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Deterministic Measurement Matrix in Compressed Sensing

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Abstract: **Compressive sensing is a sampling method which provides a new approach to efficient signal compression and recovery by exploiting the fact that a sparse signal can be suitably reconstructed from very few measurements. One of the most concerns in compressive sensing is the construction of the sensing matrices. While random sensing matrices have been widely studied, only a few deterministic sensing matrices have been considered. Originated as a technique for finding sparse solutions to underdetermined linear systems, compressed sensing (CS) has now found widespread applications in both Signal processing and Communication communities, ranging from data compression, data acquisition, inverse Problems, and channel coding. An essential idea of CS is to explore the fact that most natural phenomena are Sparse or compressible in some appropriate basis. By acquiring a relatively small number of samples in the "sparse" domain, the signal of interest can be reconstructed with high accuracy through well-developed optimization procedures. These matrices are highly desirable on structure which allows fast implementation with reduced storage requirements. In this paper, a survey of deterministic sensing matrices for compressive sensing is presented. Some recent results on construction of the deterministic sensing matrices are discussed.**

Keywords: **Deterministic measurement matrix construction, decomposition, Compressive sensing, Wireless sensor networks.**

1. INTRODUCTION

Wireless sensor networks (WSNs) are networks of autonomous, wireless sensing nodes spatially categorized over geographical vicinity with application ranges from localization systems and surveillance, to monitoring of environment for physical ground sensing and calamity avoidance. WSN nodes captures the data and then communicate them to a fusion center (FC), which are capable to stores the sensors' evaluation or forward that via a wired network for further dispensation.

Compressed sensing is a signal processing technique for efficiently acquiring and reconstructing a signal, by finding solutions to underdetermined linear systems. In a WSN, usually the readings of the sensor nodes have both spatial correlation due to the closeness of sensors' geographical locations and temporal correlation due to the smooth variations of the real world signal. These redundancies indicate that sensor data is compressible along these dimensions. Thus, CS-based design can recover the whole network data from a few active sensor nodes, which effectively reduces the overall number of transmissions from the sensor nodes and saves network power. In, cross-layer designs are proposed to optimize energy consumption in WSNs based on time division multiple access (TDMA). Multiple-input and multiple-output (MIMO) and cooperative MIMO techniques are adopted to enhance the spectral efficiency and achieve energy saving for WSNs. Hence, CS-based scheme is also an energy-efficient scheme for medium access control in WSNs.

Recently, this technique has been proposed to achieve energy efficient multiple access or routing protocol design for wireless networks. In the case of medium access control (MAC), by considering the scenario that only a small portion of transmitters are active at a certain time instant, the aggregated signal from all the transmitters can be viewed as a sparse signal in the dictionary of an identity matrix.

Recently, several deterministic sensing matrices have been proposed. We can classify them into two categories. First are those matrices which are based on coherence. Second are those matrices which are based on RIP or some weaker RIPs.

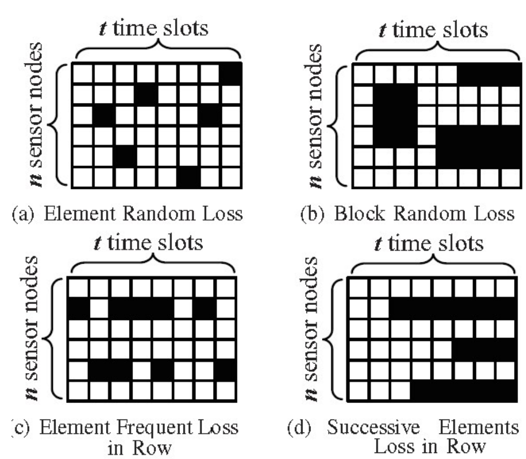

Fig.1. Data loss patterns in WSN. The tessellations illustrate the sensory matrix. The black cells represent the elements of missing data.

Data Loss Pattern:

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Traditional work usually adopts that the data loss follows an indiscriminate distribution. However, this assertion does not apply to the WSN condition. According to the nature of WSN, we amalgamate several distinctive data loss outlines.

Outline1 Element Random Loss (ERL): This is a very simplest loss pattern in which data elements in the matrix were dropped randomly and independently. As shown in Fig. 1(a), the misplaced data for ERL are randomly dispersed in the SM. The noise and collision in WSN are the root cause of random element loss.

Outline 2 Block Random Loss (BRL): Data from adjacent nodes in adjacent time slots are dropped independently and randomly. In WSN, congestion [8] always causes data loss on high-density sensor nodes during a period of time. Fig. 1(b) visualizes this scenario.

Outline 3 Element Frequent Loss in Row (EFLR): Unreliable links [23] are common phenomenon in real wireless scenarios. When the quality of link state is not good, sensory data are prone to loss due to the intermittent transmission. As shown in Fig. 1(c), in EFLR, elements in some particular rows have a higher missing probability.

Outline 4 Successive Elements Loss in Row (SELR): This pattern models that a given node starts losing from a particular time slot. This type of loss occurs when some sensor nodes are damaged or run out of energy [20], which is made visible by Fig. 1(d).

Outline 5 Combinational Loss (CL): In real world, data loss always happens as a combination of some loss patterns above.

2. LITERATURE SURVEY

T. Xue etal [1] has elaborated the role of compressed sensing in wireless sensor networks in terms of medium access and data reconstruction. A CS-based multiple access scheme that exploits sparsity in the process of medium access, as well as the spatial and time correlations that exist in natural signals were presented. A novel decision boundary was proposed to address the problem of distinguishing between active and inactive transmitters after symbol recovery. In the comparison between CSMA and their proposed CS-based scheme, they have found that increasing communication SNR enhances the throughput of both CSMA and CS-based schemes. They have demonstrated the virtue of utilizing spatial and temporal correlations in recovering data measurements of the whole network. Linghe Kong etal [2] developed an environmental space time improved compressive sensing (ESTICS) algorithm to optimize the missing data estimation. Their proposed approach significantly outperforms existing solutions in terms of reconstruction accuracy. ESTICS can successfully reconstruct the environment with less than 20% error in face of 90% missing data.

The work introduces the use of compressed sensing (CS) algorithms for data compression in wireless sensors to address the energy and telemetry bandwidth constraints common to wireless sensor nodes by Fred Chen etal [3]. Circuit models of both analog and digital implementations of the CS system are presented that enable analysis of the power/performance costs associated with the design space for any potential CS application, including analog-to-information converters (AIC). A. Dimakis, etal [4] presented a mathematical connection between channel coding and compressed sensing. The problem of accessing to global information from any single point in WSN, Yifeng Li etal [5] proposed a distributed in-network data acquisition approach, on the basis of compressive sensing, in which sparse random projections and randomized gossiping are jointly designed. In the context of unreliable distributed wireless settings, a simple random gossip algorithm was adopted. S. Qaseem, etal [6] presented a compressive sensing based opportunistic protocol for throughput improvement in wireless network. E. Candes, etal [7] surveys the theory of compressive sampling. CS theory asserts that one can recover certain signals and images from far fewer samples or measurements than traditional methods use.

Current research studies recommend that in the case of spatially sparse signals, the energy or bandwidth of RS and CS efficiency worsens since the reconstruction correctness is assured only when a huge number of sensors contribute to the measurements. It is also very difficult to design a RS matrix which suited to sparse signals and allowing a proficient network routing. It can pointed out that, on spatially sparse signals, CS methods still promises reconstruction correctness but at an increased number of measurements (e.g., M up to 50% of N), whereas for the same values of M and N, RS only opportunistically achieves reconstruction.

3. PROBLEM DEFINITION

Traditional data gathering and processing method is to use the multi-hop route to transmit data from one sensor to another. Finally the data will be transmitted to the sink node according to the route. Disadvantage of traditional method lays in the unbalanced energy consumption for each sensor and some redundant data transmissions. The sensor closer to the sink will consume more energy than other sensors. To avoid the redundant data transmissions, some researches introduce data fusion methods to process data in WSNs. More completed routing protocols and much higher computation ability will be needed for each sensor. Sometimes data fusion methods cannot solve unbalanced energy consumption problems.

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4. THE OBJECTIVES

First the adoption to compressive sampling theory for gathering each sensors monitoring value in WSNs, instead of using the traditional multi-hop routing transmission scheme for each sensor. Second, instead of using random measurement matrix to measure each sensor's monitoring value and reconstruct the original signal, the proposal is to make a simple but more efficient deterministic measurement matrix design algorithm to achieve the better data gathering and original signal reconstruction performance in WSNs. Third, extensive simulations and practical experiments of WSNs have shown that if the proper number of measurements M, has been chosen the sensors' monitoring values can be gathered efficiently as well as the energy consumption can be reduced greatly by using the proposed algorithm.

5. PROPOSED WORK

Here the proposal is to try to minimize the energy consumption rate by making use of the proposed algorithm. Then, the measurement and reconstruction of original signal rather than going for measurement of each sensor has been done. And hence it will avoid the use of multi-hop routing transmission scheme and it will use compressive sampling theory for gathering each sensor monitoring.

The basic idea is to firstly, adopt the compressive sampling theory to gather each sensors monitoring value in WSNs, instead of using the traditional multi-hop routing transmission scheme for each sensor. Secondly, instead of using random measurement matrix to measure each sensor's monitoring value and reconstruct the original signal, the proposal is to create simple but more efficient deterministic measurement matrix design algorithm to achieve the better data gathering and original signal reconstruction performance in WSNs. And sub sequentially, an extensive simulations and practical experiments of WSNs will show that if the proper number of measurements M, have been chosen then the sensors monitoring values can be gathered efficiently as well as the energy consumption can be reduced greatly by using the proposed algorithm.

The model WSN as a graph G = ({s} ∪ V,E) where s is the sink node, V = {1,2, ..., n} is the set of sensor nodes and E is the set of edges where an edge exists between two sensor nodes if they are within the communication range of each other. (Note that the framework described here can equally be applied to a cluster with n sensor nodes and a cluster head, therefore the method is scalable.) We assume that the sensors are synchronized. We consider a snapshot of the temporal-spatial field where at a particular time t, the sensors make a measurement. Let the noise-free sensor reading of sensor node i (where i = 1, ..., n) be xi. The actual (noisy or measured) sensor reading is assumed to be corrupted by an independent and identically distributed zero mean Gaussian noise of variance σ2. Let the sensor noise at sensor i be ei, then the actual sensor reading at sensor node i is yi = xi + ei. We will use x to denote the vector [x1, x2,..., xn]T where T denotes matrix transpose; the vectors e and y are similarly defined. Our goal is to obtain an approximation xˆ= [ˆx1,xˆ2, ...,xˆn] T of the true data field x. We will measure the accuracy of the approximate data field by using the relative error x−xˆx where x = ni=1 x2i denotes the 2−norm of x.

We assume that both sensing energy and energy required for computation is negligible, which are fairly typical assumptions in WSNs. The energy consumption in the WSNs is dominated by radio communications in transmitting and receiving data packets. In this paper, we will measure the energy consumption by the total number of transmissions required to collect the information on data field. The reference scenario is when all nodes in the network send the data to the sink which requires a number of transmissions of the order of n2 in the multi-hop scenario. This work distinguishes itself from other works in energy efficient adaptive sensing, e.g. in that it uses recent works in adaptive compressive sensing however and existing work in adaptive compressive sensing only takes into consideration the accuracy of the approximate data field. In order to apply adaptive compressive sensing to WSNs, our work in this paper takes both accuracy and energy into consideration. In particular, we will show that there is a "cross-layer" interaction in using adaptive compressive sensing in WSNs where one needs to take both accuracy (at the application layer) and routing into consideration.

A distinctive feature of compressive sensing is that it uses projections to collect information. For a snapshot of the noisy data field {yi}, the projection of the vector y on a projection vector p = [p1, p2 ...,pn]T is defined by the inner product pT y =E. Let us illustrate the concept of projection vectors and how projections can be calculated in a WSN with a few examples. Consider the network shown in Figure 1 with 4 sensor nodes {1, 2, 3, 4} and sink node s.

Example 1: If the projection vector p is [0.2, 0.3, 0.4, 0.1], then the projected value pT y = 0.2y1+0.3y2+0.4y3+0.1y4.

The sink can obtain this projected value without the sensors sending their sensor readings to the sink. This can be achieved by the sink passing a message along the tour S−1−2−3−4−S using source routing in the WSN. The message contains the entire projection vector p as well as a field in the message to store the intermediate result of the projection calculation. As the message travels through the tour, each sensor computes its contribution to the projected value and adds it to the intermediate result. After that, the sensor writes the new intermediate result to the message and forwards the message to the next hop. For example, sensor node 2 will receive from sensor node 1 a message with 0.2y1 as the intermediate result; sensor 2 will compute 0.3y2 and add this to 0.2y1, then it will write the sum to the message and then pass it on to the next hop. Note that the computation of this projection requires 5 wireless transmissions.

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6. COMPRESSED SENSING FOR NETWORK DATA RECOVERY

The data measurements built-up from sensing natural phenomena have compressible (sparse) representation in the frequency or the wavelet domain. In other words, DFT and DWT of the sensor readings *d* can be sparse. For example, the data of the temperature sensor readings provided by the Intel Berkeley Research lab over a period of one month exhibits both the sparsity in the frequency domain by examining the readings from all the sensor nodes at one time instant and sparsity in the wavelet domain by examining the data readings from one sensor node in consecutive time intervals. Hence, compressed sensing can be utilized to recover both the spatially and temporally correlated data measurements. In network data recovery part of the wireless sensor network, the fusion center utilizes further spatial and temporal correlations to recover the readings from all the sensor nodes over a number of consecutive time frames.

7. RESULT

Scope of the project is to investigate compressive data gathering and original signal reconstruction in wireless sensor networks (WSNs). By adopting the Compressive Sampling theory, the energy consumption can be balanced and the redundant data transmissions can also be avoided. The data transmitted can be sparse in a certain domain and CS theory can make sure that a K-sparse signal can be reconstructed from a relative small number of measurements M with a probability even up to one.
The following pie charts shows that the energy consumptions is reduced, which is obtained by using deterministic measurement matrix algorithm.

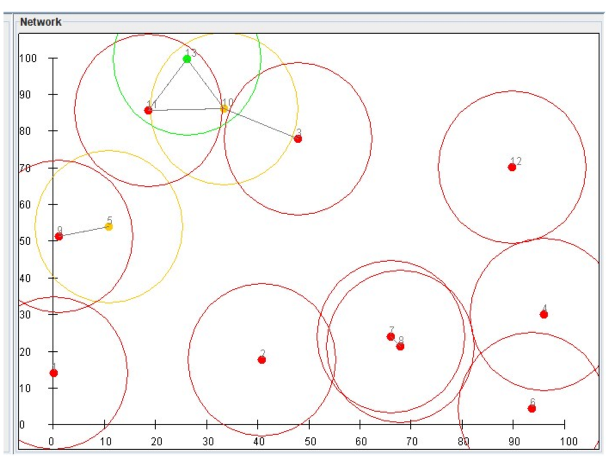

Fig 1: Sensors Having Links, Ranges & Ids

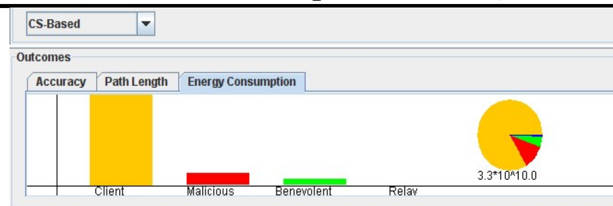

Fig 2: Pie Chart Showing Energy Consumption Using Compressive Sensing Algorithm

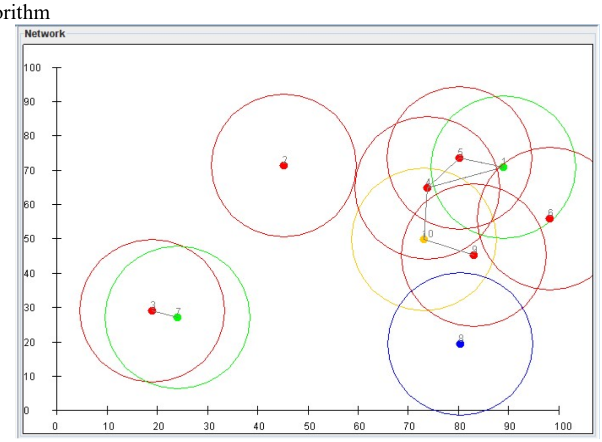

Fig 3: Sensors Having Links, Ranges & Ids

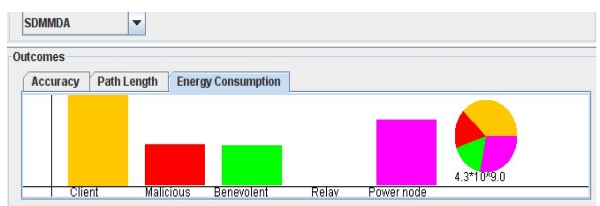

Fig 4: Pie Chart Showing Energy Consumption Using Deterministic Measurement Matrix

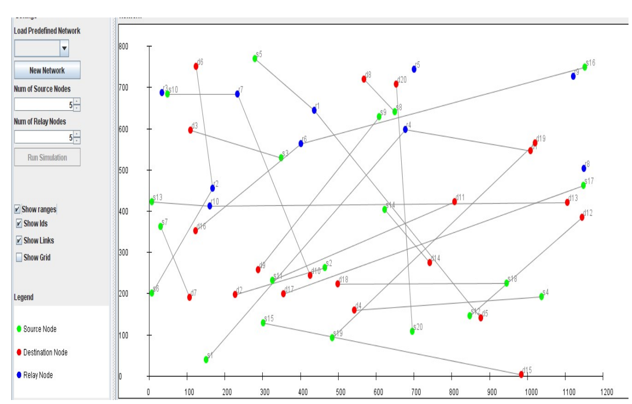

Fig 5: The Environment Showing Links Between Source, Relay And Destination

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Outcome

Mobile Node(MN)	(WMAN)Direct Trans...	WLAN Assignment-Ini...	WLAN Assignment-Fi...	Final Capacity (Mbps)
s1	0.3	r4	r4	0.3
s2	40.1	$	$	40.1
s3	38.9	$	$	38.9
s4	4.6	$	$	4.6
s5	0.5	r6	r1	0.9
s6	2.9	r2	r2	6.5
s7	66.9	$	$	66.9
s8	124.1	$	$	124.1
s9	4.9	r1	$	4.9
s10	2.6	r7	r7	3.4
s11	3.9	$	$	3.9
s12	11.7	$	$	11.7
s13	0.2	r10	r10	0.3
s14	74.0	$	$	74.0
s15	1.3	$	$	1.3
s16	0.2	r5	r6	0.3
s17	0.6	$	$	0.6

Fig 6: The Table Showing Transmission from Source to Destination Considering Relay Nodes

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