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Compressive Data Gathering using NACS in Wireless Sensor Network

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Abstract - *Wireless sensor networks are useful in such area where the human being is unable to go and monitor. Compressive sensing (CS) has been used widely for the gathering of data in wireless sensor networks for the purpose of the communication overhead recent years. Structured Random Matrix (SRM) offers a practical method to sampling. It has high sparsity, low complexity, fast computation properties and has good sensing performance comparable to that of completely random sensing matrices. In this paper, Neighbor-Aided Compressive Sensing(NACS) scheme is proposed for efficient gathering of data without any data loss in spatial and temporal correlated WSNs. During every sensing period, the sensor node sends the raw readings within the sensing period to a uniquely selected shortest neighbor. Simulation results demonstrate that compared with the conventional KCS (Kronecker Compressive Sensing) models and SRM, the proposed NACS model can achieve efficient data gathering and recovery performance with much fewer transmissions.*

Key Words: Compressive sensing, WSNs, Data gathering, Structured Random Matrix, Kronecker Compressive Sensing, Neighbor-Aided Compressive Sensing.

I. INTRODUCTION

Wireless Sensor Networks [1] (WSNs) is a collection of sensors that are spatially connected together with the network to monitor the environmental and physical condition such as pressure, sound, temperature, humidity etc. and transfer the data to the server location. Fig.1 shows the connection of sensor nodes with gateway node. Wireless sensor network is used in some of the applications like precision agriculture, medicine and health care, machine surveillance and preventive measures and so on.

Compressed Sensing or Compressive Sensing [2] is about acquiring and recovering a sparse signal in the most efficient way possible (subsampling) with the help of an incoherent projecting basis. Unlike conventional sampling methods, Compressive Sensing provides a new framework for acquiring sparse signals in a mutiplexed manner. Compressive Sensing (CS) provides a new approach to simultaneous sensing and compression that promises a potentially large reduction in sampling costs and the required number of measurements to recover the original signal. The main requirement for CS is that the signal to compress has to be sparse in some basis to be able to recover the original signal from the shorter compressed version.

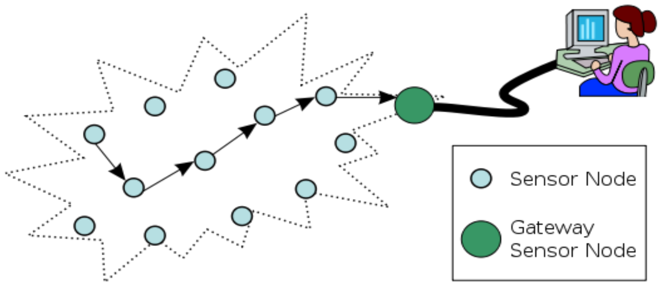

Fig -1: Wireless sensor network

Structured Random Matrix [3] (SRM) is a sensing matrix that offers a practical method of sampling. It has high sparsity, low complexity, fast computation properties and has sensing performance comparable to that of completely random sensing matrices.

Kronecker compressive sensing [4] (KCS) is recently introduced compressive sensing method to exploit general correlation patterns by combining the possibly distinct sparsifying bases from each signal dimension into a single basis matrix. In terms of improving compression performance and decreasing sensor energy expenditure with signals featuring typical WSN data characteristics, KCS has been empirically shown to outperform.

Neighbor-Aided Compressive Sensing [5] (NACS) scheme is a proposed system for data gathering through wireless sensor network for transfer of data to sink node with efficient performance.

Notations: We use boldface letters to denote vectors (lowercase) and matrices (capital), and calligraphy letters to denote sets. An entry of matrix **A** at its i-th row and j-th column is denoted as a_{ij} . The matrix **A** of size N × N is denoted as $\mathbf{A}_N$ and when **A** is the i-th matrix of a matrices set, it is denoted as $\mathbf{A}^{(i)}$. $(\cdot)^T$ denotes the matrix transpose, $\otimes$ denotes the Kronecker product, vec (**A**) stacks the columns of **A** into a column vector, and $\Re_{s,t}$ (**A**) reshapes matrix **A** of size s × t to a matrix of size p × q (st = pq).

II. EXISTING SYSTEM

SRM is a conventional technique used for a practical method of sampling data. It has low complexity, high sparsity and also fast computation properties. Sensing performance of SRM is comparable to that of randomly sensing matrices. And, KCS compressive technique is used to combine distinct sparsity bases from each signal dimension into single basis matrix. In terms of improving compression performance and decreasing sensor energy expenditure with signals featuring typical WSN data characteristics, KCS has been empirically shown to outperform single-dimensional Compressive sensing approaches. However, the SRM is not applicable for WSNs and the KCS model suffers increased data dimension which could result in degraded recovery performance.

III. PROPOSED SYSTEM

To improve the sensing performance and the energy efficiency of compressive data gathering there was several different contributions were made. Fig 2 describes the full flow of data from source node to sink node. Firstly, a neighbor aided compressive data gathering framework is proposed to exploit both spatial and temporal correlations with less data transmissions. In this technique, the sensor node just send the raw data with consecutive time slots to shortest neighbor node. The neighbor node applies the compressive sensing measurement and sends the data to the sink node. The NACS requires only one neighbor node for each sampling node, resulting in lower communication cost and higher energy efficiency. Secondly, we generalized the conception of KCS and proved that the equivalent sensing matrix can be constructed by the Kronecker product of temporal and spatial sensing matrices. Last but not least, as the main contribution, the relationship between KCS and SRM is studied, and the sensing performance of conventional KCS is further improved by introducing the idea of SRM to KCS to form equivalent sensing matrices.

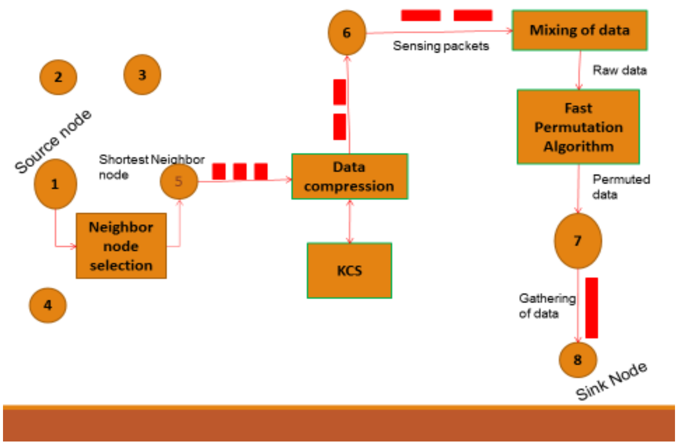

Fig - 2: System architecture

IV. MODULES

1) Configuring the nodes

Firstly, M of N nodes are randomly and uniformly selected for gathering. And gathering commands are sent to these nodes by the sink node. As shown in Fig 3 Each node of the sensor is represented by different colors. Note these nodes can also be activated by predefined periodic scheduling scheme in practice.

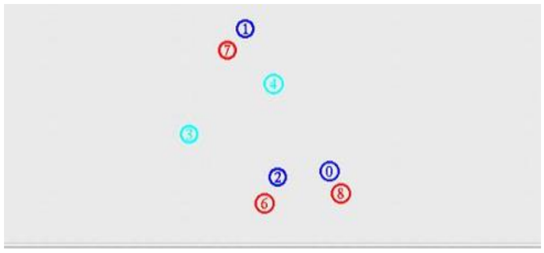

Fig - 3: creation of nodes

2) Forwarding data to neighbor node

Once a node received the gathering commands, it randomly selects a neighbor. Then, it uses its original sensor readings to form a transmission packet. After that, the node transmits the packet to the selected neighbor. Each node is set to act as a unique role between generator and neighbor, namely a node can only be sampling node or the unique neighbor of a specified sampling node. As shown in fig. 4 data is transferred from node 3 to node 5 with less data loss. If a sampling node received a transmission packet, then the node selects another neighbor of itself randomly and uniformly. The node updates the packet and transmits the packet to the updated neighbor. In case of the received second packet and the later packets, the neighbor node relays the packet to its neighbor as above. After this procedure, the updated neighbor ID list **b**′ satisfies.

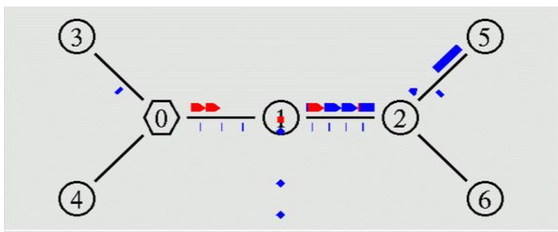

Fig - 4:Forward data to neighbor node

3) Compressing data packet

When a neighbor node received a sensing packet, firstly, it mixes the received data and its own data by Secondly, it permutes the vector using a fast permutation algorithm (Algorithm 1), whose computational complexity is $o(N)$.The fast permutation operation is equivalent to left product a permutation matrix **P**(c) Thirdly, the mixed data is reshaped to a data block of size and fast transform of the data block is computed with an orthogonal transform matrix **W**(c) .At last, the transformed data block is vectored and uniformly down sampled at random by a random down sampling matrix **D**(c) as measurements. Then the packet is updated.

Algorithm 1: Fast Permutation Algorithm

Input: Raw data sequence: $\lambda c = (\lambda 1, \lambda 2, \ldots \lambda n)$
Maximum number of iteration:n
Output: Permuted data sequence: $\lambda c = (\lambda 1, \lambda 2, \ldots \lambda n)$

for *i* **from** 1 **to** *n* **do**

Generate a random number $r \in [1, i]$

Exchange λi and λr

end for

4) Gathering neighbor node data

The proposed NACS scheme considers a realistic scenario, where the sensor readings across all the nodes exhibit both spatial and temporal correlations. Denote that the routing protocol has been initialized and the unique ID and the random seed for each node have been set. During every sensing period t, the sensor network of n nodes produces a compressible sensor reading block X ∈ R n×t . Let X = (x1, x2, . . ., xn), where xi = (x1,i , x2,i , . . ., xt,i)T is the i-th column of the reading block. The node with ID l, l ∈ χ is denoted as Θl and its generated (excluding the modified) packet is denoted as θl . The data structures of θl is given by

$$\theta_l = \begin{cases} \theta_l.src \\ \theta_l.nbr \\ \theta_l.dat \end{cases} \quad (1)$$

Where the .src field is the ID of the node who generates it, the .nbr field is the ID of the node who processes it, and the .dat field stores the data or payload of the packet. 1) Initialization: Firstly, M of N nodes are randomly and uniformly selected for gathering. The IDs of the selected nodes are denoted by l = (l1, l2, . . ., lm) ∈ χ. And gathering commands are sent to these nodes by the sink node. Note these nodes can also be activated by predefined periodic scheduling scheme in practice. 2) Forwarding: Once a node Θl , l ∈ l received the gathering commands, it randomly selects a neighbor Θb b ∈ χ. Then, it uses its original sensor readings to form a transmission packet by

$$\theta_l = \begin{cases} \theta_l.src = l \\ \theta_l.nbr = b \\ \theta_l.dat = \mathbf{x}_l \end{cases} \quad (2)$$

After that, the node transmits the packet to the selected neighbor. Each node is set to act as a unique role between generator and neighbor, namely a node can only be sampling node or the unique neighbor of a specified sampling node. If a sampling node received a transmission packet θl , then the node selects another neighbor of itself randomly and uniformly, whose ID is denoted by b ′ . The node updates the packet by θl.nbr = b ′ and transmits the packet to the updated neighbor. In case of the received second packet and the later packets, the neighbor node relays the packet to its neighbor as above. After this procedure, the updated neighbor ID list b ′ satisfies b ′ ∩ l = ∅ and for any i , j, b ′ i , b ′ j .

V. NETWORK MODEL

We consider a **single-sink multi-hop** WSN for data gathering, which consists of *N* sensors, with identification numbers (ID) of χ = {1, 2, . . . , *N* }, capable of transmitting, receiving and relaying data. The sensors are deployed randomly and uniformly in a unit square area to periodically monitor data at a pre-defined rate, and to disseminate the acquired information

to the sink. For each sensing period, the sink is responsible for obtaining an accurate reconstruction of the monitored field, i.e., to recover the readings during the sensing period of all *N* sensors. All the nodes are assumed to have an identical transmission radius *r*, and thus any two nodes are connected if their distance is smaller than *r*. It is further assumed that the condition *r*2 > ln (*N*)/(π *N*) is satisfied, which guarantees the connectivity of the whole work with high probability. The sensor observations are assumed to encompass both spatial and temporal correlation, typical for various environmental sensing applications in densely deployed WSNs. For formation of wireless sensor network we consider the 64 sensor nodes for initialize. As we proceed the source node selects the nearest neighbor node, then the CS measurement is made in the neighbor node and the compressed sensing data is passed into the sink node.

VI. PERFORMANCE COMPARISON

Performance comparison is a final simulation of network to compare the data gathering performance of other models like KSRM-0,KSRM-1, KGAU-0, KGAU-1, GAU-G with the proposed system model of NACS-0, NACS-1 to show as shown in fig.6.1 that the performance of NACS is much better than other model like global Gaussian (GAU-G), the KCS model with sensing matrices of each signal dimension as Gaussian matrices (KGAU-0) represents the optimal performance of conventional KCS model Note that the analysis was taken directly without changing of sensing parameters, In other words, the NACS model achieved superior sensing performance with much fewer transmutations (energy consumption) than the conventional KCS model. The total numbers of transmitted packets of these three models were counted with the sensing period increasing from 10 to 500. The resultant graph of simulation is based on the axis of signal sparsity and probability of exact recovery.

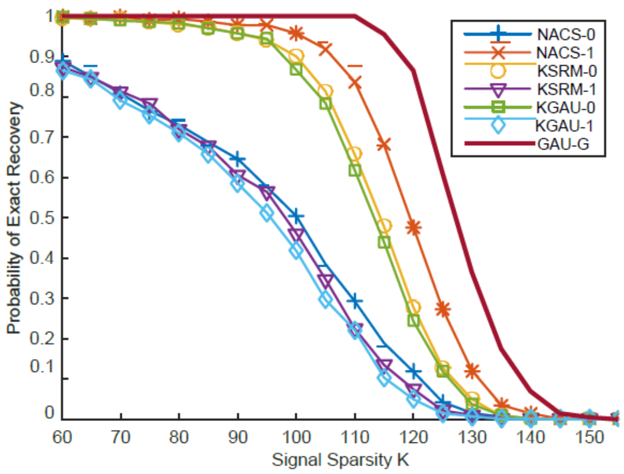

Chart 1: Performance curves: probability of exact recovery versus sparsity *K*. The curves indicate that the performance of NACS model outperforms than that of the conventional KCS model.

VII. CONCLUSION AND FUTURE WORK

NACS is proposed in this paper under the framework of KCS for efficient compressive data gathering of spatial and temporal correlated WSNs. NACS has improved the performance of conventional KCS, meanwhile, greatly decreased the data loss in WSNs. However, the recover complexity might be slightly increased. Fortunately, the decoder side always has powerful compute ability in realistic scenarios. We will take the fast and paralleled recovery algorithm as our future work.

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