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Efficient Data Gathering with Network Coding Coupled Compressed Sensing for Wireless Sensor Networks

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Abstract: This study presents an efficient communication scheme in Wireless Sensor Networks (WSNs) for data gathering, called Network Coding Coupled Compressed Sensing (NCCS). We employ network coding to adapt to the dynamic nature of WSNs, such as moving obstacles and link failure. Measurements from sensor networks are often correlated because sensors nodes nearby observe the contiguous phenomenon and the operation of the Random Linear Network Coding (RLNC) scheme is similar to that of the random projection in Compressed Sensing (CS). Therefore, we introduce compressed sensing into the Network Coding (NC), to prevent all-or-nothing impact on NC. NCCS simultaneously transmits and encodes specific packets of sensor measurements to form random projections for CS recovery. CS technology guarantees that the data gathered at all nodes are accurately reconstructed with a high probability from a very small number of projections which is less than the total number of source nodes in the network. Our simulation results show that, only less than half number of packets is required to reconstruct measurements with reasonable quality compared with the traditional network coding schemes. Also, NCCS increases the data gathering efficiency by over 20% compared to the conventional NC scheme.

Key words: Wireless sensor network, compressed sensing, network coding, mesh network, NECO

INTRODUCTION

The Wireless Sensor Network (WSN) is composed from a number of autonomous sensors and can be low-cost and large-scale deployment to observe the physical quantities, such as temperature, pressure and sounds. Because sensor nodes are usually deployed in unattended remote areas, even under very harsh conditions, the WSN network topology frequently changes because of the movement of obstacles, link failure and the discontinuous operating schedule of nodes. Moreover, most sensor data need multi-hop relays to reach the sink. Therefore, the challenge of designing a WSN involves in adapting to the dynamic characteristic of the network while taking full advantage of the broadcast nature.

In addition to leveraging the multicast network capacity, Network Coding (NC) has been considered as a promising tool to deal with this challenge in wireless networks. NC is a specific network data processing technique which utilizes the broadcast characteristics of the wireless channels in order to increase the throughput of the network. Conventionally, in a multi-hop network, a node routes a packet to the destination through a sequence of intermediate nodes by simply copying and forwarding it to the next hop node. Using NC, a node aggregates several received packets into a single packet through simple algebraic operations and then forwards it through one or more outgoing links (Ahlswede *et al*., 2000). Coupled with the broadcast nature of wireless transmissions, NC can introduce diversity and redundancy in the network in order to adapt to the dynamic changes in network topology. Only when Ho *et al*. (2006, 2003) theoretically demonstrating the design of linear encoding function using random coefficients, NC became practical to obtain throughput gain. In particular, intermediate nodes using a Random Linear Network Coding (RLNC) scheme produce outputs by linearly combining inputs with random coefficients. Chachulski *et al*. (2007) proposed a design combined

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random network coding with opportunistic routing exploits the broadcast characteristics of the wireless channels efficiently. However, these schemes are too complicated for use in WSNs and these traditional network decoding schemes have an unfavorable all-or-nothing effect. Assuming that the source nodes emit N original data blocks, then, in order to reconstructed the original data, the sink node must receive at least N linearly independent data blocks. If less than N blocks are received, it is almost impossible to restore the original block. The all-or-nothing effect will lead to serious packet loss issues which affect the entire network's throughput.

Fortunately, we can introduce CS to solve the all-or-nothing problem. While the RLNC scheme's operation is similar to the random projection operation in CS, measurements from a sensor network are either spatially or temporally correlated, because many sensors observe the same phenomenon. The core point of CS is that a N-dimensional compressible (sparse) signal which can effectively be transformed into a sparse vector under certain transforming basis, can be reconstructed from a small number of random samples which are projections onto another basis that is incoherent with the transforming basis (Candes *et al*., 2004). This approach is directly applicable to sensor network scenarios if the correlated data vector is considered as a collection of all measurements in the network at a certain time. The spatial correlation of the measurements is reflected in the data vector. Then, random projections of the data vector can be considered as random ways in which those measurements are linearly combined. The power of CS lies in the fact that only a few data packets need to be received to reconstruct all of the data from the network (Donoho, 2006). Baron *et al*. (2005) developed a distributed CS framework for sensor data compression, exploiting both temporal and spatial correlations to reduce the volume of sensor readings; however that study did not consider the transmission problems.

Rabbat *et al*. (2006) introduced a practical random compressed projection compression method for multi-hop WSNs. In that study, the communication scheme uses a simple gossip algorithm to gradually flood the network with all random projections. Although, the framework can be adapted to the dynamic network topology and unreliable transmission link, it requires a significant amount of communication and convergence time. Katti *et al*. (2007) earlier proposed combining network coding and CS but did not provide an implementation framework. Nguyen *et al*. (2010) proposed the so-called Netcompress encoding framework using RLNC at adjacent source nodes and intermediate nodes and using the l_1-minimization CS reconstruction method. However, its designs of the packet header and packet elimination mechanism are unclear.

In this study, we introduce a practical scheme for achieving efficient communication in WSNs by using NCCS. We present a detailed design of the NCCS framework, including the packet format, local encoding vector selection, measurement matrix design and the algorithm of signal reconstruction. We also use simulations to evaluate the feasibility of the framework design and the performance of NCCS. The proposed NCCS scheme can not only exploit the broadcast nature and adapt to the dynamic nature of WSNs to increase diversity but can also exploit the correlation between sensor measurements to minimize the number of received packets required for decoding. We demonstrate a significant reduction in the number of packets required for data reconstruction with reasonably high quality and demonstrate that NCCS is a competitively efficient data communication scheme in WSNs.

SYSTEM MODEL

A WSN normally consists of several distributed nodes that organize themselves into a multi-hop wireless network and typically coordinate to perform a common task. WSNs have a variety of topologies. We are interested in mesh networking (Fig. 1) which is a type of networking where each node can sense, receive, process and forward sensed data while some of them gather the data. A sensor network with a centralized architecture may collapse entirely if there is a failure in some key nodes. However, distributed control architecture can increase the reliability of the sensor network effectively. In this context, flooding-based technology is considered. Using flooding rather than specific routing to send a message from one node to another, the message is flooded to all nodes in the network including those unintended nodes. Flooding has High reliability and extremely simplicity, since there is no needs of complex routing technology such as network management, self-discovery, self-repair, overhead for conveying routing tables or routing information.

Inevitably, measurements from a sensor network (Fig. 1) are spatially correlated because many sensors observe the same phenomenon. Therefore, it is desirable to exploit this correlation. The observation of several WSNs indicates that if we appropriately arrange the data sensed by different nodes of a given WSN, the

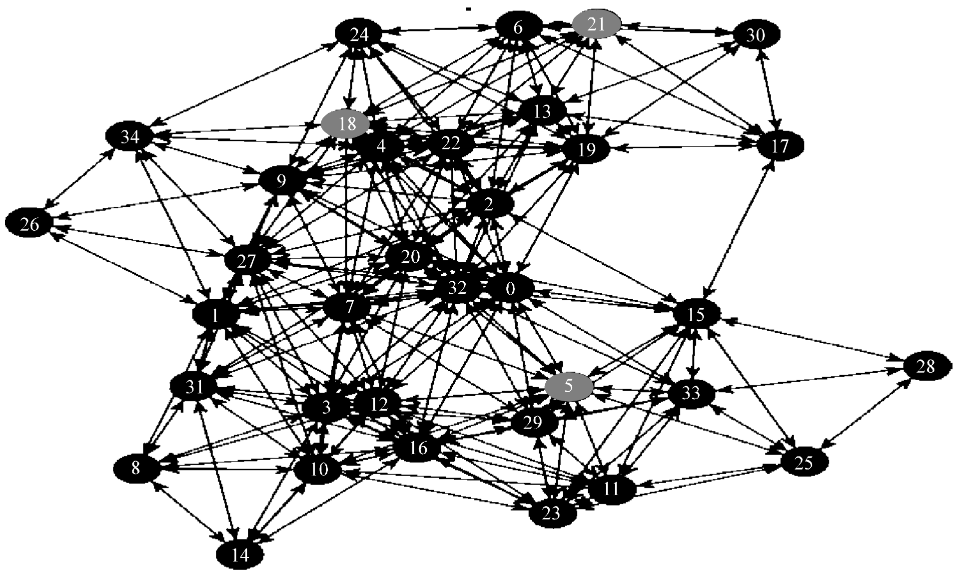

Fig. 1: Mesh topology of WSNs

arranged data will have a high compressed ratio which does not generally change if the order of nodes remains constant.

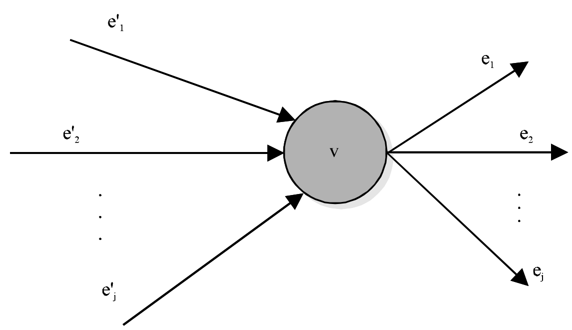

Fig. 2: Input edges and output edges of node v

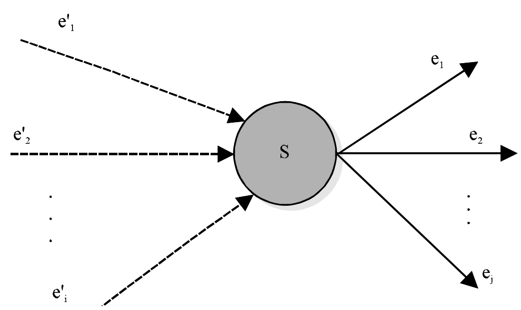

Fig. 3: Input edges and output edges of source nodes

MATERIALS AND METHODS OF NCCS

Random linear network coding: In broadcast transmission schemes, Random Linear Network Coding (RLNC) can obtain almost optimal throughput using a decentralized algorithm. For WSN scenarios where centralized network management and control are complex, RLNC effectively allows network nodes to achieve optimal performance while operating in a decentralized fashion. Thus, network nodes can operate in a distributed fashion without requiring the knowledge of the overall network configuration.

Nodes transmit random linear combinations of the received packets, with coefficients chosen using the random method (Chou *et al*., 2003). A dual radio graph (V, E) having unit capacity edges is considered with a set of source nodes $S \in V$ and a set of sink nodes $T \in V$. Each edge $e \in E$ from a node v transmits a symbol sequence y(e) as a linear combination of symbols y(e') on edges e', e' = in(v), as shown in Fig. 2.

The Local Encoding Vector (LCV) $m(e) = [m_e(e')]_{e':e' = in(v)}$ which is a randomly generated projection vector, represents the encoding function at node v for all y(e') with the same timestamp, namely $y(e) = \Sigma_{e':e'=in(v)} m_e(e')\, y(e')$. If S_i (i = 1, 2...N, N is the number of source nodes) is a source node, we introduce an artificial edge e' to maintain uniformity of notation, as shown in Fig. 3.

Each artificial edge e' of the source node s_i carries a sequence of source symbols $y(e'_i) = x_i$, $x_i = [x_{i1}, x_{i2},...x_{iL}]$, where L is the length of the source symbol packet. Thus, on any edge $e \in E$, y(e) can be represented by a linear combination $y(e) = g(e).[x_1^T, x_2^T,...x_N^T]^T$, $g(e) = [g_1, g_2,...g_N]^T$, The vector g(e) is known as the Global Encoding Vector (GCV) along edge e.

According to traditional network coding methods, by one or more time steps, any receiver $t\in T$ receiving certain symbol sequences along its incoming edges with the same timestamp can recover the source symbols $x_1, x_2 \ldots x_N$ as long as the matrix G Eq. 1 has rank N:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix} = \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1N} \\ g_{21} & g_{22} & \cdots & g_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mN} \end{bmatrix} \bullet \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1L} \\ x_{21} & x_{22} & \cdots & x_{2L} \\ \vdots & \vdots & \ddots & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{NL} \end{bmatrix} = G \bullet \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix} \tag{1}$$

Packet format: Here, we propose a packet format (Fig. 4) that eliminates the need for a centralized knowledge of the graph topology or the centralized encoding and decoding functions. The packet header field has two sections, timestamp and GCV. In real networks, packets are not received and transmitted synchronously at different nodes because they are likely to be received sequentially with other packets containing unmergeable data and packets containing mergeable data on different routes are generally subject to loss, congestion, different propagation and queuing delays, or other changes in the available bandwidth because of competing traffic. In this study, all packets with mergeable data (that are sensed at the same time slot) are considered to be in the same generation. The timestamp indicates the generation identity of the packet using an integer number. GCV is presented by N single-precision floating-point format numbers, where N is the number of source nodes of the network. We can assign an ID from the set {1, 2,...N} to each node. If a packet is forwarded by the source node with ID i, GCV will be initialized as a unit vector, where only the ith component is 1 and all others are 0, as illustrated in Fig. 5. Depending on this manipulation and Eq. 1, if some components of the received packet's GCV are nonzero, the packet contains the information regarding the source nodes for which the IDs correspond to those nonzero components. We consider that the size of each packet is 1400 bytes, just as an IP packet in the Internet. The cost of this scheme is the overhead of transmitting N+1 additional bytes in each packet. If there are 118 nodes in the WSN, then the overhead is approximately 119/1400 ≈ 8.5%.

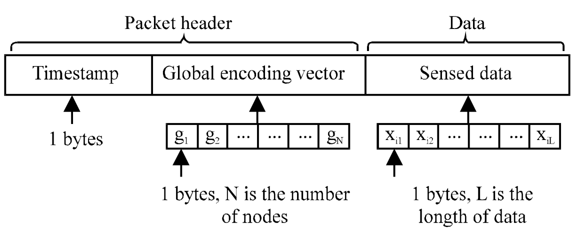

Fig. 4: Packet format

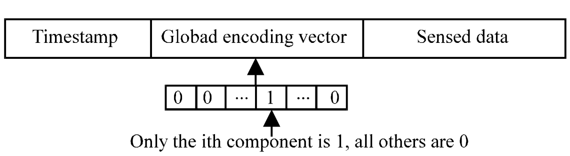

Fig. 5: Format of packet forwarded by the source node

Compressed sensing: In a WSN, any signal can be regarded as an N×1 real discrete column vector in $\mathbb{R}^N$, represented by $x = [x_1, x_2,\ldots, x_N]^T$. And any x can be represented in terms of the orthonormal basis of N×1 vectors $\psi = [\psi_1|\psi_2|\ldots|\psi_N]^T$. Using the N×N basis matrix $\Psi = [\psi_1|\psi_2|\ldots|\psi_N]$ with vectors Ψ_j as columns, a signal x can be expressed as Eq. 2, where $s = [s_1, s_2,\ldots,S_N]^T$:

$$x = \sum_{i=1}^{N} s_i \psi_i \quad \text{or} \quad x = \Psi s \tag{2}$$

Clearly, x is the representation of the signal in the time or space domain and s is the equivalent representation in the Ψ domain. The signal x is K-sparse if only K of the s_i coefficients in Eq. 2 are nonzero. The case of interest occurs when K<<N. The signal x is compressible if only a few coefficients of s are not close to zero.

Consider an under determined system:

$$y = \Phi x \tag{3}$$

where, Φ is an m×N random projecting matrix with m<N and x is K-sparse or compressible in the Ψ domain. The system can be rewritten as:

$$y = \Phi x = \Phi \psi s \tag{4}$$

According to the result in CS (Candes *et al*., 2006; Donoho, 2006), if the product matrix $\Phi\Psi$ satisfies the condition of Restricted Isometry Property (RIP), for all s, $\|s\|_0 \le K$, there exists a $\delta_{2k}\in(0, 1)$ such that:

$$(1-\delta_{2k})\,\|s\|_2^2 \le \|\Phi\Psi s\|_2^2 \le (1+\delta_{2k})\,\|s\|_2^2 \tag{5}$$

x can be reconstructed effectively by solving an l_1-minimization problem:

$$\min_{s\in\mathbb{R}^N} \|s\|_{l_1} \quad \text{s.t.} \quad y = \Phi x, x = \Psi s \tag{6}$$

Considering the RLNC system in the previous section, the GCV matrix G is generated randomly and $[x_{1j}\ x_{2j} \ldots x_{Nj}]^T$ is compressible. By constructing an appropriate G and finding the sparseness feature of the sensed signal, we can also recover the source symbol by solving the l_1-minimization problem, even when G is not full rank.

We consider the greedy algorithm to solve reconstruction problems. The orthogonal matching pursuit method, one of the most common and simple greedy approaches that finds the column of $\Phi\Psi$ most correlated with the measurements, repeats this step by correlating the columns with the signal residual which is obtained by subtracting the contribution of a partial estimate of the signal from the original measurement vector. If the measurement matrix $\Phi\Psi$ satisfies the RIP, the simplest guarantees for OMP state that for exactly k-sparse x with noise-free measurements $y = \Phi x = \Phi\Psi s$, OMP will recover x in exactly k iterations. The algorithm is formally defined as follows. Algorithm 1:

Algorithm 1

Orthogonal matching pursuit algorithm

Input: The CS observation y and a measurement matrix $\Theta = \Phi\Psi = \{\theta_i, i = 1, 2,..., N\}$, where $\Phi \in R^{m\times N}$, $\Psi \in RN\times N$

Initialization: Index $I = \emptyset$, residual $r = y$, sparse representation $s = 0 \in R^N$

Iteration:

While (stopping criterion false):

$i = \arg\max_j |\langle r, \theta_j \rangle|$

$I = I \cup \{i\}$;

$r = y - \Theta(:, I)\,[\Theta(:, I)]^T y$;

End

$S(I) = [\Theta(:, I)]^T y$;

Output: Sparse representation s and the original $x = \Psi_s$.

Local encoding vector choice: According to Jaggi *et al.* (2005), if the local encoding vectors are generated randomly and lie in a finite field of sufficient size (same as the symbols), the global encoding matrix G received at any sink node will have full rank with high probability. However, it is difficult to find a proper basis Ψ over a finite field, in which the sensed signal can be represented sparsely and $G\Psi$ satisfies the RIP of the CS theory. We select Rademacher distribution random variables in a real field to construct local encoding vectors:

$$m_i(e) = \begin{cases} +1 & \text{with probability } \frac{1}{2} \\ -1 & \text{with probability } \frac{1}{2} \end{cases} \quad (7)$$

After many multiplicative operations, the global encoding matrix G received at the sink node will be a normal distribution. In the scene of interest, for example, the Ocean Climatic Sensor Network, where the obtained data are spatially correlated, data gathered from appropriately arrayed nodes are compressible over a Discrete Cosine Transform (DCT). Next we will show that in this case, $G\Psi$ (normal distribution random matrix and discrete cosine transform) has a very good RIP property.

SIMULATION AND RESULT ANALYSIS

We performed numerical experiments using data from the US' National Oceanographic Data Center (NODC) which were collected from sensors scattered throughout the Okhotsk Sea, as depicted in Fig. 6.

The data processed by any node can be considered as shown in Fig. 7. This study aimed to design a framework for this data gathering to occur rapidly.

We employed the NECO (Joao *et al.*, 2009) simulation platform to analyze the data gathering efficiency of CSNC and NC models under mesh WSN schemes; the topological structure of the model is shown in Fig. 1. We also employed Matlab to analyze properties such as sensor data compressibility and the RIP of the practical measurement matrix.

We first evaluated the compressibility of the sensor data by mainly using temperature in our numerical study. We selected a set of temperature data simultaneously sensed by nodes scattered throughout the Okhotsk Sea. First, we randomly gathered data from these nodes. Figure 8 shows their readings and the representation over DCT and indicates that there are several relatively large coefficients. Second, after performing several tests, we chose a more appropriate node arrangement and numbered the nodes in this order; then, we collected the data of all nodes in order; the reading and its DCT representation at a certain time are shown in Fig. 9. Then, reading data in this order, we tested all the temperature data acquired from the Okhotsk Sea in 2012. The results showed that the expansion of any ordered data on DCT has only 13-16 coefficients that are not close to zero, as shown in Fig. 10.

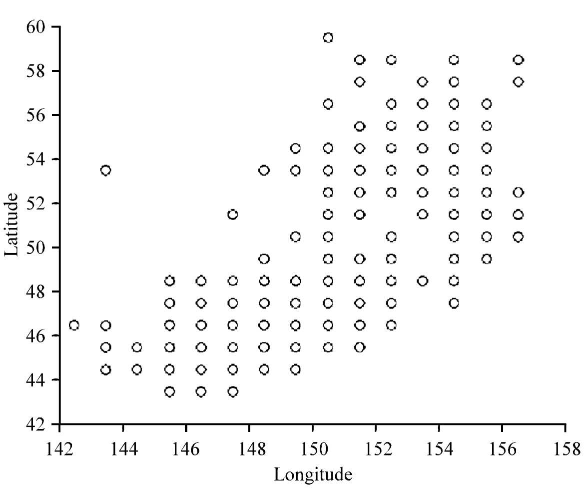

Fig. 6: Position of nodes scattered throughout the Okhotsk Sea

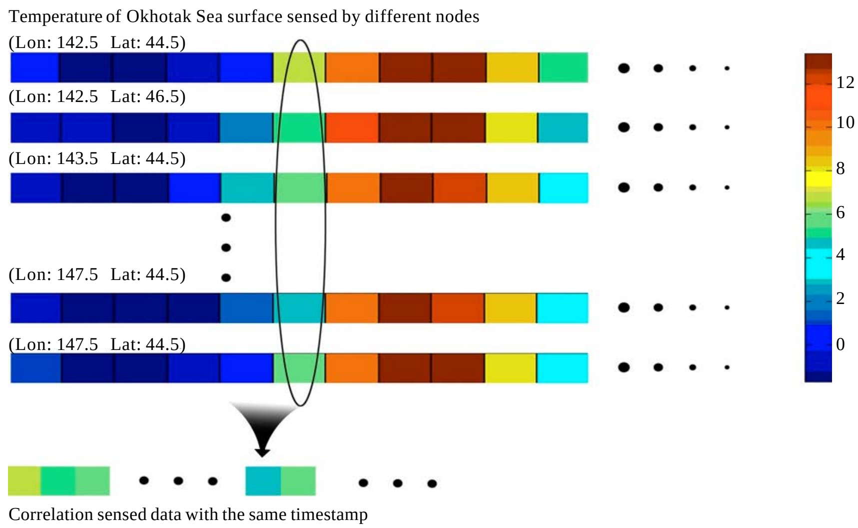

Fig. 7: Method of packeting sensed data

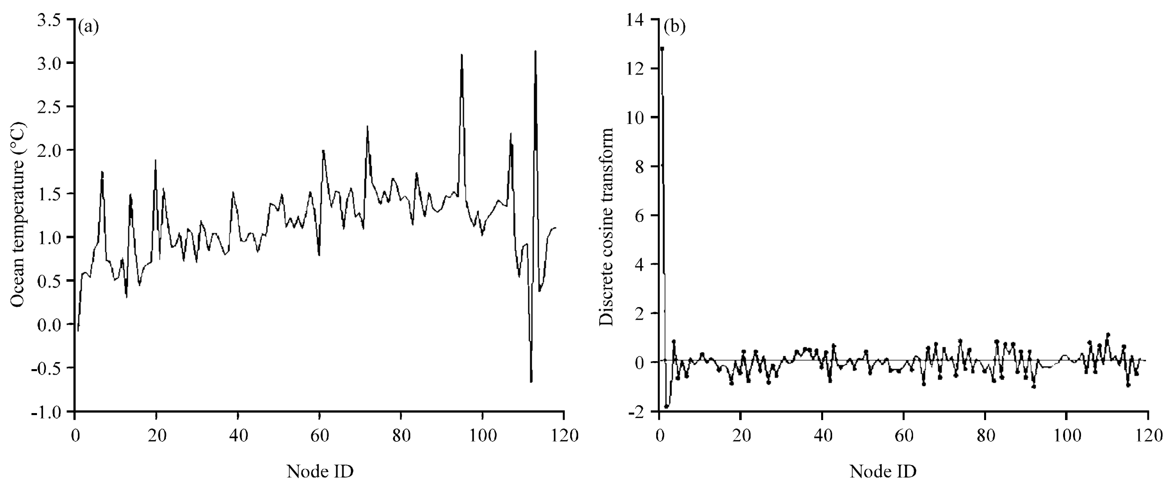

Fig. 8(a-b): Temperature readings without arrangement and their DCT representation

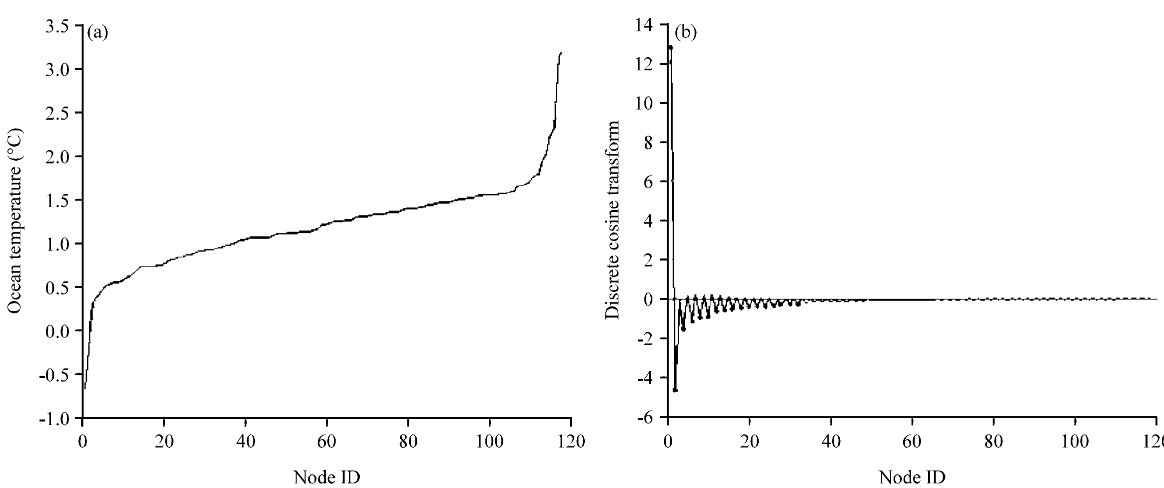

Fig. 9(a-b): Temperature readings with appropriate arrangement and their DCT representation

Here, we investigated the RIP of the measurement matrix composed of the GCV matrix and DCT matrix (GΨ). In our frame, the length of any signal x to be processed was N = 118 and its linear combination on DCT had K = 13-16 coefficients not close to zero. Therefore, we considered an m×118, m = 30, 45, 60, 75 GCV matrix randomly received at the sink node. In accordance with Eq. 5, we investigated δ for different m. Figure 11 indicates that when the rank of the received GCV matrix sink nodes measures up to 75, the measurement matrix can satisfy the RIP with high probability, so the signal x can be reconstructed exactly with high probability.

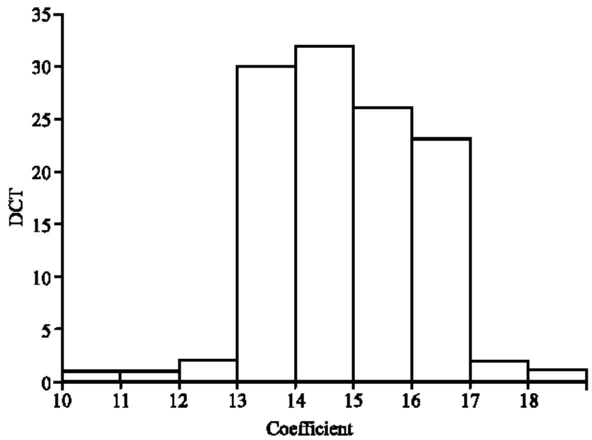

Fig. 10: Number of statistical coefficient

Next, we compared the packet transmission efficiency of NCCS and NC frames.

For the NECO simulation platform, the related parameters are presented in Table 1.

Table 1: Simulation parameter list

Parameter	NC	NCCS
No. of nodes	118	118
No. of sink nodes	1	1
Nodes' generation	Random geometric graph	Random geometric graph
Connection radius	0.35	0.35
Type of nodes	Randomic nodes	Randomic nodes
Capacity of edge	1 bit	1 bit
Link erasure probability	0.5	0.5
Protocol	NC	NCCS
LCV finite	Field, field size = 2^8	Rademacher distribution
Routing	Flooding	Flooding

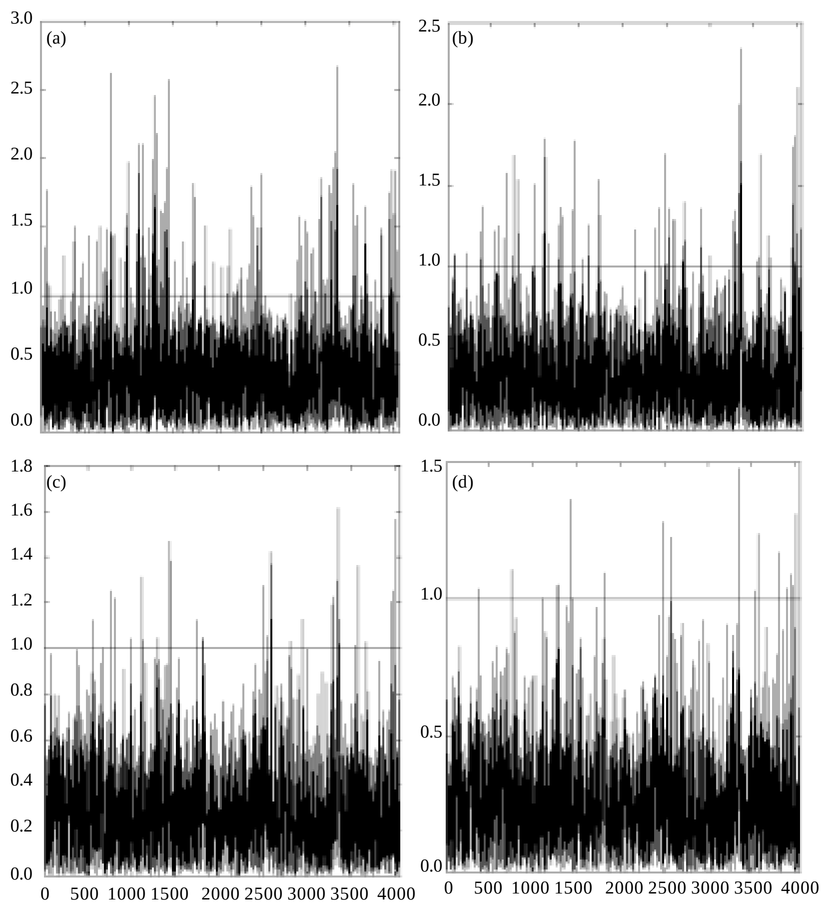

Fig. 11(a-d): Value of δ investigated under m×118, m = 30, 45, 60, 75 (a) m = 30, (b) m = 45, (c) m = 60 and (d) m = 75

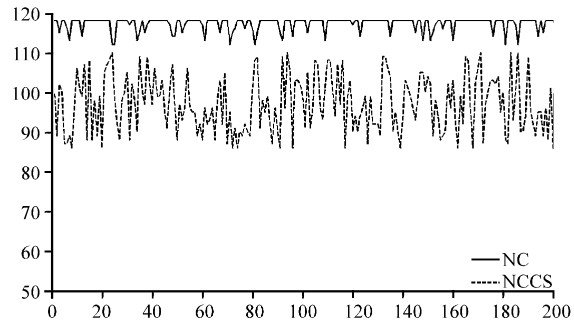

Fig. 12: Rank of the GCV matrix received by sink node under NC and NCCS

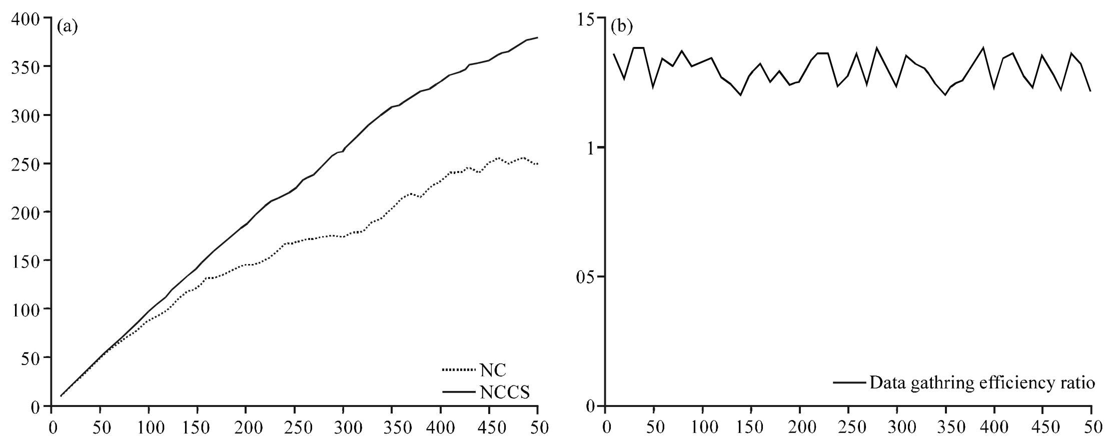

Fig. 13(a-b): Packets reconstructed (a) number of packets reconstructed under NC and NCCS and (b) Ratio of reconstructed packets number of NC and NCCS

The type of node is set to "Randomic Nodes," where any node will randomly lose its receiving or transmitting ability, leading to packet loss. Simply and without loss of generality, we randomly selected one of the 118 nodes as a sink node. Then, in each experiment, we sent 500 generations of packets. Figure 12 shows the received rank of the GCV matrix for each generation at the sink node. In the NC scheme using the finite field element as the local encoding vector, the sink node received a full-rank GCV matrix with a probability of 83.5. Also, in the NCCS scheme using Rademacher distributed random elements as the local encoding vector, the rank of the GCV matrix received by the sink node at each generation was about 85-110 which is hardly considered to be full rank but all of the ranks were larger than 75. Figure 13a shows the number of packets that are exactly reconstructed under different generation numbers of two schemes. Computing the data-gathering-efficiency ratio of two schemes as shown in Fig. 13b, the efficiency of NCCS was observed to be 20-35% higher than that of NC.

CONCLUSION AND FUTURE WORK

Communication in WSNs is mostly characterized by one or more sensor nodes forwarding the data that they collect to a centralized collector. In most cases, the sensor measurements reported by neighboring nodes are correlated. The presented NCCS scheme combines the benefits of NC and CS to achieve efficient data throughput capacity in WSNs. While CS takes advantage of the data correlations to reconstruct data with a high probability using a much smaller number of measurements than the number of source nodes in the network, the network coding scheme in NCCS leverages the broadcast nature of wireless transmissions and provides a method to efficiently aggregate and communicate those data by minimizing the communication overhead. The results obtained from our NCCS simulation show that we successfully reconstructed data with a reasonably high fidelity by using only about half the number of measurements collected by the sensor nodes in a network.

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