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Feedback based Sparse Recovery for Motion Tracking in RF Sensor Networks

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***Abstract*— Device-free motion tracking with radio tomographic networks using received signal strength (RSS) measurements has attracted considerable research efforts. 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 employ an efficient algorithm, Orthogonal Matching Pursuit (OMP), 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 next frame support. Compared with the least-square type methods, the proposed motion tracking based on feedback sparse recovery can directly determine where the targets are located in the network area and reduce the amount of measurements required for reliable tracking. Experimental results show its favorable performance.**

I. Introduction

Device-free locating and tracking (DFLT) in wireless sensor networks (WSN) is a cost-effective practice for target[1] tracking. Compared with active localization systems like global positioning system (GPS), radio frequency identification (RFID) and real-time location system (RTLS), DFLT doesn't depend on tags or devices that were attached to the targets being tracked and also needs no cooperation with the systems [1]. A number of possible sensor technologies such as optical cameras, thermal cameras, passive infrared, acoustic, vibration and ultrasoud, could be used for the purposes of DFLT. In this paper, we concentrate on radio frequency (RF) using received signal strength (RSS-DFLT) measurements. RF signals can travel through opaque obstructions without privacy concerns such as nonmetal walls, trees, and smoke while optical or infrared sensors cannot. RSS-DFLT is widely used in practical applications due to low deployment cost.

Recently, Wilson and Patwari developed a new technology for RSS-DFLT, referred to radio tomographic imaging (RTI) [2], [3]. RTI has many potential applications such as passive intrusion detection, emergency, security, surveillance and monitoring systems. For RTI applications, the scene of interest is imaged from attenuation caused by targets within wireless networks area. RTI obtains current images of the location of targets. 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. Regularization methods are applied to alleviate the singularity problem [4]. However, RTI does not indicate the actual location of targets. It can't directly work on motion tracking due to the lack of contrast needed to accurately distinguish the location of a moving target. RTI as an intermediate role, the Kalman filter is applied to track the location of a moving target with the maximum of the RTI image as the initial location [5]. It doesn't make use of the sparse nature of location finding from motion problem. Hence we propose a novel motion tracking approach by exploiting the sparse recovery power of Compressed Sensing (CS).

CS is an emerging technique that provides a framework for sparse recovery [6], [7], which indicates that sparse or compressible signals can be recovered from far fewer samples. CS was originally proposed in the signal processing community [6], [7]. The sparse nature of the location finding problem makes the theory of CS desirable for motion tracking in RF sensor networks. We cast the RTI formulation as a CS problem and employ an efficient algorithm, Orthogonal Matching Pursuit (OMP) [8], for sparse recovery. In our method, as opposed to the least-square type methods used in [3], [5], we directly determine where the targets are 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[2] of next frame.

The rest of the paper is organized as follows. The linear formulation of RTI is reviewed in section II. After that, section III details the proposed approach. Experimental results on real-data are reported in section IV. We conclude this paper in section V.

II. Linear formulation

Given a RF sensor network, as illustrated in Fig. 1, the RF signal is affected by the presence of the targets near the

[1] In this paper, "target" generally refers to either human or objects of interest that are to be tracked.

[2] the index set of the nonzero entries of x, which indicates the locations of targets.

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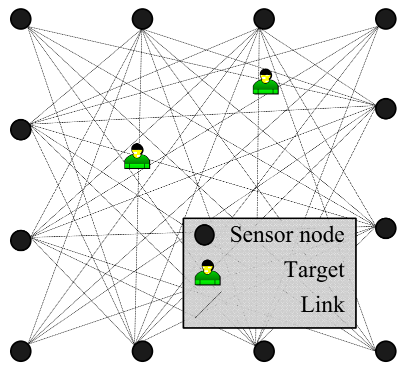


Fig. 1. A twelve RF nodes wireless sensor network. Each wireless RF node communicates with the others.

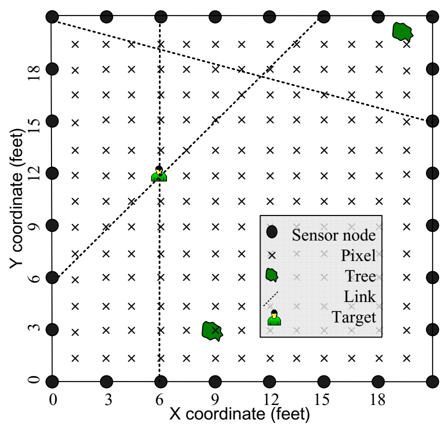


Fig. 2. The network geometry with one target locating at (6, 12). The tracked area is divided in to 13×13 pixels.

wireless links. We can infer the location of attenuating targets from pairwise received signal strength (RSS) measurements which caused by shadowing correlations between links. As shown in Fig. 2, the network area is partitioned off into a grid of pixels $\mathbf{x} \in \mathbb{R}^n$. 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 $\mathbf{y} \in \mathbb{R}^m$. This can be formulated as a linear model, give the form of

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

The link shadowing is a linear combination of the values in pixels, plus noise $\mathbf{n}$. $\mathbf{y} \in \mathbb{R}^m$ is the RSS measurements described in next subsection . $A \in \mathbb{R}^{m \times n}$ is the weight matrix of the model parameters $\mathbf{x}$. Each row of the transfer matrix A on the link i can be expressed a weighted sum of the losses in each pixel.

A. RSS measurements

When wireless nodes communicate, the received signal strength (RSS) $y_i(t)$ of a particular link i at time t is denoted as

$$y_i(t) = P_i - L_i - S_i(t) - F_i(t) - v_i(t), \tag{2}$$

where

- P_i is the transmitted power in dB,
- L_i is the static loss in dB due to antenna patterns, distance, and device inconsistencies,
- $S_i(t)$ is the shadowing loss in dB caused by the targets which attenuate the signal,
- $F_i(t)$ is the fading loss in dB due to constructive and destructive interference of narrow-band signals in multipath communication,
- $v_i(t)$ is the measurement noise.

The shadowing loss $S_i(t)$ for each link can be expressed approximately as a sum of attenuation that causes in each pixel, as shown in Fig. 3. The mathematical form is given by

$$S_i(t) = \sum_{j=1}^{n} A_{ij} x_j(t), \tag{3}$$

where $x_j(t)$ is the attenuation in pixel j at time t, A_{ij} is the weight for pixel j for link i, the definition is presented in next subsection.

We take the difference RSS measurements for RF tracking problem, since all static losses can be removed over time. The difference in RSS $\triangle y_i$ from time t_a to t_b is given by

$$\begin{aligned} \triangle y_i &= y_i(t_b) - y_i(t_a) &(4)\\ &= S_i(t_b) - S_i(t_a) + F_i(t_b) - F_i(t_a) &(5)\\ &\quad + v_i(t_b) - v_i(t_a), &(6) \end{aligned}$$

where can be rewritten as

$$\triangle y_i = \sum_{j=1}^{n} A_{ij} \triangle x_j + n_i, \tag{7}$$

where the noise n_i is the sum of fading and measurement noise

$$n_i = F_i(t_b) - F_i(t_a) + v_i(t_b) - v_i(t_a), \tag{8}$$

and

$$\triangle x_j = x_j(t_b) - x_j(t_a), \tag{9}$$

is the difference in attenuation at pixel j from time t_a to t_b. Then we get the all link difference RSS measurements, the matrix form is described as follows

$$\triangle y = A \triangle x + n. \tag{10}$$

To simplify the notation, $\mathbf{x}$ and $\mathbf{y}$ are used in place of $\triangle x$ and $\triangle y$, respectively. Finally, we get the linear formulation (1).

The RSS measurements discussed above are based on shadowing model [2], [3]. Experiments have to calibrate by taking RSS while the network is vacant from moving targets and obtain the difference RSS measurements (10). Variance based RSS measurements are reliable for multipath channel model and heavily obstructed area situations [5].

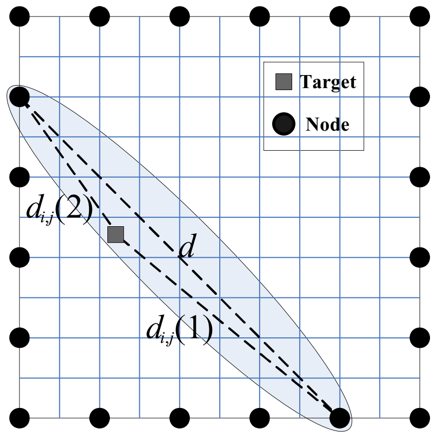


Fig. 3. Elliptical weight model, the weighted pixels for a single link in a RF sensor network are darkened in an ellipse with foci at each node location.

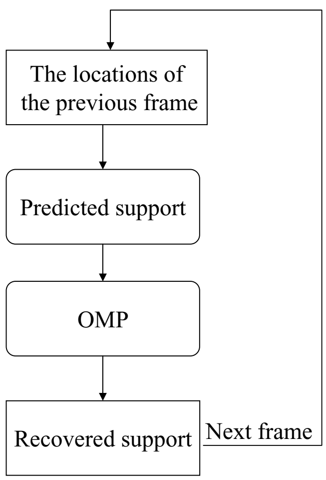


Fig. 4. Diagram of feedback structure.

B. Elliptical weight model

Weight matrix A for link shadowing can be described by an ellipsoid with foci at each pair of nodes locations [9], [2], [3], [5], as shown in Fig. 3. The weight is defined by

$$A_{ij} = d^{-1/2} \times \begin{cases} 1, & \text{if } \; d_{ij}(1) + d_{ij}(2) \leq d + \lambda, \\ 0, & \text{otherwise.} \end{cases} \quad (11)$$

where 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, and λ is the width of the ellipse. 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 0.1 in our experiments.

III. Feedback Sparse Recovery

When tracking targets from RSS measurements, it is an inverse problem from (1) to get the pixels attenuation x. x can determine how many targets are in the network area and where they are located. Generally, it formulates the inverse problem in the least-square error sense [2], [3], [5], [9]

$$\mathbf{x}_{LS} = \arg\min_{\mathbf{x}} \|A\mathbf{x} - \mathbf{y}\|_2^2. \quad (12)$$

Regularization methods were introduced into the linear model to alleviate the singularity problem and make the inverse problem stable [3], [4]. All the least-square solutions minimize the noise energy, and the results are very smooth. It must have a contrast step to estimate the location of targets. RTI does not indicate the actual location of targets, and is an intermediate step for motion tracking [5]. The solution used in [5] adopted the Kalman filter to track a moving target with the maximum of least-square solution as the initial location.

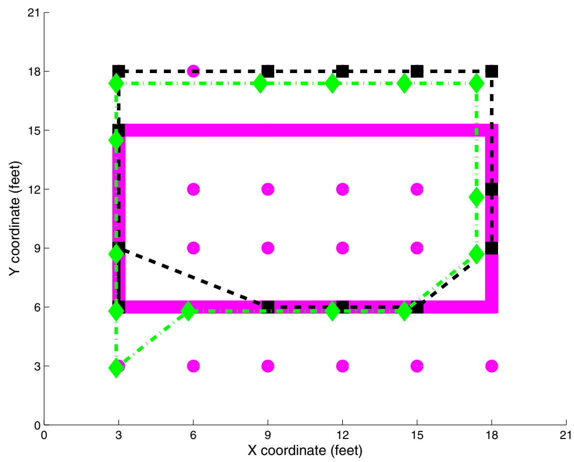
We cast the inverse problem (1) as a compressed sensing problem motivated by the sparse nature of location finding from motion problem. Sparse recovery algorithms for CS problems have two major groups, greedy algorithms and ℓ_1 norm minimization. ℓ_1 norm minimization algorithms (e.g. Basis Pursuit [10]) are not feasible solutions for motion tracking due to high computational complexity and unstable rises in measurements noise.

In this paper, we employ the Orthogonal Matching Pursuit (OMP) [8] and a feedback structure for tracking moving targets. As seen form Fig. 6, there are consecutive frames of RSS measurements. The estimated locations by previous frame $\mathbf{x}_{t-1}$ is highly correlated to the current frame $\mathbf{x}_t$. The support set of $\mathbf{x}_{t-1}$ is denoted as T_{t-1}. We utilize the RSS measurements that cross previous locations (indicated by T_{t-1}) centered 5×5, 9×9 or 17×17 blocks to predict the T_t.

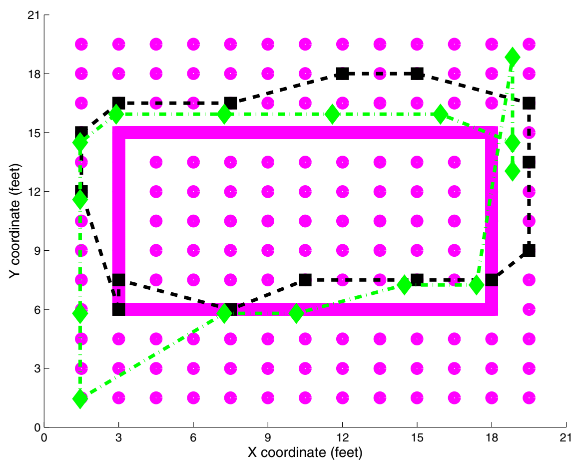
Based on the feedback structure, the OMP based tracking algorithm is presented as follow:

- **Step 1: Initialization:**
  the residual $\mathbf{r}_0 = \mathbf{y}$, the detected support $T_0 = \emptyset$, and the iteration counter $t = 1$.
- **Step 2: Support detection:**
  Find the index j that maximize the magnitude of $A^T \mathbf{r}_{t-1}$, augment the support $T_t = T_{t-1} \cup \{j\}$ and $A_t = [A_{t-1} \;\; \mathbf{a}_j]$.
- **Step 3: Residual update:**
  $\hat{\mathbf{x}}_t = (A_t^+)\mathbf{y}$
  $\mathbf{r}_t = \mathbf{y} - A_t \hat{\mathbf{x}}_t$.
- **Step 4: Halting:**
  If the t agrees with the number of targets, the current frame is completed. Predict the support T_{t+1} of the next frame, equip the next frame's RSS measurements $\mathbf{y}$ and corresponding A and process the next frame. Otherwise go to Step 2.

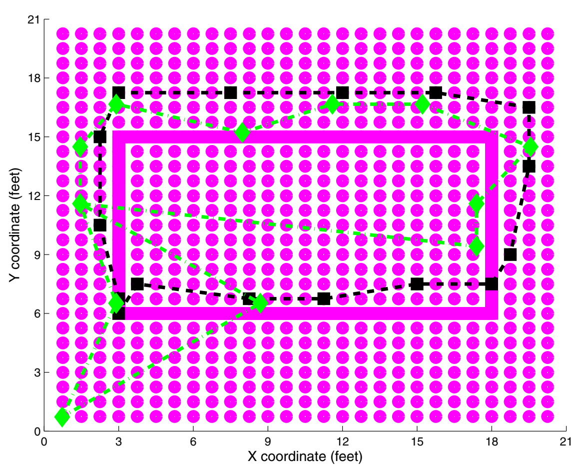
To avoid confusions, A_0 denotes an empty matrix, $\mathbf{a}_j$ denotes the j-th column of matrix A and $A^+ = (A^T A)^{-1} A^T$ is the Moore-Penrose pseudoinverse of matrix A. Fig. 6 presents the



(a) Estimated trajectory using resolution 6×6

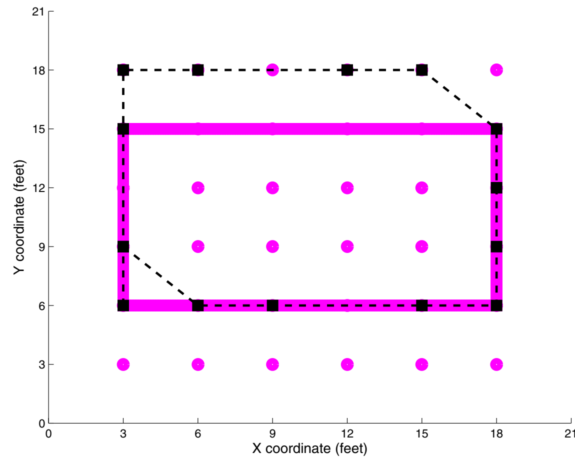


(b) Estimated trajectory using resolution 13×13

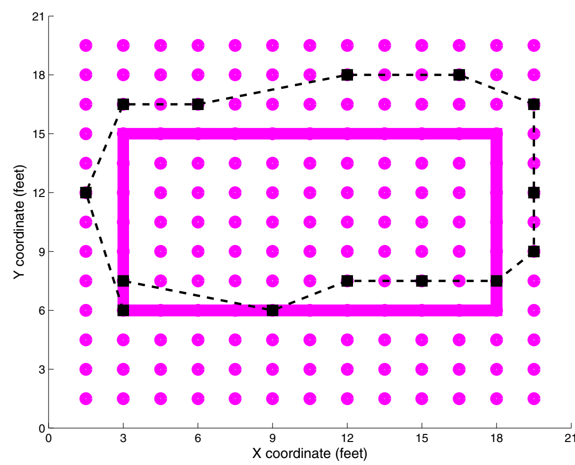


(c) Estimated trajectory using resolution 27×27

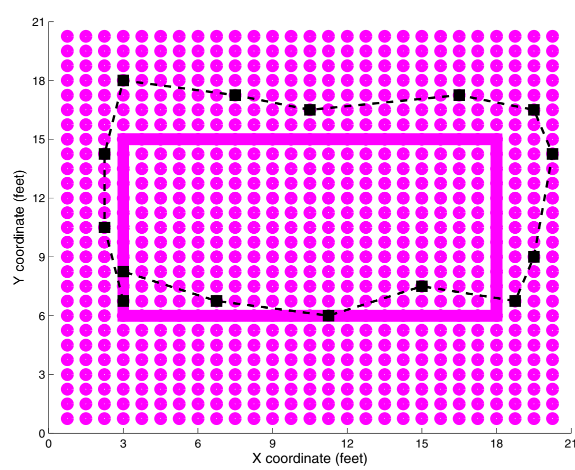
Fig. 5. The tracking trajectory with one target walked at constant velocity around the following square loop path: (3,6) to (3,15) to (18,15) to (18, 6) and back to (3,6). The megenta circle is the pixel, the black square is the location estimated by OMP, the green diamond is the location estimated by the Kalman filter method [5] and the megenta rectangle is the real moving trajectory.



(a) Estimated trajectory using resolution 6×6



(b) Estimated trajectory using resolution 13×13



(c) Estimated trajectory using resolution 27×27

Fig. 6. The tracking trajectory 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 feedback structure, and the megenta rectangle is the real moving trajectory.

detailed description of feedback sparse recovery for motion tracking.

IV. Experimental results

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 dataset is obtained from [3] http://span.ece.utah.edu/rti-data-set. A 28-nodes peer-to-peer network was deployed in a square perimeter of 21 feet $\times$ 21 feet, and each side has 8 nodes, as depicted in Fig. 2. Each node was spaced 3 feet from the neighboring nodes. Two trees surround the border of the network with approximately 1 foot diameter trunks.

RSS measurements of each link are taken at time $t = t_b$ as described in section II. Each link's measurement is an average of the two directional links from i to j and j to i. During the calibration period, the network area is vacant from moving targets. The signal strength from each link was windowed with the same time-stamp and averaged over the entire windowed samples. After calibration, all instantaneous measurements are taken as the difference from the calibration measurements, as described in (10).

To demonstrate the effect of resolution on tracking accuracy, the network area is partitioned off 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. 5 (a)-(c) show the estimated trajectory using different resolutions. Sparse recovery with OMP is more reliable than the Kalman filter method used in [5] as indicated in Fig. 5. The Kalman filter method used in [5] is unstable for motion tracking due to the initialization with the maximum of least-square solution, especially for the higher resolution. The results with different resolutions achieve similar performance in terms of average error. However, 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 [6], [7]. 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 [3], [5]. The weight matrix A can be viewed as a form of overcomplete dictionary [11]. 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 and 17×17 blocks for resolution 6×6, 13×13 and 27×27 respectively to predict the support 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. 6. 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 wireless sensor networks applications.

V. Conclusion

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 motion tracking as a CS problem and employ an efficient algorithm, Orthogonal Matching Pursuit (OMP), 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 next frame support. We demonstrate that the proposed approach achieves favorable results on real data.

Acknowledgment

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