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A REVIEW ON THE DISTRIBUTED SENSING PERSPECTIVE OF COMPRESSIVE SENSING

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ABSTRACT

Recently, compressed sensing (CS) has been considered as a tool to surpass the traditional limits of Nyquists' sampling Theory. The CS theory suggests that sparse signals and images can be reconstructed from fewer samples which are obtained at the rate far below the Nyquist rate. Also this will help to underlie procedures for sampling and compressing data simultaneously. Like many other fields, CS also found successful applications in Multi-sensor communications networks. CS is having applications in the detection and estimation of various signals in sensor networks and network monitoring, etc. This survey gives a brief idea about compressive sensing and then goes on to review different Applications on multisensory networks

KEYWORDS: Compressive Sensing, Incoherence, Sensor Networks, Sparsity, etc.,

INTRODUCTION

We are living in an era of a digital revolution that is driving the progress of new types of high resolution sensing systems with the information explosion. As a result of this, the amount of data generated by the systems has been growing in very high speed. The conventional approach of reconstructing the sensed signals from measured data obeys the famous Shannon sampling theorem, which states that the sampling rate of the signals must be minimum twice the highest signal frequency. But, in many applications, the resulting Nyquist rate is very high that result in too many samples. It may be too costly, or even physically impossible, to build a system capable of acquiring samples at the necessary rate. Thus, in spite of the astonishing advances in processing power, the acquisition and processing of signals in most of the application areas continues to pose a tremendous challenge.

In Contrary to the conventional Nyquist paradigm, the novel approach of the compressive sensing will help to address the logistical and processing challenges involved in dealing with such high-dimensional data.

CS can find sparse solutions to underdetermined linear systems and can reconstruct the signals from far fewer samples than is possible using Nyquist sampling rate. To make this in reality, CS relies on two principles: sparsity and incoherence.

Sparsity expresses the idea that the information rate of a continuous time signal may be much smaller than suggested by its bandwidth. Most of the Natural signals can be stored in compressed form, in terms of their projections on a suitable basis. When the basis is selected properly, a large number of projection coefficients will be zero so that they can be ignored. If a signal has only K non-zero coefficients in a domain, it is said to be K-Sparse. If a large number of projection coefficients of a signal are small enough and can be ignored, then that signal is said to be compressible.

In Compressive Sensing, we are concerned with two matrices - the incoherence of matrix used to sample the signal of interest (measurement matrix) and the matrix representing a basis, in which signal of interest is sparse (representation matrix). Within the CS framework, low coherence between these two matrices translates to fewer samples required for reconstruction of signal

CS is a very simple and efficient signal acquisition protocol which samples at a low rate and later uses computational power for reconstruction from the samples, which appears to be an incomplete set of measurements. CS combines the sampling and compression into one step by measuring minimum samples that contain maximum information about the signal: this eliminates the need to acquire and store large number of samples only to drop most of them because of their minimal value.

LITERATURE REVIEW

The literature review is to analyze the virtues and pitfalls of the existing algorithms and techniques. This review evaluates the benefits of the techniques used in the application of Compressive sensing in the field of distributed and multiple sensor networks. This will also try to find the gaps in existing research and methods.

Shuchin Aeron et al (5) addressed the problem of finding the sensing capacity of sensor networks for a class of linear observation models and a fixed SNR regime. They derived the bounds and provided conditions for reliable reconstruction of sparse signals. They have shown that Sensing capacity goes down as sensing diversity per sensor goes down and Random sampling of the field by sensors is better than contiguous location sampling.

Scott Pudlewski et al (14) investigated the potential of the compressed sensing paradigm for video streaming in Wireless Multimedia Sensor Networks. They designed a rate control scheme with the objectives to maximize the received video quality at the receiver and to prevent network congestion while maintaining justice between various video transmissions. Representation of Video distortion is through analytical and empirical models and the distortion is minimized based on a new cross-layer control algorithm that jointly regulates the video encoding rate and the channel coding rate at the physical layer based on the estimated channel quality

Volkan Cevher et al (7) Developed signal processing algorithms for randomly deployable wireless sensor arrays that are severely constrained in communication bandwidth. They have focused on the acoustic bearing estimation problem and shown that when the target bearings are modeled as a sparse vector in the angle space, functions of the low dimensional random projections of the microphone signals can be used to determine multiple source bearings as a solution of an $\ell 1$-norm minimization problem.

J. Oliver and Heung-No Lee (18) proposed a new compressive sensing framework for sensor networks. They considered the design of sensing matrix with the prior knowledge of the channel between the signals and the sensors. They concluded that full or partial knowledge of the channel at sensors enables effective sensing matrix design and supports a good signal recovery.

Dror Baron et al (1) have introduced the theoretical frame work for distributed compressive sensing which is based on joint sparsity of a signal ensemble. They studied three example models for jointly sparse signals and developed practical algorithms for joint recovery of multiple signals from incoherent projections.

Hung-Wei Chen et al (15) addressed the issue of fully low-cost and low-complexity video encoding for use in resource limited sensors/devices. They proposed a distributed compressive video sensing framework to directly capture compressed video data, while exploiting correlations among successive frames for video reconstruction at the decoder. At the decoder, video reconstruction can be formulated as a convex unconstrained optimization problem via solving the sparse coefficients with respect to some basic functions. The paper investigated about dynamic measurement rate allocation in block-based distributed compressive video sensing, which can adaptively adjust measurement rates by estimating the sparsity of each block via feedback information.

Guojin Liu et al (21) studied the problem of picking arrival times of primary waves received by seismic sensors, in the volcano monitoring. They developed a suite of new in-network signal processing algorithms for the accurate picking, along with signal pre-processing at sensors, sensor selection as well as signal compression and reconstruction algorithms.

Jeonghun Park et al (19) proposed a generalized Distributed Compressive Sensing which can improve sparse signal detection performance, given arbitrary types of common information which are classified into not only full common information but also a variety of partial common information. Using the scheme, they obtained the theoretical bound on the required number of measurements. They proposed a novel algorithm that can search for the correlation structure among the signals, with which the proposed scheme improves detection performance even without a priori-knowledge on correlation structure for the case of arbitrarily correlated multi signal ensembles.

Ali G et al. (8) considered the direction-of-arrival estimation problem with an array of sensors using Compressive Sensing. By using the random projections of the sensor data, beside with a full waveform recording on the reference sensor, they have reconstructed the sparse angle space scenario, giving the number of sources and their Directions of arrivals.

Waheed Bajwa et al (2) introduced the concept of Compressive Wireless Sensing for sensor networks in which a fusion center retrieves signal field information from a group of spatially dispersed sensor nodes. They have proposed a distributed matched source-channel communication scheme for estimation of sensed data at the fusion center and analyzed the same with the parameters - number of sensor nodes, the trade-offs between distortion, latency and power.

Michael Rabbat et al (3) presented a novel system for decentralized data compression and content distribution in wireless sensor networks. The system simultaneously computes random projections of the sensor data and disseminates them throughout the network using a simple algorithm. The summary statistics are stored in the network. From these measurements, reconstruction of the data at all nodes in the network is possible, provided the original data is compressible in a certain domain.

Waheed U. Bajwa et al (4) have proposed a distributed joint source-channel communication architecture for energy-efficient estimation of sensor field data at a remote destination. They analyzed the relationships between latency, power and distortion as a function of the number of sensor nodes. Their approach can be applied to a broad class of signals, which is based on the distributed computation of appropriately chosen projections of sensor data at the destination. When there is little knowledge is available about the signal field, random projections are used.

G. Coluccia et al (17) proposed a new lossy compression scheme for distributed and sparse sources under a low complexity encoding constraint. The proposed architecture is able to exploit both intra- and inter-signal correlations typical of signals monitored by a wireless sensor network. In order to meet the low complexity constraint, the encoding stage is performed by a lossy distributed compressed sensing algorithm. The novelty of the scheme consists in the combination of lossy distributed source coding and Compressive Sensing. The joint use of both allows to achieve large bit-rate savings for the same quality with respect to the non-distributed Compressive Sensing scheme.

Volkan Cevher et al (6) proposed an approximation framework for distributed target localization in sensor networks. They have shown successfully to determine multiple target locations by using linear dimensionality-reducing projections of sensor measurements. The communication requirements are better as the overall communication bandwidth requirement for each sensor is logarithmic in the number of grid points and linear in the number of targets.

M Mahmudimanesh et al (12) described how the geometrical representation of the sampling problem can influence the effectiveness and efficiency of Compressive Sensing algorithms. They introduced a Map-based model which exploits redundancy attributes of signals recorded from natural events to achieve an optimal representation of the signal.

J. Oliver and Heung-No Lee (16) proposed a new compressive sensing framework for sensor networks. They considered the design of sensing matrix with the prior knowledge of the channel between the signals and the sensors. They have shown that full or partial knowledge of the channel at sensors enables effective sensing matrix design and supports a good signal recovery.

Giorgio Quer et al (9) addressed the data gathering problem in Wireless Sensor Networks, where routing is used in combination with Compressive Sensing to transport random projections of the data. They analyzed synthetic and real data sets and compared the results against those of random sampling. They concluded that, with real data sets, it is impossible to sparsify the data while being at the same time incoherent with respect to the routing matrix.

Riccardo Masiero et al (11) have addressed the task of accurately reconstructing a distributed signal through the collection of a small number of samples at a data gathering point using Compressive Sensing in concurrence with Principal Component Analysis. Their scheme is doing the recovery of real world non-stationary signals at the data collection point through the online estimation of their spatial/temporal correlation structures. They proceeded with the analysis of data collected by indoor wireless sensor network test bed, proving that these assumptions hold with good accuracy in the considered real world scenarios.

Giorgio Quer et al (20) addressed the problem of compressing large and distributed signals monitored by a Wireless Sensor Network and recovering them through the collection of a small number of samples. They proposed a sparsity model that allows the use of Compressive Sensing for the online recovery of large data sets in real WSN scenarios, exploiting Principal Component Analysis to capture the spatial and temporal characteristics of real signals. Bayesian analysis is employed to estimate the statistical distribution of the principal components and to show that the Laplacian distribution provides an accurate representation of the statistics of real data.

Mohammadreza M et al (13) discussed how to reorder the samples of a discrete spatial signal vector by defining an alternative permutation of the sensor nodes. They proposed a method to enhance CS in Wireless Senseor Networks through improving signal compressibility by finding a sub-optimal permutation of the Sensor Networks. They have shown that sub-optimal reordering stably maintains a more compressible view of the signal until the state of the environment changes so that another up-to-date reordering has to be computed. Their method can increase signal reconstruction accuracy at the same spatial sampling rate, or recover the state of the operational environment with the same quality at lower spatial sampling rate.

Jia M et al (10) formulated the problem for sparse event detection in wireless sensor networks as a compressive sensing problem. The number of sensors can be greatly reduced to the similar level of the number of sparse events, which is very much smaller than the total number of sources. By considering the binary nature of the events, they employed the Bayesian detection. They analyzed the performance of the compressive sensing algorithms under the Gaussian noise.

CONCLUSIONS

Compressive Sensing is an exciting and progressing field that has attracted considerable attention in signal processing, computer science and other areas of Engineering. We have done a short review on the applications of compressive sensing in the field of multisensory distributed networks. The importance of data processing and communication in the multisensory environment is growing with the wide range of applications. Compressive sensing can play an effective role in managing the data deluge problem for the sensor systems .The applications of CS in multi sensor fields are reviewed along with the limitations. We feel that the review will reveal the potential of the field and it will create more interest towards compressive sensing research.

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