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ENERGY-SAVING MODEL ON DISTRIBUTED RANDOM NODES IN WIRELESS SENSOR NETWORKS

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ABSTRACT

The purpose of our study is to try to extend the life of the sensor network, without affecting the uses functions in wireless sensor networks. As our method reduces the amount of data communications and reduces the energy consumption of wireless sensor networks significantly, the compression problem in the data transferring process is solved. From the experiments, we conclude that this algorithm improves the decoding accuracy and improves the survival time of the network. Therefore, it has a great potential in the wireless sensor networks applications.

Keywords: *Random Nodes, Energy-Saving Model, Distributed, Compressed Sensing*

1. INTRODUCTION

We know that the sensor energy saving methods can significantly reduce energy consum ption, by dynamic power management (Dynamic Power Management, DPM) technologies, in order to run various parts of the system in the energy-saving mode in addition to low-power hardware node design. The most common power management strategy is detecting the intelligent module and turns it on or off. In the study, we found great savings can be achieved on energy consumption during the dynamic power management and dynamic voltage scaling, because the operating system can get all of the performance requirements of the application and can directly control the underlying hardware resources, thus make the compromise of between the performance and energy consumption.

For the inevitable loss in data transmission, wireless sensor networks can provide different accuracy of the data according to the network environment to gain a certain degree of flexibility. As the monitoring objects' properties changes over time, which leads the needs for network computing and communication also changed. In this way, we can make, to some degree, predict in the real-time scheduling algorithm, active management of energy consumption. In addition, the application layer can be designed into the main computing tasks early implementation and early termination of the algorithm, before the normal end of the algorithm, so the energy is saved in the case of small data accuracy. It has a great potential in the wireless sensor networks applications. Our study on the distributed compressed sensing model based energy-saving algorithm of wireless sensor networks, to reduce the power consumption of wireless sensor networks, has a great potential in the wireless sensor networks applications.

2. COMPRESSION PERCEPTION THEORY

We analyze the compressed sensing, also known as compressing sensing or compressed sampling, which is a signal reconstruction technique on a sparse or compressible signal. In other words, the signal is compressed, while sampling, thus largely reducing the sampling rate. The step of the compressed sensing collecting N samples is skipped, and a representation of the compressed signal is obtained directly. Compressed sensing theory use many natural signals, with the compact representation of specific basis Ψ. That is to say, these signals are "sparse" or "compressible". Because of this property, compression codes perception theory framework is very different from traditional compression process, mainly including the sparse representation of the signal, encoding measurement and reconstruction algorithms.

These days, compressed sensing theory involves three core issues:

A. The ability to have a sparse representation on over-completed dictionary design;

B. Measurement matrix is designed to meet the non-coherent or isometric binding guidelines;

C. Quick robust signal reconstruction algorithm design.

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2.1 Compression Sensing Principle

For the limited length of a real-valued one-dimensional discrete-time signal X which can be seen as a N×1dimensional column vector in space R^N , elements [n], n = 1,2, ... N. Any signal in the space can be represented by linear combination of the N x 1-dimensional base vectors [5]. To simplify the problem, it is assumed that they are normal. When we use the vector $\{\Psi_i\}_{i=1}^{N}$ as column vector to form the base matrix $\Psi = [\Psi_1, \Psi_2, \cdots, \Psi_N]$, then any signal X can be expressed as:

$$X = \Psi\Theta \tag{1}$$

Candes, Romberg, Tao and Donoho proposed the sensing theory in 2004. The theory shows that with the least number of observations in the case of approximation of the original signal, we can have no loss of information requiring to sample the signal, reducing the dimension of the signal. In other words, we can compress the fewer signal without the intermediate stage of N samples, to save the cost of sampling and transmission, and achieve the purpose of compression in the sample. Candes proved that as long as the signal in an orthogonal space is sparse, the signal can be sampled at a lower frequency (M << N), and can be reconstructed with a high probability. [6] If we set the transform coefficient of a signal X (length is N) which is sparse on the orthogonal basis or frame Ψ , we can use an observation basis which is not irrelevant to the orthogonal basis to do the linear transformation for the coefficient vector and get the observations set $Y: M\times 1$. At this point, we can use the optimization method to reconstruct the original signal X from the observation collection with a high precision and probability.

Figure 1 is the reconstruction process diagram based on compressed sensing signal.

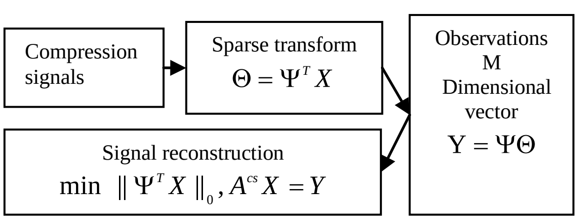

Fig 1: Reconstruction Process Based On Compressed Sensing Signal.

2.2 Sparse representation of the signals

Mathematical definition for Sparse: If the transform coefficient vectors of the signal X towards the orthonormal basis Ψ can be written in $\theta = \Psi^T X$. E.g. for 0 <p <2 and R> 0, these coefficients satisfy:

$$\|\theta\|_P \equiv (\sum_i |\theta_i|^P)^{1/P} \le R \tag{2}$$

Then the coefficient vector Θ is sparse in some sense. The best signal sparse domain is the basis and premise for compressed sensing applications. If and only if we select the appropriate basis, the sparsity of the signal can be guaranteed, in order to ensure the accuracy of signal recovery. When we study the sparse representation of signals, we can use the decay rate to show the sparse representation capabilities by transform coefficients.

2.3 Signal Reconstruction Algorithm

If the matrix Θ satisfies RIP guidelines, compression perception theory has inverse analysis of the above equation. First we solve sparse coefficient $\alpha = \Psi^T \chi$, then reconstruct the signal X (sparsity is K) from the measurement value Y (M-dimensional projection). The most direct method of decoding is to solve the optimization problem on L_0 :

$$\min_\alpha \|\alpha\|_{l_0} \quad s\cdot t \quad y = \Phi\Psi\alpha \tag{3}$$

The sparse coefficient estimation can be achieved. Because the solving process above is a NP-Hard problem, and the optimization problem with signal sparse decomposition is very similar. So scholars look for more effective ways from solving signal sparse decomposition theory. Studies have shown that, under certain conditions (minimum norm of L_1 is equivalent with the minimum norm L_0), the same solution can be obtained. That is to say, the equation above can be changed to the optimization problem with minimum norm of L_1 :

$$\min_\alpha \|\alpha\|_{l_1} \quad s\cdot t \quad y = \Phi\Psi\alpha \tag{4}$$

The optimization problem with minimum norm of L_1 , is also known as Basis Pursuit (BP), which is commonly solved as an algorithm: the interior point method and the gradient projection method. Interior point method is slow, but the result is very accurate: the gradient projection method is fast, but it is a non-accurate interior point method. In the two-dimensional image reconstruction, in order to make full use of the image of the gradient structure, we can correct an integral part of (Total Variation, TV) minimization. New fast greedy method is gradually used, such as matching pursuit (MP) and orthogonal matching pursuit (OMP). In addition, efficient algorithms also conclude iterative threshold method

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as well as a variety of corresponding improved algorithms.

3. DISTRIBUTED COMPRESSION PERCEPTUAL MODEL

Our method receives the sub-data block compression coding measurement values, by distributed data compressed sensing measurements on the encoding side; after the measurement data obtained at the decoding side, in order to overcome the huge storage and calculation problem during the distributed compression data splicing, our method does not deduct the sub-data directly, However obtains the fully compressed and measured original data by integrating of the measurement data. Finally, get the original information by the reconstruction of compressed sensing.

Since the data expanded into the one-dimensional signal is very large, this make the direct compression on measured data and reconstruction quite complex and the computation and the storage are not able to be accepted. This paper processes the data by separate columns, and each column is expressed as the signal x with length-n, so when we compress the signal x by sensing processing, then the measured value y can be obtained by the formula (5).

$$y=Ax \tag{5}$$

In formula (5) $y \in R_{m\times 1}$, m is the length of the measured data, $A \in R_{m\times n}$ the measurement matrix. The distributed compressed sensing analyze the signal x by segments, suppose x is divided by u segments, marked by $x_1, x_2, \ldots, x_u$ and the length of each segment is $n_1, n_2, \ldots, n_u$; then the measured value y_i （i=1,2,⋯,u） on the segments of x can be written to be formula(6) :

$$y_i = A_i X_i \tag{6}$$

$A_i \in R^{m_i \times n_i}$ is the i^{th} measurement matrix on the i^{th} segment of signal x; m_i is the measurement length.

From formula (6), we know that each element of the measured value y_j (j = 1, 2, ... , m) contains all of information of the elements of x, that is $y_i = A(:, j)X$, which shows each of y_j associated with the measurement of the signal values of all segments, and the measured value is obtained by linearity multiplying the measurement matrix and signal x. So, if we want to get the complete matrix A by the fusion of the segmental measurement- Ai, we need to consider the nature and characteristics of the measurement matrix. As compressed sensing theory requires the sensing matrix satisfies the condition-'restricted isometry property' and [7, 8] proved when the measurement matrix is a Gaussian random matrix, the sensing matrices satisfy the condition' restricted isometry property' with a high probability.

According to the probability theory, we know that a linear combination of two Gaussian distributions is also a Gaussian distribution. As the number of rows of the matrix Ai is less than the number of rows of the measurement matrix A, so we can guarantee that the fused measurement matrix is Gaussian random matrix which satisfies the condition- 'restricted isometry property', by the weighted linear combination of A_i .

4. ENERGY-SAVING MODEL OF WIRELESS SENSOR NETWORKS

The current researches on data compression of wireless sensor networks mainly focus in the raw data; this kind of compression algorithm removes the redundancy of raw data collected by sensor nodes to reduce transport energy consumption. For example, the spatial and temporal data correlation removal is an effective compression method. [5] described an encoding method to remove time correlation redundancy and [6] also proposed a temporal data compression algorithm based on species loop model.

These studies show good results in removing the redundancy of the original data; [7-8] also did some researches on the compression algorithm for original data. Therefore, in the communication process of the nodes, we apply the compressed sensing during the data transferring; this will reduce the amount of data transferred, increase the energy saving effect of the sensor network and reduce the data redundancy.

4.1 Compression coding on random nodes

The storage capacity of the sensor nodes is a bottleneck for the sensor network compression, as the storage space for various coding algorithm is different. The sensor nodes do not merely collect data and send data. If the storage space for the compression algorithm is too large, the space for other business in the node is shrunk. According to [5]"s coding algorithm, we need to study various encoding methods and do a good compromise between the storage space and the algorithm performance before we design the algorithm.

Here, we did a network simulation for the random wireless network model. As shown in Fig.

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2, the random wireless network is generated by simple statements such as: 'while, if'.

In our simulation, we get the adjacency Lists for weighted directed graph. We use adjacent diagram to describe one node with its neighbors for a given graph.

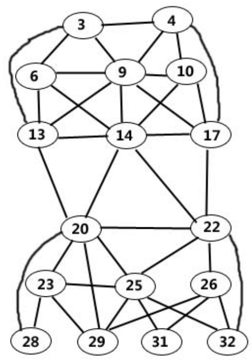

Figure 2: Network Random Topology Diagram

The random network diagram is complicated based on the random topology in Fig.2. Because it generates the chart, whatever they are truly connected, there will be a high degree of connectivity for them. The method generates a wireless network of radius r, which can ensure the connection, and then generate N random point (X, Y). For one node, other nodes in this distance(less than or equal to the radius (r) are determined neighbors of this node. For minimizing the number of solitary nodes, we can change the radius to achieve our connection expectation.

The radius used to generate the random network is the key problem of the energy-saving, as the connections number of nodes is very important, which highly affects the final performance. Connect the simulation results in order to minimize the impact of our fundamental purpose is and randomly generated chart roughly the same connections as a grid map of the same size. For getting low effects on the test result, we try to generate a nearly "same" network diagram to the random topology.

4.2 Coding algorithms

We suppose the files for encoder are $S_1, S_2, \ldots S_K$ and each of them is a source symbol, which can only be completely transferred or deleted. We also suppose each S_K having the same size (number of bits). In each clock cycle, the encoder generates a k order random binary matrix $\{G_{kn}\}$, and the output of encoder t_n is calculated by XOR S_K while $G_{kn} = 1$ for corresponding S_K in the operation, i.e.:

$$t_n = \sum_{K=1}^{K} s_K G_{Kn} \tag{7}$$

The encoding algorithm we used is shown in Figure 2. We assume a transmission sequence length is k, and each symbol is represented as $A_i (1 \le i \le k)$. The encoding process is the K input symbols through the XOR parity check matrix G, to generate the n output symbols (encoded symbols). $G = [g_1, g_2, \ldots, g_j, \ldots, g_{n-1}, g_n]$ is the checking matrix, the columns of G are called degrees-$d_j (1 \le j \le n)$ .The XOR efficacy relationship between the coded symbols- $X_j (1 \le j \le n)$ and input symbols is:

$$X_j = \sum_{i=1}^{K} \oplus([A_1, A_2, \ldots, A_k] \times g_j) \tag{8}$$

$\sum_{i=1}^{K} \oplus$ represents the XOR of the K elements in the Matrix.

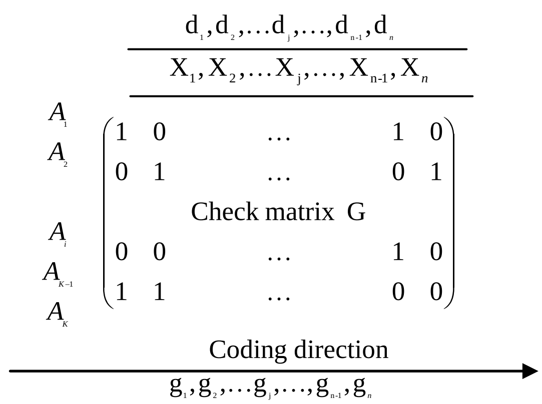

Fig 3: Coding Principle Diagram

As the sum is continuously from the XOR of different s_K, we define a new column in the semi-infinite binary matrix for every K random t_n (Fig. 3).

Thus, after the transmission of the channel and the data packet deleting, the receiving end has been receiving data packets until it receives the N packets. Why the receiving end is able to recover source file without error? We believe that the receiving end knows the connection random matrix G, G related to S_K and t_n . For example, the matrix G may be generated by a random sequence, and the receiver can also produce the same sequence used in the sender, and thus likely produce a random matrix. The sender can be randomly generated by a pseudo-random sequence k_n, which is deemed the beginning of the transmission symbols. As long as the size of the symbol is much larger than k_n (only 32bits), there is only a small impact for introducing k_n . In some programs, packets always have an opening for other uses, so the fountain codes can be

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as k_n . Simply, we called some part of the matrix-K-BY-N for "G".

5. SIMULATIONS ON THE MODEL

Simulation experiment tested via a plurality of nodes, and the simulation is for various environments. The results are as follows.

5.1. Simulation conditions

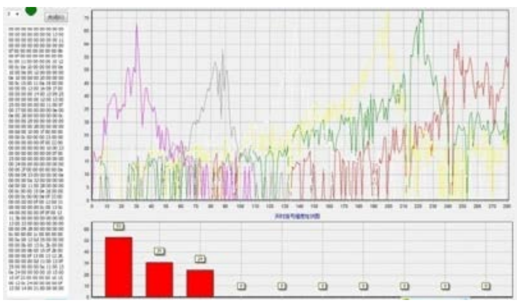

Figure 4: Six Trunk Effect Diagram On Experiment Data

Six trunk routes, with number 01, 02, 03, 05, 06, 07 (assuming the 4th route damaged) are setup in the simulation, while, the 5th route the curves is marked as white. The left border in the lower right corner of records the maximum signal strength in each route of the whole process, and the right box records the minimum value. The interval is 800mS, which is the basic unit of the X axis for the solid squiggle curve.

From the general waveform trend, it is able to determine the location information. However, problems are: The difference among curves' crest height is big, that is the maximum signal strength of each route is much different. They are 64 75 81 75 55 60. Since the box body is not enough, the first and the last route is bare board. While light rain in the test, part of the routes damaged due to the welding problems which leads a certain level of performance damage of the device-CC2591, There is a big difference among routes' welding and procurements, e.g.: different materials of inductance. Although some curves' trends are obvious, the fluctuations are big. For example, the weak signal point (red) (X = 19 at the 7th route), will be filtered out as a interference, when the host computer is taking location identification.

For part frames dropped situation, such as the frame is dropped in the 7th route at X = 41, we need to improve the wireless transmitter mechanism for avoiding the collision to increase the non-response retransmission, minimize the number of dropped frames. According to the data reported from the No. 1 route (gateway, trunk route), the signal strength of each route timely reports, and in the case of no 4th route, nodes between the 5th and the 3rd are able to transmit normally and no redundancy in the data reported.

5.2. Simulation conditions

Five trunk routes (interval is 70 m), with ID 01, 02, 03, 04, 05 (No. 4 is lack of battery), speed of routes are 60km / h (acceleration or deceleration, non-uniform).

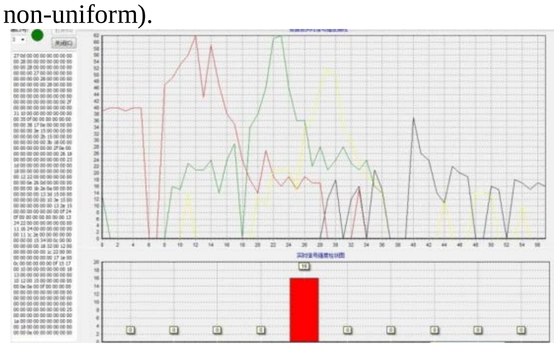

Figure 5: Five Trunk Effect Diagram On Experiment Data

The 2nd, 3th and 4th route's power is battery. As the routes are used of battery-powered many times before and we here don't have the low-power design, so the batteries are weak in this test. Because 4th route's battery not able to provide enough power, no signal from the 4th route (4th routes work well after replacing its battery). The largest signal strength of 5th route is only 37 and when the measurer approaching the 5th route, a package lost in the 5th route. So, we should improve the avoiding collision mechanism, to increase the non-response retransmission mechanism to minimize the number of dropped frames. The data transmission is not affected by the 4th route damaged and 1st; route and 5th route still link correctly and receive the data submitted from other routes/nodes.

6. CONCLUSIONS

In this paper, we firstly analyze the compression perception theory and the representation for signal sparse. Through the study on signal reconstruction algorithms, carried out a complete analysis of signal compression theory.

We proposed a distributed compressed sensing model and apply it to energy saving filed in the wireless sensor networks. The random node network application testing shows that the method is effective. However, there are still some improvement can be achieved, such as improving compressed sensing reconstruction accuracy when the data is divided into sub-blocks; reducing the

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energy consumption caused by a random number of changing nodes. These will be resolved in our future works.

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