TELKOMNIKA, Vol.11, No.11, November 2013, pp. 6624~6630
e-ISSN: 2087-278X

Strategies and Techniques for Data Compression in Wireless Sensor Networks

Wei Song[1,2]
[1]School of Information Engineering, Minzu University of China, No. 27, Zhongguancun South Street, Haidian District, Beijing, 100081, P.R.CHINA
[2]Research Institutes of Information Technology, Tsinghua University, Information Science & Technology Building, Beijing 100084, P.R.CHINA
e-mail: sw_muc@126.com

Abstract

The major challenge in designing wireless sensor networks (WSNs) is to resolve the limitation of energy and transmission capacity. Data compression, as an effective solution, is attracted many attentions. In this paper, a survey is done on the strategies and techniques for data compression in WSNs. And the data compression schemes are divided into two classes: classical methods and the potential technique based on compressed sensing. The basic procedures of each method are further analyzed, and the existing problems are also highlighted.

Keywords: *wireless sensor networks, data compression, compressed sensing*

1. Introduction

The rapid development of information, especially, the development of sensing devices and wireless tech-nology further promotes the innovation of wireless sensor networks. Wireless sensor network [1-16] is a network with large number of sensor nodes, which are deployed in a wide field by some rules or random ways. And through the wireless self-organizing way, sensor nodes will build a network to collect important data and sent the data to the distant data center. The sensor nodes in the WSNs can be connected by radio frequency, infrared, or other medium without any wire connection, such as peer-to-peer network techniques. However, if two nodes can't communicate directly, other nodes which are located near those two nodes will transmit a data packet from the source node to the destination node. Then the data from sensor nodes is gathered by the sink, which may connect to the outside world through Internet or satellite.

Due to the limitation of energy and transmission ca-pacity, the transmitted packet must be small. However, in the large-scale sensor networks, for example, the WSNs in environmental monitoring, home automation, health, military, and other applications, the data is not the small data, such as temperature, humidity [5], and they are rich data, such as image, audio, especially, the video. Other-wise, authors in [6] indicate that the energy consumption of 1 bit information transfer between 100 meters distance is equivalent to the implementation of 3000 instructions. And the 80% of power is approximately used for data transmission [5, 7]. So, to reduce the size of the trans-mitted packet is one of the important section in WSNs. Data compression technique, which can control energy consumption by make the big data into small one, has apparently become one of the key issues to be studied. Although there are many data compression algorithms, and these data compression methods are effective, but these methods, which are called traditional data com-pression algorithms [4-16] in this paper, are mostly based on the Nyquist sampling theorem. This theorem points out that sampling rate must be twice the highest frequency present in the signal of interest. And by using this theorem, some redundant data are collected firstly, but the redundant data will be compressed by some rules, such as the statistics theory, and so on. As we know that, the procedure of data collection and compression consume the energy so much that the life of the sensor nodes is shortened. Whether can we get the useful data directly, not the useless data under the condition of power limitation? That is to say, whether can we change the traditional data collection methods? The compressed sensing [17-20] gives us a new way to resolve these problems.

Received March 22, 2013; Revised June 22, 2013; Accepted July 23, 2013

The remainder of this paper is organized as the follows. In section II, some classical data compression schemes will be described. And the potential algorithm based on compressed sensing theory is analyzed in section III. Finally, a conclusion is presented in section IV.

2. Typical Data CompressionAlgorithms in WSNs

The typical algorithms of data algorithm can be classified into two fields. Ones are in the spatial domain [4-12], and the others are in the transform domain [13-17]. The algorithms in spatial domain are simpler than in the transform domain. And they use the correlation of the nodes to construct a new data set. Then is be transmitted to the data center. And the correlation method or the construction rule is the key point of the research. Algorithms in transform domain use some transformation to get the new type of the collected data. Then discover the redundancy of the data. That is to say, these algorithms find the correlation of data, not the nods, in the transform domain, because the correlation of data is not obvious in spatial to temporal domain sometimes. This section, we will analyze the typical algorithms from these two aspects, and give the detail procedure of the data compression.

2.1. Algorithm in Spatial Domain

There are many algorithms in spatial domain, and they are simple and effective. However, the compressed rate of these algorithms isn't very high, because they don't con-sider the relationship between the collected data. The typical methods are the algorithms based on the correla-tion of inter-nodes [7], the algorithm based on the order on the nodes [8], the algorithm based on pipelined [9], and the algorithm based on quantization [10-16].

1) Algorithm based on nodes correlation of inter-nodes

The correlation of the nodes can be used to construct a new data set to compress the collected data. For the nodes in WSNs are distributed in a wide area, so the distributed source coding is very effective. Every node can be recog-nized as a source. Then the data collected by the nodes can be use distributed source coding to compress. The main idea of these algorithms [7] is described in Figure 1. From this figure, we can get that, the sensor node B and node A both have an analog to digital device, but the sensor node B has a encoder, too. That is to say, the analog signal in sensor A is only transformed into digital signal ***Y***. And the analog signal in sensor B must be transformed into digital one then is encoded into the new signal P, which is as the check information. When the signal ***Y*** and P send to the data center, the signal ***Y*** and P is as the input of the encoder. The reconstruction information ***X*** is built by the data sent by sensor A, which is recognized as the raw data, and the check information ***P***. The compression procedure is realized by sensor node B. However, from this procedure, we can't find the compressed data of sensor node A. And the data of sensor node A is as the auxiliary part of sensor node B. The goal of the WSNs is to realize the energy save for the entire sensor nodes. When the sensor A is power off, the information of sensor node B can't be reconstructed, which make these algorithms lack many applications when the number of sensor nodes is big.

Table 1. Ordering Mapping Algorithm

Ordering	mapping Value
N1,N2,N3	0
N1,N3,N2	1
N2,N1,N3	2
N2,N3,N1	3
N3,N1,N2	4
N3,N2,N1	5

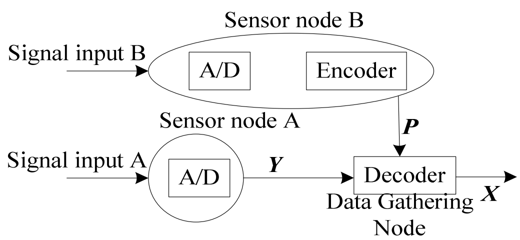

Figure 1. Distributed Coding Algorithm

2) Algorithm based on order mapping

A simple thought is that if we know the order of the sensor, we can code the collected data form these nodes by the order [8]. The basic procedure of this algorithm is as follows: data collected by the four nodes is aggregated by the aggregate node. Then the order of the other three nodes represents the value of the node4. One example is show in Table 1.

This algorithm is simple, but the reality is that the number of the sensor nodes is so many and sometimes, we mustn't know the order of the node. And the mapping value of sensor nodes may have too much that we should construct a lookup table, which is used to encode and recover the original information. But the energy con-sumption on finding the lookup table and compute the mapping value may be more than the energy on transmitting the data directly.

3) Algorithm based on pipelined

The algorithm based on pipelined is similar to the al-gorithm based on the ordering mapping. The key point of this algorithm is to aggregate the different nodes into a data set, and then transmits the new data set [9]. The redundancy is considered and removed. Figure 2 gives an example. The format of the data packet is as follows: <measured value, node ID, timestamp>. And we can get the aggregated packet like: <shared prefix, suffix list, node ID list, timestamp list>.

The number of the sensor nodes also influences the usability of this algorithm. The aggregated data set may be large enough that transmission procedure needs too much time. And the data center must know the time clearly. Otherwise, the received data may be confused easily.

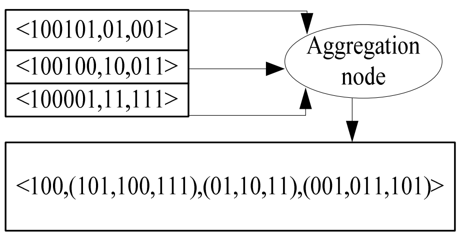

Figure 2. Pipelined Compression Algorithm

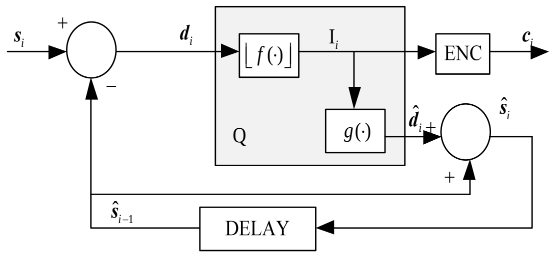

Figure 3. The Data Compression Procedure

4) Algorithm based on quantization

The data collected by single node can be quantitated of the differences between consecutive samples with differential pulse code modulation (DPCM) [10]. And different trade-offs between compression performance and information loss is determined. And this method can be used in the applications with variable compression rate. We can conclude the basic procedure in Figure 3. Where, s_i represents the signal of the sensor node, $\hat{s}_i$ is the most recent reconstructed value. The $\lfloor f(\cdot) \rfloor$ block returns the index I_i of the cell $\boldsymbol{s}_{Ii}$, which $\boldsymbol{d_i}$ belongs to. The index I_i is input to the $g(\cdot)$ block, which computes the quantized difference $\hat{d}_i$, and to the encoding block ENC, which generates the code-word $\boldsymbol{c_i}$. And the uncompressing procedure is the inverse of the compression procedure. And the data compression rate is better than the algorithm based Lightweight temporal compression [11] in terms of compression rate and complexity.

The codebook is also used in [12], and the authors in [12] use the Learning Vector Quantization (LVQ) to con-struct the codebook in the Dictionary Lookup Scheme. And their experiment results show that LVQ can improve the rate of compression effectively. With the introduced method named the Dynamic bandwidth allocation (DBA), the data compression qualities for all the sensor nodes are well balanced and maximized.

Data compressions algorithms in spatial domain are simple, and can be used in the small number of nodes in WSNs. The correlation of the collected data is not con-sidered, because it is not clear in the spatial domain. And distributed wavelet compression and distributed source coding are introduced in the data compression algorithms. For example, Distributed Lifting Wavelet uses two adja-cent high frequency data to generate a low frequency data, and the algorithms using Distributed Lifting Wavelet al-gorithm obtains better compression effect.

2.2. Algorithms in Transform Domain

In WSNs, the congestion causes an increase in the amount of data loss and delays in data transmission. So an adaptive compression-based congestion control tech-nique (ACT) in [13] for packet reduction based was developed. The detail of the procedure is showed in Figure 4. The collected data is transformed into Discrete Wavelet Transform (DWT) firstly. And the range of the data is reduced with the help of Adaptive Differential Pulse Code Modulation (ADPCM). Then the number of packets is reduced by employing Run-Length Coding (RLC) before transfer of data in source node. Then, the transformed data is classified into four groups and assigned priorities for DWT different frequency. The data is defined different quantization steps for different group. In the relaying node, the ACT reduces the number of packets by increasing the quantization step size of ADPCM in case of congestion. The destination node (usually a sink node) reverses the compression procedure. A sink node should apply inverse RLC, inverse ADPCM, and then inverse DWT.

Dong et.al [14] proposed a method based on the dis-tributed lifting factorization for reducing transmission energy consumption. The parallel and distributed computing was also been introduced into this scheme for reduce computation complexity. The inherent correlation existing between sensor readings was explored. The authors in [15] also proposed a data compression method based wavelet. They analyzed the multiple-modalities pertinence of the collected data from different sensor nodes. By the designed threshold value, the collected data is adaptive classified. And the characteristics data are abstracted to be a new matrix, and the correlation of matrix is explored the spatial and temporal correlation by wavelet transform. In [16], one dimension (1D) wavelet transform is used to capture the temporal correlation in one stream. Then some streams from one sensor were selected as the base according to the correlation coeffi-cient matrix, and the other streams from the same sensor node were expressed with one of these bases using linear regression.

These algorithms, not only in the spatial domain or the transform domain, are suitable for the small data set, such as temperature or humidity. For the rich multimedia data, such as the video, the energy consume on data transform or new data set construction are so much that new methods to compress rich data should be developed. In the next section, we will analyze the potential algo-rithm based on compressed sensing.

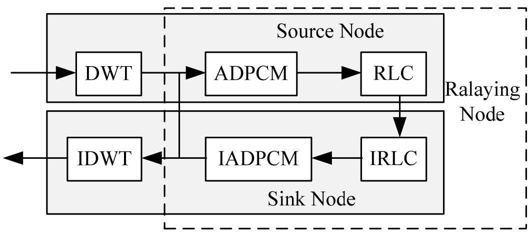

Figure 4. Adaptive Compression Scheme

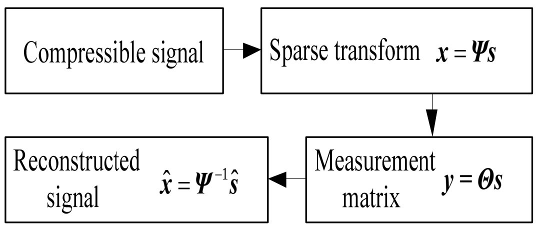

Figure 5. Theory Frame of Compressed Sensing

3. Potential Data Compressed Technique based on Compressed Sensing

In WSNs, especial in Wireless Multimedia Sensor Networks (WMSNs) [20], there are many types of signals, and the traditional compression methods are limited. In 2006, a new scheme [17, 18] named compressed sensing was proposed. Three different important respects between classical sampling and compressed sensing (CS) are as follows. First, traditional sampling theory considers continuous time signals with infinite length. However, CS focuses on measuring finite dimensional vectors in R^n. Second, CS use inner products to get the intrinsic component rather than sampling the signal at specific points in time. Third, the reconstruction process of CSisnonlinear; in contrast, signal recovery based on Nyquist is achieved through interpolation linear formula.

CS involves three main aspects: the sparse representation of signal, the measurement matrix design and signal reconstruction. There are shown below in Figure 5. In this section, we will introduce the basic procedure of CS method which can be used for data compromising effectively in WSNs.

3.1. Sparse Representation

The sparse signal means existing small amount of non-zero elements. Sparse character of signal is not obvious in time domain, but obvious in some transform domain. And according to the theory of signal processing, a one-dimensional discrete time signal ***X*** with length *N* can be expressed as a linear combination of a set of standard orthogonal basis:

$$\boldsymbol{x} = \sum_{i=1}^{N} \boldsymbol{s}_i \boldsymbol{\psi}_i \text{ or } \boldsymbol{x} = \boldsymbol{\Psi s} \tag{1}$$

Where, $\boldsymbol{s} = [\boldsymbol{s}_1, \boldsymbol{s}_2 \cdots \boldsymbol{s}_N]^{\mathrm{T}}$, $s_i = \langle \boldsymbol{x}, \boldsymbol{\psi}_i \rangle = \boldsymbol{\psi}_i^{\mathrm{T}} \boldsymbol{x}$ () is the weight vector, and $\boldsymbol{\Psi}$ is the basis matrix. We call $\boldsymbol{s}$ the *K* sparse representation of signal $\boldsymbol{x}$, if $\boldsymbol{s}$ has non zero elements with the number of *K* ($K \le N$). And that means $\boldsymbol{x}$ is compressible. For the multimedia, such as the image, the video, if we transform them into a new domain, we will find that the sparse character of signals is obvious that these signals are fit to be compressed by CS.

3.2. Design of Observation Matrix

One important section is to design observation matrix which was used to find the sparse components. And the CS method is to find the redundant information with globe observation under different methods. Assume that original signal $\boldsymbol{X}$ is sparse signal under the matrix $\boldsymbol{\Psi}$, and there are *M* different observation vector $\{\phi_j\}_{j=1}^{M}$,we can get the observation value by computing the inner product:

$$\boldsymbol{y} = \boldsymbol{\Phi x} = \boldsymbol{\Phi \Psi s} = \boldsymbol{\Theta s} \tag{2}$$

Where, $\boldsymbol{\Phi} = [\phi_1, \phi_2, \cdots \phi_M]^{\mathrm{T}}$, $\boldsymbol{\Phi\Psi} = \boldsymbol{\Theta}, (\boldsymbol{\Theta} \in R^{M \times N})$ and linear measurement value $\boldsymbol{y}$ also can be regarded as the compressed value of $\boldsymbol{x}$,and $K \le M \le N$. Equation (2) is an underdetermined equation, and there are infinite solutions. In these solutions, $\boldsymbol{s}$ must be sparse with *K*.

3.2. Signal Reconstruction

Theoretically, signal $\boldsymbol{x}$ could be exactly recovered by measurement value $\boldsymbol{y}$ through solving the optimal zeronorm:

$$\tilde{x} = \arg\min \|\boldsymbol{x}\|_0 \quad s.t. \quad \boldsymbol{\Phi x} = \boldsymbol{y} \tag{3}$$

Here, $\|\cdot\|_0$ denotes zero norm of a vector and means the number of non-zero of vector. Candes [18] and other researchers [19, 20] had pointed out that, the number of measurement *M* must meet the condition $M = O(K \log(N))$ if *K* sparse signal $\boldsymbol{x}$ want to be exactly reconstructed, and the matrix $\boldsymbol{\Phi}$ meets the requirement of Restricted Isometry Property (RIP). So, finding the sparsest signal $\hat{\boldsymbol{s}}$ is the purpose of reconstruction procedure. Then the original signal can be recovered by Equation (4), and it is can be seen as the data uncompressing procedure.

$$\hat{\boldsymbol{x}} = \boldsymbol{\Psi}^{-1} \hat{\boldsymbol{s}} \tag{4}$$

From the basic procedure of compressed sensing, we can get the conclusion that, the data compression techniques based on compressed sensing have smaller computing complex. And these algorithms are better fit the multimedia signal. The sparse of these signals are constructed firstly, that means the redundant information is not collected by the nodes. And this is the biggest difference from the traditional methods, and can save the energy effectively. The different observation matrixes decide the compression rate. So, how to find the best observation matrix, and design a better reconstruction method should be deeply researched.

4. Conclusion

Wireless sensor networks (WSNs) have attracted lots of attentions in recent years due to their potential applica-tions in many fields, such as environment protection, border protection, combat field surveillance, and so on. However, there still exist many obstacles to overcome. For example, how to prolong the life cycle of the network nodes and reduce the power consumption, how to transmit the signals like image or the video with wide bandwidth requirement, and so on. Data compression, which is used to reduce the amount of the collected data before trans-mitting, can be an effective method to solve these prob-lems. A lot of types of data compression schemes were presented recently. In this paper, we classify these schemes into classical methods and potential methods, and analyze the detail procedures of them. The traditional schemes are simple but are limited by the amount of the nodes. Sometimes, the correlation of the data is not considered. Meanwhile, the redundant information is also collected which consume the energy of the nodes much. Compared to traditional algorithms, compressed sensing theory no doubt proposes a more efficient scheme that breaks through the limitations of the Nyquist theorem, and uses the observation matrix to extract the useful infor-mation of the collected data and to find the sparse signal of the original signal. So these methods are particularly suited to Wireless Sensor Networks, especially to Wireless Multimedia Sensor Networks for reducing memory and computational resources effectively. But the design of observation matrix and the recovery procedure of the original signal should be considered according to the character of the collected data. Therefore, in the future, wireless sensor networks, especially the wireless multimedia sensor networks, will have more extensive prospects with development of Compressed Sensing.

Acknowledgments

This work was supported in part by the National Basic Research Program of China (973 Program) under Grant (No.2011CB302601) and Grant (No.2012CB315800) and in part by the N ational Natural Science Foundation of China (NSFC) Grants, (No.61222213,No.61170290, and No.60736012), and supported by the Fundamental Research Funds for the Central Universities (No.1112KYQN40,No.1112KYZY49, No.0910KYZY55), and Cultural heritage protection science and technology project of Cultural relics bureau (No.20110135). Our gratitude is extended to the anonymous reviewers for their valuable comments and professional contributions to the improvement of this paper.

References

[1] He NH, Li HS, Gao J. Energy-saving Routing Algorithm Based on Cluster inWSN. *TELKOMNIKA*. 2013; 11(2): 839-847.
[2] Nasri M, Helali A, Sghaier H, Maaref H. Efficient JPEG 2000 Image Compression Scheme for Multihop Wireless Networks. *TELKOMNIKA*. 2011; 9(2): 311-318.
[3] Chen X, Li F, Wang L. Fault-Tolerant Method for Detecting Coverage Holes of Wireless Sensor Networks.*TELKOMNIKA*. 2012; 10(4): 876-882.
[4] Marcelloni F, Vecchio M. A Simple Algorithm for Data Compression in Wireless Sensor Networks. *IEEE Communications Letters*. 2008; 12(6): 411-413.
[5] Pottie J, Kaiser WJ. Wireless Integrated Network Sensors. *Communications of the AC*. 2000; 43: 51-58.
[6] Kimura N, Latifi S. *A Survey on Data Compression in Wireless Sensor Networks*. In Proceedings of International Conference on Information Technology: Coding and Computing. LasVegas. 2005; 2; 8-13.
[7] Yin YG, Ding GG. Study on Data Compression in Wireless Sensor Networks. *Computer Applications and Software (In Chinese)*. 2010; 27(7): 1-4.
[8] Petrovie D, Shah RC, Ramchandran K, et al. *Data Funneling: Routing with Aggregation and Compression for WirelessSensor Networks*. In Proceedings of First IEEE International Workshop on Sensor Network Protocols and Applications. Anchorage. 2003; 156-162.

[9] Ariei T, Gedik B, Ahunbasak Y, et al. *PINCO: a Pipelined In Network Compression Scheme for Data Collection in Wireless Sensor Networks*. In Proceedings of 12th International Conference on Computer Communications and Networks. Dallas. 2003; 539-544.
[10] Marcelloni F, Vecchio M. Enabling Energy-efficient and Lossy-aware Data Compression in Wireless Sensor Networks by Multi-objective Evolutionary Optimization. *Journal of Information Sciences*. 2010; 180(10): 1924-1941.
[11] Schoellhammer T, Greenstein B, Osterweil E, Wimbrow M, Estrin D. *Lightweight Temporal Compression of Microclimate Datasets*. in 29th Annual IEEE International Conference on Local Computer Networks. San Francisco. 2004; 516-524.
[12] Song L, Gunopulos D, Kalogeraki V, Lonardi S. *A Data Compression Technique for Sensor Networks with Dynamic Bandwidth Allocation*. In TIME '05 Proceedings of the 12th International Symposium on Temporal Representation and Reasoning. Burlington. 2005; 186-188.
[13] Lee JH, Jung IB. Adaptive-Compression Based Congestion Control Technique for Wireless Sensor Networks. *Sensors (Basel)*. 2010; 10(4): 2919–2945.
[14] Dong H, Lu JG, Sun YX. Distributed Wavelet Compression in Wireless Sensor Networks. *Chinese journal of sensor and actuators*. 2007; 20(11): 2481-2486.
[15] Zhu TJ, Lin YP, Zhou SW, Xu XL. Adaptive Multiple-modalities Data Compression Algorithm Using Wavelet for Wireless Sensor Networks. *Journal on Communications*. 2009; 30(3): 48-53.
[16] Zhang JM, Lin YP, Zhou SW, Ouyang JC. Harr Wavelet Data Compression Algorithm with Error Bound for Wireless Sensor Networks. *Journal of Software*. 2010; 21(6): 1364-1377.
[17] Donoho D. Compressed Sensing. *IEEE Transactions on Information Theory*. 2006; 52(4): 1289-1306.
[18] Candes EJ, Wakin MB. An Introduction To Compressive Sampling.*IEEE Signal Processing Magazine*. 2008; 25(2): 21-30,.
[19] Ji J, Li X, Wang Q. A Synthetic Aperture Radar Image Compression Algorithm Based on Compressed Sensing. *Advanced Science Letters*. 2012; 7(3): 320-322.
[20] Pudlewski S, Prasanna A, Melodia T. Compressed-Sensing-Enabled Video Streaming for Wireless Multimedia Sensor Networks. *IEEE Transactions on Mobile Computing*. 2012; 11(6): 1060-1072.