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Research of a Multimedia Sensor Networks Related Supporting Set of Image Compressed Sensing Algorithm

JiaZhen-Liang

(Software Technology Vocational College, North China University of Water Resources and Electric Power, Zhengzhou 450045, China)
2869595881 @qq.com
Feng gai-e (shanxi youthvocational college,Shanxi Youth Vocational College,TaiYuan 030032,China)

Abstract

In the light of the huge data traffic and limited energy supply in Multimedia Sensor Networks (MSN), a Compressed Sensing (CS) algorithm based on correlated sparse support sets was proposed in this paper. A correlated support sets sparse model for image data of MSN was established by the correlation among the support sets of image data coefficients from different nodes, and then a new CS reconstruction algorithm was designed according to this model. By cutting down the number of subspace need to search in iterations of greedy algorithms, the algorithm can lower the measurements requirement without sacrificing reconstruction accuracy, leading a significantly reduction of the data traffic for the accurate recovery of image data in MSN. The performance of the algorithm is validated using analysis and experimental results.

Keywords: *multimedia sensor networks; compressed sensing; support sets; image reconstruction; sparse model*

1. Introduction

It is the bottleneck constraining the development and application of wireless sensor network technology that node energy is limited [1]. For the Multimedia Sensor Networks (MSN) that collects objects' images and video information, the need to reduce node energy consumption and extend network lifecycle is more urgent [2]. As the Compressed Sensing (CS) emerged in recent years [3-5], data can be compressed by using the redundancy of multimedia sensor network data, and reduce the transmission of redundant information so as to provide ideal solution to reduce network node energy consumption.

Due to the existence of wavelet transformation, discrete cosine transform and other relatively mature image sparse transform methods, most of the early image compressed sensing methods use these existing transforms while with the study focused on aspects of measurement and reconstruction algorithm [6-8]. In order to overcome normal wavelet transform's defects of poor direction choice and translation invariance, *etc.* researchers use 3D Dual-tree Complex Wavelet Transform (3D DTCWT) [9] and wavelet tree structure [10-11] for sparse transform of network image data and have obtained a sparse representation superior to the traditional wavelet transform. It have been proposed in

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literature [12] and literature [13] respectively that distributed multimedia data compressed sensing algorithm and inter-frame correlation algorithm for video image perception are used. Compared with the previous image sparse transforms, the above algorithms can use the correlation between sensor network data for the transmission amount needed for further data reconstruction. But traditional sparse transform is still the basis in constructing sparse model among data, and the correlation between the structures of different node data cannot be reflected.

Aiming at the problems existing in current researches, a multimedia sensor networks related supporting set of image compressed sensing algorithm is proposed in this paper, and based on this, design and its corresponding image compressed sensing reconstruction algorithm is collaborated, reflecting the correlation of multimedia sensing network node data sparse coefficient-supporting set. The amount of sub-space needed to be searched in reconstruction algorithm iteration of this sparse model collaborating design has been significantly reduced, and the number of measurement needed in reconstructing network data accurately. The results have shown that compared with the current multimedia sensing network compressed sensing algorithm, algorithm in this paper can effectively reduce the transmission amount of data needed in reconstructing network images on the premise of guaranteeing accuracy of reconstruction, and further reduce network node energy consumption.

2. Problem Description

Suppose the J multimedia sensing nodes are scattered in the monitored area at random, form wireless network through self-organizing way, and collect and process information of specific images in the network-covered regions in a collaborative manner. In consideration of the image data collected by each node at a certain moment during the work of multimedia sensing network, x_j ($j \in \{1,2,..., J\}$) is used to represent the image data collected by the j node. In order to reduce the data transmission amount between nodes in measurement process, a pseudo-random sequence measurement matrix $\boldsymbol{\Phi}_j$ will be produced locally to measure data collected by nodes before each node sending data.

$$\boldsymbol{y}_j = \boldsymbol{\Phi}_j \boldsymbol{x}_j \quad (1)$$

Herein, $\boldsymbol{x}_j \in R^N$, $\boldsymbol{y}_j \in R^M$, $\boldsymbol{\Phi}_j \in R^{M \times N}$, $M << N$. The measured value is transmitted by each node to Sink node, which will get $J \times M$ dimensional measured value vector $\boldsymbol{y} = [\boldsymbol{y}_1, \boldsymbol{y}_2, ..., \boldsymbol{y}_J]^T$, and the relation between it and image data collected by each node can be expressed as:

$$\boldsymbol{y} = \boldsymbol{\Phi} \boldsymbol{x} \quad (2)$$

Herein, $\boldsymbol{x} = [\boldsymbol{x}_1, \boldsymbol{x}_2, ...\boldsymbol{x}_J]^T \in R^{JN}$ is the original image data, and $JM \times JN$ is the measurement matrix.

It is made of J random matrix sub-blocks. Note that the process of reconstructing original data by formula (2) can be seen as the sparse signal reconstruction problem in the theory of compressed sensing. Due to $M << N$, the linear equation, the x of which is to be got, is in the underdetermined state with numerous solutions, so the solution-solving problem of the underdetermined linear equation can be transferred 1 as the norm minimization problem[4]:

$$\arg\min \|x\|_1 \text{ s.t. } y = \boldsymbol{\Phi} x \quad (3)$$

Solution of formula (2) can be obtained through solving a 1 norm minimization.

Because in most cases, the sparseness of natural images is not ideal, so before it is reconstructed by using compressed sensing theory, it needs sparse transformed to obtain the sparse representation in its transform-domain. Give the matrix $\boldsymbol{\Psi}$, then the original image data x can be written as:

$$x = \boldsymbol{\Psi}\boldsymbol{\theta} \quad (4)$$

Herein, $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots \theta_J]^T \in R^{JN}$, ψ is sparse transform matrix, and

$$\boldsymbol{\Psi} = \begin{bmatrix} \psi & 0 & \cdots & 0 \\ 0 & \psi & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \psi \end{bmatrix}_{JN \times JN}$$

Wavelet transform or discrete cosine transform and other normal sparse transform is used in most of current network image compressed sensing algorithm. However, Multimedia sensor network image not only has the sparseness of the image itself, but also makes full use of the correlation between image data supporting set of each node, which can further reduce the transmission amount of network data. Therefore, for effective use of the sparseness of network image data, a supporting set of sparse model of multimedia sensor network image data is constructed in this paper, and image data reconstruction algorithm is designed aiming at this sparse model.

3. Relevant Supporting Set of Reconstruction Algorithm

Note the signal images collected by multimedia sensor network node at the same moment as $x_j \in R^N$ ($j \in \{1,2,\dots, J\}$), first make sparse transform of the images of each node using the compressibility of each node's image itself:

$$x_j = \psi \theta_j \quad (5)$$

Herein, sparse coefficient vector is $\theta_j \in R^N$. Because there is redundancy and correlation between the image information collected by each node when the same object is observed by multimedia sensor network node in the limited region, and after the sparse transform of each node image, the sparse coefficient vector non-zero element's location, namely, the supporting set, also has similarity. Therefore, consider the correlation between network image data's supporting set, and if the image transform coefficients of all the J nodes are combined into a single vector $\boldsymbol{\theta}$, then the definition of sparse image of multimedia sensing network supporting set can be as follows:

$$T_K = \left\{\boldsymbol{\theta} = [\theta_1, \theta_2, \dots \theta_J]^T \; s.t. \theta_j(n) \neq 0\right\} \quad (6)$$

Herein $n \in \Omega$, $\Omega \subseteq \{1,2,\dots, N\}$, $|\Omega| = K$ ($|\Omega|$ refers to the amount of element in the set Ω).

In order to make sparse decomposition to network image data in the above sparse model, the mixed norm of image data sparse coefficient matrix $\boldsymbol{\Theta} = \left[\theta_1^{\mathrm{T}}\ \theta_2^{\mathrm{T}} \cdots\ \theta_N^{\mathrm{T}}\right]$ is defined as follows:

$$\|\boldsymbol{\Theta}\|_{(p,q)} = \left(\sum_{n=1}^{N} \|\boldsymbol{\theta}_n\|_p^q \right)^{1/q} \quad (7)$$

Then through solving the following mixed norm optimization problem, the optimal sparse solution to the network image in the formula (6) model can be obtained as well as the supporting set sparse decomposition algorithm $T(\boldsymbol{\Theta}, K)$:

$$\boldsymbol{\Theta}_{T_K} = \arg\min_{\boldsymbol{\Theta}' \in R^{J \times N}} \|\boldsymbol{\Theta} - \boldsymbol{\Theta}'\|_{(2,2)} \text{ s.t. } \|\boldsymbol{\Theta}'\|_{(2,0)} \le K \quad (8)$$

In order to give full play to the effectiveness of supporting set sparse model and aiming at the corresponding reconstruction algorithm of network image data supporting set of sparse decomposition design, the steps of the algorithm can be described as follows:

Put in: compressed sensing measurement matrix $\boldsymbol{\Phi}$, measurement vector $\boldsymbol{y}$, and sparse matrix $\boldsymbol{\psi}$

Put out: Reconstruction network data $\hat{\boldsymbol{x}}$

Initialize: take the value of $j = 1,2,\ldots,J$ each time, $\hat{\theta}_{j,0} = 0$, residual value $r_j = y_j$, $i = 0$

Step1: $i \leftarrow i+1$

Step2: $\boldsymbol{b}_{(j,i)} \leftarrow \hat{\boldsymbol{\theta}}_{j,i-1} + \left(\boldsymbol{\Phi}_j \boldsymbol{\psi}\right)^{\mathrm{T}} \boldsymbol{r}_{j,i}$ (update the estimated value of sparse coefficient)

Step 3: $\hat{\boldsymbol{\theta}}_{(j,i)} \leftarrow T\left(\boldsymbol{b}_{(j,i)}, K\right)$ (sparse decomposition)

Step 4: $\boldsymbol{d}_{(j,i)} \leftarrow \boldsymbol{y}_j - \boldsymbol{\Phi}_j \left(\boldsymbol{\Phi}_j \boldsymbol{\psi}\right)^{\mathrm{T}} \hat{\boldsymbol{\theta}}_{(j,i)}$ (Update the residual value)

Step5: Judge the termination condition: $\left\|\boldsymbol{d}_{(j,i)}\right\|_2 \ge \left\|\boldsymbol{d}_{(j,i-1)}\right\|_2$. If it is satisfied, put out the final solution; if it is not satisfied, return to Step 1.

Final solution: $\hat{\boldsymbol{x}}_j = \boldsymbol{\psi} \hat{\boldsymbol{\theta}}_{(j,i-1)}$

4. Algorithm Analysis

In this section, the lower limit of measured number needed in the reconstruction of algorithm proposed is deduced theoretically. Because the measurement needed for reconstruction is correlated with the amount of sub-space in spares signals, so in the proving process, the length of reconstruction must be clarified as N first as well as the quantitative relationship between the lower limit of measurement needed by the sparse vector with the sparseness as K and the amount of K dimensional sub-space in K dimensional real number space, and then obtain the measurement needed for reconstruction by combing the amount of sub-space in signal space in supporting set sparse model and the amount of dimensions in sub-space.

Theorem: For any $t > 0$, when, the probability of N dimensional sparse vector with the sparseness as K being able to be reconstructed by the measurement of M is no less than $1 - e^t$, and herein, L is the amount of K dimensional sub-space, and is RIP constant.

Proof: It can be concluded from the lemma 5.1 conclusion of Literature [5] that, if for any $0 < \varepsilon < 1$, the measurement matrix $\boldsymbol{\Phi}$ meets:

$$P\left(\left|\|\boldsymbol{\Phi}\boldsymbol{x}\|_2^2 - \|\boldsymbol{x}\|_2^2\right| \geq \varepsilon \|\boldsymbol{x}\|_2^2\right) \leq 2e^{-c\frac{M}{2}\varepsilon} \quad (9)$$

Then for any one of K dimensional sub-space, there is:

$$(1-\delta)\|\boldsymbol{x}\|_2 \leq \|\boldsymbol{\Phi}\boldsymbol{x}\|_2 \leq (1+\delta)\|\boldsymbol{x}\|_2 \quad (10)$$

Establish $1-2\left(\frac{12}{\delta}\right)^K e^{-c\frac{\delta}{2}M}$ with the probability no less than , herein c is the constant.

Therefore, the joint probability that all the L sub-spaces do not meet RIP is $L \cdot 2\left(\frac{12}{\delta}\right)^K e^{-c\frac{\delta}{2}M}$, and the probability that N dimensional sparse vector with the sparseness as K can be accurately reconstructed by measurement with the amount of M is $1-2L\left(\frac{12}{\delta}\right)^K e^{-c\frac{\delta}{2}M}$. It can be obtained by combining lemma condition that:

$$1-2L\left(\frac{12}{\delta}\right)^K e^{-c\frac{\delta}{2}M} \geq 1-e^{-t} \quad (11)$$

That is

$$M \geq \frac{2}{c\delta^2}\left(\ln(2L) + K\ln\frac{12}{\delta} + t\right) \quad (12)$$

It can be obtained from the sparse model defined by formula (6) that, the sparseness of image signals in supporting set sparse image T_K and the sub-space dimension is JK, the amount of subspace is C_N^K, put it into formula (12), it can be obtained that when

$$M \geq \frac{2}{c\delta^2}\left(K\left(\ln\left(\frac{2N}{K}\right) + J\ln\frac{12}{\delta}\right) + t\right)$$

The probability that the N dimensional sparse vector with the sparseness as K can be accurately reconstructed is less than $1-e^{t}$, so the conclusion is proven.

The above conclusions show that the lower measurement limit to the algorithm proposed in this paper and $JK + K\log(N/K)$ same amount are significantly less than then measurement needed by traditional compressed sensing reconstruction algorithm and $JK\log(N/K)$ same amount, and as the multimedia sensor network expands its scale, when the amount J of nodes is far more than $\log(N/K)$, then the lower measurement limit needed for reconstruction is similar with the same amount with the sparseness K . Thus, algorithm in this paper can effectively reduce the amount of data needed to be transmitted for accurate reconstruction, and achieve the goal of further reducing node energy consumption.

5. Simulation

In order to verify the correctness and validity of algorithm proposed in this paper, MATLAB software is used in this part for simulation experiments. The CUP type of computer used in the experiment is Intel Core2 T5550. In the experiment, Lena image with the definition rate as 256×256 is selected as the node data, and during the measurement of each node, 30% of the actual amount is selected, that is M / N =0.3.

(a) Original Lena Image (b) Algorithm in this Paper (RSNR=19.26dB)

(c) Data Correlation （d）3D DTCWT
（RSNR= 17.77dB） （RSNR=16.15dB）

Figure 2. Comparison between Reconstructed Image and Original Image

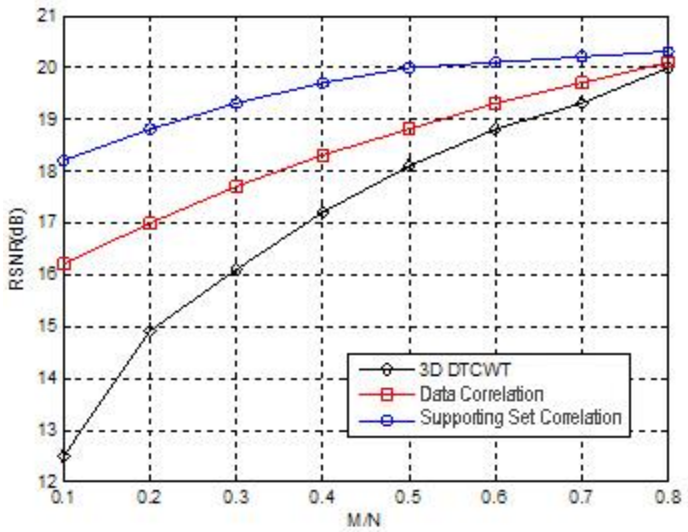

Figure 3. Comparison of Reconstruction SNR in Different Measurements

In order to compare the reconstruction performance of algorithm in this paper and other algorithms in the situation of different data transmission, in the experiment, the transform measurement increase between 0-0.8, and for each measurement, repeat the experiment for 100 times, and calculate the average value of reconstruction SNR to measure the reconstruction quality in this measurement. The SNR curve shown in Figure.3 can reflect the reconstruction performance of algorithm in this paper in different measurements more comprehensively. It can be seen from the reconstruction results that when there are many times of measurement, the performance of algorithm in this paper is similar to other algorithms, both of which can obtain relatively high reconstruction accuracy, but when there are not many times of measurement, the performance of algorithm in this paper is significantly superior to other algorithms, and the less the amount, the more obvious the advantage.

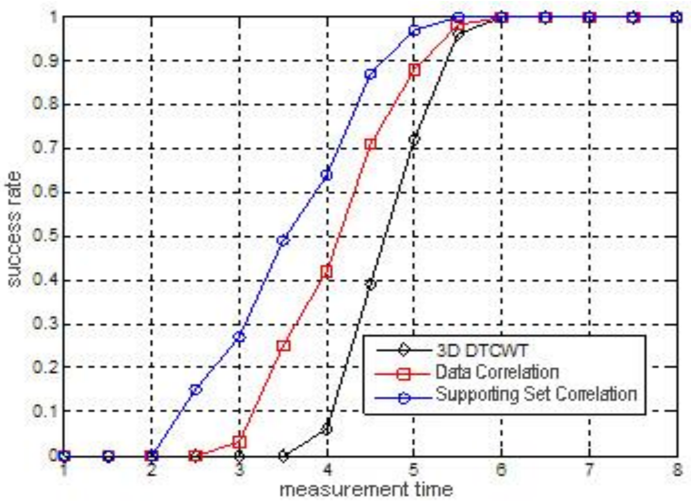

Figure 4. Comparison of Success Rate of Image Data Reconstruction

In the above experiment, the measurement calculation time of various measurements is recorded, and the reconstruction is successful when the RSNR of image reconstruction is above 18dB with the times of successful reconstruction indifferent measurements collected. The success rate of reconstruction is the comparison of times of success and times of experiments, and the curve like in Figure.4 about the relation between reconstruction success rate and measurement and calculation time is obtained. It can be seen that compared with traditional algorithms, the algorithm in this paper can achieve higher reconstruction accuracy with the same measurement and calculation time, while to obtain the same reconstruction accuracy, the algorithm in this paper needs less measurement and calculation time than tradition algorithms.

6. Conclusion

In this paper, the multimedia sensor network image reconstruction algorithm based on supporting set of sparse model is supposed. By constructing the supporting set of sparse model of network image data, correlation between each website node data spares coefficient supporting sets can be mined, so as to reduce the amount of sub-space needed to be searched in the iteration of reconstruction algorithm by using this model. Compared with traditional compressed sensing reconstruction algorithm, network data compressed sensing algorithm based on supporting set correlation can use the correlation between network image data more effectively, reduce the measurement needed in reconstruction of network data, thus further reduce the energy consumption in the transmission of network image data.

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Authors

JiaZhen-Liang, (1976.3-) Lecturer, Master, Research Orientation: Computing Network;

FengGai-e, (1968.9-) Associate professor, Research Direction: software development