Neighbor Aided Compressive Data Gathering In Wireless Sensor Networks

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***Abstract*— The integration is energy efficient paradigms which is between data collection methods in Wireless Sensor Networks (WSNs) and Compressive Sensing (CS). This paper introduces a new structure to construct fast and efficient sensing matrices for practical compressive sensing, called structured random matrix (SRM). Compressive sensing (CS) decreases the amount of data transmission and balances the load of traffic throughout the network. In this paper, a neighbor aided compressive sensing (NACS) scheme is proposed for efficient data gathering in spatial and temporal correlated WSNs. The Base Station (BS) implements a CS reconstruction algorithm to recover all raw sensor readings precisely based on a certain number of measurements. Each sensor neighborhood measurements for both one hop and multi hop transmissions is to forward compressive sensing and the Base Station are to be considered. The NACS model can achieve vastly recovery performance and receptions with much fewer transmissions.**

Keywords—Compressive Sensing, WSNs, Neighbor Aided Compressive Sensing, Kronecker Compressive sensing

I. INTRODUCTION

Wireless sensor networks(WSN)[10] have received significant attention due to their flexibility and have been deployed widely in applications ranging from health monitoring of environment, traffic, structural, and critical infrastructure, many applications need sensors to periodically sense and send sensory data to a remote central unit (e.g. sink) for processing, often through multi hop paths These energy limited sensors, once arrayed, may receive little or no maintenance; hence gathering data in the most energy efficient manner becomes critical for the longevity of WSNs. one of the most efficient methods for collecting sensed data en route to the sink is through aggregation. One form of data aggregation denotes to the process of computing statistical metrics, which provides a instant of the data collected by the sensors and avoiding expensive transmissions of all sensed data, typically from a large number of sensors to a possibly distant sink. Sensors are small and inexpensive wireless devices that live on pre-charged batteries that drain power quickly. Saving energy in WSNs is always a critical problem that focuses on data gathering methods to extend the network lifetime.

Compressed sensing [1] is a signal processing system for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear system. This is based on the principle that, through optimization, the sparsely of a signal can be exploited to recover it from far fewer samples.

In every sensor network applications, such as Industrial observing, environmental monitoring systems, Sensor nodes require to gather data periodically and transfer them to the sink through multi hops. According to experiments, data communication takes energy consumption of sensor nodes. So it has become an important problem to reduce the amount of data transmissions in sensor networks. In sensor networks compressive sensing (CS) opens new technique for data collection and target localization in. The sub spatially reduce the amount of data transmissions and balance the traffic load throughout the entire network by CS. Compressive sensing address the inefficiencies by directly obtaining a compressed signal representation without going through the intermediate stage of obtaining N samples.

Different sensing frameworks have been investigated. Among them Structured Random Matrix (SRM) offers a practical method to sampling. And it has high sparsity, low complexity and fast computation properties and has sensing performance comparable to that of completely random sensing matrices. Kronecker [4] product sparsifying bases join the structures encoded by the sparsifying bases for each signal dimension into a single matrix. On each signal dimension, the sequence of independent multiplexing operations used to implement kronecker product measurement matrices. The propose Kronecker product conditions as sparsifying bases for multidimensional signals to jointly model the signal structure along each of signal dimensions. In certain cases, for example Kronecker product wavelet bases, are obtained by theoretical bounds for the rate of decay of the signal coefficient magnitudes for certain kinds of data. This rate of decay is dependent on the rates of decay for the coefficient magnitudes of sections of the signals across the different dimensions using the individual bases.

In this paper, several contributions have been made to improve the sensing performance and the energy efficiency of compressive data gathering. Firstly, a neighbor-aided data gathering framework is proposed to develop both spatial and temporal correlations with much less data transmissions. In this paper propose a new paradigm of generating measurements combined with two ways of gathering those CS measurements to the BS. When a sensor is randomly picked to generate Compressive Sensing measurements, all nodes within its neighborhood send their readings to it. Sensor node generates a linear measurement by multiplying the received data and it including its own reading to a random Gaussian vector. The measurement is sent to the base station by two proposed methods: first one is directly to the BS or through in-between sensors.

The total power consumption at each method and then is compare in both simulation and analysis results. The network's characters are considered and suggested for further energy saving. In this section, consider some gathering algorithms employing CS for energy saving purposes proposed two techniques for obtaining CS measurements. Sensors locally multiply their data to a pseudorandom number in randomized gossiping method, then pass the products to their neighbors based on a transmission range.

II. PRELIMINARIES AND NETWORK MODEL

A. Compessive sensing basic

1) Signal sparsity presentation: Signals are to be sparse in a proper domain In order to apply CS.

$$\phi = \phi_{i,j} \in \Re^{N\times N} \tag{1}$$

A signal $y = [y_1 y_2 ... y_N]$ $T \in RN$ is defined to be k-sparse if it has a sparse representation: $y = \phi\theta$ and θ has only k non-zero elements.

2) Signal sampling: a k- sparse signal can be recovered from only M measurements and they are under sampled (M ≪ N) denoted as $x = [x_1 x_2 ....x_M]$ is $T \in R_M$ Based on the CS paradigm. The CS measurements are generated by vector $y = \psi_x$, where $\psi = [\psi_{i,j}] \in R_M \times N$ is called the measurement matrix and is often a dense Gaussian matrix or a sparse binary matrix

3) Signal recovery: The k-sparse signal reconstruct with high possibility from only $M = O(k \log N / k)$ CS measurements employing the following l1 optimization problem

$$\hat{\theta} \ \arg\min \|\theta\|_1, \text{ subject to } y = \Phi\Psi\theta, \tag{2}$$

Where $\|\theta\|_1 \sum_{i=1}^{n} |\theta_i|$ and $\hat{x} = \Psi\hat{\theta}$. The l1 optimization problem can be solved with linear programming techniques such as Basis Pursuit (BP).

B. Related work

Data collection [2] methods in general have been studied well in many research studies for WSN also for mobile. Sensor network (MSNs). In this section, only consider some gathering algorithms employing Compressive Sensing for energy saving purpose proposed two techniques for obtaining CS measurements. In randomized gossiping method, sensors are multiply their data to a PR number, the products are passed to their neighbors and it based on a transmission range. These products are added up together to form measurements for the CS recovery process at the BS. The other method uses cluster-heads to gather data routing methods to collect CS measurements. In these methods each CS measurement is created from all sensors.

To the best of our knowledge, this work is the first to investigate the integration between CS and sensor neighborhoods. CS measurements are generated from M and N random sensor neighborhoods and are transmitted to the BS for CS recovery processes.

C. Network model

Let as consider a single-sink wireless sensor network, it is used for data gathering which consist of N sensors, with Identification numbers (ID) of $x = \{1,2,...., N\}$ accomplished of transmitting, receiving and conveying data. The sensors are organized and send out randomly in a unit square area to periodically monitor data.

That a pre-defined rate, and to distribute the acquired information to the sink. The sink for gaining an accurate reconstruction of the monitored field, for each sensing period. It's also recover the readings during the sensing period of all N sensors. For all nodes Radius r is identical transmission, and thus any two any nodes are connected if their distance is smaller than r. the sensor observations are assumed to encompass both spatial and temporal correlation.

III. NEIGHBOR AIDED COMPRESSIVE DATA GATHERING

A. Data gathering protocols

In this paper the data gathering protocol is proposed. The proposed NACS scheme is considered a realistic scenario, where the sensor readings across all the nodes exhibit both spatial and temporal correlations.

During every sensing period t, the sensing network of n nodes produce a compressible sensor reading block $X \in \Re^{n\times t}$ .And it includes, Initialization, Forwarding ,Mixing, Gathering. The data structures of θ_l is given by

$$\phi_l = \begin{Bmatrix} \phi_l.src \\ \phi_l.nbr \\ \phi_l.dat \end{Bmatrix} \tag{3}$$

Where the .src is the ID of the node who generates it, the .nbr is the ID of the node who processes it, and the .dat stores the data of the packet.

1) Initialization:

M and N nodes are first randomly selected for gathering. The identification number of the selected nodes are denoted by $l = (l_1\ l_2,..., l_{m)} \in x$. Collecting information are sent to those nodes by the sink node.

2) Forwarding:

When a node $\Theta_l, l \in I$ received collecting information, it randomly selects a neighbor $\Theta_b b \in x$. It uses its original sensor readings to form a transmission packet by,

$$\phi_l = \begin{Bmatrix} \phi_l.src = l \\ \phi_l.nbr = b \\ \phi_l.dat = x_l \end{Bmatrix} \qquad (4)$$

Afterward, the node transmit the data to the designated neighbor.

3) Mixing:

Once a neighbor node and received a sensing packet, it mixes the received packet and its own packet by,

$$\alpha_c = \begin{bmatrix} \phi_l.dat \\ v_c \end{bmatrix} = \begin{bmatrix} v_l \\ v_c \end{bmatrix} \qquad (5)$$

Then, Fast permutation algorithm used to permutation.it permutes the vector α_c .

4) Gathering:

On the assumption that the packet data is mixed and processed, across conventional routing protocol the neighbor node sends the packet to the sink node. The sink node get M packets, which can be expressed

$$\text{By } \phi_{l_i} = \begin{Bmatrix} \phi_{l_i}.src = l_i \\ \phi_{l_i}.nbr = l_i \\ \phi_{l_i}.dat = D_{(b_i')}\left(I_e \otimes W_{(b_i')}\right)\left(p_{b_i'}\begin{bmatrix} v_{l_i} \\ v_{b_i'} \end{bmatrix}\right) \end{Bmatrix} \qquad (6)$$

B. Structure formulation

For easiness, let $D_{(b_i')} = D_p, W_{(b_i')} = W_d$, and $P_{(b_i')} = P_p$,the measurements of the sink node can be expressed by,

$$U = \theta_p \Re^{s,t}_{p,q}(X) D_q \qquad (7)$$

Based on the nature of probability, $\Phi_q = D_q = D_q I_q R_q$ and it can be vectored as.

$$\begin{aligned} U &= \left(\Phi_q \otimes \Phi_p\right)x \qquad (8) \\ &= \left(D_q I_q R_q \otimes D_p F_p R_p\right)\omega\xi \\ &= DFR\omega\xi \end{aligned}$$

This denotes KCS satisfies the qualification of SRM model. The NACS model proposed to further improve the performance of KCS by introducing the idea of SRM to its framework.

M and N random chosen sensors send data from their neighborhoods defined by the transmission range R to the BS. In NeiCS nodes which do not get any example asking for data after the listening period can go to sleep to save energy. Besides, M sensors are picked randomly at each surveillance time can help balance energy for such networks. In this section additionally gives two ways to transmit measurements from each random neighborhood to the BS: one-hop directly and multi-hop through active nodes, which are analyzed and formulated in the next section.

One-hop and multi-hop algorithm can work well with fault tolerance in the network. Since we only take one measurement from each neighborhood separately, each node is only responsible to the others within its neighborhood.

IV RESULTS AND DISCUSSION

For simulation NS2 has been used. The below figure show 1350 X1100 with 43 number of sensor nodes. The network is spitted into three regions and each region has one Access Point. There is a common Base station and Access point for three regions. Some sensor nodes act as L-AP (local access point).

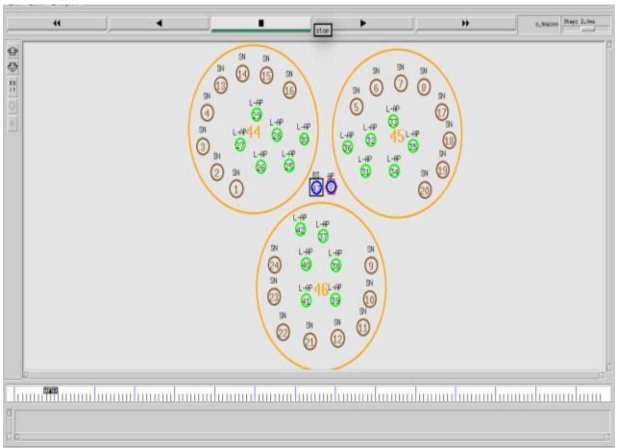

Fig.1 sensor node deployment with AP, BS

This results shows that impact of weight on data aggregation from AP. Then Access point 1, access point 2 and access point 3 are compared in accordance with amount of data gathered.

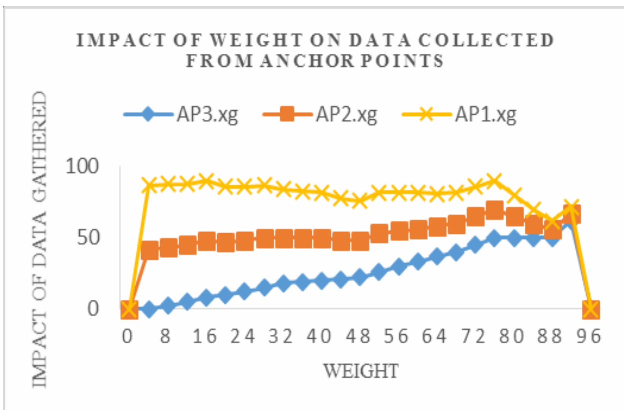

Fig.2 Impact of weight on data collected

This results shows that Impact of weight on data aggregation from different sensors. Sensor2.xg sensor8.xg and sensor16.xg are compared in accordance with amount of data gathered and weight.

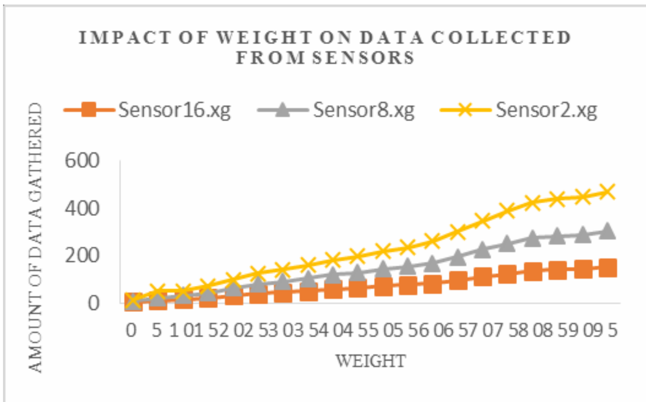

Fig.3 Impact of weight on data collected from sensors

The given result shows that Comparison of Average data collection latency.1hop.xg, 2hop.xg, 3hop.xg and 4hop.xg are compared in accordance with average packet latency in minutes and number of nodes. Then the latency is different in one hop from another hop. In hop1 latency is high and also future work is to reduce latency.

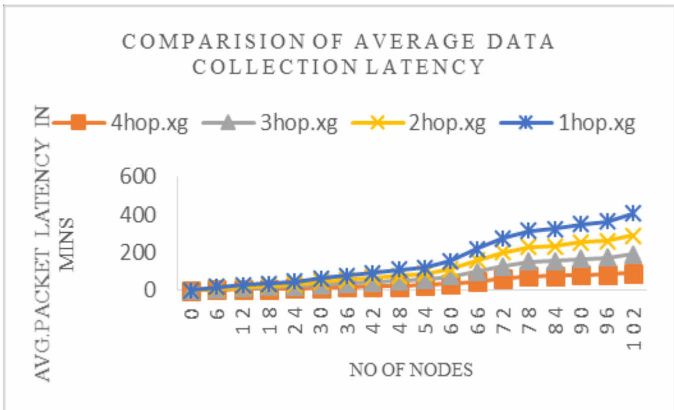

Fig.4 Data collection latency

While comparing both COMpSense1.xg and J-COMpSense1.xg the proposed system achieves better network lifetime and consequently the energy consumption is reduced. In accordance with the energy consumption during compressive data gathering, in future the computation energy depends on the chips used and the communications cost relies on the distance and the data length, then the energy consumption of the protocol could be evaluated by complexity analysis and counting the number of transmitted packets of each sensing period.

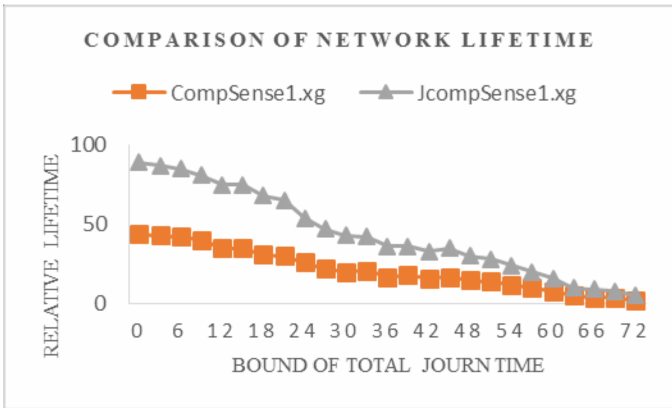

Fig.5Comparison of Network lifetime

V CONCLUSION AND FUTURE WORK

This work proposed a new NACS model for efficient compressive data gathering of spatial and temporal correlated WSNs. By using the spatial temporal compressive sensing algorithm in the proposed system, better network lifetime performance has been achieved when compared to the existing system. The sensor node transmit the data packet to the other node through local access point, then the packets are further transmitted to the different regions by the base station. At the BS the packets are compressed and energy consumption is reduced. And so the memory space is greatly reduced but this algorithm achieves high latency value. In future work this may be overcome by adopting various algorithm and techniques.

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