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A New Method Based on Cluster Applied in Wireless Sensor Networks

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Abstract: At present, wireless sensor networks are attracting great attention and there are many research topics yet to be studied. Data collection in wireless sensor networks research is one of the most fundamental problems. In this study, we discuss the application of a new compression technique called compressive sensing in wireless sensor networks. In order to solve the problem efficiently, we present the principle of compressive sensing. The regional scope of the incident is calculated by the analysis of spatial correlation of data, and an algorithm of clustering is proposed. On this basis, each node senses the original data, based on the theory of compressed sensing. The data is sparse representation, and its observations are sent and stored in its cluster head, when a mobile collector enters the cluster head communication range, the sensor nodes will perform the data collection. Theoretical analysis and relevant simulation comparison indicate that this approach is energy efficient, high throughput and can effectively extend the networks lifetime.

Key words: Data gathering, WSNs, compressive sensing, spatial correlation, clustering

INTRODUCTION

These Wireless Sensor Networks (WSNs) imitate the intelligence capability, but on a wider distributed scale, with more faster and more effective ways which can be used for different application (Cheng *et al*., 2010). Wireless Sensor Networks (WSNs) are composed of tiny, battery-powered devices, and sensor nodes. Data collection is in the process of work that nodes are constantly gathering information about a physical object or process, and transmitting the information through the wireless antenna. Data is sent to far away in the form of multiple hops sink node (or called base station). WSNs consist of a large number of wireless sensor nodes and a central Fusion Center (FC).

Data gathering is one of the most important operation in the WSNs, which is an effective method to the appropriate data, collected directly related to the effects of WSN's application (Heinzelman *et al*., 2000; Jindal and Psounis, 2006; Luo *et al*., 2009) Because sensor nodes have limited energy and storage, limited computing and processing and communication capabilities, therefore, how to make wireless sensor networks can operate over a long period of time is of great importance. In the process of data collection to meet the needs of application is to solve the node energy consumption (Lindsey *et al*., 2002). Charge imbalance, problems such as data collection delay is the main challenge for data gathering. This study proposes a data gathering scheme based on compressive sensing.

PRINCIPLE OF COMPRESSED SENSING

In a conventional electronic system, an analog-to-digital converter based on the Shannon sampling theorem can convert analog signals to digital signals. The theorem says that if a signal is sampled at a rate twice, or higher, the maximum frequency of the signal, the original signal can be exactly recovered from the samples. It is shown on Fig. 1.

Compressive sensing (CS) is a signal acquisition and compression framework recently developed in the field of signal processing and information theory. Donoho, 2006, Donoho and Tanner, 2010)says that the Shannon sampling rate may lead to too many samples; probably not all of them are necessary to reconstruct the given signal. Therefore, compression may become necessary prior to storage or transmission (Baron *et al*., 2005; Gurbuz *et al*., 2007).

The process of CS can be described as flowing: when a signal is sparse in a transform domain of sparse form, compressed perception theory to less measurement signal reconstruction is measured accurately. It is shown on Fig. 2.

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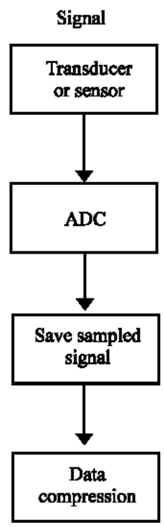

Fig. 1: Conventional compression

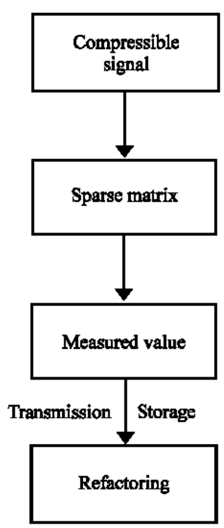

Fig. 2: Theory framework of compressed sensing

A measurement matrix $\phi \in R^{M \times N}$ $(M << N)$ and signal x are the known conditions (Mahmudimanesh *et al*., 2009). Then the signal measurement process is as follows:

(1)

where, x is the original signal, y is the measured values, Ψ is a sparse matrix, and ϕ is the measure matrix. For transmission of sparse matrix sparse degree is K.The signals(x) are sparse representation in transform domain (Ψ). A can be said by the sensor (projection) matrix ($\phi\Psi$). From the type, we can see that the information of measured values(x) is less than the original image signal

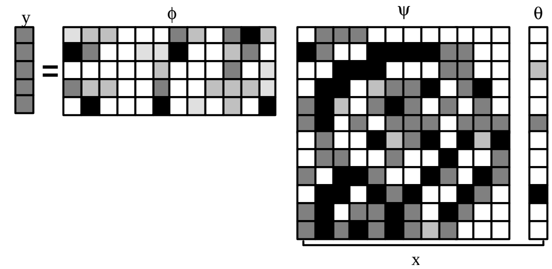

Fig. 3: The process of compressed sensing

of the amount of information, thus greatly improve the process of signal transmission.

Reconstruction of CS can be obtained by solving the type:

(2)

Measured value is known, and as the sensing matrix. But the type is a NP (Non-deterministic Polynomial, non-deterministic Polynomial) problem, literature [2] showed that, when the projection matrix (A) satisfy certain conditions, $\|\theta\|_0$ can be obtained by solving the above problem $\|\theta\|_1$ namely:

(3)

It indicates that in order to reduce the number of sampling values, can be achieved by solving the non-convex problems. $\|\theta\|_p$,0<p<1, instead of the question $\|\theta\|_0$.

$$\min \|\theta\|_p, \quad 0 < p < 1, \quad \text{s.t. } y = A\theta \tag{4}$$

where:

$$\|\theta\|_p = \left(\sum_i x_i^p\right)^{1/p}$$

In conclusion, CS reconstruction problem can by solving the question of $\min \|\theta\|_p,\ 0 < p \le 1,\ \text{s.t. } y = A\theta$. The process of measurement is shown in Fig. 3.

CLUSTER-BASED DATA GATHERING

Sensor networks may be performing data-centric routing, which can allow for in-network processing of information(Baronti *et al*., 2007; Wang *et al*., 2003). In particular, to reduce total energy consumption, data from correlated sensors can be compressed at intermediate nodes when they are routed. We examine how the appropriate joint routing and compression strategy can depend on the degree of correlation between the sources. The CS-based signal acquisition and compression are done by a simple linear projection at each sensor node.

We consider the sensor networks to be divided into multiple clusters with a cluster-head for each cluster. Every sensor node directly transmits the data to the closest cluster-head. The cluster-head gathers data from the sensor nodes in its cluster, aggregates the collected data, and directly transmit it to the sink. To be ensured fairness with regard to energy usage, cluster-heads are rotated for every round of data gathering. The optimal number of cluster-heads is to maximize the node lifetime and to reduce the overall energy consumption depending on several parameters, including the network topology and the relative costs of computation and communication.

The decision of how a sensor node to become a cluster-head for a round depends on the percentage P of cluster-heads for the network (an input parameter to the algorithm), whether the sensor node has been a cluster-head in the last 1/P rounds. If r is the round number and G is the set of nodes that have not been cluster-heads in the last 1/P rounds, probability of senor node n∈G to become each cluster-head is given by:

$$T(n) = \frac{P}{1\text{-}P \times (r \bmod \frac{1}{P})} \tag{5}$$

We find that it is difficult to find an optimal number of cluster-heads to simultaneously minimize the energy consumption and delays in the data gathering. If we choose more cluster-heads, there could be fewer transmissions within a cluster and with each cluster operating, so a delay might be lower. But several cluster-heads will transfer the locally aggregated data over long distances to the sink. If we operate with fewer clusters, the regular sensor nodes end up with spending more energy in transmitting their data to a distantly located cluster-head and because of a larger cluster size, there will be more delay occurred within each cluster to gather data in them. The design problem and the lack of a concrete model to select cluster-heads based on the available energy level at the nodes have been the motivation for the subsequent development of more energy efficient data gathering algorithms. We need to find the optimal method to solve the problem.

Clusters algorithm proposed in this study is according to the cycle run. Each cycle is divided into clusters establishment and data transmission of two stages (Gupta and Kumar, 2000; Yang, 2011). In the stage of establishing a cluster, each sensor node competition is as a cluster head. Cluster nodes in the cluster head node is selected, which is the issue of broadcast messages, so the rest of the cluster head nodes according to the received signal strength independently will be to join the cluster, and to join the cluster head nodes sending message. Cluster head nodes receive all members to join the request message, within the cluster node allocation for each members TDMA mode transmission time slot, and give the TDMA scheduling radio to cluster all the members of the node. Algorithm is described as follows:

- **Step 1:** Initialization, the unique ID for each node distribution, in probability Choose part of the nodes in the network cluster: become a candidate, and 1 to jump to its neighbor nodes broadcast messages
- **Step 2:** All neighbor nodes receive information, has the most to choose from Max of d jump neighbor on the number of nodes N, update data
- **Step 3:** If the number of N if greater than the number of 1. Choose the minimum hop count, most node residual energy as cluster heads
- **Step 4:** Iteration d rounds, until each node can be in the d jumped adjacent within the judge whether oneself have the highest probability to become cluster head
- **Step 5:** After d iteration, if a node is still a TCH, Stating it as cluster heads, and d jump to its neighbor broadcast the news
- **Step 6:** Received the news of the d jumped neighbor withdrew from the cluster head election process, and as a member of the cluster within the nodes

IMPLEMENTATION BASED ON CS METHOD FOR WIRELESS SENSOR NETWORKS

After to perceive events area clustering, data collection based on compression perception Process is as follows:

- **Step 1:** Perceive a certain quantity of each node is set (i.e., signal) as follows: the length is N, in order to carry on the sparse representation, the signal can be transform:

$$x = \sum_{i=1}^{N} \alpha_i \Psi_i$$

Among them, Ψ (i =1N) is the base vector. The same signal is the equivalent of said to x and. When α is under an orthogonal basis expansion coefficient in a certain order of magnitude of present exponential decay, we can recognize the signal x is sparse. Signal sparse representation is compressed the priori conditions of perception

- **Step 2:** Design a base M*N bits are not related with transform matrix (M<<N) d measurement phi on signal x. We can get the measurements (y)

$$y = \phi x \text{QUOTE } y=\phi x \quad (6)$$

Measured value y is an M×1 matrix, which makes measurement objects from N to M dimension. The design requirements of signal measurement matrix in the process of transfer from x to y, K were measured by a measured value won't destroy the information of the original signal. We ensure the accuracy of signal reconstruction. Due to the signal sparse representation is x.

(7)

- **Step 3:** Cluster heads will transmit y values to the Sink node
- **Step 4:** Sink node according to the known ψ, ϕ and y, is to refactoring $\hat{\alpha}$

In a norm able to accurate reconstruction of sparse signals K high probability. This problem into a convex optimization problem, and can be converted into linear programming problem to solve.

For a conventional sensor system, we suppose that the system designer has decided to gather all the uncompressed samples at a location, say to one of the sensors, in order to exploit inter-sensor correlation. At every collection point, joint compression can be made to and compressed information can be sent to every FC. This option has some drawbacks. First, gathering the samples from all the sensors and jointly compressing them will cause a transmission delay. Second, a lot of onboard power should be spent at the collaboration point. Third, the sensor should be collocated so that the information can be gathered at collaboration location. It is shown on Fig.4.

The CS method is aimed to acquire compressed samples. If a high-dimensional observation vector x exhibits in a certain domain. CS provides the direct method for the signal compression. (It is shown on Fig. 7.) It is to compress high-dimensional signal x into the low-dimensional signal y. In the CS-based sensor network schemes, each sensor compresses the observed signals using a simple linear projection and transmits the samples to the FC. Then, the FC will joint reconstruct the received signals. So each sensor can not to communicate with its neighboring sensors for joint compression.

In order to test the performance of the proposed scheme, we refer to the tool of Matlab2009. The simulation experiment mainly examines the traditional solutions and the compression perception of relationship between transmission power,throughput and the time delay.

When the original data are compressed, every sensor node produces much smaller traffic volume that may be transmitted to the FC at a much lower transmission power (It is shown on Fig. 6.) and with a smaller time delay (It is shown on Fig. 7.).

It requires a routing strategy that ensures that the battery energy as well as the throughput is optimized in such a way that the duration of the correct functioning of the WSNs. For example, the network lifetime is maximized. The aggregate throughput in Fig. 8 of the overall system with source nodes sending data to the sinks shows that with CS method 38% more data are delivered to the sink compared to data delivered with conventional method.

Conventional method does not show significant improvement with increasing number of

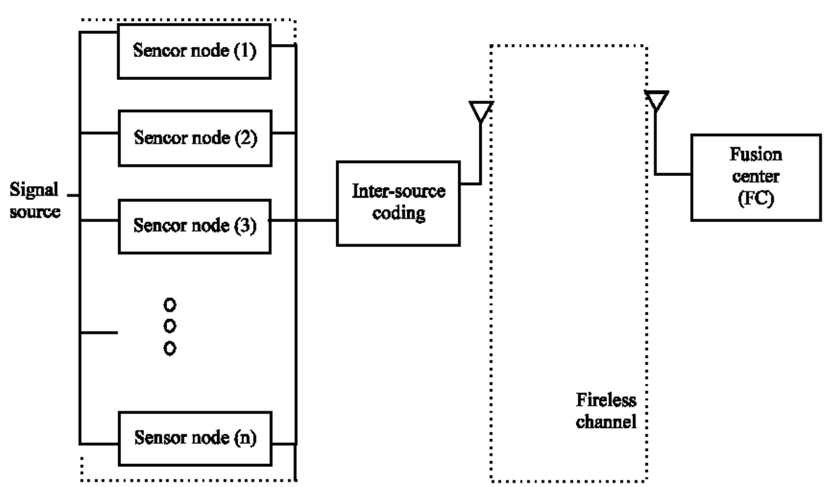

Fig. 4: Conventional sensor system

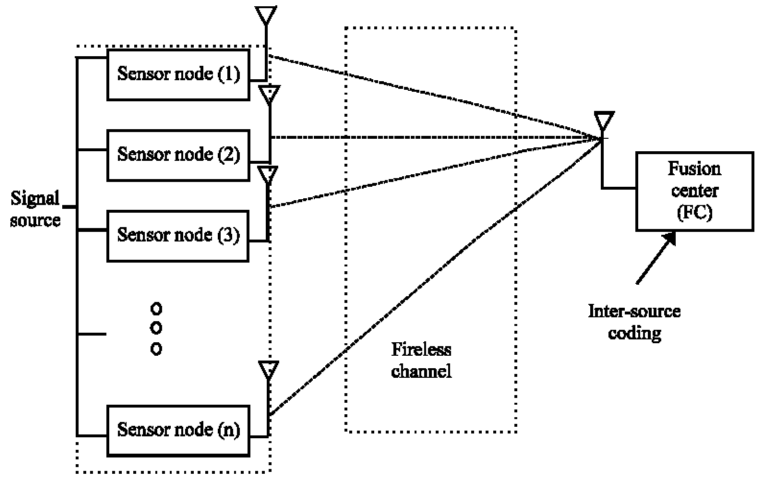

Fig. 5: CS scheme

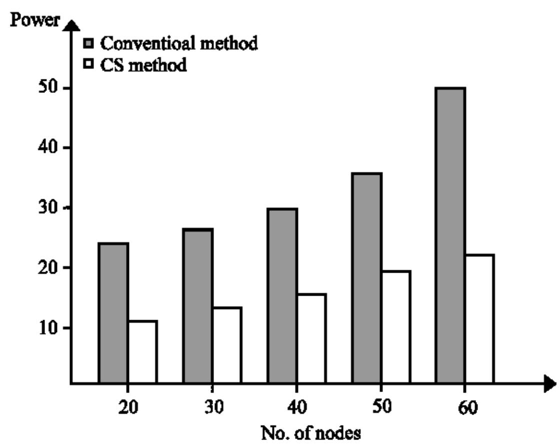

Fig. 6: Comparison of transmission power

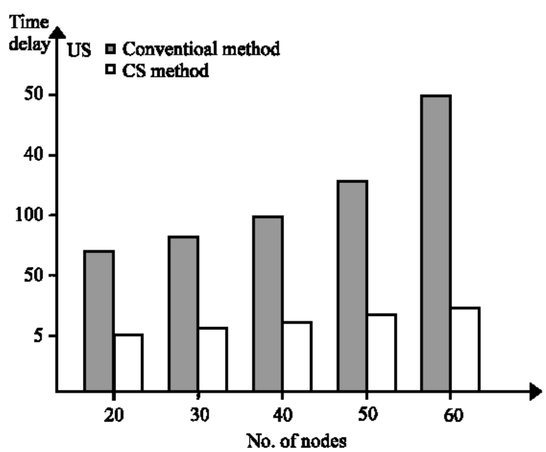

Fig. 7: Comparison of time delay

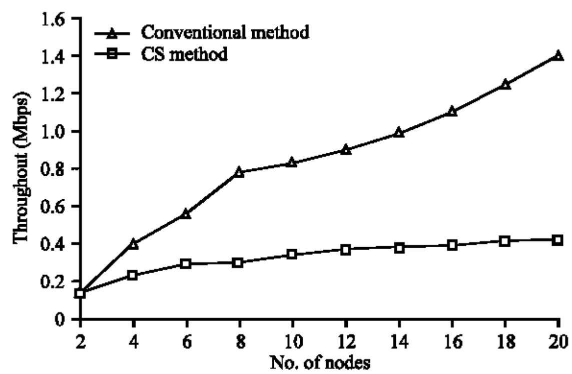

Fig. 8: Comparison of throughput by the number of nodes

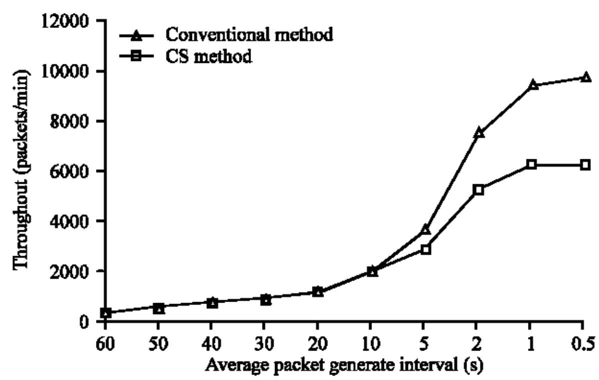

Fig. 9: Comparison of throughput by average packet generate interval

sink nodes in receiving data from source nodes in all instances.

We can compare throughput between CS method and conventional method by the average packet generate throughput. The result is shown on Fig. 9. When average packet generate interval is about 1 second, the throughput of the CS method than the conventional method is superior to 13%.

CONCLUSION

The study presents firstly the principle of compressive sensing, and then the regional scope of the incident is calculated by the analysis of spatial correlation of data, and an algorithm of clustering is proposed. On this basis, each node senses the collecting data based on the compressed sensing. And its observations are sent and stored in its cluster head, when a mobile collector enters the cluster head communication range, it will achieve the data collection. The theoretical analysis and relevant simulation results show that this approach is energy efficient, high throughput, and can effectively extend the networks lifetime. This approach will be applicable to the WSNs.

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