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# SPATIO TEMPORAL CORRELATION AWARE DYNAMIC DATA AGGREGATION FOR WIRELESS SENSOR NETWORKS

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***Abstract*—** Wireless sensor networks (WSNs) consist of large numbers of scattered sensor nodes embedded in physical space for continuous and accurate monitoring of various physical conditions. Since reliability and energy conservation are the two key considerations in WSNs, data aggregation should be exploited in order to save energy and thereby increase the lifetime of the network. Distributed Data Storage (DDS) is an efficient approach for the reliable data access. The DDS scheme based on Compressive Sensing (CS) reduces the number of transmissions and receptions during the data dissemination process which ensures an energy efficient network structure. A new class of DDS scheme, referred to as Spatio-Temporal Adaptive Compressive Sensing (ST - ACS), is proposed to reconstruct sparse or compressible signals from small number of measurements. The proposed scheme exploits both the spatial and temporal correlations among sensor readings which significantly provide an improved recovery performance with reduced number of transmissions and receptions, resulting in much higher energy efficiency. This energy efficient data collection can be proved by the adaptive node sampling method which provides more accurate data recovery than the existing approaches. Such a substantial data aggregation makes the proposed algorithm feasible in practice.

***Keywords*—** Compressive Sensing, Distributed Data Storage, Spatial Correlation, Temporal Correlation and Wireless Sensor Networks.

## I. INTRODUCTION

Wireless Sensor Networks (WSNs) are spatially distributed autonomous sensor nodes to monitor physical or environmental conditions, such as temperature, sound, pressure, etc. and to cooperatively passtheir data through the network to a main location. The more modern networks are bi-directional, also enabling control of sensor activity. The development of wireless sensor networks was motivated by military applications such as battlefield surveillance; today such networks are used in many industrial and consumer applications, such as industrial process monitoring and control, machine health monitoring, and so on. The design of a WSN depends significantly on the application, and it must consider factors such as the environment, the application's design objectives, cost, hardware and system constraints. Unlike other networks, WSNs are designed for specific applications. Each application differs in features and requirements [1].

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For volatile WSNs environments, to provide both high data availability and integrity guarantees, a data storage scheme was proposed in [2]. The decentralized coding algorithms for distributed storage in [3] are used to solve the problem related to the required number of storage nodes and source packets, in the scenarios where network nodes are vulnerable because of limited energy or a hostile environment. However, they need a large amount of wireless transmissions and receptions during the data dissemination process.

A new advanced technique in sampling theory, known as compressive sensing (CS) [4] allows representation of original signal by considering the minimum number of measurements. A clustering algorithm for random and uniform topology in WSN [5] has been proposed. In WSNs, sensor nodes with similar readings can be grouped such that, it is enough to report a single reading from the entire group. A representative node is selected from each cluster to do the reporting job. This helps to increase the battery life of sensor nodes. However, efficiently identifying sensor groups and their representative nodes is a challenging task.

To balance the energy consumption of the entire network and extend the lifetime of the network, a self adaptive and self organized clustering protocol referred as Low Energy Adaptive Clustering Hierarchy (LEACH), has been proposed in [11]. It is a typical representation of hierarchical routing protocol which includes distributed cluster formation. The mechanism of correlated data gathering based on compressed sensing [9], utilizes the joint correlation pattern of a multidimensional WSN signal ensemble via Kroneckersparsity basis. It significantly reduces the data traffic in correlated data gathering multi-hop WSNs. This signal compression and acquisition method can be used to exploit the inherent temporal and spatial correlation of the sensor signals.

A data gathering technique[7] for a denser wireless sensor network structure, the spatial correlation among them can be utilized for data compression. It effectively utilizes the compressive sensing method to reconstruct the compressible signals. The spatial proximity of nodes and the temporal behaviour of the sensing operation causes the observations sensed to be associated spatio-temporally [10]. However, due to unfavorable environmental conditions and low energy resources available in WSN, there are instances when the nodes lie within the same spatial space and measure the same attribute yet the observations sensed by them are not related. Here, this mechanism identifies the degree of association or disassociation between the nodes.

In this paper, we consider both the spatial and temporal (spatio-temporal) correlations among the sensor readings to enhance the energy efficiency of DDS and propose a new class of distributed data storage method, referred as Spatio-Temporal Adaptive Compressive Sensing (ST - ACS).The sensed readings are subjected to constitute separable sensing matrices. The Kronecker product framework is used for an efficient data recovery from the minimum number of samples. Simulation results demonstrate that, compared with the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, one of the conventional hierarchical routing protocols decreases the number of transmissions and receptions with almost the best recovery performance.

## II. PRELIMINARIES AND SYSTEM MODEL

### A. Fundamentals of Compressive Sensing

The CS theory has established that a compressible signal can be accurately recovered from a relatively small number of measurements. Basically, the rationale behind CS is centered upon two main pillars as below.

*Sparsity*: With an orthogonal basis (dictionary) $\mathbf{\Psi} \in \mathrm{R}^{N \times N}$,a signal vector $\mathbf{x} \in \mathrm{R}^{N}$ is considered compressible and $K$- sparse if $\mathbf{x}=\mathbf{\Psi}\boldsymbol{\theta}$, where the coefficient vecto r$\boldsymbol{\theta}\in\mathrm{R}^{N}$ has atmost$K(K\leq N)$ nonzero entries. It has been established in[9] that sensor readings in a WSN are often compressible due to the spatial and temporal correlation.

*Sampling*: Given the $K$-sparse signal $\mathbf{x}$ and a sensing matrix

$\mathbf{\Phi} \in \mathrm{R}^{M \times N}$ , CS is capable of recovering $\mathbf{x}$ reliably from the observationvector$\mathbf{y}\in\mathrm{R}^{M}(M\ll N)$with

$$\mathbf{y} =\mathbf{\Phi}\mathbf{x}=\mathbf{\Phi}\mathbf{\Psi}\boldsymbol{\theta}, \quad (1)$$

providedthattheequivalentmeasurementmatrix$\mathbf{A}=\mathbf{\Phi}\mathbf{\Psi}\in \mathrm{R}^{M \times N}$ satisfies RIP [4] or in most practical scenarios, low mutual coherence [4]. The mutual coherence of a matrix $\mathbf{A}$ is defined as

$$\mu(\mathbf{A}) = \max_{1 \leq i \neq j \leq N} \frac{|\langle a_i, a_j\rangle|}{\|a_i\|_2 \|a_j\|_2}, \quad (2)$$

where $a_i$and $a_j$ denote the columns of $\mathbf{A}$. According to [4], a smaller value of $\mu(\mathbf{A})$ will lead to a more accurate recovery of$\mathbf{x}$.

*Sparse Solution*:Under this scheme, three properties of matrices; the spark, the mutual incoherence and the restricted isometry property have recently been introduced in CS. These properties for matrices that are Kronecker products and show how these properties relate to those factors. For the mutual incoherence the results for sums of Kronecker products can be used.

### B. System Model

We consider a WSN with $N$ nodes randomly and uniformly distributed in a unit square area. $N$ nodes are assumed to have an identical transmission radius $r$, and thus any two nodes are connected if their distance is smaller than $r$.According to [8], this guarantees the connectivity of the whole network with a high probability. Each node is assumed to have a large storage capacity, thereby allowing multiple data packets to be stored. Sensor readings are assumed to exhibit both spatial and temporal correlations.

## III. PROPOSED SCHEME

In a hierarchical wireless sensor network structure, the Spatio-Temporal Adaptive Compressive Sensing (ST - ACS)is performed. The system is considered to have n number of nodes with a large storage capacity, which are scattered randomly in the desired environment in order to monitor the corresponding environmental conditions.

### A. Spatial Correlation Model

The proposed scheme of similarity based cluster formation increases the life time of the network by forming effective cluster regions. Here, each node will send the basic configurations such as node identification, residual power, measured data, etc. to their neighboring nodes within their transmission radius. Based on the received details each node analyzes their characteristics and identifies their level of superiority with respect to their neighbors. As a result, the node with the highest energy level will take the role as a Cluster Head (CH).

Each cluster head will collect the corresponding data (sensed information) from their neighbors and compare with their available information. The sensor readings having more similarities with that of the cluster head will be considered as the Cluster Members (CMs) to the respective cluster heads. Therefore, the network

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structure consists of number of clusters each with a single CH and the respective highly correlated CMs. Each distributed cluster is responsible for sensing and measuring the physical phenomenon of data in the sensor region. The spatially correlated data, aggregated at the CHs are processed and stored according to the Compressive Sensing (CS) based distributed data storage scheme. Adaptive sampling is performed in order to improve the level of CS. Then the appropriate data will be sent to the sink node.

The correlations among the sensor nodes with respect to the neighboring clusters can also be considered effectively with the help of the Pearson correlation estimator. Since CHnodeverifies the data accuracy for their respective distributed cluster, it reduces the power consumption, data redundancy and communication overhead which in turn increase the lifetime of the networks. The resultant characteristics of the proposed scheme are compared with the LEACH protocol [11] and that reveals the effectiveness of the Trend and Magnitude based Similarity Clustering scheme.

### B. Time Correlation Model

Data collected at different time intervals from a specific sensor may be correlated if the set of collected data varies in a similar way. This is referred as temporal correlation. Due to the nature of the physical phenomenon, there is a significant temporal correlation among each consecutive observation of a sensor node and gathered data is usually similar over a short-time period. Thus, in these cases, sensor nodes do not need to transmit their readings if the current reading is within an acceptable error threshold regarding the last reported reading. The sink node can just assume that any unreported data is unchanged from the previously received ones. The degree of correlation between consecutive sensor measurements might vary according to the characteristics of the phenomenon.

Since the data generated by sensor nodes duringcontinuously monitoring periods usually are of hightemporal correlation, it indicates that there areredundant data in the successive data sequence,which causes unnecessary data transmission andenergy consumption. Here, we focuson data transmission reduction and correspondingenergy saving between sensor nodes and aggregators. The proposed time correlation scheme utilizes ARIMA model [14] to predict the dataof next several periods at both ordinary sensors andaggregators based on the same amount of recentlysensed values. The ordinary sensors and aggregators work coordinately to reduce the amount of messagestransmitted within the network.

The main idea behind this scheme is to decrease the number of transmitted data values between sensor nodes, aggregatorsand sink node by utilizing time series prediction model. This can effectively save the energy of wireless sensor nodes while keeping the predicted data values within application-defined error threshold.

### C. Spatio-Temporal Correlation Model

The spatio-temporal correlation happens when the nature of the collected data has both spatial and temporal correlations, i.e., nodes close geographically have the same reading that is similar to the previous one. In this case, solutions that use both correlations can takeadvantage of the nature of the detected event to decrease the number of reported data. This model combines both the effective trend and magnitude based similarity clustering and ARIMA model based temporal correlation. Thus the proposed ST-ACS scheme yields a reliable and efficient data recovery with reduced number of transmissions.

The recovery accuracy is improved by Kronecker product structure [6]. The metrics used to make performance comparisons are the normalized mean absolute error(MAE) which isused to evaluate the recovery accuracy and the number of transmissions which is to measure the level of energy efficiency.

## IV. SIMULATION RESULTS

The simulation of our proposed scheme considers the reference network comprising of 100 nodes distributed randomly in an area of 100 m × 100 m along with a Base Station (BS) which is located at the position of (50, 50).The other required parameters under consideration are the amount of transmission energy = 50 nJ/bit, Efs= 10 pJ/bit/$m^2$ and Emp= 0.0013 pJ/bit/$m^4$. The energy for data aggregation is set as EDA = 5 nJ/bit/signal.The transmission radius of each node is taken as a radius of 25m. The cluster heads are responsible for aggregating their corresponding cluster member's data.

The mean absolute error is estimated for various values of error threshold and the related variations are plotted in the form of a graph in Fig. 1.

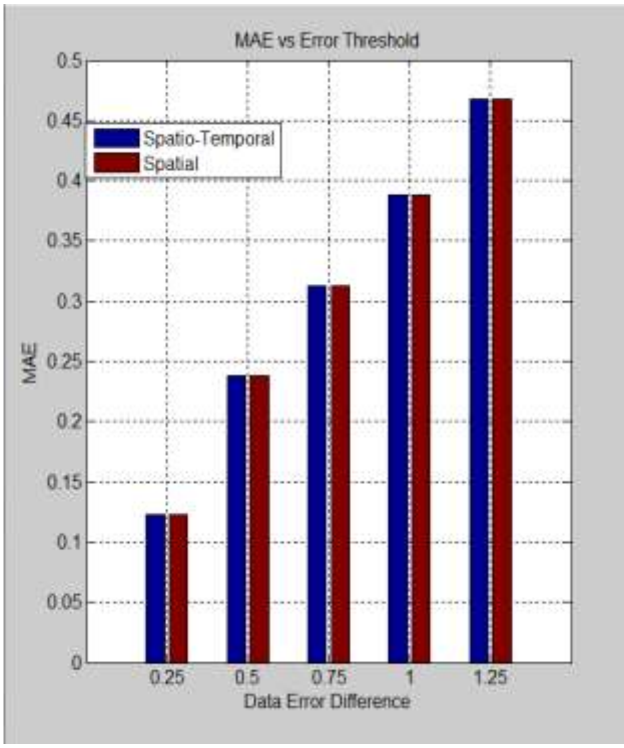


**Figure 1 : MAE Vs Threshold**

The relationship between the network energy levels and the different values of error threshold is depicted in the below Fig. 2.

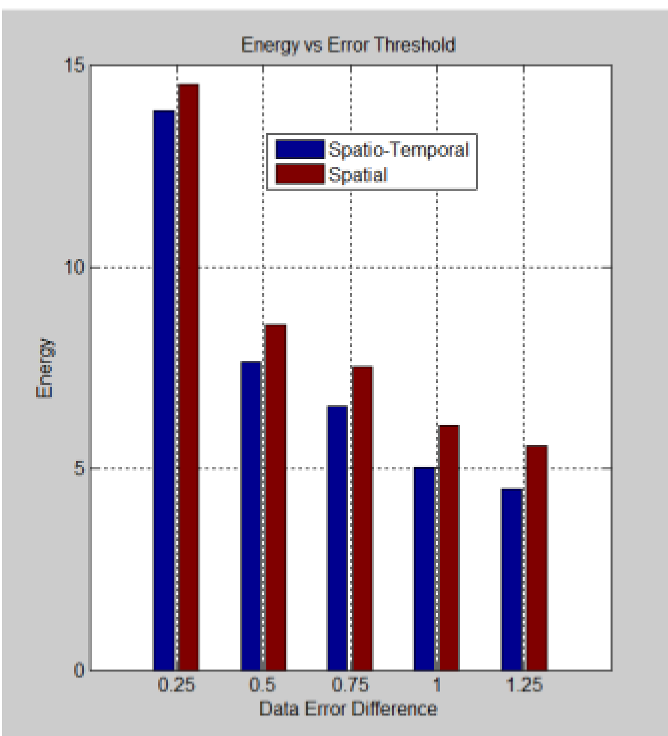


**Figure 2 : Energy Vs Threshold**

The accuracy level of data is represented in Fig. 3 with respect to the actual data representation obtained from the individual node measurements.

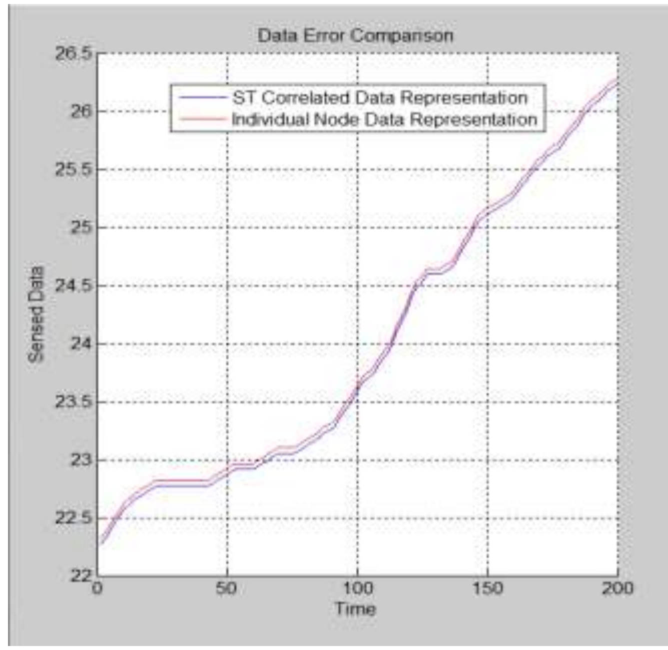


**Figure 3 : Accuracy Level of Data**

The reduced energy consumption of the nodes by using the proposed ST-ACS scheme is evident from the following Fig. 4.

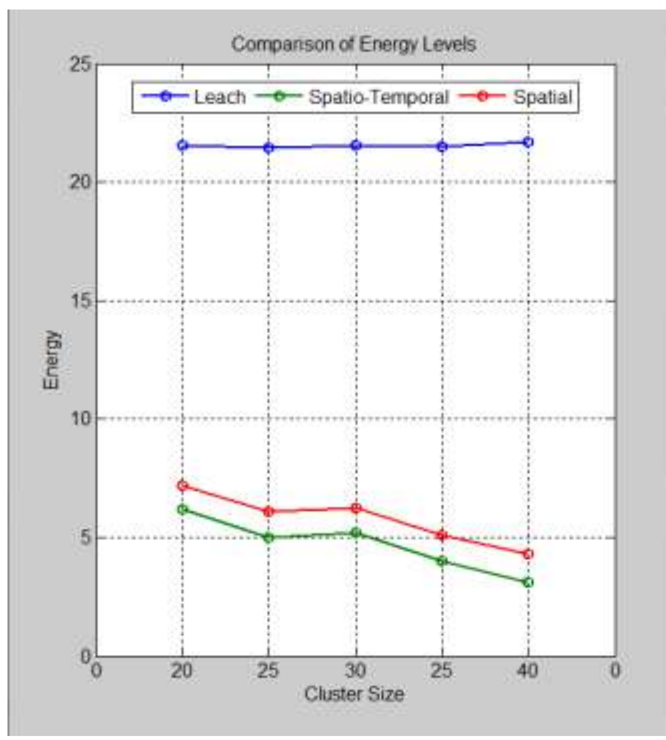


**Figure 4 : Comparison of Energy Levels**

# V. CONCLUSION

Thus, the optimum performance of the proposed ST-ACS scheme is validated from the simulated results. By an effective utilization of spatialand temporal correlations among the sensor readings, this scheme provides an improved energy efficiency and reliable data recovery.

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