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TDL: Two-dimensional localization for mobile targets using compressive sensing in wireless sensor networks

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ABSTRACT

Many applications in wireless sensor networks (WSNs) (*e.g.*, traffic monitoring, environment surveillance and intruder tracking) rely heavily on the availability and accuracy of targets' locations. Compressive sensing (CS) has been widely applied to localization as it asserts that a small number of samples will suffice for sparse or compressible signal recovery. Despite much progress in CS-based localization, existing solutions mainly consider static targets and often perform poorly for mobile targets.

In this paper, we develop a novel two-dimensional localization (TDL) framework for mobile targets using compressive sensing. TDL is composed of two modules: (i) spatial localization module (SLM) that first achieves localization at sampling times by exploiting the sparse nature of Received Signal Strength (RSS) vector in space domain, and (ii) temporal localization module (TLM) that then achieves localization at all times by exploiting the compressible nature of location vector in time domain. Furthermore, two practicable measurement matrices are constructed to conduct linear measurements. We analyze the flexibility and effectiveness of TDL in theory. Extensive numerical evaluations with real mobility traces further confirm the superior performance of our localization framework.

1. Introduction

1.1. Motivation

Wireless sensor networks (WSNs) attract much attention as they promise an ability to monitor the physical world *via* a lot of small and inexpensive sensors. Location awareness is highly critical to many applications in WSNs, such as geographic routing [1], disaster response [2], environment surveillance [3], and vehicle tracking [4]. The Global Positioning System (GPS) [5] is widely used to obtain location information in WSNs. However, there are several situations (*e.g.*, indoors, under the ground, or in urban environments) where GPS does not work well due to the lack of line of sight to multiple satellites. Moreover, due to the constraints on hardware cost, it is undesirable and unfeasible to equip each target with a GPS.

The limitations of GPS have motivated researchers to develop a large body of literatures on localization. However, most of these localization schemes fail to localize mobile targets as they are designed for static targets. For static targets, it is not a problem because their positions are unlikely to change once determined. However, for mobile targets, it is a significant challenge since they may change their positions at any time.

As a matter of fact, most targets in WSNs are mobile. For example, rescuers move in a disaster area, soldiers move in a battlefield, animals move in a habitat, and vehicles move in a city. There are only a limited number of researches that consider the problem of mobile target localization. Moreover, these researches only use a maximum speed to constrain the distance between a target's positions during two consecutive time intervals while they do not fully exploit the hidden compressible nature of the target's positions during all time intervals.

Another simple approach to mobile target localization is to divide time into several time intervals. In each interval, a target can be considered static and localized using static localization methods. However, the localization accuracy of this approach depends heavily on the resolution of time division. To achieve accurate localization, high resolution of time division is needed, posing great challenges to hardware equipments in terms of sampling, storage and calculation.

Compressive sensing (CS) technique [6,7] provides a new solution to the problem of mobile target localization. As a novel signal sampling paradigm, CS asserts that a small number of samples will suffice for original signal recovery. To achieve this, CS relies on two key components: sparsity and incoherence.

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- *Sparsity* expresses the idea that many real-world signals are sparse or compressible in the sense that they have concise representations when expressed in some representation basis.
- *Incoherence* expresses the idea that the sparse signals in some representation basis must be spread out in another domain where they are sampled. In other words, incoherence indicates that unlike the signals of interest, the sampling waveforms should have extremely dense representations in the representation basis.

We observe that the spatial signal (*e.g.*, RSS vector) and the temporal signal (*e.g.*, location vector) are sparse or compressible in appropriate representation bases. Motivated by the observation, we investigate the solution to mobile target localization using compressive sensing.

1.2. Our work and contributions

There are two key challenges in applying CS technique to our problem. (1) How to find proper representation bases in which the original signals can be sparsely represented. (2) The measurement matrix in our context is restricted by physical constraints. In primal literature, the measurement matrix is usually specified by a dense matrix, *e.g.*, Gaussian matrix, as it exhibits very low coherence with any representation basis. However, it should be noted that the dense measurement matrix is not feasible in practice. As a matter of fact, each measurement is a linear combination of multiple samples of the underlying signal [8]. It almost requires all samples of the signal since there are nearly no empty columns in the dense measurement matrix. This obviously goes against compressive sensing theory.

In this paper, we leverage compressive sensing to develop a two-dimensional localization framework for mobile targets. The localization framework takes full advantage of the sparse or compressible nature of signals to highly reduce the data collection needed for accurate localization in both space and time domains. The main contributions of this paper can be summarized as follows.

- We propose a novel two-dimensional localization framework for mobile targets. The framework is composed of a spatial localization module (SLM) and a temporal localization module (TLM).
- We design appropriate representation bases by exploiting the sparse or compressive nature of signals in both space and time domains. It is validated that these representation bases can sufficiently sparsify the underlying signals.
- We develop two simple and practical measurement matrices to conduct linear measurements. We demonstrate that they are highly incoherent with designed representation bases.
- We perform extensive simulations to evaluate the performance of TDL with various parameter settings. The superiority of TDL compared with other approaches is validated by the simulation results.

The remainder of this paper is organized as follows. A brief review of related work is presented in Section 2. We introduce background of compressive sensing and mathematically formulate the problem in Section 3. Section 4 provides detailed descriptions on our localization framework. The matrix design and performance analysis are given in Section 5. Section 6 demonstrates the performance of our localization framework through extensive numerical evaluations. Section 7 gives a discussion about the localization framework. Finally, we conclude the paper in Section 8.

Notations: we use bold uppercase (lowercase) letters to denote matrices (vectors). $(\cdot)^{\mathrm{T}}$denotes the transpose, $(\cdot)^{-1}$denotes the inverse, $\|\cdot\|_p$ denotes the p-normal, $\langle\cdot\rangle$ denotes the inner product, $min(\cdot)$ denotes the minimization operator, and $max(\cdot)$ denotes the maximization operator.

2. Related work

In this section, we first review the applications of CS in WSNs, and then summarize the existing researches on target localization.

2.1. CS applications in WSNs

Compressive sensing has been widely applied to data collection in WSNs because of its ability to reduce signal samplings significantly and balance energy consumption across sensors [9]. In single-hop WSNs, Compressive Wireless Sensing (CWS) [10] considers the spatial correlation among sensor readings and reduces the latency of data gathering by delivering the linear projections of sensor readings. Distributed Compressive Sensing (DCS) [11] extends CWS to time domain by considering both spatial and temporal correlations among sensor readings. DCS studies joint sparsity models and joint data recovery algorithms without considering multi-hop communication and in-network data processing. Compressive Data Gathering (CDG) [12,13] addresses the large-scale data gathering problem in multi-hop WSNs. CDG uses dense measurement matrices for CS projections, not achieving as much energy reduction as sparse matrices. Mahmudimanesh et al. [14] significantly enhance CDG by balancing computation and communication loads over all sensors. There are fundamental differences between the aforementioned applications and the application in this paper. On one hand, we are interested in using a few sensor readings to estimate mobile targets' locations while the aforementioned applications aim at reconstructing all sensor readings. On the other hand, the aforementioned applications consider the spatial or temporal correlation of the same signal while we explore the spatial or temporal correlation of different signals, *i.e.* the spatial correlation of RSS readings and temporal correlation of targets' locations.

2.2. Target localization

We classify existing target localization researches into four categories: (i) non-CS based static target localization, (ii) CS based static target localization, (iii) non-CS based mobile target localization, and (iv) CS based mobile target localization.

(i) *Non-CS based static target localization:* These methods are either range-based or range-free. Range-based methods [15–18] first use *Received Signal Strength* (RSS), *Time of Arrival* (ToA), *Time Difference of Arrival* (TDoA), or *Angle of Arrival* (AoA) to measure the distances or angles between unknown nodes and anchors with known positions, and then use trilateration, triangulation, or maximum likelihood to determine the positions of unknown nodes. These methods are simple but have two significant drawbacks: (1) they are sensitive to fading, noise and non-line of sight, and (2) it is often not affordable to equip all nodes with ranging capability. On the contrary, range-free methods [19–21] do not require the hardware support for measuring distances or angles. Instead, they exploit the network connectivity or proximity relationship between nodes. Range-free methods are easy to implement in WSNs, but they only achieve a low level of accuracy in most situations.

(ii) *CS based static target localization:* Localization Via Spatial Sparsity (LVSS) [22] is the first work to apply compressive sensing to localization problem. LVSS discretizes the area of interest into a grid so that the localization problem is formulated as a sparse signal recovery problem. The authors also propose a Bayesian framework [23] for the localization problem and provide sparse approximation to its optimal solution. The drawback of these methods is that a localization dictionary is needed at each sensor. By formulating multiple targets' locations as a sparse matrix, Feng et al. [24] propose a CS based indoor localization approach. The approach is only able to localize single target though it is designed for multiple targets. A clustering method