WSN image acquisition method based on interleaving extraction and block compressed sensing

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Abstract

Aiming at disadvantages of current wireless sensor network in the aspect of image acquisition, this thesis proposes a WSN image acquisition method based on Interleaving Extraction and Block Compressed Sensing (IE-BCS). The method uses interleaving extraction to divide an original image into several sub-images at an encoding terminal, then compressive sampling and encoding for each sub-image by means of observation matrix weighted BCS and transmits data to a decoding terminal by their own independent channels. Next, the decoding terminal chooses corresponding decoders according to reception situations and reconstructs the original images by solving sparse optimization problems. Experimental results show that the method can save hardware resources effectively and improve robustness of image transmission.

Keywords: compressed sensing, interleaving extraction, observation matrix, block strategy

1 Introduction

As Wireless Sensor Network (WSN) develops and quantity of information requirements grows increasingly, how to transmit images and video signals with high quality in network seems to be quite important. The current image acquisition method based on WSN utilizes a digital camera to acquire image information, compresses images by JPEG encoding algorithm and transmits data by wireless communication after segmenting and packing them. Then, data arrive at a user terminal after being transmitted by many nodes. Next, the user analyses the received data package in order to recover original images. Although the foregoing method can realize image acquisition and wireless transmission favourably, the following problems still exist:

1) image sampling follows Nyquist sampling theorem, which results in the situation that the size of data stored and processed by sensor nodes is large and increases nodes' consumption of power supply;

2) if there are several image sampling nodes in the network, data transmission quantity in the network will be increased sharply, which will easily lead to problems, for instance, network congestion; and

3) data of wireless transmission tend to be affected by environment and energy factory easily, so users cannot recover original images correctly if situations like error codes or packet loss appear in transmitting procedure.

Directing at deficiencies of WSN in the aspect of image acquisition, this thesis proposes a WSN image acquisition method based on Interleaving Extraction and Block Compressed Sensing (IE-BCS). Firstly, the method carries out interleaving extraction for an original image to obtain several mutually independent descriptions. Then, it uses the BCS method of the weighted observation matrix to implement compressive sampling and encoding for each description, and transmits them to a decoding terminal by their own independent channels. Next, the decoding terminal chooses corresponding decoders according to reception situations and reconstructs the original image by solving sparse optimization problems. Because the method utilizes compressed sensing (CS) technology, it can effectively reduce data sizes of network transmission, decrease pressure on nodes' computation and storage and lower nodes' consumption of power supply. At the same time, each description can independently recover images with acceptable quality, which not only improves robustness of image transmission but also solves the problem that images cannot be reconstructed correctly because of packet loss in the transmitting procedure.

2 Compressed sensing theory

Compressed Sensing theory is a new signal acquisition theory proposed by D. Donoho and E. Candès et al. in 2006 [1-3]. The theory indicates that when the signal is sparse or compressible in a transform domain, the measurement matrix non-coherent of transformation matrix can be used to linear project transform coefficient into the low dimensional observation vector. This projection maintains the required reconstruction signal information, and through further solving sparse optimization, can precisely

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or high probability accurately reconstructs the original high dimensional signal from the low dimensional vector. The CS theory properly compresses data when signals are acquired so that original signals can be reconstructed accurately by a few sample points, which will largely reduce sampling frequency of low image signal and cost of data storage and transmission.

The specific process of compressed sampling is shown in Figure 1. It is assumed that there is a signal $X \in R^n$. If the signal X is compressible in a certain orthogonal basis or a compact framework Ψ, get the transformation coefficient $\Theta = \Psi^T X$. Use a measurement matrix $\Phi \in R^{m \times n}$ ($m << n$), which satisfies restricted isometry property (RIP), to carry out linear transformation for the coefficient vector Θ and obtain the transformed vector $Y \in R^m$. Then, an optimization solution method can be used to reconstruct the original signal X from the vector Y accurately or high probably.

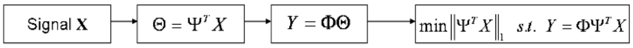
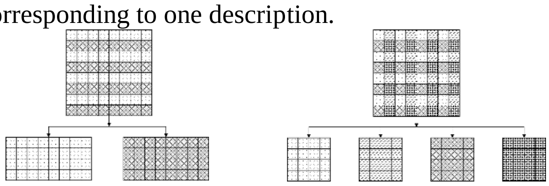


FIGURE 1 The specific process of compressed sampling

3 Key technology of the method based on IE-BCS

3.1 INTERLEAVING EXTRACTION

The principle of interleaving extraction is that adjacent pixels in an image are equally distributed to different descriptions to the largest extent. The interleaving extraction method shown in Figure 2 is used to segment an original image into 2 or 4 sub-images and each sub-image is corresponding to one description.



a) 2 sub-images b) 4 sub-images

FIGURE 2 Image division process by interleaving extraction

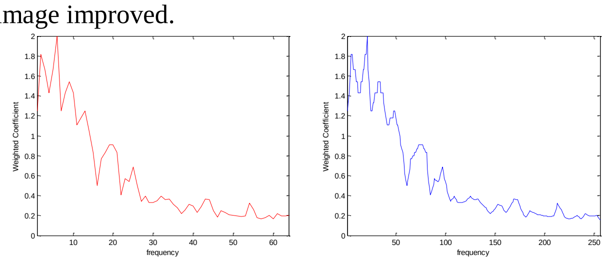
3.2 THE BCS OF WEIGHTED OBSERVATION MATRIX

Application of compressed sensing theory in image signal is commonly used in block compressed sensing method [4, 5]. The conventional BCS divides a whole image into some equal-sized sub-blocks, and then observes and constructs each sub-block independently. It owns the advantage of small observation matrix and of low computation complexity. To specify, the conventional BCS first divides an image of $I_m \times I_n$ into sub-blocks and assumes the size of each sub-block as $n_B \times n_B$, then scans each sub-block and generates the vector X_i containing N_B ($n_B \times n_B$) elements, and next observes them with an identical observation matrix $\Phi_B \in R^{M_B \times N_B}$ ($M_B < N_B$) and gets the observation value $Y_i \in R^{M_B}$, that is, $Y_i = \Phi_B X_i$. After the observation value gained, all of the sub-blocks are restored with the construction algorithm, and last are combined to form up the whole image.

As Gaussian random matrix is irrelevant with most matrixes of fixed orthogonal basis [3], the conventional BCS means usually applies independent and identically distributed Gaussian random matrix as the observation matrix. But the measurement disregards the relationship of the reconstruction precision of the images with different frequencies to the overall quality of the reconstructed images, and thus results in reconstructions of poor quality. The BCS of weighted observation matrix proposed in this research is an improvement to the conventional BCS, and is a way of weighted processing the elements of different frequencies in the observation matrix to make the images of low frequencies higher reconstruction precision, and to improve the overall quality of the reconstructed image.

3.2.1 Weighted Processing of the observation matrix

According to the characteristics of human visual system, human eyes have greater sensitivity to the low frequency components of the image data. Therefore, the reconstruction error in low frequency components determines the quality of the reconstructed image. In accordance with the principle of the DCT transform, The DCT low frequency coefficient of an image distributes in the upper left corner of the DCT coefficient matrix, while the high frequency coefficients in the lower right corner, and the main energy of the image is concentrated in the low frequency regions of the image. Therefore, the JPEG quantization table got processed, generating weighted coefficient matrix, which was then Zig-Zag ordering, creating weighted coefficient curve, as shown in Figure 3. The weighted coefficient curves reveals: when weighted processing each element in the observation matrix, the larger the weighted value of the matrix elements computing the data in the low frequency positions of the image. The higher the reconstruction precision of the image data in the low and medium frequency part; but the weighted value of the matrix elements computing the data in the high frequency positions of the image is comparatively small, and the construction errors are comparatively bigger. As the low frequency components are the main factors affecting the image quality, this method can make the overall quality of the reconstructed image improved.



a) 8×8 blocks b) 16×16 blocks

FIGURE 3 Weighted coefficient curve of different blocks

When weighting the observation matrix, first the weighted coefficient should be sequenced by Zig-Zag in the same way as image sub-blocks generate vectors, forming the weighted coefficient vector W_B in the length of N_B and the vector element $w_B(n)$. Then each element in each line of the original measurement matrix Φ_B multiplies each element in the corresponding position of the weighted vectors:

$$\phi_B{}'(m,n)=\phi_B(m,n)w_B(n),(m=1,2,...,M_B,n=1,2,...,N_B) \quad (1)$$

and thus, forming the weighted measurement matrix $\Phi_B{}'$. As to a whole image, the interrelationship among the observation matrix, the image data and the observation values is as Equations (2), among which $l=(I_m\times I_n)/N_B$.

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_l \end{bmatrix} = \begin{bmatrix} \Phi_B{}' & 0 & \dots & 0 \\ 0 & \Phi_B{}' & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \Phi_B{}' \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \vdots \\ X_l \end{bmatrix}. \quad (2)$$

3.2.2 Contrast of the reconstruction results before and after the observation matrix weighting.

Lena, Cameraman, Boats and Fruits grey images in the size of 256×256 selected as the test images, the reconstruction results by Gauss random matrix Φ_B and weighted measurement matrix $\Phi_B{}'$ were analysed. The experiment adopted DCT to transform the sparsity of the images, and l_1-minimization algorithm to reconstruct the images, and the simulation were divided into two block sizes of 8×8 and 16×16. The simulation results are as Figure 4.

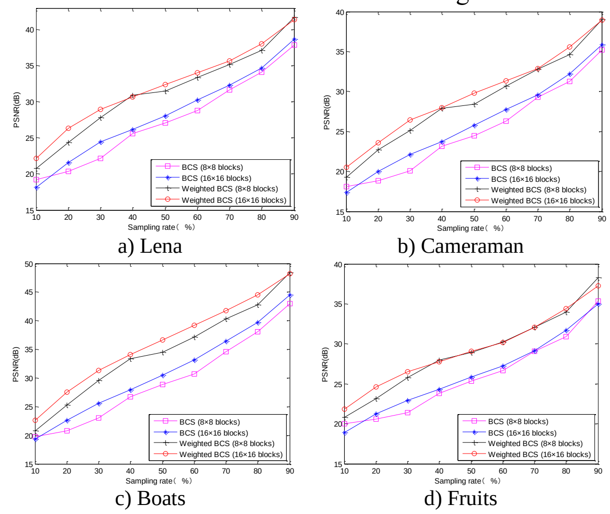


FIGURE 4 The results of reconstructed images by different observation means

From the comparison between the reconstruction results by BCS before and after the weighted observation matrix at an identical sampling rate, such can be observed that the PSNR of the reconstructed grey images of Lena, Cameraman, Boats and Fruits through weighted observation matrix have been raised 4dB, 3.7dB, 5.1dB and 3.1dB respectively than the average, and among them the reconstruction quality of the 16×16 block is better than the 8×8 block. This method proposed simply processes the measurement matrix in a weighted way but does not add to the computation complexity, and proves to enable the reconstruction precision to greatly increase with the sampling rate unchanged.

4 IE-BCS system frame work

IE-BCS system is composed of an encoding module and a decoding module. 4-descriptions are used as an example to introduce composition and specific functions of each module.

4.1 ENCODING MODULE

The function of the encoding module is that it implements interleaving extraction and BCS encoding for the original image, as shown in Figure 5. The specific processing procedure is shown as follows.

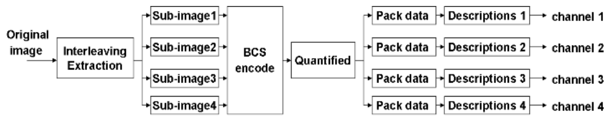


FIGURE 5 Encoding module

1) Implement interleaving extraction for the original image to generate 4 sub-images.

2) Divide each sub-image into sub-blocks with the size of 8×8 or 16×16, carry sparse conversion for each sub-block and use a weighted measurement matrix to sample and encode the transformation coefficient. When an encoder/ decoder is designed, seeds generating random matrix are fixed at both ends to ensure that the same measurement matrix is used when observation is carried out at the encoding terminal and reconstruction is performed at the decoding terminal.

3) Pack data after being quantified and transmit them into the decoding terminal by their own independent channels. It is worth mentioning that a uniform quantification method is applied to the process of quantification.

4.2 DECODING MODULE

The function of the decoding module is that it receives and analyses data packages in channels, and select corresponding decoders according to reception situations to decode each description, as shown in Figure 6. The specific processing procedure is shown as follows.

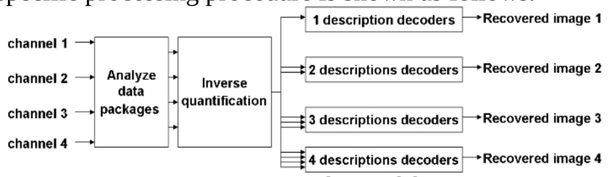


FIGURE 6 Decoding module.

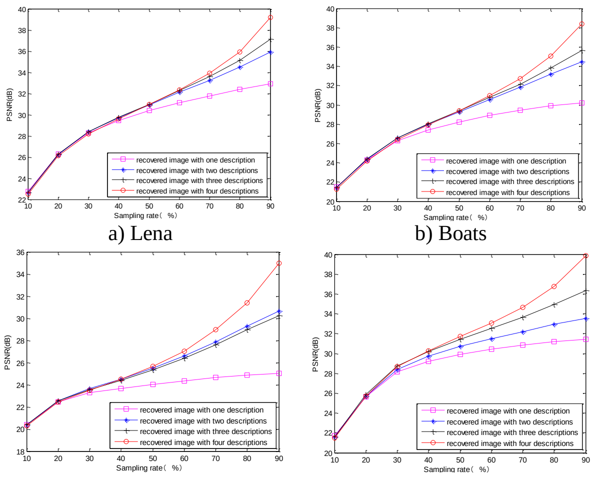
1) Receive data packages in channels and select corresponding decoders according to reception situations. The principle by which decoders are selected is that description decoders will be selected if complete descriptions are received. In another word, if each description is received completely, decode each description, respectively, combine them crosswise and obtain complete images. Otherwise, decode complete descriptions only and use interpolation algorithm to recover approximate images.

2) Analyse data packages and process them by inverse quantification to obtain an observed value of the transformation coefficient.

3) Reconstruct the original transformation coefficient from the observed value by solving sparse optimization, and then use inverse sparse conversion to reconstruct the original image.

5 Simulation experiment

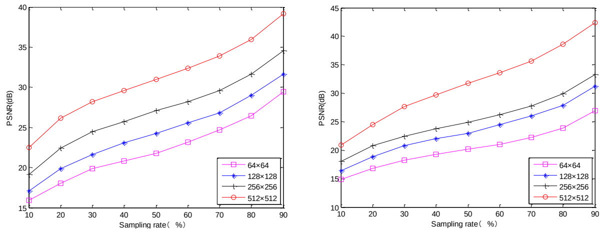
In MATLAB environment, Lena, Boats, Barbara and Peppers grey images in the size of 512×512 are selected as the test images. Utilize the interleaving extraction to divide the original image into 4 sub-images, segment each sub-image into sub-blocks with the size of 16×16, use DCT to carry out sparse conversion for sub-blocks, adopt the weighted measurement matrix as a measurement matrix and use l_1 – minimization algorithm for reconstruction the images. The reconstruction results of the method based on IE-BCS at different sampling rates are shown in Figure 7. Results of 4-description reconstruction images with different sizes are presented in Figure 8.



a) Lena b) Boats

c) Barbara d) Peppers

FIGURE 7 Reconstruction results of the method based on IE-BCS at different sampling rates



a) Lena b) Cameraman

FIGURE 8 Results of 4-description reconstruction images with different sizes

Test results show that reconstruction quality (PSNR) of images have close relationship with the sampling rate and the number of descriptions, which are received completely. When the sampling rate is lower than 30%, the reconstruction quality of images obtained by each decoder is basically the same. As the sampling rate is improved, the reconstruction quality of images is improved obviously. When the sampling rate is higher than 30%, the larger the number of descriptions, which are received completely, is, the better the reconstruction quality of images is. When the sampling rate exceeds 70%, the original image can be reconstructed favourably on the premise that only one complete description is needed. According to Figure 8, it can be known that the larger the image size is, the higher the smoothing degree of sub-images generated by interleaving abstraction is, and the better the reconstruction effect is. Since the method based on IE-BCS adopts a block processing method and ensures complexity of the observation process will not be changed with the image size, the method is more appropriate for processing high-definition images.

6 Discussion and conclusion

This thesis proposes a WSN image acquisition method based on IE-BCS. The methods utilizes the block compressed sensing theory and the interleaving extraction technology, so it can reduce pressure on nodes' computation and storage effectively and decrease data sizes of network transmission. In addition, this thesis also improves the traditional BCS method and puts forward the BCS method weighted by a measurement matrix, which enhances precision of image reconstruction. Meanwhile, it uses 4 international standard test images to carry out an experiment. Results indicate that the method can save hardware resources efficiently and improve robustness of image transmission.

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