Greedy Detection Estimation for Target Tracking with RF Sensor Networks

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Device-free motion tracking with RF sensor networks using received signal strength (RSS) measurements is an emerging technology. Since the motion scene to be reconstructed can often be assumed sparse, i.e., it consists only of several targets, the Compressed Sensing (CS) framework can be applied. We cast the motion tracking as a CS problem and present an efficient algorithm, named the Greedy Detection Estimation (GDE), for sparse recovery. Furthermore, we exploit a feedback structure which leads to a substantial reduction of the amount of measurements. The feedback structure utilizes the prior knowledge (locations of targets) in time sequence to predict the support of next frame. The experimental studies are presented to demonstrate that the GDE offers an attractive alternative for sparse signal recovery; in addition, it is more favorable than non-CS based method for target tracking.

Keywords: Sparse Recovery, Motion Tracking, RF Sensor Networks.

1. INTRODUCTION

Device-free passive localization and tracking (DFLT) in wireless sensor networks (WSN) is a cost-effective technique for tracking targets.[1] Compared with the active techniques, such as global positioning system (GPS), radio frequency identification (RFID) and real-time location system (RTLS), The DFLT doesn't require the targets to carry devices. A number of possible sensor technologies including optical cameras, thermal cameras, passive infrared, acoustic, vibration and ultrasound, could be used for the purposes of DFLT. Radio frequency (RF) signals can travel through opaque obstructions without privacy concerns, such as nonmetal walls, trees, and smoke while optical or infrared sensors cannot. Using received signal strength (RSS) measurements in RF based DFLT is preferable to many WSN applications.

Recently, Wilson and Patwari developed a new technology for DFLT, referred to radio tomographic imaging (RTI).[2, 3] The scene of interest is imaged from attenuation caused by targets present in wireless network area. RTI obtains current image of the locations of targets. The extension of RTI employs the maximum of the image as an initialization and applies Kalman Filter to track the targets.[4] RTI explores a linear model which relates the attenuation field to signal strength measurements. The least-square solution for the linear formulation is an ill-posed inverse problem by nature. However, RTI does not indicate the actual locations of targets due to lack of contrast needed to accurately distinguish the locations. It doesn't make use of the sparse nature of location finding from motion problem. Hence we propose a new approach by exploiting the sparse recovery power of Compressed Sensing (CS).

CS is an emerging technique that provides a framework for sparse recovery,[5, 6] which indicates that sparse or compressible signals can be recovered from far fewer samples. CS was originally proposed in the signal processing community[5, 6] and has been applied to WSN applications in Refs. [7, 8]. The sparse nature of the location finding from motion problem makes the theory of CS desirable for motion tracking in RF sensor networks. Inspired by Refs. [7, 8], we cast the RTI formulation as a sparse recovery problem and present an efficient algorithm for compressed measurements and sparse

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recovery. The proposed algorithm is called Greedy Detection Estimation (GDE). In our method, as opposed to least-square type methods used in Refs. [3, 4], we directly determine where the targets located in the network area. Furthermore, we exploit a feedback structure which leads to a substantial reduction of the amount of measurements. The feedback structure utilizes the prior knowledge (locations of targets) in time sequence to predict the support (i.e. the index set of the nonzero entries which indicate the locations of targets) of next frame.

The rest of the paper is organized as follows. The problem formulation and the proposed approach are presented in section 2. After that, section 3 details the experimental results on simulated data and real data. Finally, we conclude this paper in section 4.

2. METHOD

2.1. Problem Formulation

Consider a RF sensor network, as illustrated in Fig. 1, the RF signal is affected by the presence of the targets near the wireless links. We can infer the locations of attenuating targets from pairwise RSS measurements which caused by shadowing correlations between links. As shown in Fig. 1, the network area is divided into grid pixels $\mathrm{x} \in R^n$. The amount of radio power attenuation describes each pixel's value. The attenuation of unique two-way links (the communication between any pair of distinguishable nodes.) can be denoted as $\mathrm{y} \in R^m$. This can be formulated as a linear model, take the form of

$$\mathrm{y} = A\mathrm{x} + \mathrm{n}. \tag{1}$$

The link shadowing is a linear combination of the values in pixels, plus noise n. $\mathrm{y} \in R^m$ is the difference of RSS measurements that the instantaneous RSS value vector subtracts the average background RSS value vector. $A \in R^{m \times n}$ is the weight matrix of the model parameters x. Each row of the weight matrix A on the link i can be expressed a weighted sum of the losses in each pixel. The weight matrix A for link shadowing can be described by an ellipsoid with foci at each pair of nodes locations,[2, 3] as shown in Fig. 2. d is the link distance between the nodes, $d_{ij}(1)$ and $d_{ij}(2)$ are the distance from pixel j to the two nodes for link i. If a pixel falls inside the ellipse, it is weighted and normalized by square root of the link distance, otherwise, the weight is set to zero. The elliptical width parameter λ is a tradeoff between modeling error and tracking performance. For the most accurate tracking, we set λ to 0.01 in our experiments.

2.2. The Proposed Method

When tracking targets from RSS measurements, it is an inverse problem from Eq. (1) to get the pixels attenuation x. x can determine where the targets are located in the network area. Generally, it formulates the inverse problem in the least-square error sense,[2, 3]

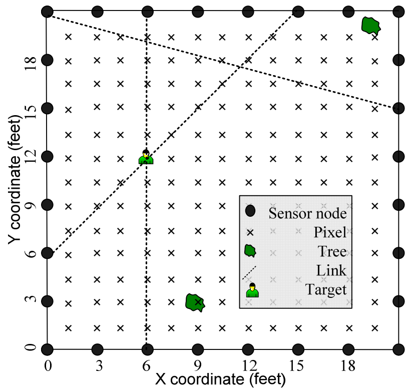


Fig. 1. The network geometry with one target locating at (6, 12). The tracked area is divided into 13x13 pixels.

$$\mathrm{x}_{LS} = \arg\min \left\| A\mathrm{x} - \mathrm{y} \right\|_2^2 . \tag{2}$$

Regularization methods were introduced into the linear model to alleviate the singularity problem and make the inverse problem stable.[2, 3] All least-square solutions minimize the noise energy, and the results are very smooth. It must have a contrast step to estimate the locations of targets. Thus RTI does not indicate the actual locations of targets.

We cast the inverse problem Eq. (1) as a compressed sensing problem motivated by the sparse nature of location finding problem. Sparse recovery algorithms for CS problems have two major classes, greedy algorithms and ℓ_1 norm minimization. The ℓ_1 norm minimization algorithms (e.g. Basis Pursuit[9]) are not feasible solutions due to high computational complexity and unstability rises in measurements noise.

In this paper, we consider the greedy algorithms for target traking. The greedy sparse recovery algorithms, e.g. orthogonal matching pursuit (OMP)[10], iterate between 2 main steps:

1. **Support detection**: the algorithms detect the support of the signal x, i.e. select atoms of measurement matrix A which have been used to generate y, in other words, determine active atoms in sparse representation of a signal x. In some literatures, this step also is called basis selection or atom selection.
2. **Signal estimation**: update the signal x by the detected support using the least-squares solution.

Recently, Amini et al. proposed a new sparse recovery algorithm, referred to iterative detection estimation (IDE).[11] IDE derives an activity function $\mathrm{g}(\mathrm{x}, \mathrm{y})$ from a binary hypothesis testing problem using the Bernoulli-Gaussian model. The detection step presents as follow

$$\mathrm{g}(\mathrm{x}^t, \mathrm{y}) = \left| \mathrm{x}^{t-1} + A^T r \right| > Th; \;\; r = \mathrm{y} - A\mathrm{x}^{t-1}, \tag{3}$$

where Th is a threshold to identify active atoms, t denotes the iteration index. In real applications, it is hard to determine the threshold Th for correct detection. We employ a hard thresholding for support detection. The basic idea behind this method is borrowed from iterative hard thresholding (IHT).[12] IHT processed as follows and use the iteration with initialization $\mathrm{x}^0 = 0$

$$x^t = H_k(x^{t-1} + A^T(y - Ax^{t-1})), \quad (4)$$

where k is the true underlying sparsity level of signal x, $H_k(a)$ is the hard thresholding that sets all but the largest in magnitude k elements of a to zero. Thus, we present a new algorithm, termed greedy detection estimation (GDE). The detailed description of the proposed algorithm is presented as follows

Step 1: Initialization:

Initialize $x^0 = 0$, the residual $r^0 = y$, the detected support set $I_0 = \varnothing$, and the iteration counter $t = 1$.

Step 2: Support detection:

$x^t = H_k(x^{t-1} + A^T r^{t-1})$, update the support set I_t and corresponding submatrix A_{I_t}. We use the convention that A_0 is an empty matrix and A_{I_t} is the submatirx of A corresponding support set I_t.

Step 3: Signal estimation[1]:

$x^t = 0; x^t_{I_t} = A^+_{I_t} y,$

$r^t = y - Ax^t,$

where $A^+ = (A^T A)^{-1} A^T$ is the Moore–Penrose pseudoinverse of the measurement matrix *A*.

Step 4: Halting:

Increment t, and return to **step 2** if the residual norm great than a error threshold, otherwise the algorithm is terminated. The recovered signal x has nonzero entries in support set I_t and corresponding support vector lies in $x^t_{I_t}$.

GDE and IDE can be seen as generalized two stage thresholding (TST).[13] However, TST combines the support set of x^t and x^{t-1}. GDE employs the hard thresholding to select the largest k magnitudes greedily without a prior threshold. If sparsity level k is not available, TST[13] would apply to estimate k adaptively with an oracle heuristic.

Furthermore, we develop a feedback structure to track moving targets. As seen from Fig. 3, there are consecutive frames of RSS measurements. The estimated locations by previous frame x_{i-1} is highly correlated to the current frame x_i. The support set of x_{i-1} is denoted as T_{i-1}. We utilize the RSS measurements that cross previous locations (indicated by T_{i-1}) centered 5×5, 9×9 or 17×17 blocks to predict T_i.

3. EXPERIMENTAL RESULSTS

To assess the performance of the proposed approach, we conduct experiments on computer simulations and real RTI dataset.

3.1. Computer Simulations

We assess the sparse recovery performance in terms of phase

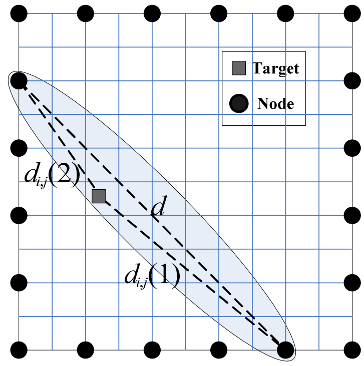


Fig. 2. Elliptical weight model. The weighted pixels for a single link in a RF sensor network are darkened in an ellipse with foci at each node location.

transitions.[13, 14] Let $\rho = k/m$ be a normalized measure of the sparsity and let $\delta = m/n$ be a normalized measure of problem indeterminacy. We obtain a two dimensional phase space $(\delta,\rho) \in [0,1]^2$ measuring the sparse recovery performance. The phase space is divided into two regions by a curve. The lower right region indicates the success of sparse recovery. The curve dubbed as phase transition curve. Detailed definition of the phase transition curve is described in Refs. [13, 14]. A higher phase transition curve indicates better sparse recovery performance.

The problem suit (A, x) is nearly similar to Refs. [13, 15]. Let A be a random matrix with i.i.d. Gaussian entries and each column be normalized with unit norm. We fixed $n = 400$, sampled 16 different linearly spaced sparsity $\rho \in [0.05, 0.5]$ and indeterminacies $\delta \in [0.05, 0.5]$. We take 100 times Monte Carlo problem instances and declare exact recovery if $\|x - \hat{x}\|_2 / \|x\|_2 < 0.01$. In IDE initiate iteration, we set $Th_1 = \max|A^T y|/2$ and $Th_{t+1} = Th_t/2$ for following iterations. According to the observation of Ref. [15], greedy methods exhibit superior performance for sparse vector distributed Gaussian. We generate k sparse vector distributed Gaussian. Fig. 4 and Fig. 5 present the recovery performance of IHT, IDE and GDE for sparse vector distributed Gaussian. It shows that GDE outperforms IHT and IDE.

3.2. Target Tracking Application

To validate the effectiveness of the proposed method, the experiments were conducted on a real outdoor environment using an IEEE 802.15.4 (Zigbee) protocol in the 2.4GHz frequency band network. The RTI dataset[3] is available online at http://span.ece.utah.edu/rti-data-set. A 28 nodes peer to peer network was deployed in a square perimeter of 21 feet × 21 feet and each side has 8 nodes, as depicted in Fig. 1. Each node was spaced 3 feet from the neighboring nodes. Two trees surround the border of the network with approximately 1 foot diameter trunks. The difference of RSS measurements y was obtained by the instantaneous RSS value vector subtracting the average background RSS value vector. Each link's measurement is an average of the two directional links

[1] Note that IDE developed two methods for estimation step, this paper employs the 'x-space approach'.

from i to j and j to i. The background RSS value vector was measured when the network area was vacant from targets.

To demonstrate the effect of resolution on tracking accuracy, the network area was divided into 3 different resolutions 6×6, 13×13 and 27×27. The experiment spanned a 14 seconds' period from 11:29:58 to 11:30:11. One target walked at constant velocity around the following square loop path: (3, 6) to (3, 15) to (18, 15) to (18, 6) and back to (3, 6) in network area. Fig. 6 shows the estimated trajectories using different resolutions. The results indicate that target tracking using GDE is more reliable than the Kalman filter method used in Ref. [4]. The Kalman filter method used in Ref. [4] is unstable for motion tracking due to the initialization with the maximum of least-square solution, especially for the higher resolutions. The results with different resolutions achieve similar performance in terms of average error. However, target tracking using higher resolution achieves higher precision level.

We have discussed a direct method for target tracking using sparse recovery. In addition, CS theory provides a novel framework to recover sparse signal with fewer measurements. This motivates us to utilize compressed measurements for motion tracking by feedback information. It is unreliable due to singularity in least-square solutions used in Ref. [4]. The weight matrix A can be viewed as a form of overcomplete dictionary. We project the original space to a much lower dimensional space to compress measurements. Specifically, we utilize the RSS measurements that cross previous frame locations centered 5×5, 9×9, or 17×17 blocks for resolution 6×6, 13×13 and 27×27 respectively to predict the support set of next frame. To make stable, we randomly select RSS measurements and corresponding rows of weight matrix A apart from feedback structure. The estimated trajectories using feedback sparse recovery are presented in Fig. 7. It is reliable for tracking, however, with only 120 RSS measurements. Taking fewer RSS measurements consumes less communication resource and energy. It is appealing in WSN applications.

4. CONCLUSIONS

In this paper, we propose a feedback structure for applying the emerging compressed sensing (CS) into motion tracking in RF sensor networks. Motivated by the sparse nature of location finding from motion problem, we cast the target tracking as a CS problem and solve it by the proposed Greedy Detection Estimation (GDE) algorithm. Furthermore, we exploit a feedback structure which leads to a substantial reduction of the amount of measurements. The feedback structure utilizes the prior knowledge (locations of targets) in time sequence to predict the next frame support. We demonstrate that the proposed approach achieves favorable results on both simulation data and real measurements data.

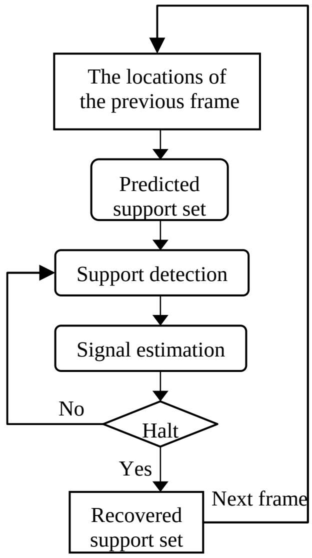


Fig. 3. Diagram of the feedback based target tracking.

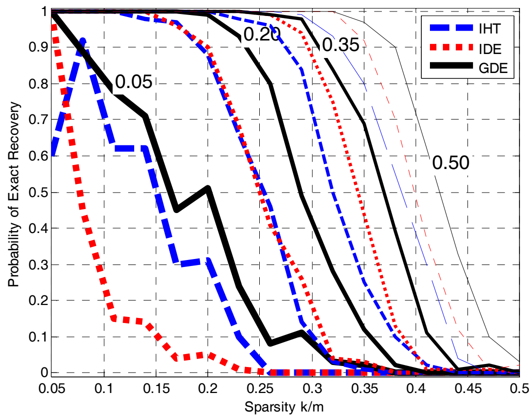


Fig. 4. Recovery rates of IHT, IDE and GDE for 4 different indeterminacies (m/n, labeled) and sparse vector distributed Gaussian.

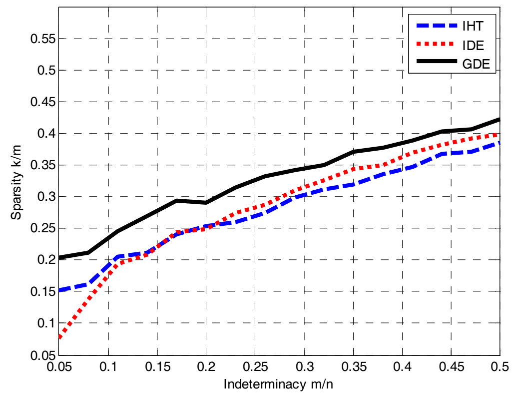
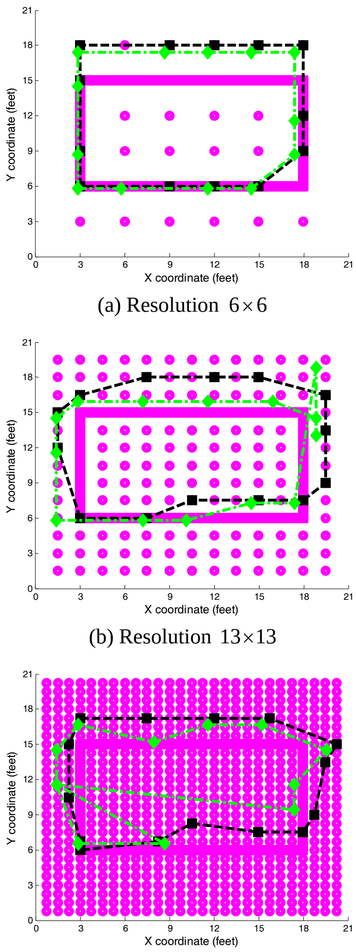


Fig. 5. Phase transitions of IHT, IDE and GDE for sparse vector distributed Gaussian.

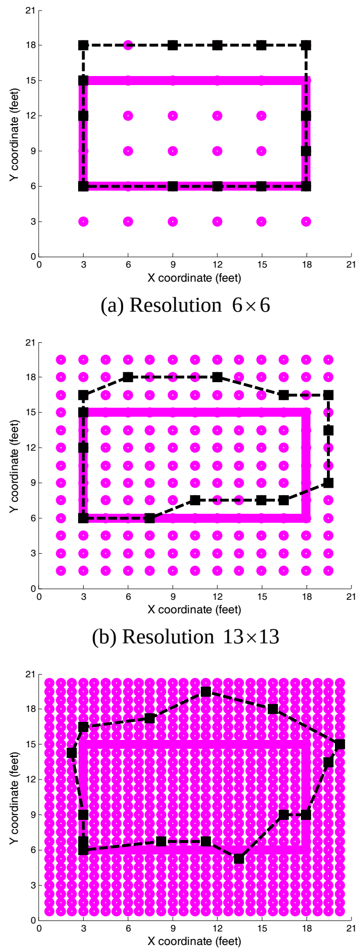


(a) Resolution 6×6

(b) Resolution 13×13

(c) Resolution 27×27

Fig. 6. The tracking trajectories with one target walked at constant velocity around the following square loop path: (3, 6) to (3, 15) to (18, 15) to (18, 6) and back to (3, 6). The megenta circle is the pixel, the black square is the location estimated by GDE, the green diamond is the location estimated by the Kalman filter method and the megenta rectangle is the real moving trajectory.



(a) Resolution 6×6

(b) Resolution 13×13

(c) Resolution 27×27

Fig. 7. The tracking trajectories using feedback based sparse recovery. One target moves in the same path as Fig. 6. The megenta circle is the pixel, the black square is the location estimated by feedback structure,and the megenta rectangle is the real moving trajectory.

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