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Distributed compressive sensing in heterogeneous sensor network

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ABSTRACT

In this paper, we apply distributed compressive sensing (DCS) in heterogeneous sensor network (HSN). Combining different types of measurement matrices and different numbers of measurements, we firstly investigate three different scenarios in which HSN is used for signal acquisition. In the first scenario, there are two different types of measurement matrices. One is Gaussian measurement and the other is Fourier measurement, and each sensor applies the same numbers of measurements. In the second scenario, all sensors use the same type of measurement matrices but the number of measurements are different with each other. The third scenario combines different types of measurement matrix and distinct numbers of measurements. Our simulation results show that in Scenario I, when the common sparsity is considerable, the DCS scheme can reduce the number of measurements. In Scenario II, the reconstruction situation becomes better with the increase of the number of measurements. In both Scenarios I and III, joint decoding that use different types of measurement matrices performs better than that of all-Gaussian measurement matrices, but it performs worse than that of all-Fourier measurement matrices. Therefore, DCS is a good compromise between reconstruction percentage and the number of measurements in HSN.

1. Introduction

Compressive sensing (CS) is an emerging, rapidly growing field of signal processing and information theory. It predicts that sparse high dimensional signals can be recovered from highly incomplete measurements by using efficient algorithms [1]. Currently, numerous recovery algorithms have been developed to solve the problem. These algorithms can be classified as $L1$-minimization types [2] and greedy types, such as orthogonal matching pursuit (OMP) [3] and compressive sampling matching pursuit (CoSaMP) [4].

So far, many works have been reported on CS for sensor networks (SN). In [5] Liang demonstrated that the sense-through-foliage UWB radar signals are very sparse, which means CS could be applied to radar sensor networks to tremendously reduce the sampling rate. In [6] CS has been shown as an efficient and effective signal acquisition and sampling framework for wireless sensor networks (WSN), which can be used to save transmittal and computational power significantly at the sensor node.

Currently, people use DCS as the communication strategy [6] of a CS-based system in SN. DCS extends the theory and practice of compressive sensing to multi-signal, distributed settings [7]. In DCS we aim to recover the data acquired from a group of j ($j \geq 2$) sensors from compressive measurements that are obtained either independently [7,8] or collaboratively [9–11]. In our work, we focus on the DCS signals that are each individually sparse in some basis and are encoded independently and recovered

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jointly. Considering the scenarios investigated in this work, we use the sparse common and innovations model, which is labeled joint sparsity model-1 (JSM-1) in [7].

HSN consists of sensor nodes with different ability, such as different computing power and sensing range. Once the HSN is deployed, targets are detected using one or more sensing modalities such as optical, mechanical, acoustic, thermal, RF and magnetic sensing. In fact, to ensure robustness and enhance performance, a sensor fusion approach is required [12]. Compared with conventional sensor networks, deployment and fusion rules are more complex in HSN. On one hand, HSN possess dissimilar energy resources: some sensors may directly connect to electrical energy systems without energy constraints, whereas others are powered by limited batteries with different capacities; on the other hand, sensors in HSN can have diverse mobilities: wired nodes connected to electrical energy systems are more likely to be stationarily exploiting fixed communication channels, while wireless sensors carried by vehicles or humans are allowed to move, which brings in variations in communication [13]. A radar sensor network (RSN) not only provides spatial resilience for target detection and tracking compared to traditional radars, but also alleviates inherent radar defects such as the blind speed problem [14]. In [15], Liang et al. proposed optimized energy allocation scheme based on different fusion approaches for both single moving target and multiple moving targets. The proposed approaches not only optimize the energy allocation in heterogeneous radar sensor networks (HRSNs), but also offer an appropriate tradeoff between resource consumption and target detection performance.

In this work, we assume three scenarios in which HSN is used for signal acquisition. In the first scenario, there are at least two types of measurement matrices in the whole HSN system. However, each sensor has the same numbers of measurements. In the second scenario, the situation is completely opposite. All sensors use the same type of measurement matrices but the numbers of measurements are different with each other. In the third scenario, there are two different types of sensors. Each uses different measurement matrix and different numbers of measurements.

In [16,17], DCS has been applied in conventional SN and shows the superior potentials over non-CS methods, but they have not applied DCS into an HSN. To the best of our knowledge, this is the first time that the investigation in DCS adopted in HSN and the analysis of different types of measurement matrices, i.e., Gaussian and Fourier measurement matrices, at the same time.

The remainder of this paper is organized as follows. Section 2 describes the necessary background on CS. Section 3 describes DCS and JSM-1 in HSN, and proposes three scenarios in HSN. Section 4 presents simulation result and analysis. Finally, Section 5 summarizes our investigation.

2. Compressed sensing

First we give a brief overview of the CS framework. Consider a real-valued, finite-length, one-dimensional, discrete-time signal x, which can be viewed as an $N \times 1$ column vector in $\mathbb{R}^N$. Using the $N \times N$ basis matrix Ψ with the vectors $\{\psi_i\}$ as columns, a signal x can be expressed as

$$x = \sum_{i=1}^{N} s_i \psi_i \quad \text{or} \quad x = \psi s \tag{1}$$

where s is the $N \times 1$ column vector of weighting coefficients $s_i = \langle x, \psi_i \rangle = \psi_i^T x$.

The signal x is K-sparse if it is a linear combination of only K basis vectors. The case of interest is when $K \ll N$. For such a sparse signal, consider a general linear measurement process that computes $M < N$ inner products between x and a collection of vectors $\{\phi_j\}_{j=1}^{M}$ as in $y_j = \langle x, \phi_i \rangle$. Arrange the measurements y_j in an $M \times 1$ vector y and the measurement vectors ϕ_j^T as rows in an $M \times N$ matrix Φ. Then, by substituting Ψ from (1), y can be written as

$$y = \Phi x = \Phi \Psi s = \Theta s, \tag{2}$$

where $\Theta = \Phi\Psi$ is an $M \times N$ matrix. Generally, Φ is fixed and does not depend on the signal x.

Because $M < N$, the recovery of the signal x from y is ill-conditioned. However, if x is K-sparse and the K locations of the nonzero coefficients in s are known, then the problem can be solved provided $M \geq K$. Some widely used properties are that Φ should satisfy the Restricted Isometry Property (RIP) and incoherence.

RIP was introduced by Candes and Tao [18]. The measurement matrix Φ satisfies RIP of order K. Let Φ_T, $T \subset \{1, 2, \ldots, N\}$, be the $K \times |T|$ submatrix obtained by extracting the columns of Φ corresponding to the indices in T. Define the K-restricted isometry constant δ_K of Φ which is the smallest quantity such that

$$(1-\delta_K)\|x_T\|_2^2 \leq \|\Phi_T x_T\|_2^2 \leq (1+\delta_K)\|x_T\|_2^2, \tag{3}$$

for all subsets T with $|T| \leq K$ and all real coefficient $\{x_j\}$, $j \in T$.

These two properties can be achieved with high probability simply by selecting Φ as a random matrix which would allow us to recover as many entries of x as possible with as few as M measurements. Here are some measurement matrices commonly utilized in CS framework.

- *Gaussian measurements*: Here we assume that the entries of the $M \times N$ sensing matrix Φ are independently sampled from the normal distribution with mean zero and variance $1/M$.
- *Binary measurements*: Suppose that the entries of the $M \times N$ sensing matrix Φ are independently sampled from the symmetric Bernoulli distribution $P(\Phi_{mi} = \pm 1/\sqrt{M}) = 1/2$.
- *Fourier measurements*: Consider the $N \times N$ Discrete Fourier Transform (DFT) matrix W with entries

$$W_{\omega,t} = \exp\left(-\frac{2\pi i \omega t}{n}\right), \omega, t \in \{0, 1, \ldots, n-1\}. \tag{4}$$

Suppose now a random vector $X \in \mathbb{C}^N$ which picks a random row of W (with uniform distribution). It follows from Parseval's inequality that M is isotropic. And the rows of the $M \times N$ random matrix Φ are independent copies of X.