Data Sorting-based Adaptive Spatial Compression in Wireless Sensor Networks

Siguang Chen[1], Jincheng Liu[1], Kun Wang[1], Zhixin Sun[1] and Xuejian Zhao[1]
[1] Key Lab of Broadband Wireless Communication and Sensor Network Technology of Ministry of Education, Nanjing University of Posts and Telecommunications
Nanjing 210003, Jiangsu-China
[e-mail: sgchen@njupt.edu.cn, 18083768322@163.com, {kwang, sunzx, zhaoxj}@njupt.edu.cn]
*Corresponding author: Siguang Chen

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Abstract

Wireless sensor networks (WSNs) provide a promising approach to monitor the physical environments, to prolong the network lifetime by exploiting the mutual correlation among sensor readings has become a research focus. In this paper, we design a hierarchical network framework which guarantees layered-compression. Meanwhile, a data sorting-based adaptive spatial compression scheme (DS-ASCS) is proposed to explore the spatial correlation among signals. The proposed scheme reduces the amount of data transmissions and alleviates the network congestion. It also obtains high compression performance by sorting original sensor readings and selectively discarding the small coefficients in transformed matrix. Moreover, the compression ratio of this scheme varies according to the correlation among signals and the value of adaptive threshold, so the proposed scheme is adaptive to various deploying environments. Finally, the simulation results show that the energy of sorted data is more concentrated than the unsorted data, and the proposed scheme achieves higher reconstruction precision and compression ratio as compared with other spatial compression schemes.

Keywords: Wireless sensor networks; spatial correlation; hierarchical network; data sorting; spatial compression

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1. Introduction

Wireless sensor networks (WSNs) have become increasingly important because of its ability to monitor and manage physical or environmental information for various intelligent services [1]. WSNs have been applied in many fields, such as the military, industry, environmental monitoring and healthcare [2-3].

However, the existent challenges of practical operation are due to the small batteries of sensor nodes, and it is infeasible to recharge them or deployed new nodes in many scenarios. In this case, how to prolong the lifetime of sensors has become a critical issue [4]. As we know, WSN has following two notable properties. Firstly, the overhead of messages transmission occupies most of energy consumption. When overwhelming messages transmitted to sink node, sink node will suffer heavy burden of data processing. What's worse, the relay nodes near sink node will consume their energy faster. When these nodes exhausted, WSN will be broken [5]. Secondly, sensing data reported from sensor nodes often exhibit a certain degree of correlation. It's feasible to compress signals by utilizing some certain compression schemes. Exploiting spatial correlation among signals not only reduces the number of transmissions, but also decreases the energy consumption of the entire WSN. Thus this topic becomes a research focus [6]. With these observations, we can compress the message transmitted in the WSN. With the decrease of transmitted signals, the network congestion alleviates greatly.

Chen et al. [7] developed a spatial compression scheme by applying compressed sensing (CS) to compress spatial correlated data. The CS requires the original signals have sparse representation in some particular bases or dictionaries. This property limits the application areas of compressed sensing. In [8], Kong et al. proposed a novel CS-based approach to develop a space time improved CS algorithm to enhance the reconstruction accuracy. The feature of this approach is that the signals are transformed into a long vector. Although the correlations are exploited fully, the computational complexity of reconstruction process is high. The works [9-10] studied Huffman coding and Lempel-Ziv-Welch (LZW) scheme to achieve textual data compression. These two compression schemes provide lossless text compression. Nevertheless, they cannot be applied in the data compression of WSN directly. Because the textual data are composed of finite set of alphabets, however, the reports of sensing nodes are continuous values.

The work [11] proposed a data compression scheme for WSNs by applying wavelet transform. The work [12] investigated image signal compression scheme for WSNs by applying discrete cosine transform (DCT), the idea of injecting image compression method to WSNs is encouraging. As we know, DCT and wavelet transform are widely used in image compression and the sensing data in WSN. In work [13], an algorithm called RIDA presented a novel paradigm to compress data by using logical mapping in WSNs. Each sensor only sends the large transformed coefficients to the relay nodes. Wang et al. [4] constructed a multi-compression scheme to achieve layered-compression, where reduced zigzag scan (RZS) is the core of proposed scheme. This work injected the DCT method to signal compression and developed a novel spatial compression scheme. The compression scheme is simple, but the signal recovery accuracy is low, especially in some extreme cases. Meanwhile, it assumes the correlation among signals are strong, in this case, most of the coefficients in transformed matrix are rather small. The rigid compression method wastes the sensors' energy in the WSNs. Nguyen et al. [14] proposed an improved RZS to compress spatial signals. Compared with the former scheme, the improved RZS sorts the original data in ascending or descending order in relay nodes. After taking sorting step, a larger proportion of original signal energy is focused on the coefficients in the upper-left side. However, the improved compression scheme still overlooks the disadvantages of this kind of rigid compression scheme. The drawback is that it discards some last coefficients instead of selectively deletes the small coefficients. In addressing the problem, recently, a compression scheme [15] selectively discards the small coefficients to compress the data which is proposed. But the coefficients in this scheme are not the smallest.

Motivated by the existing problems and the novel idea of exploring spatial correlation in prior literatures, we combine the advantages of the compression schemes above, and propose a data sorting-based adaptive spatial compression scheme (DS-ASCS) in this paper.

The first contribution is that our work designs a layered network model. The proper design of network model guarantees the effective implementation of layered compression scheme.

Secondly, we investigate the data sorting of the received signals in cluster head node which can explore the correlation of signals better, and that means the DCT coefficients of sorted data become more concentrated, i.e., the signal energy will focus on the few significant elements. It's useful for deleting small coefficients in compression process.

Thirdly, based on the previous two contributions we propose a data sorting-based adaptive spatial compression scheme, which includes zigzag scan method and adaptive spatial compression algorithm (ASCA), and can explore the spatial correlation among signals deeply and completely. The proposed scheme reduces the amount of data transmissions and obtains high compression and reconstruction performance by sorting original sensor readings and selectively discarding the small coefficients in transformed matrix. Meanwhile, the proposed scheme is adaptive to various deploying environments.

Finally, the simulation results confirm that the DS-ASCS outperforms the other similar spatial compression schemes. In contrast with those compression schemes, the proposed scheme possesses lower reconstruction error at the same compression ratio and has more stable reconstruction property.

The rest of this paper is organized as follows. Section 2 introduces the background knowledge of DCT. In Section 3, the layered-network model is presented. In Section 4, we present the DS-ASCS in detail. In Section 5, compared with previous schemes, the related simulations are given to certify the sorted data is more focused than unsorted, and examine the advantages of proposed scheme. Finally, conclusions are drawn in Section 6.

2. Background of DCT

As we know, discrete cosine transform (DCT) plays a vital role in video compression due to its near-optical decorrelation efficiency [10]. DCT is an orthogonal transformation encoding method, and it's used to remove the spatial redundancy of image and extract significant values of the image. Transformation coding transforms the image intensity matrix (time-domain signal) into coefficient space (frequency domain signal) [12]. The formula of two-dimensional (2D) DCT used in this paper is written as follows:

$$t_{i,j} = \frac{2c(i)c(j)}{k}\sum_{x=0}^{k-1}\sum_{y=0}^{k-1}\cos\frac{i\pi(2x+1)}{2k}\cos\frac{j\pi(2y+1)}{2k}s_{i,j} \tag{1}$$

where $c(i)=\sqrt{2}$ if i =1 and $c(i)=1$ otherwise. In signal compression of WSN, on the one hand, DCT maps the signal in spatial domain to coefficient domain to decrease the direct relations among DCT coefficients. On the other hand, compared with unsorted data, the coefficients of sorted data are more concentrated on the upper-left part of the transformed matrix [15]. This property provides us the possibility to deeply explore the correlation among sensors readings.

For transformed data matrix, we utilize inverse 2D-DCT to reconstruct original data matrix. The reconstruction process is lossless. The formula of inverse DCT is written as follows:

$$s_{i,j} = \frac{2}{k}\sum_{x=0}^{k-1}\sum_{y=0}^{k-1} c(x)c(y)\cos\frac{x\pi(2i+1)}{2k}\cos\frac{y\pi(2j+1)}{2k}t_{x,y}. \quad (2)$$

The energy of strongly correlated spatial signals reflects in frequency domain always concentrate in some particular areas, i.e., the distribution of coefficient matrix possesses some rules. In particular, DCT compacts those important coefficients in the upper-left part of transformed matrix, while leaving other insignificant values in the opposite side. In this way, we can compress the signal matrix according to these laws. After the image transformed by DCT, the correlation among DCT coefficients becomes smaller. And most of the energy of image concentrates in some small number of coefficients located in the upper-left part [16].

3. Network Model

This section illuminates our hierarchical network framework. The planar graph of proposed network framework is shown in **Fig. 1**.

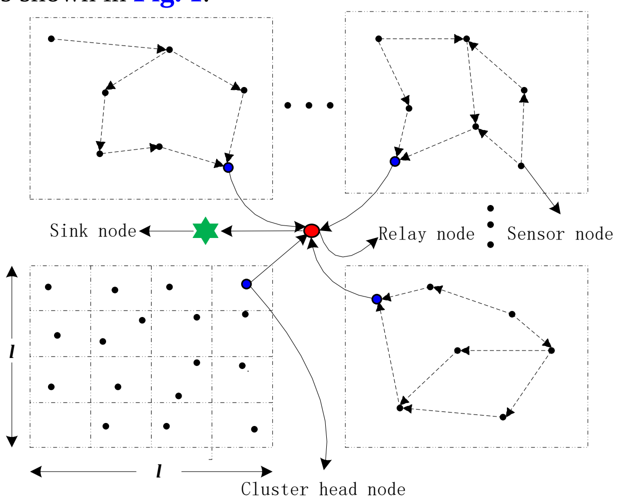


Fig. 1. Planar graph of proposed WSN framework

In our proposed network scenario, we construct a multi-layer WSN, where N nodes are uniformly and randomly deployed in a unit area. The neighboring nodes observe the same phenomenon, so the sensing data of neighboring sensors are always spatially correlated.

We recursively divide the observation area into α clusters. And each cluster contains $l \times l$ grids, where l is a small integer. The ideal situation is one grid contains one sensing node. In this case, the relay node takes the sensing reports from sensing node as the value of grid. However, due to the randomness of deploying sensor nodes, the number of sensor nodes in each grid is uncertain. In the observation area, a grid may possibly contain zero node. To deal with this problem, once the upper layer relay nodes detect the case that one grid doesn't report sensing data, they take the average value of the corresponding adjacent grids. On the other hand, if there are more than one sensing node in one grid, the relay node takes the average value of their sensing reports as the grid's value.

In this way, we establish a relation between DCT and spatial compression scheme in WSN.

We arrange all kinds of nodes into three layers in **Fig. 2**, where a node in layer i+1 contains α clusters in layer-i. With the layered structure network, we achieve the goal of layered-compression. We select a node as cluster head node, and the rest of nodes in cluster are used to report the sensing readings to head node. The head nodes in layer-1 collect and compress sensing data from the corresponding $l \times l$ grids. In layer-2, we define the node as relay node which is used to further collect and compress the signals from the corresponding α clusters in its lower layer. The data passed through each layer will be spatially compressed by the DS-ASCS. Finally, the sink node in layer-3 receives the compressed signals, and reconstructs the orginal signals.

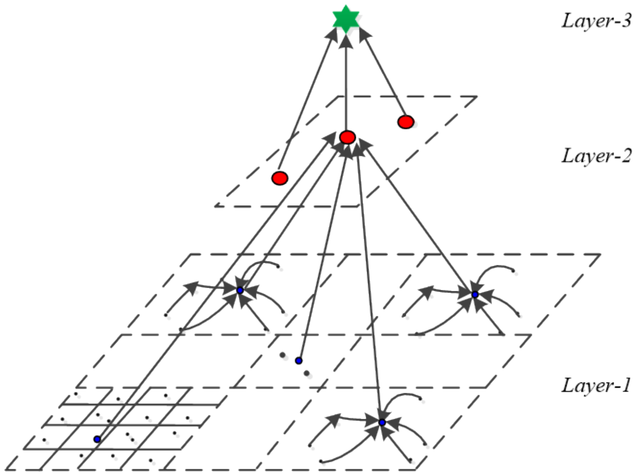


Fig. 2. System architecture of proposed WSN framework

4. Data Sorting-based Adaptive Spatial Compression Scheme

The existent works proposed to exploit spatial correlation in WSN can be classified into several categories, where one of the classical compression schemes is proposed in work [4].

In [4], Wang et al. proposed a RZS compression method, the processing node applies DCT method on original data matrix, the last several coefficients of transformed matrix are forced to abandoned. Although RZS scheme achieves the goal of data layered-compression and provides us a novel data compression method, the RZS scheme is rigid and the reconstruction precision is low. In [14], Nguyen et al. proposed an improved RZS, however, the improved scheme still has the inherent drawback.

Based on the classical idea of spatial compression and the existing problems in previous works, we propose a DS-ASCS in this section. The sorted data reduces the correlation of coefficients, and the proper deletion of small coefficients guarantees the signal recovery with high precision.

According to the layer number, the steps of DS-ASCS are given as follows: layer-1 compression, layer-i (i>1) compression and decompression at the sink. In order to facilitate the understanding, some concepts need to be defined and the relation between them will be explained. The compression ratio $\lambda (0 \le \lambda < 1)$ is defined as the reduction in size relative to the uncompressed size through each layer. The compression ratio λ is defined as:

$$\lambda = 1 - \frac{compressed(size)}{uncompressed(size)} . \tag{3}$$

The compression ratio λ in this section is hard to set, because the number of coefficients below the threshold δ is based on the correlation among sensors readings. In the first layer compression, the length of compressed vector depends on the threshold δ. In a word, compression ratio λ varies along with the threshold δ. Meanwhile, the correlation of grids' values in different clusters is dubious. Due to this reason, the threshold is an empirical value.

1) Layer-1 Compression Process: In this subsection, lay-1 compression is presented. The cluster head node in cluster *k* collects and sorts 2D signal in a time slot *t* is represented as $M_k \in R^{l \times l}$, where *k* denotes the index of cluster. The (*i*, *j*)-th entry of M_k is denoted as $s(i, j)$, which corresponds to data sample of grid (i, j), and $M_k^{(s)} \in R^{l \times l}$ denotes the sorted matrix of $M_k \in R^{l \times l}$. The specific mapping relations between M_k and $M_k^{(s)}$ is recorded in $O \in Z(1, l^2)$, the format of O is given as follows:

$$O = [offset(M_k(1,1)), offset(M_k(1,2)), ..., offset(M_k(l,l))] \tag{4}$$

which records the offset of the original elements.

The cluster head node generates a new matrix $M_k^{(T)} \in R^{l \times l}$ by implementing 2D-DCT on $M_k^{(s)} \in R^{l \times l}$. The elements of $M_k^{(T)}$ are denoted as $t(i, j)$ ($1 \le i, j \le l$). Based on the property of DCT, a smaller $\mu(M_k^{(s)})$ will lead to a sparser transformed matrix $M_k^{(T)}$. The coherence of matrix $M_k^{(s)}$ is defined as

$$\mu(M_k^{(s)}) = \max_{1 \le i < j \le l} \frac{\left|\langle a_i, a_j \rangle\right|}{\|a_i\|_2 \|a_j\|_2} \tag{5}$$

where a_i and a_j denotes the two different columns in $M_k^{(s)}$.

After the sorted original data matrix $M_k^{(s)}$ transformed by 2D-DCT, the distribution of elements in transformed matrix $M_k^{(T)}$ depends on the correlation among sorted signals. The more correlated among sorted spatial signals, the more energy gathered in upper left corner.

Considering the signals of one cluster are highly correlated. Especially after the sorting process, the signal correlation is improved. Sensor nodes in different regions observe different physical phenomena, the reports of different nodes belong to different observed regions may be variable from each other. In this case, it's highly possible that the values of different regions' transformed matrix $M_k^{(T)}$ are quite different. This property requires us to set different thresholds according to the correlation among the signals in different observed regions.

After the sorted original data matrix transformed by 2D-DCT, the zigzag scan [17] will be implemented on the transformed matrix. Zigzag scan method and adaptive spatial compression algorithm (ASCA) are two components of DS-ASCS. Zigzag scan is applied to transform the transformed matrix into a one-dimension vector $v_k \in R^{1 \times l^2}$, and ASCA is used to compress data. The procedure of zigzag scan can be interpreted in mathematical language. Assume there is a matrix, whose size is $N \times N$. The symbols $i, j (1 \le i, j \le N)$ represent the number of row and column of the matrix, respectively. And $I(i, j)$ is the index of original elements. The formula of zigzag scan is shown as follows:

$$p = \begin{cases} t(t-1)/2 + t - \min(i, j) - 1, \\ \quad i \geq j, t \bmod 2 = 1 \\ N(N+1)/2 + (N+t)(N-t-1)/2 + t - \min(i, j) - 1, \\ \quad i < j, t \bmod 2 = 1 \\ t(t-1)/2 + t + \max(i, j) - N, \\ \quad i \geq j, t \bmod 2 = 0 \\ N(N+1)/2 + (N+t)(N-t-1)/2 + t + \max(i, j) - N, \\ \quad i < j, t \bmod 2 = 0 \end{cases} \tag{6}$$

where $t = N - abs(i - j)$, and p is the index of position in transformed vector.

The path of zigzag scan is shown in **Fig. 3**.

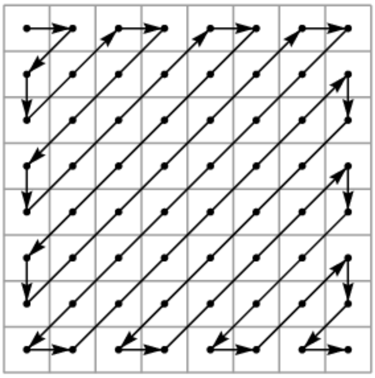


Fig. 3. Zigzag scan

The summary of zigzag scan is given as follows: zigzag scan method begins at the upper-left corner of $M_k^{(T)}$ and sequentially scans the diagonals of $M_k^{(T)}$. The zigzag scan method stops when it scans the last coefficient of $M_k^{(T)}$ [18]. The result of zigzag scan is shown in **Fig. 4**.

1	2	3	4	...	22	23	24	25
1	2	6	11	• • •	15	20	24	25

Fig. 4. The result of transformed vector v_k

Algorithm. 1 Adaptive spatial compression algorithm

Input: Vector v_k, threshold δ
Output: Compressed vector $v_k^{(c)}$
begin
    Initialize threshold δ=10^{-3}
    for i= l^2 to 2
        if $|v_k(i)|$ <= δ
            I. record i
            II. discard $v_k(i)$
        end
    end
end

Then, we assume that each element in transformed matrix is denoted as $t_{i,j} \in M_k^{(T)}$, where $1 \le i, j \le l$. Instead of using (i, j) denotes each element, we apply a one-dimension vector to represent the index of each cluster. Then we compress the transformed vector $v_k \in R^{1\times l^2}$ by applying ASCA. The scan procedure is started from the end of this vector. Because the small coefficients are mainly distributed in the end of the vector. In this case, a lot of time for scanning is saved. Finally, the coefficients less than δ are abandoned, and we get the compressed vector and the indices of discarded elements.

After getting the compressed vector $v_k^{(c)} \in R^{1\times(\lambda \cdot l^2)}$, we define the format of transmitted packet in *k*-th cluster head node denoted by r_k. r_k has three independent components, they are given by

$$r_k = \begin{cases} r_k(1) = [v_k^{(c)}, t] \\ r_k(2) = I \\ r_k(3) = O \end{cases} \tag{7}$$

where *I* is a set consists of the indices of discarded coefficients, *t* is the corresponding time slot, and *k* denotes the index of cluster. The symbol *O* records the offset of the original elements.

We transmit r_k to the corresponding relay node of lay-2. According to the property of DCT, our compression scheme keeps most significant values of the matrix $M_k^{(T)}$. With the value of compression ratio λ increases, the precision of reconstructed signal decreases.

2) Layer-*i* ($i \ge 2$) Compression Process: Relay nodes in layer-*i* further compress the data from the corresponding α clusters of its lower layer. Based on the received signal, we set a lager experience-based threshold δ' at relay nodes in higher layer.

In layer-*i* compression, we further reduce the length of vector $v_k^{(c)}$ (passed from the layer *i*-1) by discarding the coefficients of $v_k^{(c)}$. Recall that the vector $v_k^{(c)}$ doesn't arrange the coefficients in a certain order. Therefore, we can reduce the size of sensing data with a larger threshold δ' in layer-*i* ($i \ge 2$) and keep the significant coefficients of transmitted data.

3) Decompression Process: In order to reduce the computation overhead of sensor nodes, the decompression procedure is performed at sink node. The sink node obtains a matrix from the relay nodes of lower layer, and the set of compressed signals is

$$v = (v_1^{(c)}, v_2^{(c)}, ..., v_\alpha^{(c)}) \tag{8}$$

where $v_k^{(c)} = [M_k^{(T)}(1,1), M_k^{(T)}(1,2), M_k^{(T)}(2,1), ...]$ denotes the reserved coefficients. The specific indices of coefficients are unknown to us. For each lay-1 cluster *k*, the sink node recovers the corresponding vector $v_k^{(R)}$ to a two-dimensional matrix $M_k^{(R)}$. According to the location information in received package *I*, sink node fills the discarded coefficients of $v_k^{(c)}$ with zeros in the first step of reconstruction process, where *I(i)* is the index of discarded coefficients. Then we use formula (2) to recover $v_k^{(R)}$ and obtain reconstructed matrix $M_k^{(R)} = (r_{i,j})_{l\times l}$. The final reconstruction operation is to rearrange the order of $M_k^{(R)}$ into $M_k^{(r)} = (\tilde{s}_{i,j})_{l\times l}$ based on the location information recorded in *O*.

Note that since the matrix $M_k^{(T)}$ is incomplete, the recovery matrix $M_k^{(r)}$ may not be necessarily equals to the original matrix M_k. The compression ratio λ decides both the size of compressed sensing reports and the precision of recovery signals, it is a trade-off between these two metrics.

5. Performance Analysis

In this section, we evaluate the recovery performance of the proposed scheme with compression schemes in [4, 14, 15] via simulations. The algorithm bubble sort [19] is utilized to sort the original data. Based on the numerical comparisons, we confirm that the sorted data has stronger correlation than unsorted data. The results also show that the proposed scheme enhances the signal reconstruction performance.

5.1 Performance Analysis: Sorted and Unsorted Data

In this subsection, in order to ensure the reliability and universality, 1×1000 sensing readings whose variance is 9 are used in this simulation.

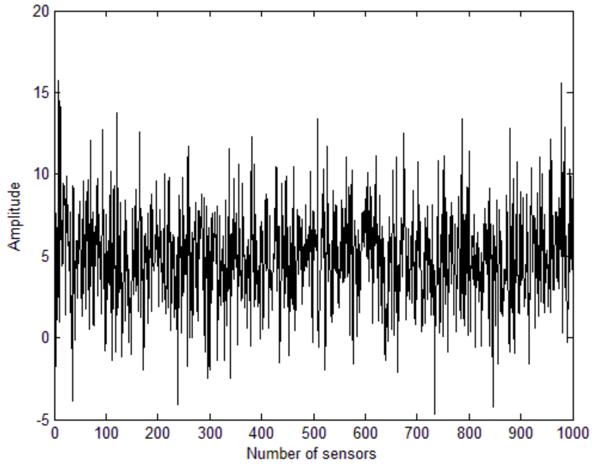


Fig. 5. Unsorted original data

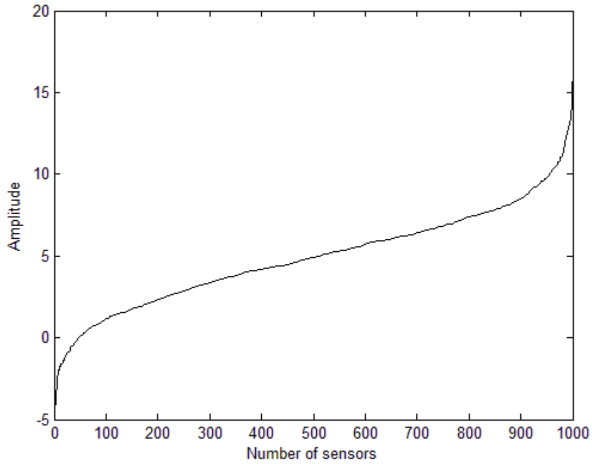


Fig. 6. Sorted data in ascending order

Fig. 5 depicts the original 1×1000 sensing readings whose variance is 9. In **Fig. 5** , the data is in chaos and disorder. In oreder to increase the relevance of original data, we sort the data in ascending order. The sorted data is shown in **Fig. 6.** From the figures above, we can see that the data in **Fig. 6** is much smoother than the data in **Fig. 5**. **Figs. 7** and **8** confirm the data in **Fig. 6** is more related than the data in **Fig. 5** while the DCT is applied on them.

Figs. 7 and **8** also depict the distribution of DCT coefficients of unsorted and sorted data, respectively. The signal energy of them almost focuses in relatively small numbers of significant coefficients. In particular, the DCT coefficients of sorted data are more concentrated on the few numbered coefficients.

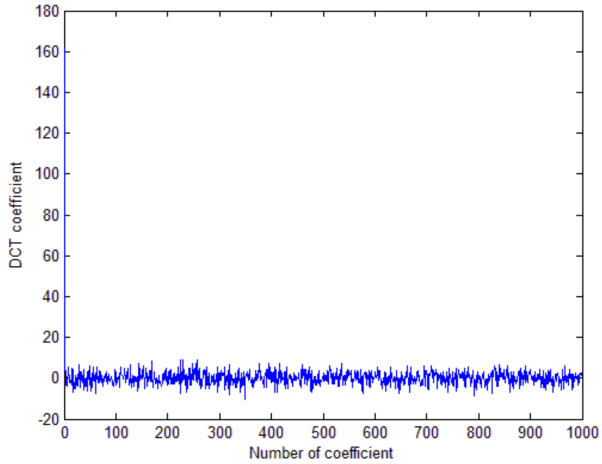


Fig. 7. Transformed unsorted data in DCT

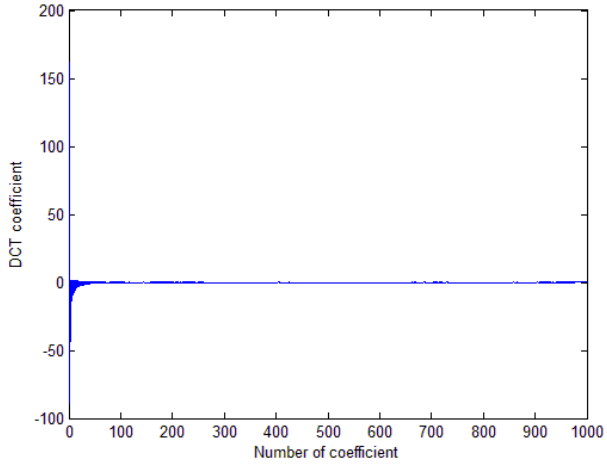


Fig. 8. Transformed sorted data in DCT

In **Fig. 9**, the judgment threshold is set to be 1. By implementing DCT on the series of random data whose variance are {0, 1, 2, …, 10}, it can be seen that, with the increase of variance, the number of coefficients of unsorted data below the threshold drops faster. Combined with figures above, we can draw a conclusion that the DCT coefficients of sorted data is more concentrated. Moreover, regardless of type of data, compared with unsorted data, its coefficients always concentrate in a smaller number. In other words, it is feasible to strengthen the whole system's adaptability through sorting the original data. In addition, by sorting data, we can explore the spatial correlation more complete and deep.

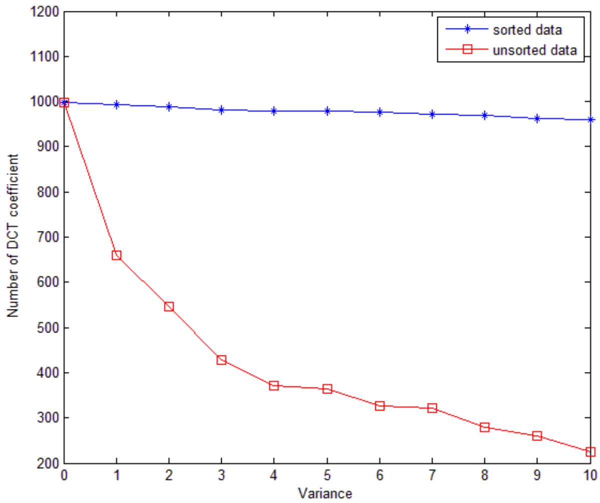


Fig. 9. The contrast between sorted and unsorted data

5.2 Performance Analysis: Data Recovery

In this subsection, we provide a certain network to evaluate the recovery performance of our compression scheme. In the meantime, we compare the simulation results of recovery accuracy with other compression schemes. For simplicity, in the simulation scenario, we assume the WSN consisting of 25 sensing nodes, and divide these sensors into only 1 cluster. The architecture of WSN is a two layers network.

The parameters are initialized as follows. We set the system parameters $\alpha = 1$, $l = 5$ and the compression ratio λ varies with the compression threshold δ. The range of compression ratio λ in experiment is from 0 to 0.6.

In the simulation figures, 'with RZS' denotes the compression scheme proposed in [4]; 'with improved RZS' denotes the compression scheme proposed in [14]; 'with ASCS' denotes the adaptive compression scheme proposed in [15]; 'with DS-ASCS' denotes the proposed compression scheme in this paper. 'Compression ratio' is defined as equation (3). Similar with [20], in order to measure recovery accuracy, we define recovery error ratio as follows:

$$\gamma = \sum_{i=1}^{l} \sum_{j=1}^{l} \left| s_{i,j} - \tilde{s}_{i,j} \right| \tag{9}$$

where $\tilde{s}_{i,j}$ denotes the reconstructed data of each grid, $s_{i,j}$ denotes the original data. 'Recovery accuracy' is defined to be $\xi = 1 - \gamma$ and which is utilized to evaluate the reconstruction performance of compression schemes. Due to the small size of constructed WSN, we use bubble sort [19] to sort the original data.

Fig. 10 shows the reconstruction accuracy of above four compression schemes in different compression ratios. Observed from the figure, the curves show that the recovery accuracy decreases gradually with the increase of compression ratio. Specifically, the ASCS and DS-ASCS improve the recovery performance significantly. On the contrary, the recovery of RZS and improved RZS is not as expected. Overall, the DS-ASCS outperforms other compression schemes significantly in terms of recovery accuracy. For instance, when compression ratio $\lambda = 0.6$, the recovery accuracy of DS-ASCS is 0.9518, to achieve the same reconstruction precision, ASCS and improved RZS have to decrease λ to 0.16, and the compression ratio of RZS is nearly reduced to 0.

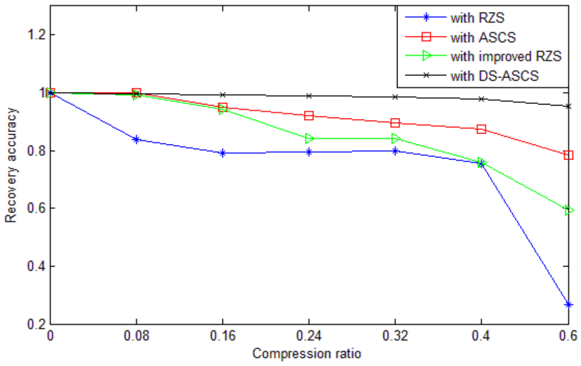


Fig. 10. The recovery accuracy in different compression ratios

Meanwhile, as compared with other schemes, the performance of the DS-ASCS is more consistent. When λ varies from 0 to 0.6, the recovery accuracy drops from 1 to 0.9518. This is because, on the one hand, we increase the correlation of original data by sorting them, in this case, the signal energy is more concentrated on smaller numbered coefficients. On the other hand, we selectively discard the coefficients by setting an empirical threshold. The inherent drawback of RZS is that it mechanically discards the last several coefficients. This rigid compression scheme will discard some important coefficients unintentionally. The threshold-based scheme resolves the inherent defect of conventional scheme, and further explores the spatial correlation among sensor readings.

In summary, as the spatial correlation is explored more complete and deep by the DS-ASCS, our scheme is more advantageous and stable than the other schemes. Moreover, our scheme reduces the number of transmissions and alleviates the congestion of the whole network.

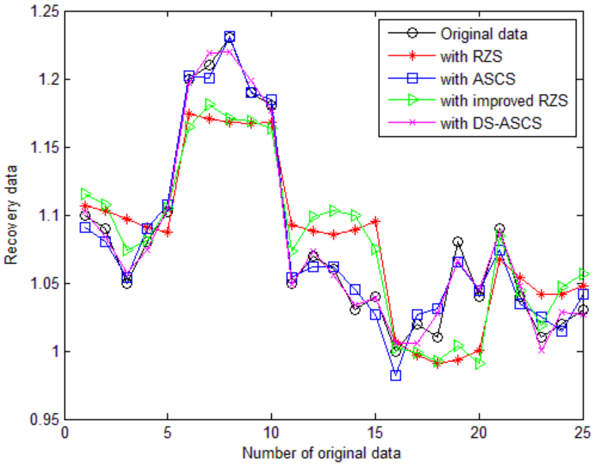


Fig. 11. The comparison among recovery curves with four schemes when compression ratio λ =0. 6

Fig. 11 displays the comparison among original signals and reconstructed signals with different compression schemes when compression ratio $\lambda = 0.6$. The recovery curves show that the recovery signal with DS-ASCS is closer. Although other schemes preserve important characteristics of sensing reports in different degrees, they lose some important detail of original signals.

Combining **Figs. 10** and **11** we can derive that the performance of our scheme is better than the schemes [4], [14] and [15].

6. Conclusion

Based on the spatial correlation of sensor readings, this paper proposed a DS-ASCS to improve the recovery performance of compressed data. This scheme could reduce the number of transmissions and decrease the reconstruction error. In the meantime, the proposed scheme was more adaptive to various deployed environments. Finally, the simulation results further confirmed the advantages of the DS-ASCS. However, DS-ASCS still had following drawbacks. The deployed environment of our proposed compression scheme was noiseless, but most of the real environment was noisy. Meanwhile, the compression threshold was an empirical value which means it can be judged by human experience. To deal with the drawbacks above, we will deploy the three-layered WSNs in noisy environment to evaluate the compression scheme. And more researches on self-adaptive control need to be done in the future work. In addition, we will consider introducing the network resource optimization and secure commumunication ideas [21-23] into our research scheme.

References

[1] N. K. Suryadevara, S. C. Mukhopadhyay, S. D. T.Kelly et al, "WSN-based smart sensors and actuator for power management in intelligent buildings," *IEEE/ASME Transactions on Mechatronics* , vol. 20, no. 2, pp. 564-571, Apr. 2015. Article(CrossRef Link).

[2] D. S. Ghataoura, J. E. Mitchell and G. E. Matich, "Networking and application interface technology for wireless sensor network surveillance and monitoring," *IEEE Communications Magazine*, vol. 49, no. 10, pp. 90–97, Oct. 2011. Article(CrossRef Link).

[3] P. Cheong, K. F. Chang, Y. H. Lai et al, "A zigbee-based wireless sensor network node ultraviolet detection of flame," *IEEE Communications Magazine*, vol. 49, no.10, pp. 90-97, Oct. 2011. Article(CrossRef Link).

[4] Y. C. Wang, Y. Y. Hsieh and Y. C. Tseng, "Compression and storage schemes in a sensor network with spatial and temporal coding techniques," in *Proc. of IEEE 67th Vehicular Technology Conference*, pp. 148-152, 2008. Article(CrossRef Link).

[5] C. T. Ee and R. Bajcsy, "Congestion control and fairness for many-toone routing in sensor networks," in *Proc. of ACM International Conference on Embedded Networked Sensor Systems*, pp. 148 -161, 2004. Article(CrossRef Link).

[6] D. Ganesan, B. Greenstein, D. Estrin, et al., "Multiresolution storage and search in sensor networks," *ACM Transactions on Storage*, vol. 1, no. 3, pp. 277–315, 2005. Article(CrossRef Link).

[7] S. Chen, M. Wu, K. Wang et al., "Compressive network coding for error control in wireless sensor networks," *Wireless Networks*, vol. 20, no. 8, pp. 2605-2615, Oct. 2014. Article(CrossRef Link).

[8] L. Kong, M. Xia, X. Liu et al., "Data loss and reconstruction in wireless sensor networks," *IEEE Transactions on Parallel and Distributed Systems*, vol. 25, no. 11, pp. 2818-2828, Nov. 2014. Article(CrossRef Link).

[9] M. Nelson and J. L. Gailly, "The data compression book (2nd edition)," *MIS: Press*, New York, USA, 1996. Article(CrossRef Link).

[10] A. Diego, N. Gonzalo and S. Kunihiko, "Stronger lempel-ziv based compressed text indexing," *Algorithmica*, vol. 62, no. 1-2, pp. 54-101, Feb. 2012. Article(CrossRef Link).

[11] J. Ning, J. Wang, W. Gao et al, "A wavelet–based data compression technique for smart grid," *IEEE Transaction on Smart Grid*, vol. 2, no. 1, Mar. 2011. Article(CrossRef Link).

[12] L. Makkaoui, V. Lecuire and J. Moureaux, "Fast zonal DCT-based imagecompression for wireless camera sensor networks," in *Proc. of International conference on Image Processing Theory, Tools and Applications (IPTA)*, pp. 126–129, 2010. Article(CrossRef Link).

[13] T. Dang, N. Bulusu and W.C. Feng, "Rida: A robust informationdriven data compression architecture for irregular wireless sensor networks," in *Proc. of 4th European Conference on Wireless Sensor Networks (EWSN'07)*, pp. 133–149, 2007. Article(CrossRef Link).

[14] M. T. Nguyen and K. A. Teague, "Distributed DCT-based data compression in clustered wireless sensor networks," in *Proc. of 11th International Conference on the Design of Reliable Communication Networks (DRCN)*, pp. 255-258, 2015. Article(CrossRef Link).

[15] F. Douak, R. Benzid and N. Benoudijit, "Color image compression algorithm based in the DCT transform combined to a adaptive block scanning," *AEU-International Journal of Electronics and Communications*, vol. 65, no. 1, pp.16-26, Jan. 2011. Article(CrossRef Link).

[16] Y. P. Huang, W. Lu and W. Sun et al, "Improved DCT-based detection of copy-move forgery in images," *Forensic Science International*, vol. 206, no.1-3, pp. 178-184, Mar. 2011. Article(CrossRef Link).

[17] S. Kahveci, Chen. G and X. D. Wang, "Zigzag-coded modulation for high-speed fiber optical channel," *Journal of Optical Communications and Networking*, vol. 4, no.5, pp. 382-391, May. 2012. Article(CrossRef Link).

[18] X. Ji, S. Bai, Y. Guo et al., "A new security solution to JPEG using hyper-chaotic system and modified zigzag scan coding," *Communications in Nonlinear Science & Numerical Simulation*, vol. 22, no. 1-3, pp. 321-333, May. 2015. Article(CrossRef Link).

[19] O. Astranchan, "Bubble sort: an archaeological algorithmic analysis," *ACM SIGCSE Bulletin*, vol. 35, no. 1, pp. 1-5, Jan. 2003. Article(CrossRef Link).

[20] A. Masoum, N. Meratnia and P. J. M.Havinga, "A distributed compressive sensing technique for data gathering in wireless sensor networks," *Procedia computer Science*, vol. 21, pp.207-216, Sep. 2013. Article(CrossRef Link).

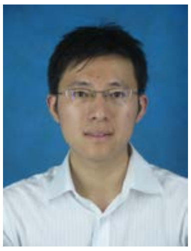
[21] G. Han, Y. Dong, H. Guo et al., "Cross-layer optimized routing in wireless sensor networks with duty cycle and energy harvesting," *Wireless Communications and Mobile Computing*, vol. 15, no. 16, pp: 1957-1981, Nov. 2015. Article(CrossRef Link).

[22] H. Zhang, H. Xing, J. Cheng et al., "Secure resource allocation for OFDMA two-way relay wireless sensor networks without and with cooperative jamming," *IEEE Transactions on Industrial Informatics*, 10.1109/TII.2015.2489610. Article(CrossRef Link).

[23] G. Han, J. Jiang, N. Sun et al., G. Han et al., "Secure communication for underwater acoustic sensor networks," *IEEE Communications Magazine*, vol. 53, no. 8, pp: 54-60, Aug. 2015. Article(CrossRef Link).

Siguang Chen is currently an Associate Professor at Nanjing University of Posts and Telecommunications. He received his Ph.D. in information security from Nanjing University of Posts and Telecommunications, Nanjing, China, in 2011. He finished his Postdoctoral research work in City University of Hong Kong in 2012. From 2014 to 2015, he also was a Postdoctoral Fellow in the University of British Columbia. His research interests are in the area of wireless sensor networks, data compression, dependable and secure network coding and the interplay between network coding and compressed sensing.

Jincheng Liu received his B.E. degree in electronic information engineering from Chongqing University of Posts and Telecommunications, Chongqing, P. R. China, in June 2014. He is currently pursuiting a master degree at the college of the Internet of Things in Nanjing University of Posts and Telecommunications. His current research interests include compression sensing and spatio-temporal compression scheme in wireless sensor network.



Kun Wang received the Ph.D. in College of Computer Science, Nanjing University of Posts and Telecommunications in 2009. He is an Associate Professor in College of Internet of Things, Nanjing University of Posts and Telecommunications, Nanjing, China. His current research interests include information security, ubiquitous computing and wireless communications technologies.

Zhixin Sun received his Ph.D. from Nanjing University of Aeronautics and Astronautics, Nanjing, China, in 1998. He finished his postdoctoral research work in Seoul National University in 2002. Currently, he is a Professor of Nanjing University of Posts and Telecommunications. His current research interests include computer network and security, network multimedia communications and network management and protocol.

Xuejian Zhao received his M.S. and Ph.D. degrees both in computer application technology from Nanjing University of Aeronautics and Astronautics, Nanjing, China in 2007 and 2011, respectively. In 2011, he joined as Lecturer in the college of Internet of Things, Nanjing University of Posts and Telecommunications, where he is currently an Associate Professor. His research interests include wireless sensor networks, ad hoc networks and big data.