements" *10th ACM/IEEE IPSN*, 342–353, 2011.
15. Kanso, M. A. and M. G. Rabbat, "Compressed RF tomography for wireless sensor networks: Centralized and decentralized approaches," *5th DCOSS*, 173–186, 2009.
16. Song, H., T. Liu, X. Luo, and A. Agrawala, "Feedback based sparse recovery for motion tracking in RF sensor networks," *6th IEEE ICNAS*, 203–207, 2011.
17. Wang, J., Q. Gao, X. Zhang, and H. Wang, "Device-free localization with wireless networks based on compressing sensing," *IET Communications*, Vol. 6, No. 15, 2395–2403, 2012.
18. Patwari, N. and J. Wilson, "Spatial model for human motion-induced signal strength variance on static links," *IEEE Transactions on Information and Security*, Vol. 6, No. 3, 791–802, 2011.

19. Agrawal, P. and N. Patwari, "Correlated link shadow fading in multi-hop wireless networks," *IEEE Transactions on Wireless Communications*, Vol. 8, No. 8, 4024–4036, 2009.
20. Patwari, N. and P. Agrawal, "Effects of correlated shadowing: Connectivity, localization, and RF tomography," *2008 ICIPSN*, 82–93, 2008.
21. Rubinstein, R., A. M. Bruckstein, and M. Elad, "Dictionaries for sparse representation modeling," *Proceeding of the IEEE*, Vol. 98, No. 6, 1045–1057, 2010.
22. Chen, S. S., D. L. Donoho, and M. A. Saunders, "Atomic decomposition by basis pursuit," *SIAM Review*, Vol. 43, No. 1, 129–159, 2001.
23. Tropp, J. and A. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," *IEEE Transactions on Information Theory*, Vol. 53, No. 12, 4655–4666, 2007.
24. Candes, E. J., M. B. Wakin, and S. P. Boyd, "Enhancing sparsity by reweighted l_1 minimization," *Journal of Fourier Analysis Application*, Vol. 14, Nos. 5–6, 877–905, 2008.
25. Antoniou, A. and W.-S. Lu, *Practical Optimization: Algorithms and Engineering Applications*, Springer, 2006.
26. Dattorro, J., *Convex Optimization and Euclidean Distance Geometry*, Meboo Publishing, Palo Alto, CA, 2005.