Hindawi Publishing Corporation
Journal of Sensors
Volume 2014, Article ID 805423, 8 pages
http://dx.doi.org/10.1155/2014/805423

Research Article

1-Bit Compressive Data Gathering for Wireless Sensor Networks

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Received 20 February 2014; Revised 23 April 2014; Accepted 23 April 2014; Published 15 May 2014

Academic Editor: Athanasios V. Vasilakos

Compressive sensing (CS) has been widely used in wireless sensor networks for the purpose of reducing the data gathering communication overhead in recent years. In this paper, we firstly apply 1-bit compressive sensing to wireless sensor networks to further reduce the communication overhead that each sensor needs to send. Furthermore, we propose a novel blind 1-bit CS reconstruction algorithm which outperforms other state-of-the-art blind 1-bit CS reconstruction algorithms under the settings of WSN. Experimental results on real sensor datasets demonstrate the efficiency of our method.

1. Introduction

Due to the vast practical and potential unlimited applications, wireless sensor networks keep attracting more and more attention from both research and industry community [1]. In order to design efficient wireless sensor networks, fundamental research aspects, such as topological control [2], multihop fair access [3], energy-efficient routing [4–6], and data aggregation protocols [7, 8], must be thoroughly explored.

In typical wireless senor networks, deployed sensor nodes periodically collect sensory data and send them to sinks (or base stations) via shared wireless channels. Since sensor node only has limited computation capability and energy power, it is desirable to design simple and energy-efficient data gathering (or aggregation) method to reduce data transmission consumption of each sensor.

Observing that the sensory data from natural phenomenon usually has intratemporal and interspatial correlation, various methods have been proposed to make use of those characteristics [9]. Recently, Wei et al. [7] proposed a prediction-based data aggregation which combined Grey model and Kalman filter. Guo et al. [8] tried to find the potential law of history data with the help of particle swarm optimization and neural network and thus reduce the unnecessary transmissions based on the deviation between the actual and the predicted value at each sensor node. Beside those effective methods, another promising taxonomy is compressive sensing (CS) [10, 11] based approaches. Compressive sensing can exactly recover signals with only few nonzero elements or few nonzero coefficients under some transform domain, such as wavelet basis or discrete cosine transform, from very few projections.

Wang et al. [12] first exploited the interspatial correlation of sensory data between sensor nodes in large scale wireless sensor networks using compressive sensing. In this method, each sensor node is classified as encoding sensor node or data sensor node. Encoding sensor nodes add and store the weighted sensory data sent from data sensor nodes, and then base station or collector can recover all the sensory data by querying only small portion of the encoding sensor nodes. The method is fully distributed but, in order to generate the projections, the communication overhead between sensor nodes is relatively large.

In [13], the authors proposed an energy-efficient compressive data gathering (CDG) method in large scale multihop WSNs. In this method, a spanning tree rooted at the base station will be generated, and the tree contains all the sensor nodes. Giving an M by N projection random matrix $\Phi_{M\times N}$ ($M < N$), each leaf node sends projection vector with length M to its parent node along the spanning tree. After receiving the projection vectors from all its children nodes, the intermediate nodes add the vectors and then send the result vector to its own parent node. In the end, the base station can recover all the original sensory data from the final projection vector. Similar to CDG scheme, Luo et al. [14] and Xiang et al. [15] proposed a hybrid CS method. In this approach, each leaf node only needs to send its own single sensory data instead of projection vector to its parent node. More recent work in this direction is focusing on designing optimized sparse projection matrix [16, 17].

Though the communication overhead can be reduced, the CDG-based methods that utilize interspatial correlation have at least the following two costs. The first is that the projection spanning trees need to be regenerated even if there is only a single sensor node leaving or joining, and the second is that accurate time synchronization is required between sensor nodes.

Xu et al. [18] proposed a hierarchical data aggregation using compressive sensing (HDACS) scheme to address the local sparsity instead of global sparsity.

Intratemporal correlation was first utilized by using compressive sensing in [19]. Observing that the sparsity of sensory data may vary at different time period, Wang et al. [20] suggested using intelligent compressive sensing to adaptively adjust the number of projections that each sensor node needs to send.

Caione et al. [21] evaluated the computation overhead of generating different projection matrices and concluded that sparse binary matrix has the lowest generating computation overhead. Also, the authors successfully recover sensory data of projections from multiple sensor nodes using distributed compressive sensing [22].

In [23–26], matrix completion technology [27], which is the extension of compressive sensing, has been used in WSNs to reduce the sampling and transmission cost. The basic idea is that, instead of using uniform sampling, each sensor node randomly samples and sends sensory data to base station under a certain probability. After receiving all the incomplete sensory data from sensor nodes, base station can form a low rank incomplete matrix and recover missing sensory data using matrix completion method.

More recently, 1-bit CS has attracted more and more attention for the ability to balance the cost of refined quantization and the cost of additional measurements [28]. In this paper, we focus on intratemporal correlation and first apply 1-bit CS to data gathering in WSNs.

The remainder of this paper is organized as follows. In Section 2, we describe the basic theory of 1-bit CS and then propose our 1-bit CS framework and new algorithm. In Section 3, we evaluate the efficiency of our method using real WSN datasets. At the end, we conclude the paper and present future research work.

2. Proposed Framework and Algorithm

2.1. 1-Bit CS. Instead of transmitting the full quantized projections directly, 1-bit CS only sends the sign of projection values, such as

$$b = \operatorname{sign}(\Phi s), \tag{1}$$

where sign is a sign function, such that $\operatorname{sign}(y) = \begin{cases} 1, & y \geq 0, \\ -1, & y < 0. \end{cases}$, Φ is a given $M \times N$ Gaussian random matrix, $s \in R^N$ has only K ($K \ll N$) nonzero elements, and $b \in \{1, -1\}^M$. Now the problem is trying to recover sparse signal s from sign measurement b.

Boufounos and Baraniuk [28] first showed that we can accurately reconstruct normalized $\hat{s}$, through

$$\hat{s} = \arg\min_{s} \|s\|_1, \quad \text{s.t. } B\Phi s \geq 0, \ \|s\|_2 = 1, \tag{2}$$

where $\|\cdot\|_1$ and $\|\cdot\|_2$ denote the l_1-norm and l_2-norm of a vector, respectively, and $B := \operatorname{diag}(b)$ is an $M \times M$ diagonal matrix whose diagonal elements are from the element of vector b. Also, the constraint $B\Phi s \geq 0$ in (2) imposes on the consistency requirement between the 1-bit measurements and the solution, and the constraint $\|s\|_2 = 1$ limits the solution to a unit l_2 sphere which also means the estimated $\hat{s}$ loses the scale information.

In [28], the authors relaxed the constraint and used fixed-point continuation (FPC) algorithm solving the below alternative model:

$$\hat{s} = \arg\min_{s} \|s\|_1 + \lambda \sum_i f\left((B\Phi s)_i\right) \quad \text{s.t. } \|s\|_2 = 1, \tag{3}$$

where λ is a tuning parameter and

$$f(x) = \begin{cases} \dfrac{x^2}{2}, & x < 0, \\ 0, & x \geq 0. \end{cases} \tag{4}$$

BIHT [29] currently is one of the fastest and accurate reconstruction algorithms which solve the following model:

$$\hat{s} = \operatorname*{argmin}_{s} \sum_i f\left((B\Phi s)_i\right) \quad \text{s.t. } \|s\|_0 \leq k, \ \|s\|_2 = 1. \tag{5}$$

But model (5) needs the sparse level K as the prior information that is not practical in WSNs.

We classify reconstruction algorithms without the prior requirement of sparsity level as blind 1-bit CS.

In [30], the authors proposed an efficient blind 1-bit CS method, which was restricted step shrinkage (RSS) algorithm, to solve model (2). This algorithm used trust-region methods for nonconvex optimization on a unit l_2 sphere and has provable convergence guarantees.

Blind 1-bit CS algorithms are an ongoing research direction, which has attracted more and more attention in recent years [31, 32].

In the next subsection, we exploit the compressible feature of sensor data and propose a novel blind 1-bit CS framework and a new reconstruction algorithm based on BIHT.

2.2. Our Framework and Algorithm. In WSNs, the measurements that each sensor node collects have intratemporal correlation and thus can be sparsified under certain transform basis. For example, as we can see from experiment section, the sensory data from two real WSN datasets can be represented by only very few coefficients under discrete cosine transform (DCT). We assume the projections of sensory data that each sensor node needs to send are vector b $(\in \{1,-1\}^M)$ and

$$b = \operatorname{sign}(\Phi x), \tag{6}$$

where x $(\in R^N)$ is the original sensory data and Φ is a given $M \times N$ Gaussian random projection matrix. Suppose that x can be sparsified as coefficients s by an orthogonal transform matrix Ψ $(\in R^{N\times N})$, such that $x = \Psi s$; then (6) can be rewritten as the equation below:

$$b = \operatorname{sign}(\Phi x) = \operatorname{sign}(\Phi\Psi s) = \operatorname{sign}(As), \tag{7}$$

where $A = \Phi \times \Psi$. Equation (7) is equal to (1) and can be used by base station to recover the normalized coefficients s.

Though the scale inforamation is lost during the projection operation, the measurements in WSNs have only finite precision. Motivated by this fact, we first propose 1-bit data gathering CS framework in WSNs that is presented in Algorithm 1. The main idea in our framework is that each sensor node sends extra norm value of x to base station.

Observing that only a small portion of coefficients dominate the energy of s, and those coefficients almost centralize at the beginning of s (see Figures 1 and 2 in the next experiment section as examples), we propose a new blind 1-bit CS algorithm for WSN based on BIHT [29]. We call our algorithm BBIHT, and the details are described in Algorithm 2.

In our BBIHT algorithm, we compute all the BIHT solutions given the sparse level arranging from 1 to max_K (from steps 2 to 5 in Algorithm 2). The problem now is how to find the best solution with the highest accuracy among all the BIHT solutions. Our BBIHT was motivated by observing the fact that the variance among the rows of all the BIHT solutions with different sparse level can indicate the best sparse level with the highest accuracy. That is to say, if the variance is larger than threshold *stop_var,* which is a relative small value, we can tell that the related sparse level is not the best sparse level and then previous sparse level is the best sparse level (from steps 7 to 12 in Algorithm 2).

As we can see from Algorithm 2, the reconstruction accuracy of our BBIHT mainly depends on the reconstruction accuracy of BIHT with the best sparse level. Also, adjusting the value of max_K can affect the computing time and reconstruction accuracy. For example, when max_K equals 1, we only need to compute BIHT once; thus the computing time is the lowest, but, at the same time, the reconstruction accuracy is the poorest.

In the next section, we can find that BBHIT works pretty well in real WSN datasets.

3. Experimental Results

In this section, we run extensive numerical experiments on two real WSN datasets to demonstrate the effectiveness of our algorithm. The first dataset is a real world trace from Intel Berkeley Research lab and we choose the temperature information collected by sensor node with number 1 on March 2, 2004 [33]. Another dataset is the temperature data collected in the Pacific Sea at (7.0N, 180W) on March 29, 2008 [34]. All experiments were performed using MATLAB on the same computer. The simulation codes of 1-bit FPC and RSS, which are the state-of-the-art 1-bit blind CS algorithms, are all from the original authors.

3.1. Sparsity of the WSN Datasets. Figures 1 and 2 are the DCT coefficients of the two datasets, respectively. As we can see from the results, few coefficients dominate the energy, and most of the coefficients are nearly zero. In fact, the first 4 DCT coefficients of Pacific Sea dataset occupy more than 99.97% energy. Thus, the two datasets can be sparsified under DCT transform and thus can be compressed using CS and 1-bit CS.

3.2. Reconstruction Experiments. The setup for our experiments is as follows. The elements of matrix $\Phi \in R^{M\times N}$ follow i.i.d. Gaussian distribution with zero mean and $1/M$ variance. $\Psi \in R^{N\times N}$ is a DCT orthogonal transform matrix. δ and *stop_var* in BBHIT are set to 0.1 and 0.01, respectively.

We performed 200 trials, and in each trial we fixed the length of reading vector x as 250 and varied M from 25 to 500. The sign measurements are computed as in (6). We obtain estimated $\hat{x}$ using RSS [30], 1-bit FPC [28], and our BBHIT introduced in this paper, respectively.

The average signal-to-noise ratio (SNR) for each original sensory data x with respect to estimated $\hat{x}$ was computed. Here SNR is denoted by

$$20\log_{10}\left(\frac{\|x\|_2}{\|x-\hat{x}\|_2}\right). \tag{8}$$

Figures 3 and 4 present the SNR values for Pacific Sea dataset and Berkeley Research lab dataset using RSS, 1-bit FPC, and BBIHT algorithms, respectively. The results demonstrate that BBIHT algorithm can achieve relatively higher accuracy than RSS and 1-bit FPC algorithms, especially for the Pacific Sea dataset, which is sparser than the other dataset. Also, as depicted in the figures, we can see that when M/N equals 1 (that means we only use 1 bit for each projection), the SNR is still higher than 20 db. Thus, BBIHT can significantly reduce the communication overhead while still achieving a reasonable high accuracy.

When M/N equals 1, Figures 5 and 6 show the results of reconstructed readings from all the 1-bit blind CS algorithms and original readings for the two datasets, respectively. As we can see, reconstructed readings of our BBIHT and RSS fit the original readings well for both the datasets, since both of them have good SNR value.

3.3. Comparison of Compression Ratio. Usually, sensor reading in WSN is IEEE single-precision floating point value; in order to present the traditional CS projection value 24 bits are needed. For example, the value of CS projection for Pacific Sea dataset lies between −914.8860 and 1.1418e + 03,

Sensor node's operation:
(1) Sample and buffer sensory data x, then generate projection $b \in \{1, -1\}^M$ computed from (6);
(2) Calculate the norm value of original sensory data $norm\_x = \|x\|_2$;
(3) Send $norm\_x$ and projection b to base station.
Base station's operations:
(1) After receiving $norm\_x$ and projection b from the sensor node, base station solves (7) and get normalized coefficients $\hat{s}$ from **blind_1_bit_cs** (A, b), here blind_1_bit_cs function can be any blind CS reconstruction algorithm that needs no prior sparse level information.
(2) Computing the estimated original sensory data $\hat{x} = (\Psi^T * \hat{s}) \times norm\_x$, here Ψ^T is the transpose of Ψ, and $\Psi^T \times \Psi = I$.

ALGORITHM 1: Proposed 1-bit CS framework.

```
Initialization: max_K = δ × N (0 < δ < 1), S = zeros(N, max_K), stop_var = 0.01, best_k = 1
    for k = 1 : 1 : max_K
        ŝ = BIHT(A, b, k); //using BIHT as the 1-bit CS reconstruction algorithm with given sparse level k
        S(:, k) = ŝ;
    end
    for i =1 : 1 : max_K //find the best sparse level
            tmp = S(i, i: max_K); //get the non-zero
                        // elements of row i
            if var(tmp) > stop_var //stop criticism
                  best_k = i − 1;
                  Break;
            end
    end
    return S(:, best_k); //the best reconstructed signal
```

ALGORITHM 2: BBIHT reconstruction algorithm.

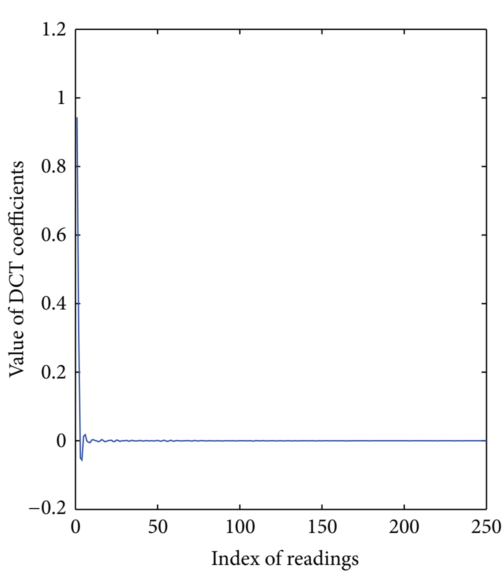

FIGURE 1: DCT coefficients of Pacific Sea dataset; $N = 250$.

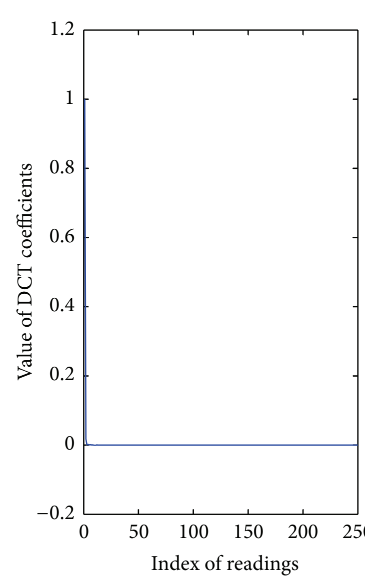

FIGURE 2: DCT coefficients of Intel Berkeley Research lab dataset; $N = 250$.

and 16 bits are not enough to store the projection. Thus, the compression ratio of traditional CS is

$$\frac{M \times 24}{N \times 24} = \frac{M}{N}. \tag{9}$$

In CDG scheme the best compression ratio is 0.1 (Section 5.1 in [13]).

In our BBIHT schema, we only need 1 bit to store each projection and 24 bits to store the extra norm value $norm\_x$

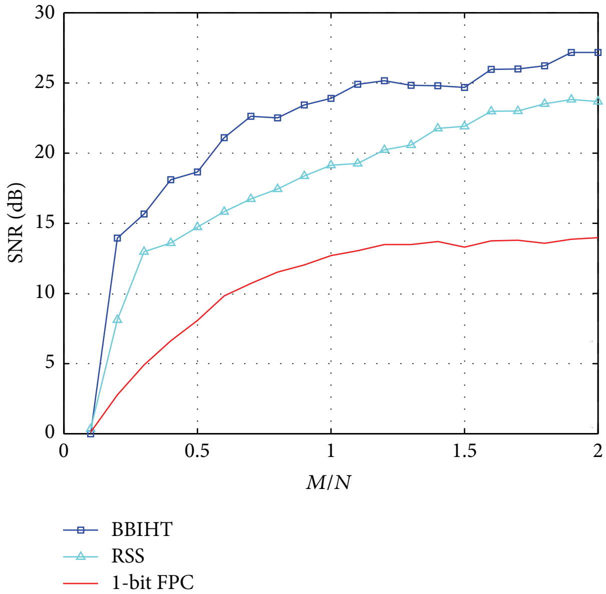

Figure 3: SNR for Pacific Sea dataset; $N = 250$. M varied from 25 to 500.

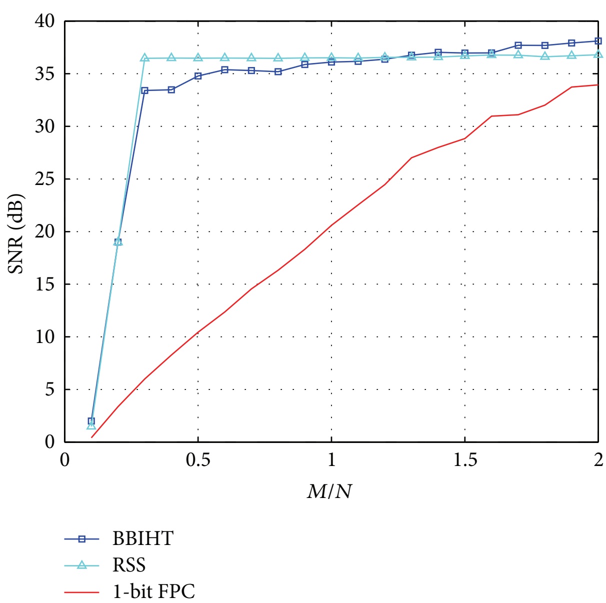

Figure 4: SNR for Berkeley Research lab dataset; $N = 250$, M varied from 25 to 500.

in Algorithm 1. Thus, the compression ratio of BBIHT in our experiment is

$$\frac{M \times 1 + 24}{N \times 24} = \frac{M/24 + 1}{N}. \tag{10}$$

When $M > 1$, which is always the case, BBIHT compression ratio $(M/24 + 1)/N$ is less than M/N. Hence, BBIHT significantly reduces the communication overhead more than traditional CS methods and can still achieve a reasonable reconstruction accuracy. For example, as depicted in Figures 3 and 5, we can see that the SNR of Pacific Sea dataset is higher

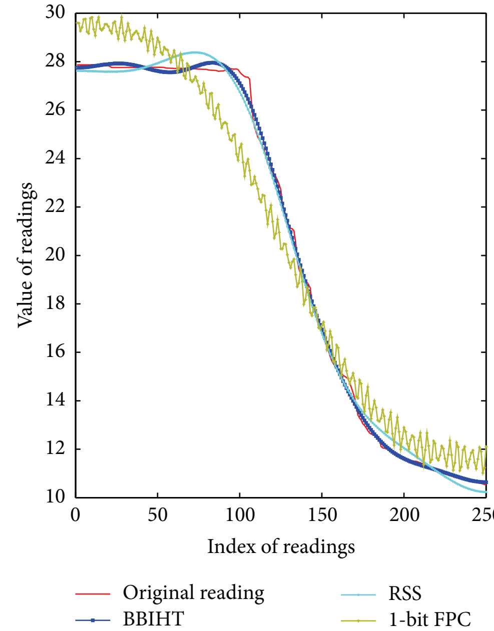

Figure 5: Original readings versus reconstructed readings for Pacific Sea dataset; $N = 250$; $M/N = 1$.

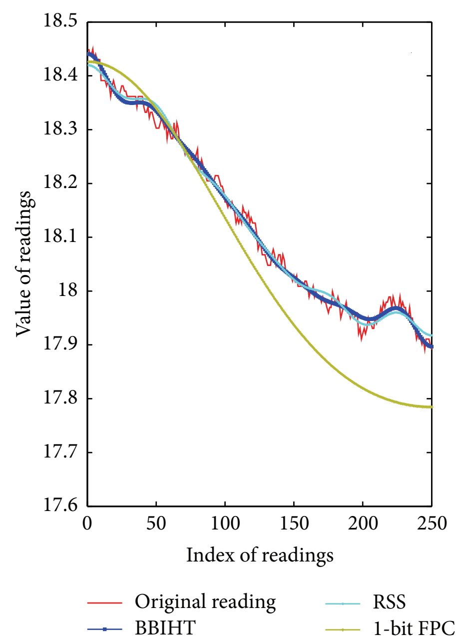

Figure 6: Original readings versus reconstructed readings for Intel Berkeley Research lab dataset; $N = 250$; $M/N = 1$.

than 20 db and the accuracy is enough when $M/N = 1$. In this case, the BBIHT compression ratio is $(250/24 + 1)/250 = 0.046$.

3.4. Average CPU Time. Figures 7 and 8 are the average CPU time of the three blind 1-bit CS algorithms for the two datasets, respectively. We can see that the average CPU time of our BBIHT is below 1 second when M/N is less than 1.

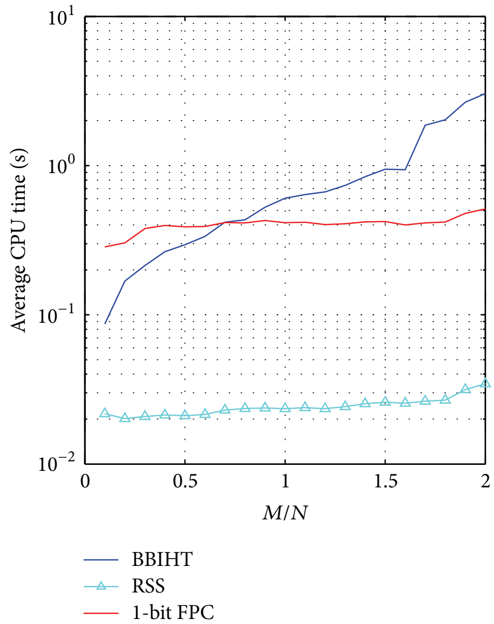

Figure 7: Average CPU time for Pacific Sea lab dataset; $N = 250$, and M varied from 25 to 500.

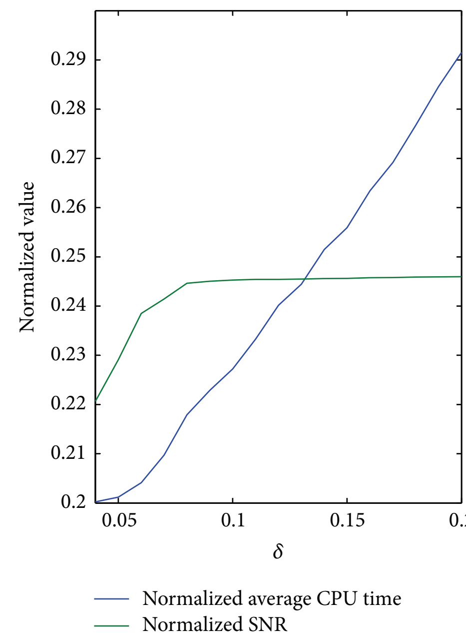

Figure 9: Normalized average CPU time and SNR for Pacific Sea lab dataset; $M/N = 1$, and δ varied from 0.04 to 0.2.

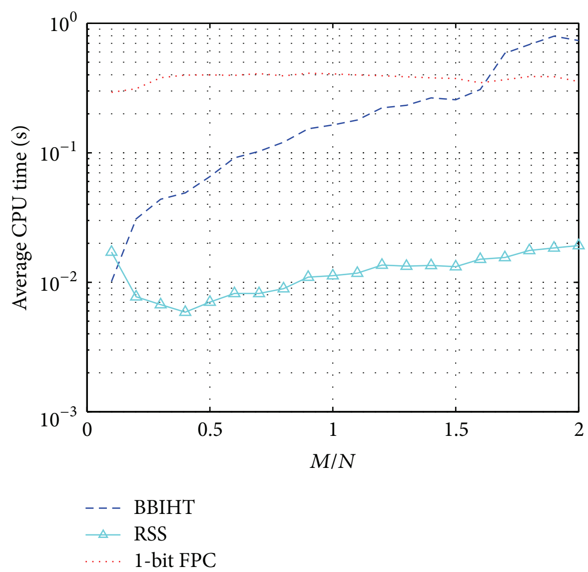

Figure 8: Average CPU time for Intel Berkeley Research lab dataset; $N = 250$, and M varied from 25 to 500.

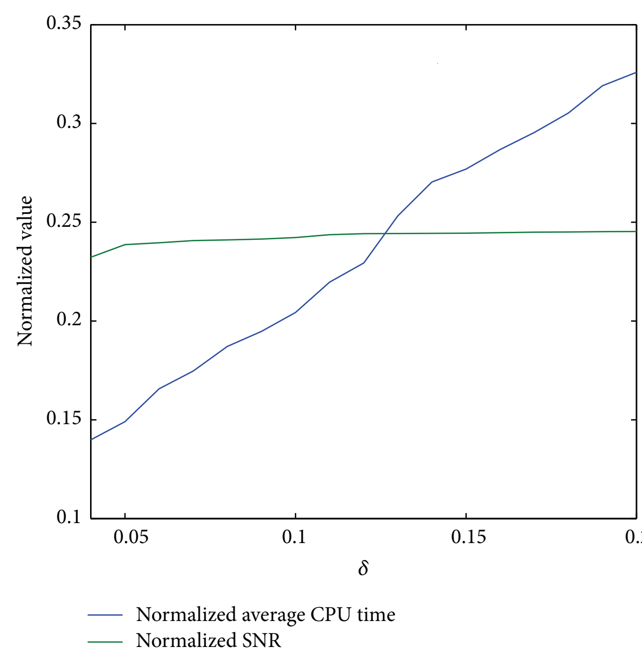

Figure 10: Normalized average CPU time and SNR for Intel Berkeley Research lab dataset; $M/N = 1$, and δ varied from 0.04 to 0.2.

Also, note that we can adjust δ in Algorithm 2 to balance the computation overhead and SNR accuracy, because δ controls the running rounds of BIHT (from steps 2 to 5 in Algorithm 2) and the searching range for the best sparse level (from steps 6 to 12 in Algorithm 2). Figures 9 and 10 give out the normalized value of CPU time and SNR under different δ value.

As we can see from the results, the CPU time decreases almost linearly when δ decreases. But SNR is almost the same when $\delta > 0.08$ for Pacific Sea dataset and $\delta > 0.05$ for Intel Berkeley dataset; the reason is that the max_$K(= \delta \times N)$ still covers the actual best sparse level K around those values. In practical scene, δ can also be optimally estimated by analyzing historical sensory data to minimize the CPU time while still achieving good SNR.

4. Conclusion and Future Work

In this paper, we have first presented a framework and a new blind 1-bit CS algorithm for the data gathering in WSNs. Experiments on two real world sensor datasets reveal our preliminary but interesting results; that is, we can achieve much more compression ratio, which means less communication overhead, and the reconstruction accuracy is still reasonable and acceptable.

Thorough theory analysis of our BBIHT and more experiments on other kind of real sensor datasets with different tuning parameters are remaining as our future work.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work was supported in part by the Opening Fund of Top Key Discipline of Computer Software and Theory in Zhejiang Provincial Colleges at Zhejiang Normal University (no. ZSDZZZZXK28). The authors would like to thank Zaiwen Wen for sharing the implementation of the original RSS algorithm.

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