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ENERGY EFFICIENT COMMUNICATION IN WIRELESS SENSOR NETWORKS USING COMPRESSIVE DATA GATHERING

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Abstract— **In this paper, we propose to use compressed sensing to reduce cost of data transmission in Wireless Sensor Network (WSN). We propose to exploit spatial and temporal correlation in sensor data by applying compressed data gathering that is based on compressed sensing. Simulation results show that the communication cost is significantly reduced by the proposed scheme with sufficiently less mean square error in reconstructing the original data at the sink.**

Keywords— **Wireless Sensor Network, Data Gathering, Joint Sparsity, Sparse signal reconstruction, Energy Preservation.**

I. INTRODUCTION

Wireless Sensor Networks (WSN) are widely used in various applications these days such as environment monitoring, health care monitoring, industrial and structure monitoring etc. In all these applications, power restricted sensor nodes of WSN collect raw data and transmit it to a distant sink. Since, sensor nodes possess power constraints, the available power at the sensor nodes need be utilized more efficiently. Sensor nodes basically perform sensing of data from the surrounding and local pre-processing of the data within its limited memory and computational power. Finally, the nodes transmit their sensed data to the sink via multi-hop communication while also relaying data sensed at other nodes in the network.

Among various operations consuming available battery power at the sensor node, multi-hop communication consumes a major portion of the available power. So, communication cost reduction in WSN is a major challenge which has attracted the attention of research fraternity these days. In an attempt to achieve this, it is noted that the communication cost can be reduced significantly by effectively compressing the data to be transmitted.

In WSNs, the sensor nodes are closely deployed in the field. Therefore, sensor nodes tend to measure or sense similar phenomenon. Thus, sensor readings of adjacent nodes bear large correlation among them. Also, environmental data generally do not change abruptly but changes gradually and slowly over time resulting in large temporal correlation. So, the existing correlation, both spatial and temporal, may be exploited efficiently to reduce redundancy in sensor data thereby compressing the data for cost-effective communication.

Recently, a novel paradigm of compressed sensing has evolved which is based on the phenomenon of sparse signal. According to this phenomenon, a sparse signal may be recovered exactly from far fewer number of samples than that of the traditional Nyquist rate. Compressed sensing involves simultaneous sensing and compression of the data which requires very less computational power to compress data and hence can be conveniently performed at resource constrained sensor nodes. The recovery of original signals from very less samples is a tedious task which is done at the sink with no power limitation.

Due to high spatial and temporal correlations in sensor reading, it may be represented as a sparse signal in some orthonormal basis. Subsequently, compressed sensing can be applied on the transformed signal to achieve high order of compression. Consequently, communication cost is reduced to a great extent which helps to save energy thereby achieving a longer network lifetime of the sensor network.

In this paper, we propose to reduce overall communication cost by efficiently applying compressive sensing for data gathering in WSN, also known as compressive data gathering. Here we apply compressive data gathering to exploit spatial and temporal correlations, that exist in sensor networks, to compress the data. Recovery is performed at the sink using two different recovery algorithm namely Simultaneous Orthogonal Matching Pursuit (SOMP) and M-FOCul Under-determined System solver (M-FOCUSS). Both these algorithms tend to recover multiple signals simultaneously.

The rest of the paper is organized as follows. In Section II, mathematical overview of compressed sensing is discussed in brief. Application of compressed sensing to WSN data gathering, i.e. compressed data gathering, is explained in a nutshell, in Section III. Distributed compressive sensing and joint sparsity models for WSN are explained in Section IV. Our proposed compressive data gathering scheme is explained in Section V. In Section VI, we present our simulation results. Finally, conclusions are drawn in Section VII.

II. Compressed Sensing

Compressed sensing (CS) [1] is a sampling paradigm in which sampling and compression occur simultaneously. The data rate at which signal is sampled is far less than the traditional Nyquist rate. Thus, CS can be seen as a linear dimensionality reduction technique. This dimensionality reduction of signal requires very less computational overhead which may be achieved locally at sensor nodes with less energy requirement. The tractable recovery of this under-sampled signal at the sink node is non-linear and complex but may be easily done at the sink as sink nodes are not resource constrained.

Consider an N -dimensional, discrete time, real-valued signal $\boldsymbol{x}$ such that $\boldsymbol{x} \in \mathbb{R}^N$. Using an $N \times N$ orthonormal basis $\Psi \in \mathbb{R}^N$, the signal $\boldsymbol{x}$ may be represented as

$$\boldsymbol{x} = \Psi \boldsymbol{s} \quad (1)$$

where $\boldsymbol{s}$ is an N -dimensional sparse vector. The signal $\boldsymbol{x}$ is said to have sparsity k iff there are k non-zero elements in $\boldsymbol{s}$, where $k \ll N$. Let, $\boldsymbol{y}$ be an M-dimensional measurement vector formed by M linear projections of the signal $\boldsymbol{x}$, where $M \ll N$. Thus, $\boldsymbol{y}$ may be represented as

$$\boldsymbol{y} = \Phi \boldsymbol{x} = \Phi \Psi \boldsymbol{s} = \boldsymbol{D} \boldsymbol{s} \quad (2)$$

where Φ is an $M \times N$ measurement matrix that is incoherent w.r.t Ψ and satisfies the Restricted Isometry Property (RIP), and $\boldsymbol{D} = \Phi\Psi$ is an $M \times N$ matrix known as Dictionary.

As $M \ll N$, solving the under-determined system of equation of (2) requires additional constraints to obtain a unique solution. A simple way to achieve this is *regularization*. The optimization problem involves objective function $\mathbf{J}(\boldsymbol{s})$, defined as

$$\underset{\boldsymbol{s}}{\arg min}\ \mathbf{J}(\boldsymbol{s}) \quad \text{subject to } \boldsymbol{y} = \boldsymbol{D}\boldsymbol{s} \quad (3)$$

The commonly used objective functions suggested in literature are the ℓ_0, $\ell_1$or $\ell_p$norm. The Euclidean norm $\ell_2$minimization results in unique but non-sparse solution because $\ell_2$norm is a convex function and any convex function promises uniqueness. So, $\ell_2$norm is not an appropriate solution to the CS problem. In some literature, ℓ_0 norm minimization is considered. However, it leads to a non-convex optimization problem which is NP-hard to solve. Accordingly, sub-optimal algorithms have been developed to find an approximate solution. Various sub-optimal sparse signal recovery algorithms found in the literature are Orthogonal Matching Pursuit (OMP) [2], Simultaneous Orthogonal Matching Pursuit (SOMP) [3] etc. The various algorithms based on ℓ_1 norm minimization are Basic Pursuit [4], The FOCul Underdetermined System Solver (FOCUSS) [5], and so on.

III. Compressive Data Gathering

Compressive Data Gathering (CDG) proposed by Luo et al. in [6] creatively uses CS theory for load balancing among all the sensor nodes of the WSN thereby effectively saving energy by reducing the communication cost which in turn increases the network life. Consider a chain type topology in which data collected at one node is routed to the sink through a series of other nodes (also known as motes) in between in multi-hop fashion. This is known as baseline data gathering scheme, as depicted in Fig. 1. In this scheme the nodes nearer to the sink will soon run out of resources resulting in the failure of the entire sensor network.

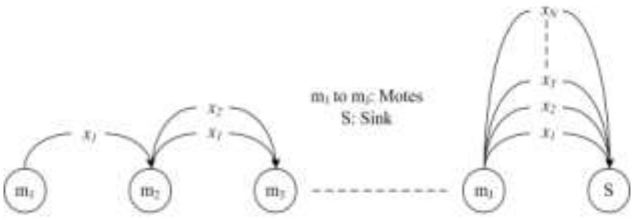

Fig. 1. Baseline Data Gathering Scheme

In order to avoid this problem of uneven load distribution, Luo et al. proposed data gathering based on compressive sensing for judicious load balancing. As sensor nodes are densely deployed in the field under observation and they read data more frequently than the rate of change in the environment, the sensor readings exhibit huge spatial as well as temporal correlations among the sensed data. By exploiting these correlations, the sensor reading can be sparsely represented in some orthonormal basis. Thus, redundant data may be removed by using compressed sensing and load may be evenly distributed among all the sensor nodes. As depicted in Fig. 2, this particular data gathering scheme delivers weighted sum to the sink.

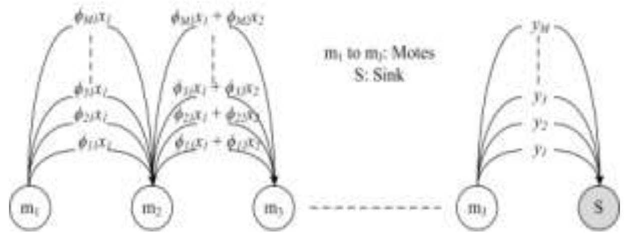

Fig. 2. Compressive Data Gathering

Thus, by using CDG, data is compressed significantly without much computational overheads. Also, CDG helps to distribute the load on all the sensor nodes in the network more evenly thereby accomplishing load balancing. This results in increased network lifetime of the entire network as compared to the baseline data gathering.

IV. DISTRIBUTED COMPRESSIVE SENISING

In WSN, each node sends a signal to the sink. Hence multiple signals are to be recovered at the sink. Extension of CS to simultaneous multiple vector is known as distributed compressive sensing (DCS). DCS can be used to recover multiple sensor signals at sink which are highly correlated and thus, can be expressed as jointly sparse. In [7], authors have suggested three joint sparsity models (JSMs) as discussed briefly below.

A. Joint Sparsity Model I

In this model, each signal is composed of two components – *sparse common component* present in all the signals and *sparse innovations* unique to each and every signal, given as

$$\boldsymbol{x}_j = \boldsymbol{z_c} + \boldsymbol{z_j}, \forall\, j = 1,2,3,\cdots,J \quad (4)$$

where $\boldsymbol{z_c}$ is the common component to all $\boldsymbol{x}_j$ and has sparsity k_c in basis Ψ and $\boldsymbol{z_j}$ is unique to every $\boldsymbol{x}_j$ having sparsity k_j in the same basis Ψ.

B. Joint Sparsity Model II

In this model, all signals are constructed from the same sparse set of basis vectors, but with different coefficients values. That is,

$$\boldsymbol{x_j} = \Psi \boldsymbol{s_j}, \forall\; j = 1,2,3,\cdots,J \quad (5)$$

where each $\boldsymbol{s_j}$ is in general different but have same sparsity k. JSM-II can be considered as a special case of JSM-I with $k_c = 0$ and $k_j = k$.

C. Joint Sparsity Model III

This model is similar to JSM-I in which the common component is no longer sparse in any basis. That is, it has *non-sparse common component* and *sparse innovation.*

V. PROPOSED EFFICIENT COMPRESSIVE DATA GATHERING

Sensor data in a WSN is highly correlated and exhibit both spatial and temporal correlations. Compressive data gathering can be used to exploit both spatial correlation and temporal correlations to achieve high compression. In this paper we propose to exploit spatial as well as temporal correlation, similar approach was proposed in [8], but in this paper we also compare the reconstruction performance using different recovery algorithms in terms of MSE of the proposed scheme. We tend to compare performance using SOMP and MFOCUSS recovery algorithms.

Let $\boldsymbol{X} = [x_{nj}]$ be the $N \times J$ matrix composed of sensor readings collected by J sensor nodes over N time instances. The, rows of $\boldsymbol{X}$ exhibit spatial correlation and the columns of $\boldsymbol{X}$ exhibit temporal correlation. As rows are spatially correlated, there exists a $J \times J$ orthonormal basis $\Theta \in \mathbb{R}^J$ in which all rows of $\boldsymbol{X}$ are sparse with support size of k_s such that $k_s \ll J$. Similarly, columns are temporally correlated so there exists an $N \times N$ orthonormal basis $\Psi \in \mathbb{R}^N$ in which all columns of $\boldsymbol{X}$ are sparse with support size of k_t such that $k_t \ll N$. This scenario is similar to JSM-II described in Section IV. Therefore, we may write,

$$\boldsymbol{X} = \Psi \boldsymbol{S} \Theta^T \quad (6)$$

where $\boldsymbol{S}$ is sparse matrix representation of $\boldsymbol{X}$.

Since $\boldsymbol{X}$ is sparse, we choose a measurement matrix Φ of dimension $M \times N$ where $M \ll J$ and is incoherent with an orthonormal basis Ψ for temporally correlated data. Similarly, we choose a measurement matrix Ω of dimension $L \times J$ where $L \ll N$ and is incoherent with an orthonormal basis Θ for spatially correlated data. Therefore,

$$\boldsymbol{Y} = \Phi \boldsymbol{X} \Omega^T = \Phi \Psi \boldsymbol{S} \Theta^T \Omega^T = \boldsymbol{D_t} \boldsymbol{S} \boldsymbol{D_s} \quad (7)$$

where $\boldsymbol{Y}$ is a matrix of dimension $M \times L$ formed by linearly projected measurements of $\boldsymbol{X}$. $\boldsymbol{D_t}$ and $\boldsymbol{D_s}^{\boldsymbol{T}}$ are the over-complete dictionaries for temporal and spatial correlated data respectively. As observed, NJ number of samples are compressed to only ML number of samples by applying DCS.

VI. SIMULATION RESULTS

Simulations were carried out with the help of real data set of sensor readings of environment monitoring deployed at EPFL. The readings of this data set are spatially and temporally correlated. In our work, we used readings of ambient temperature and relative humidity recorded by $J = 8$ closely located sensor nodes at an approximately equal distance from the sink at $N = 512$ successive time instances.

The readings were spatially and temporally correlated and were sparsely representable in Hadamard basis Ψ and Θ. The temporal sparsity of signal $k_t = 3 \ll N = 512$ and spatial sparsity of signal $k_s = 1 \ll J = 8$. The entries of measurement matrices are i.i.d Gaussian with zero mean and variance $1/M$ and $1/L$, respectively. The recovery algorithms used are SOMP and MFOCUSS. The performance of recovery by either of these algorithms was measured in terms of Mean Square Error given by

$$MSE = E\left(\frac{||X-X_0||_F^2}{||X_0||_F^2}\right) \quad (8)$$

The number of measurements M is fixed at 4 while L is varied from 2 to 200. By exploiting spatio-temporal correlation simultaneously, the compression ratio ranging from 512:1 to 5.12:1 was achieved. MSE for this compression ratio is depicted in Fig. 3 and Fig. 4 using SOMP and MFOCUSS recovery algorithms for relative humidity and ambient temperature data, respectively.

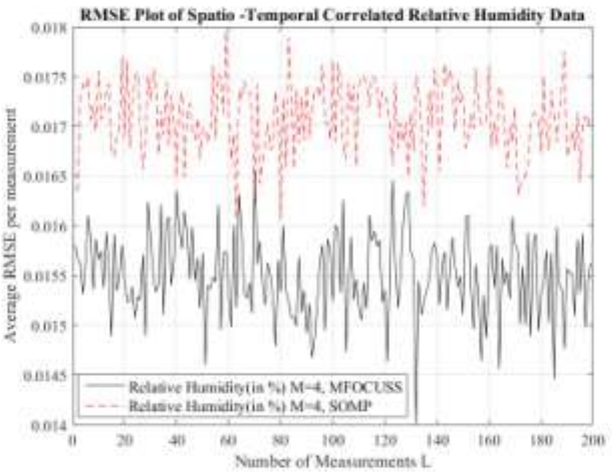

Fig. 3. MSE plot of recovered Relative Humidity data

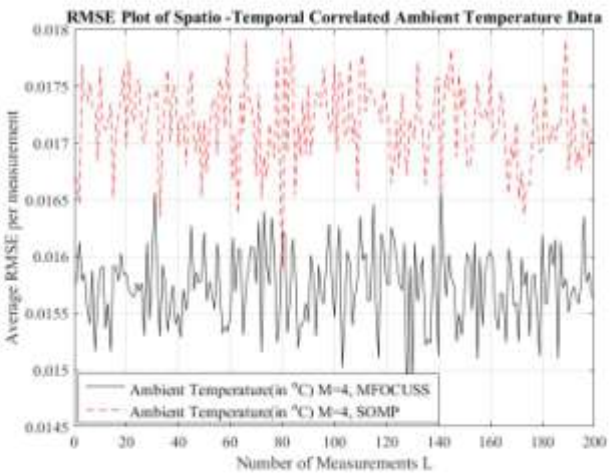

Fig. 4. MSE plot of recovered Ambient Temperature data

It can be observed from Fig. 3 and Fig. 4 that by using compressive data gathering huge compression of sensor data is achieved with negligible mean square error.

VII. CONCLUSION

Results depict that our proposed scheme is efficient to achieve high order of compression in large scale WSN. Simulation results show that our proposed scheme effectively reduces communication cost to a great extent with negligible MSE. Also, M-FOCUSS algorithm gives better performance as compared to that of SOMP algorithm for reconstructing same signals from equal number of compressed samples.

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