A Realistic Distributed Compressive Sensing Framework for Multiple Wireless Sensor Networks

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***Abstract*—In this paper, we propose a new compressive sensing framework for sensor networks. Unlike the conventional approaches, we consider the design of sensing matrix with the prior knowledge of the channel between the signals and the sensors. We determine that full or partial knowledge of the channel at sensors enables effective sensing matrix design and supports a good signal recovery. We discuss some of our key results and scope for our future research.**

***Index Terms*—Compressive Sensing, Sensing matrix, Sensor networks.**

I. Introduction

Compressive sensing (CS) is an emerging signal acquisition technique that recovers a sparse signal from few linear measurements [1]. Due to its popularity, CS is currently applied in many areas such as coding, signal processing and wireless sensor networks [2]. In this paper, we present a new CS framework for wireless sensor networks.

We consider a sensor network consisting of S sensors connected to a centralized fusion center. Each sensor measures a desired sparse signal and then compresses the sensed signal using a sensing matrix. The compressed measurements from different sensors are sent to the fusion center for joint recovery of the sparse signals. Unlike the conventional framework [3], we consider realistic scenarios in which there exists channel between the signal to be sensed and the sensor, such as in underwater acoustic systems and seismic sensor systems. We observe that the signals thus acquired have a lot of redundancy which can be handled efficiently by the proper design of sensing matrices using the prior knowledge of the channel.

In this paper, we consider a wireless sensor network having S number of sensors deployed at random locations. Let $\boldsymbol{s}$ denote an K-sparse signal of length N ($K \ll N$). The signal received at the j-th sensor can be modeled by $\boldsymbol{x}_j = C_j \boldsymbol{s}$, where C_j is an $(N+L-1) \times N$ matrix which models the delay dispersed channel between the intrinsic source to the j-th sensor. The sparse signal at the j-th sensor is then compressed by an $M \times (N+L-1)$ random Gaussian matrix F_j [1] to obtain the linear measurement $\boldsymbol{y}_j = F_j \boldsymbol{x}_j$. The joint received vector obtained at the fusion center can then be modeled as

$$\boldsymbol{y} = FC\boldsymbol{s} + \boldsymbol{n} \tag{1}$$

where $\boldsymbol{y} = [\boldsymbol{y}_1^T, \cdots, \boldsymbol{y}_S^T]^T$, F is a block diagonal matrix with F_js as the diagonal entries and $C = [C_1^T \cdots C_S^T]^T$. The goal of the fusion center is to recover $\boldsymbol{x}_j$s and the intrinsic sparse signal $\boldsymbol{s}$, from $\boldsymbol{y}$.

One of the key challenges in our framework is the design of a good sensing matrix at each sensor. With the existence of the channel, the conventional Gaussian sensing matrix in (1) may not be enough to capture the maximum information because the sensing matrix design now has to depend on the characteristics of the channel. Therefore, we would like to utilize the channel information in the sensing matrix design. If the channel matrix C_j is exactly available at the j-th sensor, then one would like design the sensing matrix F_j based on C_j. At the fusion center we reconstruct the sparse signal by L_1 minimization with the recovery matrix $A = FC$. The incoherence of A, which should be low for good signal recovery, now depends on C_js. Our aim is to design good sensing matrices F_js based on the exact or partial knowledge about C_js such that the recovery matrix A behaves incoherently. In addition, it would be interesting to investigate the minimum measurements required for either exact or approximate recovery of the sparse signals under this realistic conditions.

II. Discussions

We have carried out a preliminary investigation to determine the number measurements needed at the fusion center for exact signal recovery when the channel is known. Our preliminary study exposes a few surprising results obtained by incorporating additional channel information for sensing matrix design. Unlike the conventional theory which demands $O(K \log N)$ measurements for the unique L_1 solution, we show that, only sub-sparse measurements from each sensor is needed to obtain perfect L_1 signal recovery at the fusion center. This achievement is possible since we properly use the available channel information for signal acquisition. From our preliminary studies we found that as the number of sensors increases, the measurements needed for a given probability of recovery decrease.

III. Conclusions and Future Work

In this paper, we have proposed a compressive sensing framework with application to wireless sensor networks. In our framework, we have considered the design of sensing matrices to obtain a low coherent recovery matrix by making use of the prior knowledge of the channel. We would like to proceed in the following directions for our future research:

- Given the channel matrices C_js exactly or partially, how to design good sensing matrices F_js such that A is incoherent?
- What is the relationship between the channel parameters and the coherence of the recovery matrix?
- What is the condition for the unique L_0 solution? How is this condition related to the channel parameters?
- What is the equivalence relation for the existence of the unique L_1 solution? How does it depend on the channel parameters?
- What is the restricted isometry property (RIP) in this practical situation?
- How much information can we obtain from a sensor network given coverage and sensor density?
- How does the correlation among the sensors affect the information obtainable from the network?

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