PERFORMANCE ANALYSIS OF COMPRESSIVE DATA GATHERING SCHEME FOR WIRELESS SENSOR NETWORK

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ABSTRACT

In the area of wireless sensor networks, measurements that significantly vary from the normal pattern of sensed data are regarded as outliers. The possible sources of outliers include noise and errors, events, and malicious attacks on the network. The compressive data gathering, which is grounded on the recent breakthroughs in compressive sensing theory, has been suggested as a feasible access for wireless sensor network. In this paper, we investigate the impact of outlying sensor readings on data gathering, and propose an approach based on the compressive sensing theory to recover the original signal when it is under the effect of noise. Our design is validated by a comparison based simulation work, and comparison is executed along the basis of Average Relative Error (ARE) that is the average of the proportion between the remainder of the estimated reading and the true reading vs. the true interpretation.

Keywords- Compressive Sensing, Wsns, Compressive Data Gathering, Nyquist, Sparsity

I. INTRODUCTION

A wireless sensor network (WSN) typically consists of a large number of small, low-cost sensor nodes distributed over a large area with one or perhaps more powerful sink nodes gathering readings of sensor nodes. The sensor nodes are integrated with sensing, processing and wireless communication capacities. Each node is usually equipped with a wireless radio transceiver, a small microcontroller, a power source and multi-type sensors such as temperature, humidity, light, heat, pressure, sound, vibration, etc. The WSN is not only used to provide real-time data about the physical world but also to detect time-critical events. A wide variety of applications of WSNs include those relating to personal, industrial, business, and military domains, such as environmental and habitat monitoring, object and inventory tracking, health and medical monitoring, field observation, industrial safety, etc. In many of these applications, real-time information mining of sensor information to quickly make intelligent decisions is all important. Data measured and collected by WSNs is often treacherous. The quality of the data set may be borne on by noise & error, dropping values, duplicated data, or discrepant information. The traditional approach of reconstructing signals or images from measured data follows the well-known Shannon sampling theorem which says that the sampling rate must be twice the highest frequency. Likewise, the fundamental theorem of linear algebra suggests that the number of collected samples (measurements) of a discrete finite-dimensional signal should be at least equally great as its length (its dimension) in order to ensure reconstruction. This principle underlies most devices of current technology, such as analog to digital transition, medical imagery or audio and video electronics. The novel theory of compressive

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sensing (CS) — also recognized under the terminology of compressed sensing, compressive sampling or sparse recovery — provides a fundamentally new approach to data acquisition which overcomes this common wisdom. It anticipates that certain signs or images can be recovered from what was previously thought to be highly incomplete measurements (data).

II. COMPRESSIVE DATA GATHERING

The data gathering sensor network finds a diversity of applications in infrastructure and habitat monitoring. It is anticipated that the number of sensor nodes deployed could be along the order of hundreds or thousands. In general, data transmissions are accomplished through multi-hop routing from individual sensor nodes to the data sink. Successful deployment of such large scale sensor networks faces two major challenges in effective global communication cost reduction and in energy consumption load balancing. The need for global communication cost reduction is obvious because such sensor networks typically are composed of hundreds to thousands of sensors, generating tremendous amount of sensor data to be delivered to data sink. It is very much desired to take total advantage of the correlations among the sensor data to trim back the monetary value of communication. Existing approaches adopt in-network data compression, such as entropy coding or transform coding, to reduce global traffic. Nevertheless, these approaches introduce significant computation and control overheads that often not suited for sensor network applications.

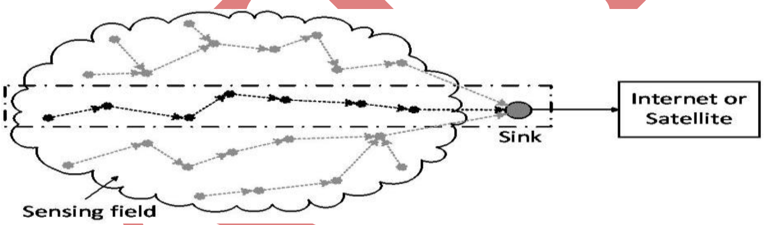

Fig.1 Compressive Data gathering sensor network.

The basic thought of the proposed compressive data gathering (CDG) is pictured in Fig. (1) Instead of receiving individual sensor readings, the sink will be sent a few weighted sums of all the readings, from which to restore the original data. To transmit the i^{th} sum to the sink, s_1 multiplies its reading d_1 with a random coefficient φ_{i1} and sends the product to s_2. Upon getting this message, s2 multiply its reading d2 with a random coefficient φi2 and then charges the sum φi1d1 + φi2d2 to s3. Likewise, each node SJ contributes to the relayed message by adding its own product.

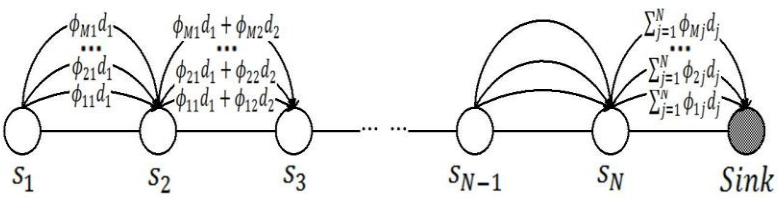

Fig.2 Data gathering sensor network

It is some other significant feature of compressive sensing used in compressive data gathering that practical reconstruction can be executed by using effective algorithms. Since the stake is in the vastly under sampled case, the linear system describing the measurements is underdetermined and therefore has infinitely many answers. The central idea is that the sparsity helps in keeping apart the original vector. The first naive approach to a reconstruction algorithm consists in seeking for the sparse vector that is coherent with the linear measurements. This contributes to the combinatorial $\ell 0$-problem which unfortunately is NP-hard in general. There are basically two approaches for tractable alternative algorithms. The first is convex relaxation leading to ℓ_1-minimization — also known as basis pursuit whiles the second construct greedy algorithms. This overview focuses on ℓ_1-minimization. By now basic properties of the measurement matrix which ensure sparse recovery by ℓ_1-minimization are known: the null space property (NSP) and the restricted isometry property (RIP). The latter demands that all column sub-matrices of a certain size of the measurement matrix are well-trained. This is where probabilistic methods come into gaming because it is rather difficult to break down these properties of deterministic matrices with minimal amount of measurements. Among the provably good measurement matrices are Gaussian, Bernoulli random matrices, and partial random Fourier matrices.

III. SYSTEM MODEL METHODLOGY

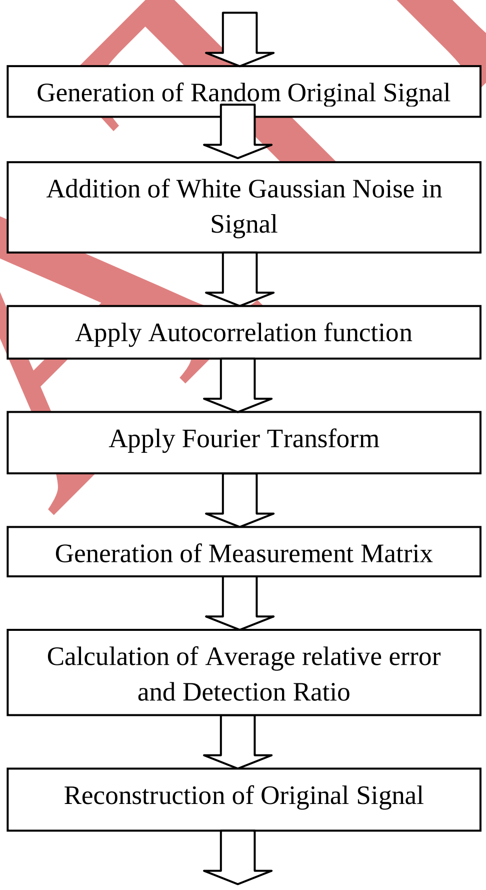

Fig.3 **Methodology** for Compressive Data Gathering Scheme for WSN

3.1 Generation of Random original Signal

First of all, the original signal **x** should be created to simulate the signal exist in the nature world. Base on the theory, this signal should be sparse in some domain. As it is created in Matlab, definitely, it is a digital signal. The data length N of the original signal **x** will be set to 900 and the sample frequency will be 100MHz [18]. The sine wave will be constructed as equation (1) :

$$X = B(i)\sin(2 f(i) t + \theta(i)) \qquad i = 1, 2\ldots, N \qquad (1)$$

Where X = the original signal,

B(i) = the amplitude,

f (i) = the frequency,

t = the time,

θ(i) = the phase of the signal.

3.2 Addition of White Gaussian Noise in Signal

AWGN is a basic noise model used in Information theory to mimic the effect of many random processes that occur in nature.

- 'Additive' because it is added to any noise that might be intrinsic to the information system.
- 'White' refers to the idea that it has uniform power across the frequency band for the information system. It is an analogy to the colour white which has uniform emissions at all frequencies in the visible spectrum.
- 'Gaussian' because it has a normal distribution in the time domain with an average time domain value of zero [18].

The addition of noise to the signal is shown in equation (2) :

$$W_i = X_i + N \qquad i = 1, 2\ldots, N \qquad (2)$$

Where W_i = signal after adding Noise,

X_i = the original signal,

N = noise added to the signal.

3.3 Apply Autocorrelation function

The autocorrelation function can be used for the following two purposes:

- To detect non-randomness in data.
- To identify an appropriate time series model if the data are random.

The function i.e. used on signal in eq. (2) is shown in eq.(3) :

$G_i = (W_i) \text{ corr } (W_i);$ $\quad i = 1, 2\ldots, P$ (3)

Where G_i = signal after applying autocorrelation function,

W_i = signal after adding Noise.

3.4 Apply Fourier Transform

Use the FFT to change the original signal **y** from time domain to frequency domain. The functions of FFT in Matlab can be used directly to compute the fast discrete Fourier transform of signal **y** and rearranges the result of FFT by moving the zero frequency components to the middle of the spectrum [14].

The function i.e. used on signal in eq. (3) is shown in eq. (4) :

Gf = fftshift (fft (G, N))/N (4)

Where Gf = signal after applying Fourier transform

G = signal after applying autocorrelation function

N = No. of sensors nodes

3.5 Generation of Measurement Matrix

The digital signal x is presented as Nx1 vector in Matlab. In order to collect the elements of this vector a measurement matrix should be created to sample this vector. As said in the theory Section 1.5.1.4, the random matrix can fulfill the conditions of CS with overwhelming probability for the measurement matrix [14]. The matrix will be SxP dimensions matrix. The M value is calculated through the equation (6).

The function i.e. used for generation of measurement matrix shown in eq.(5):

A = randn (M, N) (5)

Where A = Generated measurement matrix

M = Number of measurements

N = No. of sensors nodes

3.6 Reconstruction of Original Signal

As mentioned before, in this case, convex optimal method will be used to get the sparsest solution to reconstruct the sparse signal T. In Matlab, CVX which is Matlab-based modelling system for convex optimal programming will be used for convex optimal.

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IV. PROPOSED MATHEMATICAL MODEL FOR COMPRESSIVE DATA GATHERING SCHEME

4.1 Autocorrelation function on original signal

Let's say autocorrelation function R applied to the Original random signal x (Nx1) and it will give the signal let's say y (Nx1):

$$R = \sum_{n=0}^{\infty} x[n]\, x[n-j] \tag{6}$$

4.2 Sparse representation of the auto-correlated signal

Signal y (Nx1) will have a sparse expression on the represent basis £ (N x N), N is the data length of signal y [18]:

$$Y = £k \tag{7}$$

Where y=autocorrelated signal

£ = represent basis

k = sparse represent of original signal

4.3 Acquire the measurement value by measurement matrix

Use the measurement matrix Φ (M x N) to acquire the measurement value A, M is the measurement number [18]:

$$A=y€=€£k \tag{8}$$

Where € = measurement matrix

4.4 Reconstruction of signal

Choose an adaptive algorithm to reconstruct k depending on the known £, €and A.

Using the inverse matrix of £ to reconstruct the original signal y*[18]:

$$Y^* = £^{-1} T^* \tag{9}$$

V. SIMULATIONS

In this section, we evaluate the performance of compressive data gathering in sensor networks. After providing the simulation setup the proposed scheme is analysed for Average Relative Error. The simulation is performed in MATLAB 2011b.The proposed scheme gives the low ARE when sensors are corrupted by noise.

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5.1 SIMULATION SETUP

5.1.1 Initialization of Parameters

There are some Network parameters are shown in table 4.1.This table gives the value of different parameters like Sampling frequency, number of nodes, number of spikes of original signal etc.

Table 1 Network Parameters [22]

Parameter	**Description**	**Value**
F_s	Sampling Frequency	100MHz
N	Number of Sensor Nodes	900
k	Number of spikes of original signal	10
c	constant	2.5
M	Number of measurements	80
x	Original signal	random
N	Noise	10db,20db

5.2 VALIDATION OF RESULTS

5.2.1 Average Relative Error (ARE)

Let Xi and Xi^ be the true and the estimated reading, respectively. The average relative error (ARE) is defined to be the average of the ratio between the difference of the estimated reading and the true reading *vs.* the true reading [22]:

$$ARE=\sum_{i=1}^{V} | Xi - Xi\hat{} | / Xi \div V \quad (10)$$

Where Xi = the true original signal,

Xi^ = the estimated signal,

V = No of iterations

The simulations results of proposed scheme, CS, Entropy and Wavelet are compared in the terms of Average Relative Error with respect to the Signal to Noise Ratio as shown in Fig.5.5.proposed scheme has shown much improvement in reducing ARE as compare to CS, Entropy and Wavelet. We report our simulation results, with each representing an average over 50 runs.

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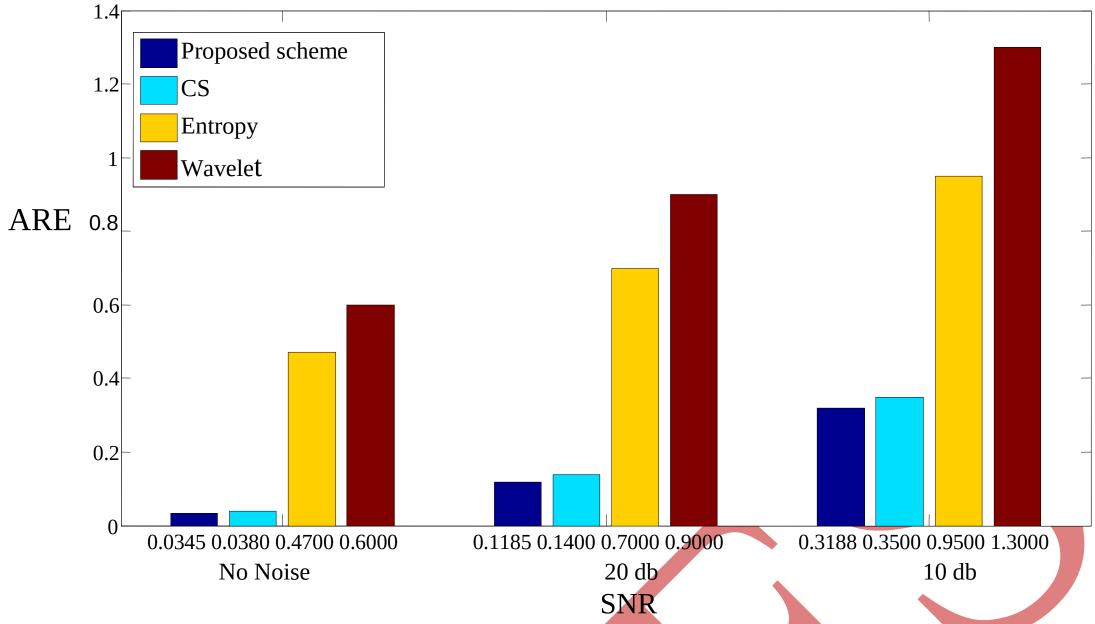

Fig.4 Comparison of all Schemes for ARE

5.2.2 Aggregated results for overall improvement for ARE

The comparison table 5.1 shows the overall comparison between Proposed Scheme, CS, Entropy and Wavelet in terms of ARE.

Table 2 Comparison of all Schemes for ARE

Added Noise	**ARE**			
	Proposed Scheme	**CS**	**Entropy**	**Wavelet**
No Noise	0.0345	0.0380	0.4700	0.6000
20 db	0.1185	0.1400	0.7000	0.9000
10 db	0.3188	0.3500	0.9500	1.3000

VI. CONCLUSION

The Proposed Scheme combines the traditional sampling and compression, based on it, the sparse signal will be sampled beyond the constraints of the Nyquist theory. After running the simulation in MATLAB, the proposed scheme is analysed for ARE by adding 20 db, 10 db and no noise to the signal and it is found that ARE is reduced between recovered signal and the original signal by 15.36%, 8.92% and 9.22% respectively, as compared to Compressive Sensing (CS) Scheme. So the Simulation part reduces the amount of samples and keeps the main information of the signal successfully. So it can be concluded on the basis of results that introducing the Autocorrelation function in Compressive Data Gathering scheme reduces the Average Relative Error. Future work includes deriving variations of the proposed strategy, testing, and comparing them with other well-known methods on real-world data sets.

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