LCS: Compressive Sensing based Device-Free Localization for Multiple Targets in Sensor Networks

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***Abstract*—Without relying on devices carried by the target, device-free localization (DFL) is attractive for many applications, such as wildlife monitoring. There still exist many challenges for DFL for multiple targets without dense deployment of sensor nodes. To fit the gap, in this paper, we propose a multi-target localization method based on compressive sensing, named LCS. The key observation is that given a pair of nodes, the received signal strength (RSS) will be different when a target locates at different locations. Taking advantage of compressive sensing in sparse recovery to handle the sparse property of the localization problem, (i.e., the vector which contains the number and location information of k targets is an ideal k-sparse signal), we presented a scalable compressive sensing based multiple target counting and localization method i.e., LCS, and rigorously justify the validity of the problem formulation. The results from our realistic deployment in a 12m×12m open space are promising. For 12 people with 24 nodes, the worst localization error ratio and counting error ratio of our LCS is no more than 8.3% and 33.3% respectively.**

I. INTRODUCTION

With the expanding of human activity range, wildlife is increasingly threatened. The key issue of protecting wildlife is how to find out their behavioral and ecological patterns [1]. One of the most important information for wildlife is the location information. However the following four challenges exist in the wildlife localization:

1) *Sparse deployment:* a basic requirement for monitoring wildlife is that artificial equipments do not disturb the wild environment and the living habits of wildlife. Thus, one should use as less devices as possible.

2) *Device-free localization* (*DFL*): it is hard to attach devices to animal bodys and zoologists do not favor to do so. Thus the DFL (i.e., targets do not carry any devices) is needed for monitoring wildlife.

3) *Multiple target counting and localization*: population statistical number and location information deeply attract the interest of zoologists since it is important for zoologists to find out changes in population size and migration trajectory.

4) *Scalability*: Wildlife lives in the wild environment, and move around large-scale areas. However, most of recent localization approaches are small-scale localization method [4]-[7] due to the specific application environmentn.Thus a scalable localization method is needed.

One of the key problems arises: *how to count and locate multiple targets using a DFL method under a large sparse deployment area?*

In this paper, LCS (device-free localization based on compressive sensing), a compressive sensing based device-free multiple target counting and localization method in sensor networks has been proposed.

In order to achieve high accuracy, most of recent localization approaches rely on dense deployment of sensors [5]. In this work, we present a sparse deployment scenario under which LCS can also achieve high localization accuracy. One of the most popular DFL approaches is the RSS based DFL method since it does not need additional devices for WSN. The RSS interference caused by targets is essential for the RSS based DFL method [4]-[7], so finding a practical model that can be applied in the real world for the DFL is still an open issue. In this paper, we consider target locations as sparse signal and propose to reconstruct the signal using the compressive sensing (CS) [2]. Here we assume that the targets are sparse compared with the number of grids utilized to represent the locations of targets. We choose to employ CS because of its advantage in sparse recovery. We also provide a rigorous proof for the applicability of CS in this particular problem context, since the necessary Restricted Isometry Property (RIP) [2] is satisfied. Moreover, the existing DFL methods [4]-[7] divide the monitoring area into grids with a particular grid size in consideration of reducing localization error. In order to achieve high localization accuracy, we conduct a comprehensive analysis about how to choose the grid size. We also tackle the problem of counting and localizing targets in a large-scale area.

The main contributions of this paper are outlined as follows:

1) We propose a CS based multiple target device-free localization method and prove that the product of the sensing matrix obeys RIP with a high probability.

2) We develop a generic approach to locate multiple targets in a large-scale area and show how to choose the grid size to achieve high localization accuracy.

3) Performance of the LCS method has been evaluated through extensive experiments in realistic deployment and large-scale simulations. The results illustrate the effectiveness and advantages of the LCS method.

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The rest of the paper is organized as follows. We give the deployment and measurement in Section II. In Section III, we present the problem formulation for CS based multiple target DFL approach. In Section IV, the LCS has been verified by experiments. We conclude this work in Section V.

II. Deployment and Measurement

Consider K targets randomly located in an isotropic free space with the size of $a \times b$, which is equally divided into N grids with the side length of ω. We divide $2M$ nodes into the TX-node group $\{TX_1, TX_2, \ldots, TX_i, \ldots, TX_M\}$ and the RX-node group $\{RX_1, RX_2, \ldots, RX_k, \ldots, RX_M\}$. Next, we put two groups of nodes on both sides of the monitoring area respectively and each node is placed on the midpoint of a grid side, as illustrated in Fig. 1. Note that only when $i=k$, the pair of TX_i and RX_k are counted as a link. The total number of unique two-way links is M. *Intuitively, it is a sparse deployment scenario.*

When wireless nodes communicate, the radio signals pass through the physical area of the network. The targets within the area may diffract, scatter, absorb or reflect the transmitted signal. The received signal strength (in dB) $R_{i,j}$ of link i ($1 \le i \le M$) when a target locates at grid j ($1 \le j \le N$) is given by

$$R_{i,j} = P_i - L_i - D_{i,j} + S_{i,j} - Q_i\,, \tag{1}$$

where P_i is the transmission power of link i, L_i is the radio propagation fading of link i, due to path loss and related to the antenna patterns, etc., $D_{i,j}$ is the diffraction fading of the link i, due to a target locates at grid j and blocks the LOS path of link i (e.g., target 1 shown in Fig. 1), $S_{i,j}$ is the scattering gain of the link i, due to a target locates at the NLOS path, (e.g., target 2 in Fig. 1 introduces an additional path which can increase the received power), and Q_i is other fading losses such as absorb, multipath effect, etc.

We use the RSS dynamic measurement to quantify the interferences caused by the target. We denote $R_{i,j}$ and F_i as the RSS measurement of link i when a target locates at grid j and outside of the monitoring area respectively. Considering (1), in a dynamic environment P_i, L_i and Q_i will not change [8], thus we can get the RSS dynamic measurement $\Delta R_{i,j}$ caused by a target located at grid j and received by link i as

$$\Delta R_{i,j} = R_{i,j} - F_i = -D_{i,j} + S_{i,j}\,. \tag{2}$$

Moreover, [7] and [5] show that the diffraction fading and the scattering gain is a function of the location of a target respectively, thus the RSS dynamic based DFL is feasible.

In this paper we assume that *if a particular link be interfered then it must be interfered by only one target* (this can be easily satisfied in practice since the effective location area is limited, please refer to Fig. 4).

III. Localization Based on Compressive Sensing

This section shows how to count and locate multiple targets using the RSS dynamic measurement we extracted before and develops a generic large-scale counting and localization approach. Two proofs related to the localization accuracy are given and the validity of the problem formulation is rigorously justified.

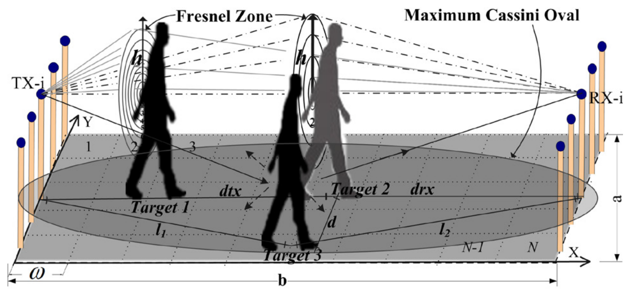


Figure 1. Deployment view and RSS measurement model

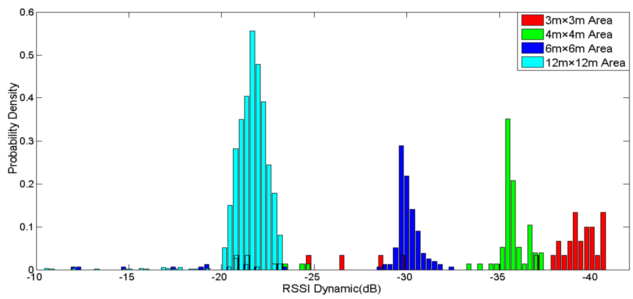


Figure 2. RSS dynamic measurements distribution. In this paper, we conducted intensive experiments under 4 kinds of monitoring areas, i.e., 3m×3m, 4m×4m, 6m×6m, 12m×12m. From the link of a particular area we can get the RSS dynamics when a target is at different grids. Note that the RSS dynamic measurements of each link composed the rows of sensing matrix. The results show that: (i) The larger monitoring area is, less the RSS dynamic measurements are; (ii) The RSS dynamic measurements generally approximate satisfy Gaussian distribution.

A. Problem Formulation

This work applies the CS theory to a device-free counting and localization method for multiple targets in sensor networks. Since the monitoring area has been divided into N grids, let the locations of the K targets over N grids denoted by a vector

$$\Theta = [\theta_1, \theta_2, \cdots, \theta_j, \cdots \theta_N]^T, \tag{3}$$

where $\theta_j \in \{0,1\}$. If there is one target located at grid j, $\theta_j=1$; otherwise $\theta_j=0$. Thus the number of targets $K = \sum_{j=1}^{N} \theta_j$. The vector Θ has a k-sparse nature, usually the number of targets K is much smaller than the number of grids N, i.e., $K<<N$, thus only K elements of Θ are nonzero. Furthermore, the number of measurements (links) M also is smaller than the number of grids N, i.e., $M<N$. Since Θ is k-sparse, according to the CS theory, rather than measuring the N-dimensional k-sparse signal Θ directly, RSS dynamic measurements $Y_{M\times 1}$ in an M-dimensional space are conducted to recover Θ, i.e., obtain the number and location information on K targets from M measurements at once. Thus the multiple target counting and localization can be effectively solved by the CS theory. With some channel model simplification and according to the CS theory we have

$$Y_{M\times 1} = A_{M\times N} \cdot \Theta_{N\times 1} + n\;, \tag{4}$$

where n is the measurement noise. A is the M by N sensing matrix, under which the measured signal has sparse coefficients Θ. $A_{M\times N}$ is defined as

$$A_{M\times N}=\begin{bmatrix}\Delta R_{1,1} & \Delta R_{1,2} & \cdots & \Delta R_{1,N}\\ \Delta R_{2,1} & \Delta R_{2,2} & \cdots & \vdots\\ \vdots & \vdots & \Delta R_{i,j} & \vdots\\ \Delta R_{M,1} & \cdots & \cdots & \Delta R_{M,N}\end{bmatrix}, \tag{5}$$

where $\Delta R_{i,j}$ is the RSS dynamic measurement caused by a target located at grid j and received by link i. For the $N\times 1$ vector Θ, it has been proved that if A holds the RIP and the number of measurements obeys $M=O(K\log(N/K))$ [2], then the solution can be obtained from the ℓ_1-minimization with relaxed constraints for reconstruction Θ exactly,

$$\min\|\Theta\|_{\ell_1} \quad \text{subject to} \quad \|A\Theta-Y\|_{\ell_2}<\varepsilon, \tag{6}$$

where ε bounds the amount of noise in the measurement data.

Equation (6) is theoretically solvable in polynomial time [2], $\ell 1$-minimization is computationally expensive when N is large. However the complex computation is conducted on the server. Moreover, we apply the Greedy Matching Pursuit (GMP) [3] to count and locate multiple targets. Since the GMP algorithm recovers signals without requiring prior knowledge of the sparsity level, i.e., the number of targets K is unknown in a practical application. According to [3], if A satisfies the RIP with a constant $\delta<1/K$ for all $(K+1)$-sparse vectors, GMP always reconstructs the sparse signal correctly, i.e., predicts the locations of all targets without error. We will later justify that A obeys the RIP and show that the requirement for constant δ can be easily satisfied.

B. Localization Under Large-Scale

There are two drawbacks in the above localization method. One is that the method cannot cover the large-scale area due to the limitation of the transmission range. Another is that the noise may submerge the RSS dynamics caused by targets. Since the longer link length is, the weaker RSS dynamics are, as shown in Fig. 2. One appropriate way to overcome these drawbacks is to cover the large-scale area with several subareas or divide the monitoring area into small subareas respectively, and in each subarea use the method we mentioned before.

We assume that the large-scale monitoring area is covered by T equal size subareas. K targets are scattered randomly and uniformly in the total area. Each subarea has its own sensing matrix characterizing the RSS dynamics due to the target locating at different grids of the current subarea. Denote the sensing matrix of subarea t as an $M\times N$ matrix A_t, $t=1,2,\ldots,T$, Then the sensing matrix A_{total} of the total area is defined as

$$A_{total}=\begin{bmatrix}A_1 & 0 & \ldots & 0\\ 0 & A_2 & \ldots & 0\\ \ldots & \ldots & A_t & \ldots\\ 0 & 0 & \ldots & A_T\end{bmatrix}_{MT\times NT.} \tag{7}$$

The unknown vector containing the number and location information of K targets is denoted by an $NT\times 1$ vector,

$$\Theta_{total}=[\Theta_1;\Theta_2;\cdots\Theta_t;\cdots;\Theta_T]^T, \tag{8}$$

where Θ_t is an $N\times 1$ vector that denotes the number and location information of targets in subarea t. Then the CS recovery algorithm can be applied to count and locate multiple K targets from the large-scale monitoring area.

C. Localization Accuracy and Formulation Validity

1) *How to choose ω?*

Theorem 3.1: The sufficient condition to achieve high localization accuracy is that the grid side length ω satisfies

$$\sqrt{ab/K}\,10^{-\frac{1}{2}\sqrt{\frac{a}{bK}}}<\omega<\sqrt{ab/K}, \tag{9}$$

where K is the number of targets , and $a\times b$ is the size of areas.

Proof: According to CS [2], the minimum samples required to exactly recover a signal is $O(K\log(N/K))$, i.e.,

$$M>K\log(N/K). \tag{10}$$

Based on the description of section III, $M=a/\omega$, $N=ab/\omega^2$, and thus (10) can be written as

$$a/\omega>K\log[ab/(\omega^2K)]. \tag{11}$$

It is hard to get the explicit and exact solutions of the above inequality, so we find out the approximate solutions of (11). Note that usually the number of targets K is smaller than the number of grids N, i.e., $K<N=ab/\omega^2$. Thus,

$$\omega<\sqrt{ab/K}. \tag{12}$$

It is easy to derive that $a/\omega>a/\sqrt{ab/K}$. If ω satisfies the following inequality

$$a/\sqrt{ab/K}>K\log[ab/(\omega^2K)], \tag{13}$$

then ω must also satisfy (11). Taking (12) and (13) into account, we have

$$\sqrt{ab/K}\,10^{-\frac{1}{2}\sqrt{\frac{a}{bK}}}<\omega<\sqrt{ab/K}. \tag{14}$$ ■

2) *Does A obey RIP?*

Theorem 3.2: When the number of sensors $M=O(k\log(N/k))$, the probability for A (after normalization) to satisfy

$$1-\delta\le\|Ax\|_{\ell_2}^2\big/\|x\|_{\ell_2}^2\le 1+\delta \tag{15}$$

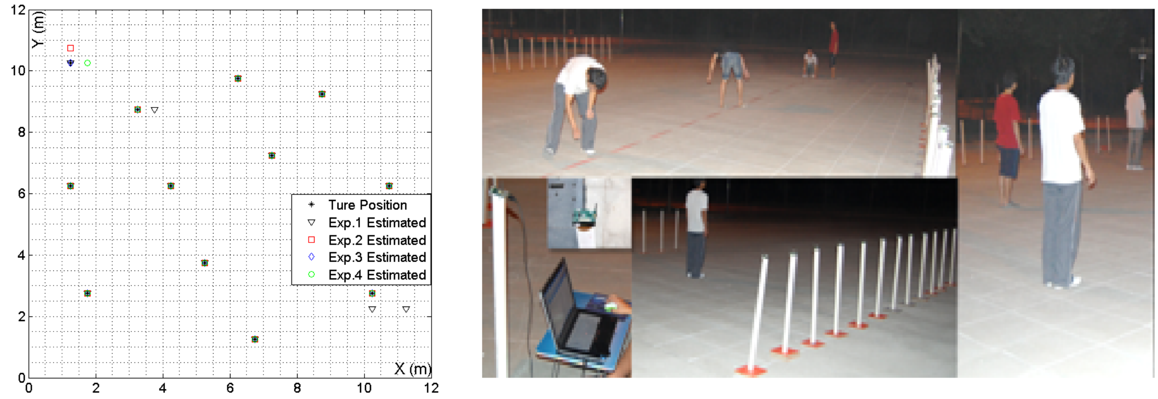
for all k-sparse vector x tends to 1 (i.e., A obeys RIP).

Proof: We find that the elements $\Delta R_{i,j}$ of sensing matrix A follow the Gaussian distribution, as demonstrated in Fig 2. Consider a row vector of A:

$$\langle A'\rangle_i=\eta\langle\Delta R_{i,1},\Delta R_{i,2},\cdots\Delta R_{i,j}\cdots\Delta R_{i,N}\rangle, \tag{16}$$

where $\Delta R_{i,j}$ satisfies the Gaussian distribution with mean of u_0 and variance of δ_0 and η is the normalization constant

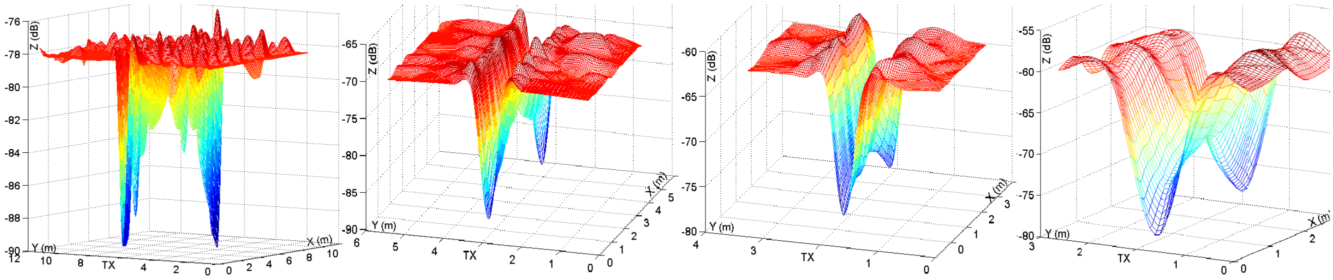
$$\eta=1/(\sigma_0\sqrt{M}). \tag{17}$$



(a) Experimental results

(b) Deployment of the experiment

Figure 3. Localization results of 12 targets



(a) Exp.1 Link length=12m

(b) Exp.2 Link length=6m

(c) Exp.3 Link length=4m

(d) Exp.4 Link length=3m

Figure 4. RSS distribution properties. In our previous experiment, during the sensing matrix setup phase we have conducted intensive experiments to get the RSS samples when a target locates at different grids. It is shown that the RSS distribution demonstrates the following 3 properties :(i) The average RSS varies when the target locates at different grids; (ii) The RSS is approximately same when the target locates at symmetrical grids about the midpoint of LOS link. (iii) The effective monitoring area, which is composed with the effective diffraction area (show as the bottom area) and the effective scattering area (show as the small bumps outside but close to the LOS area), is limited.

Since all targets are randomly distributed in the area, the product of $\langle A^{'}\rangle_i$ and a k-sparse vector x, i.e., $\langle A^{'}x\rangle_i$, follows the Gaussian distribution with the mean of u and the variance of

$$\sigma^2 = \eta^2 \cdot \sigma_0^2 \cdot \sum_{h=1}^{k} x_h^2 \,, \qquad (18)$$

where x_h $(1 \le h \le k)$ is the h-th nonzero element of x. As such, $\|Ax\|_{\ell_2}^2$ satisfies χ^2-distribution (the degree of freedom is M) with the mean of $M\sigma^2$ and the variance of $2M\sigma^4$. Since $M \gg 1$, $\|Ax\|_{\ell_2}^2/\|x\|_{\ell_2}^2$ can be approximated by the Gaussian distribution with the mean of

$$M\sigma^2 \Big/ \sum_{h=1}^{k} x_h^2 = M \cdot \eta^2 \cdot \sigma_0^2 = 1 \,, \qquad (19)$$

and the variance of $2/M$. According to the Chernoff bound,

$$\Pr\left\{\left|\|Ax\|_{\ell_2}^2/\|x\|_{\ell_2}^2 - 1\right| > \delta\right\} \le 2\exp(-\delta^2 M/8). \qquad (20)$$

Since the possible number of k-dimensional subspaces of A is $C_N^K \le (eN/K)^K$, the probability that there exists a k-sparse x which satisfies $\left|\|Ax\|_{\ell_2}^2/\|x\|_{\ell_2}^2 - 1\right| > \delta$ is at most

$$(\frac{eN}{k})^k \cdot 2\exp(-\frac{\delta^2 M}{8}) = 2\exp(-\frac{\delta^2 M}{8} + k\log(\frac{N}{k}) + 1)\,. \qquad (21)$$

Note that when M=O(Klog(N/K)), (21) tends to 0. Thus, the probability of (15) to be satisfied tends to be 1. Moreover, according to [2], δ should not be too close to one, which can be easily satisfied in this paper since we have $\delta < 1/K$. ■

IV. Localization Method Verification

Next, we verify that LCS can count and locate multiple targets under a sparse deployment in real world.

A. Experimental Setup

We conducted four experiments to verify the effectiveness of LCS at an open-space of size 12m×12m. 12 people with the height of 1.75m acted as our targets. The sensor nodes used in our experiment are MICAZ [9]. Based on our empirical knowledge, the node has the best propagation performance when it is 0.95m off the ground. Each *TX* node transmits one packet every second. We connected one node to a notebook via a MIB520 [9] to act as the sink, as shown in Fig. 3(b) Note that the smaller the side length ω is, the more the test grids are. In order to enrich our experiments, we try to find out the minimum ω which satisfies (11), i.e., the lower bound of the exact solutions of Theorem 3.1. We set ω=0.5m where M=a/ω=24>Klog[$ab/(\omega^2 K)$]≈20.17. For each experiment, we use T equal subareas to cover the monitoring area and each

TABLE I. EXPERIMENTAL PARAMENTERS

	Subarea number (T)	Subarea size (A)	Subarea links number (M)	Subarea grids number (N)
Exp. 1	1	12m×12m	24	576
Exp. 2	4	6m×6m	12	144
Exp. 3	9	4m×4m	8	64
Exp. 4	16	3m×3m	6	36

subarea deployed M links as we described before. The parameters in experiments are shown in the Table I.

The LCS system has two phases: Establishing sensing matrix phase and Localization phase.

Establishing sensing matrix phase: Before targets enter into the area, link i ($1 \le i \le M$) of subarea t ($1 \le t \le T$) will recodes RSS scans for 0.5 minutes and the mean of those scans is denoted by F_i. Then we ask one person to go through all grids of the subarea t. In the subarea t, link i recodes relatively stable RSS scans for 0.5 minutes when the person locates at grid j and the mean of those scans is denoted by $R_{i,j}$. The sensing matrix A_t of subarea t can be acquired by (2) and (5). There is no need to go through all grids of T subareas under the same target, since the T subareas are approximating the same. Therefore, the sensing matrixes of T subareas are also the same. We can obtain the sensing matrix A_{total} of the total area by (7).

Localization phase: In the 12m×12m area, 12 people randomly stand at the center of 12 different grids. All $M \times T$ links record the relatively stable RSS samples for 0.5 minutes. We used the difference between the mean sample values of link i and F_i as the element of $Y_{M\times 1}$. Note that all 4 experiments used the same $Y_{M\times 1}$. Finally, through the GMP, we can estimate the number and the locations of the 12 people.

B. Experimental Analysis

We start by introducing two performance metrics: (i) The counting error (COE) [3], i.e., the ratio of the miss-counted target number to the total target number. (ii) The localization error (LOCE) [3], i.e., the ratio of the distance between the true and the estimated locations to the grid side length ω.

Statement: (i) If our algorithm reports a target locates at a grid, then the center of the grid is used as the estimated location. (ii) According to [3], we also do not consider the localization error if a particular target is missing-counted. That is if COE=1, in order to make LOCE meaningful, we set LOCE=1.

Fig. 3(a) shows that all of the 4 experiments can achieve a similar high level of localization accuracy. The worst performance of the 4 experiments (i.e., Exp. 1) is that COE= 33.3% and LOCE= 8.3%. There are 4 counting errors for Exp.1, i.e., the true position is (10.25, 2.75) while LCS counted it twice at (10.25, 2.25) and (11.25, 2.25), moreover the LCS cannot count the three collinear targets (targets with coordinate of y=6.25m). For Exp.1, there are two localization errors at (3.25, 8.75) and (10.25, 2.75).

This section demonstrates that the LCS can device-freely count and locate multiple targets under a realistic sparse deployment with a good performance.

V. CONCLUSION

This paper has investigated the problem of the DFL for multiple targets in sensor networks based on CS. We have first presented a sparse deployment scenario under which the DFL is feasible. Then we have proposed a scalable CS based multiple target counting and localization method and proved that the product of sensing matrices obeys RIP, which validates our CS-based problem formulation. In order to achieve high localization accuracy, most of the recent work divides the monitoring area into grids with a particular grid size while a relaxed value range has been verified in our present scenario. Additionally, the results of experiments have illustrated the effectiveness and advantages of the proposed LCS method.

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