Available online at www.sciencedirect.com
ScienceDirect
ELSEVIER
The Journal of China Universities of Posts and Telecommunications
February 2016, 23(1): 22–30
www.sciencedirect.com/science/journal/10058885
http://jcupt.bupt.edu.cn

Image compression scheme based on PCA for wireless multimedia sensor networks

Zhou Wei[1], Sun Lijuan[1,2] (✉), Guo Jian[1,2], Liu Linfeng[1,2]

1. College of Computer, Nanjing University of Posts and Telecommunications, Nanjing 210003, China
2. Jiangsu High Technology Research Key Laboratory for Wireless Sensor Networks, Nanjing 210003, China

Abstract

In combination of the characteristic of the network architecture of wireless multimedia sensor networks (WMSNs), a distributed multi-node cooperative network (DMCN) model is designed by using the concept of in-network processing to improve their energy, memory and computational power. To balance the energy consumption of the network, according to roles division, camera nodes and common nodes are cooperated to accomplish the workload of image acquisition, compression and transmission. Camera nodes gather images and send blocking images to the common nodes in cluster. Common nodes adaptively compress the partitioned images by using a noise-tolerant distributed image compression (NDIC) algorithm based on principal component analysis (PCA) called NDIC-PCA algorithm and send the compressed data to the cluster head node. Then, the cluster head node sends the compressed image data to the station. Simulation results demonstrate that, DCNM can effectively balance the energy consumption of network and largely extend the network lifecycle. In addition, compared with previous algorithms, the proposed NDIC-PCA algorithm achieves higher peak signal to noise ratio without decreasing compression ratio.

Keywords wireless multimedia sensor networks, image compression, principal component analysis, node collaboration

1 Introduction

With the development of complementary metal oxide semiconductor (CMOS) technology, the single-chip camera has been considerably developed in recent years. Its modules are easily embedded into inexpensive radio equipment, which greatly facilitates the popularization of imaging applications in WMSNs [1]. The combination of multimedia source cameras which can capture images or videos and inexpensive communication apparatus has been a hotspot in WMSNs.

WMSNs is normally consist of a large number of common nodes which can collect simple environmental data (such as temperature, vibration, etc.) and camera nodes which can capture images. In addition to the common characteristics of self-organizing, multi-hop routing, resource-constrained [2], it also has the new characteristics of complex tasks, the ‘uniform’ distribution of processing and transmission energy [3], which presents a huge challenge.

In WMSNs, the multimedia information processing research aims at addressing how to efficiently realize coding and transmitting of images, videos and other multimedia information in the condition of limited processing power and energy. The power consumption of traditional WSNs mainly concentrates in the wireless transceiver and its distribution presents the ‘gathering’ state. In WMSNs, the power consumption of the wireless transceiver and data processing is roughly equal, which presents ‘uniform’ distribution. So how to effectively reduce the energy consumption of a single node and balance energy distribution throughout the network to extend the life cycle of the entire network by utilizing the features of WMSNs has attracted more and more attention of researchers [4].

In recent years, distributed image compression has been a subject of intense study and many efforts have been

Received date: 11-08-2015
Corresponding author: Sun Lijuan, E-mail: sunlj@njupt.edu.cn
DOI: 10.1016/S1005-8885(16)60004-3

made. Wu et al. introduced an energy efficient distributed image compression in resource-constrained multi-hop wireless networks based on wavelet transform [5]. Lu et al. suggested multi-node cooperative acquisition and compression by adopting dual-orthogonal lapped transform [6] and JPEG2000 task split method [7]. Han et al. [4] introduced a multi-node image compression and transmission scheme based on singular value decomposition (SVD) to balance the network energy consumption and prolong the network life time. Mowafi et al. introduced a novel geometrical model to extract the spatial correlation characteristics of heterogeneous camera nodes in WMSNs, taking into consideration the different sensing radii and the angles of view of the camera nodes [8]. Yu et al. proposed a distributed compressed sensing scheme for image signal compression and reconstruction, which is to exploit the inter-correlation of the blocks that split from the image [9]. Furthermore, image compression methods based on PCA has been extensively studied in the field of image compression [10–13]. In this paper, we design a DMCN model by using cooperative characteristic of multi-node to save their energy and maximize the network lifecycle. Camera nodes gather images and send blocking images to the common nodes in cluster. Common nodes adaptively compress the partitioned images by using a NDIC-PCA algorithm and send the compressed data to the cluster head node. Then, the cluster head node sends the compressed image data to the station. In addition, the proposed NDIC-PCA algorithm can achieve high peak signal without decreasing compression ratio.

The main contributions of this work are summarized as follows:

1) We design a DMCN model. The image compression task of camera node is effectively decomposed to common nodes, in order to save energy and extend the network lifecycle. Simulation results demonstrate that DMCN can effectively balance the energy consumption of network and largely extend the network lifecycle.

2) We propose a NDIC-PCA algorithm. As far as we are aware of, this is the first scheme that use PCA for multi-node cooperative image compression in WMSNs. Simulation results demonstrate that, compared with previous algorithms, NDIC-PCA algorithm achieves higher peak signal to noise ratio without decreasing image compression ratio.

The rest of this paper is organized as follows. Preparation work is summarized in Sect. 2, Sect. 3 introduces the proposed methods, including DMCN model, noise-tolerant distributed image compression algorithm based on PCA and description of the specific program. Sect. 4 represents experimental results and demonstrates the performance improvement by using the proposed method. Finally, we conclude this paper in Sect. 5.

2 Preparation works

PCA was proposed by Turk et al. of MIT Media Lab [14], it is based on K-L transformation, which is an orthogonal transformation. The n-dimensional features are mapped to k-dimensional space ($k<n$), and the k-dimensional features are new orthogonal features called principal components. It is reconstructed out of k-dimensional features, rather than simply removing the remaining $n-k$ dimensional features from the n-dimensional features. As the k principal components cover the majority of features of the original data information, the PCA is widely used in data reduction and data compression.

Given the data matrix $\boldsymbol{X}_{m\times n}$ ($m \geqslant n$), it consists of the sample data which has been centralized, and, we have

$$\sum_{i=1}^{m} \boldsymbol{x}_i = 0 \tag{1}$$

If the original image data $\boldsymbol{A}$ is not centralized, the Eq. (1) is not established, so the data $\boldsymbol{A}$ should be average-removed as follows:

$$\boldsymbol{X}_{ij} = \boldsymbol{A}_{ij} - \bar{\boldsymbol{A}}_j \tag{2}$$

The mean value can be given by:

$$\bar{\boldsymbol{A}}_j = \frac{1}{m}\sum_{i=1}^{m} \boldsymbol{A}_{ij} \tag{3}$$

Then we solve characterized covariance matrix of the matrix $\boldsymbol{A}$ with each column of the matrix $\boldsymbol{A}$ as a sample, the covariance matrix can be defined as follows:

$$\boldsymbol{C}_{n\times n} = \left(c_{i,j}, c_{i,j} = \mathrm{cov}(\mathrm{dim}_i, \mathrm{dim}_j)\right) \tag{4}$$

Where dim_i, dim_j is a column of the matrix, $i, j = 1, 2, ..., n$.

The covariance matrix $\boldsymbol{C}_{n\times n}$ is obviously a symmetric matrix. Then we solve the eigenvalues $(\lambda_1, \lambda_2, ..., \lambda_n)$ and the eigenvectors $(\boldsymbol{v}_1, \boldsymbol{v}_1, ..., \boldsymbol{v}_n)$ of the matrix $\boldsymbol{C}_{n\times n}$. Eigenvalues are arranged in descending order $\lambda_1' \geqslant ... \geqslant \lambda_n'$, and eigenvectors are adjusted accordingly $\boldsymbol{v}_1', \boldsymbol{v}_2', ..., \boldsymbol{v}_n'$. We use Schmidt method to unitize eigenvectors to $\boldsymbol{u}_1, \boldsymbol{u}_2, ..., \boldsymbol{u}_n$. By calculating the cumulative contribution rate of eigenvalues, we get $B_1, B_2, ..., B_n$. According to a given extraction efficiency η, if $B_k \geqslant \eta$, then we extract the k principal components $\boldsymbol{u}_1, \boldsymbol{u}_2, ..., \boldsymbol{u}_k$. Finally, the projection can be given by:

$$\boldsymbol{Y}_{m\times k} = \boldsymbol{U}_{n\times k}^{\mathrm{T}} \boldsymbol{X}_{m\times n} \tag{5}$$

where $\boldsymbol{U}_{n\times k} = (\boldsymbol{u}_1, \boldsymbol{u}_2, ..., \boldsymbol{u}_k)$ and $\boldsymbol{Y}$ is the low dimensional data after extraction.

In many cases, the eigenvalues $\boldsymbol{B}_i$ reduce extremely fast from B_1 to $B_2, B_3, ..., B_k$, and the contribution rate of the first 10% (even 1%) of eigenvalues accounts for more than 99% of all. Therefore, we can use the first k eigenvalues (the former principal components) to approximate the original matrix. Due to the nature of the digital image with a matrix structure, so it is why the PCA can be applied to image compression.

To reconstruct the image data, first, we can get the approximation of average-removed original image matrix by Eq. (5). The inverse transform formula can be given by:

$$\hat{\boldsymbol{X}}_{m\times n} = \boldsymbol{U}_{n\times k} \boldsymbol{Y}_{m\times k} \tag{6}$$

Then we can get the matrix $\hat{\boldsymbol{A}}$ by plus each column of the matrix $\hat{\boldsymbol{X}}$ and the mean value: $\overline{\boldsymbol{A}}$, $\hat{\boldsymbol{A}}$ is an approximation of the original matrix. Therefore, we can compress the original image data in a certain degree by saving the three matrices: $\boldsymbol{Y}_{m\times k}$, $\boldsymbol{U}_{n\times k}$, $\overline{\boldsymbol{A}}_{1\times n}$. Image compression ratio ρ can be calculated as follows:

$$\rho = \frac{nn}{mk + nk + n} \tag{7}$$

Principle of de-noising based on Maximum variance theory

It is generally considered that signal has larger variance while noise has a smaller variance in signal processing. The essence of the PCA is to choose projection axis with largest variance by selecting the suitable sample points, in order to minimize loss of information after dimensionality reduction. For instance, if the sample variance of the projection on the horizontal is much larger than that on the vertical axis, then we consider the projection on the vertical axis is caused by noise. Therefore, the best k-dimensional feature is that the sample variance in each dimension are large after the n-dimensional sample points converted to k-dimensional space.

First, as the mean of sample data is 0 after projection, the variance can be given by:

$$\frac{1}{m}\sum_{i=1}^{m} (\boldsymbol{x}^{(i)\mathrm{T}} \boldsymbol{u})^2 = \frac{1}{m}\sum_{i=1}^{m} \boldsymbol{u}^{\mathrm{T}} \boldsymbol{x}^{(i)} \boldsymbol{x}^{(i)\mathrm{T}} \boldsymbol{u} = \boldsymbol{u}^{\mathrm{T}} \left(\frac{1}{m}\sum_{i=1}^{m} \boldsymbol{x}^{(i)} \boldsymbol{x}^{(i)\mathrm{T}} \right) \boldsymbol{u} \tag{8}$$

where $\frac{1}{m}\sum_{i=1}^{m} (\boldsymbol{x}^{(i)\mathrm{T}} \boldsymbol{s})^2$ is represented by λ and $\frac{1}{m}\sum_{i=1}^{m} \boldsymbol{x}^{(i)} \boldsymbol{x}^{(i)\mathrm{T}}$ is represented by $\boldsymbol{\Sigma}$. Then the above equation can be described as follows:

$$\lambda = \boldsymbol{u}^{\mathrm{T}} \boldsymbol{\Sigma} \boldsymbol{u} \tag{9}$$

As $\boldsymbol{u}$ is a unit vector and $\boldsymbol{u}^{\mathrm{T}} \boldsymbol{u} = 1$. The both sides of the above equation are premultiplied by $\boldsymbol{u}$, such as $\boldsymbol{u}\lambda = \lambda \boldsymbol{u} = \boldsymbol{u}\boldsymbol{u}^{\mathrm{T}} \boldsymbol{\Sigma} \boldsymbol{u} = \boldsymbol{\Sigma} \boldsymbol{u}$. Then we can get

$$\boldsymbol{\Sigma} \boldsymbol{u} = \lambda \boldsymbol{u} \tag{10}$$

where λ is the eigenvalue of $\boldsymbol{\Sigma}$, and $\boldsymbol{u}$ is the eigenvector of $\boldsymbol{\Sigma}$. So the best straight line of the projection is eigenvector corresponding to the largest eigenvalue, the next eigenvector corresponding to the second largest eigenvalue, and so on.

Therefore, the eigenvectors corresponding to the k largest eigenvalues are the best k-dimensional features which are orthogonal after the eigen decomposition of the above covariance matrix. Then the new samples can be obtained through the following transformation:

$$\boldsymbol{y}^{(i)} = \begin{bmatrix} \boldsymbol{u}_1^{\mathrm{T}} \boldsymbol{x}^{(i)} \\ \boldsymbol{u}_2^{\mathrm{T}} \boldsymbol{x}^{(i)} \\ \vdots \\ \boldsymbol{u}_k^{\mathrm{T}} \boldsymbol{x}^{(i)} \end{bmatrix} \in \mathbb{R}^k \tag{11}$$

where the j-dimensional data is projection of $\boldsymbol{x}^{(i)}$ on $\boldsymbol{u}_j$.

Because the small dispersion characteristics can be discarded by selecting the k largest u, so we can effectively remove noise by using PCA to compress image data, and the quality of the recovered image can be improved.

3 Image compression scheme based on PCA

3.1 DMCN model

Due to limited energy of sensor node, large-scale network nodes, complex actual application environment, and the difficulty of replacing battery in WMSNs, how to save limited battery power of a single node and extend the network lifetime on the premise that the monitoring images can be captured, compressed and transmitted successfully is one of the core objectives.

We design a DMCN model which can decompose the complex high-energy work by taking full advantage of characteristics of WMSNs. Although the data compression increases computational pressure on sensor node, but it can greatly reduce the communication task in WMSNs.

Furthermore, distributed data compression can effectively balance the energy consumption of individual nodes and it is beneficial to prolong the lifetime of entire network. Thus we adopt cluster-type layer network topology model for image compression [15–16]. First, we divide the nodes into camera node and common nodes. Then, we make assumptions as follows:

All nodes in the network has a unique id number, they are static, unmovable and the location information is known to all nodes. Besides, location information can be obtained by global position system (GPS) receiver or other location service [17].

1) Ensure time synchronization [18].

2) In order to save cost and energy, camera node only monitors the area of interest. Different monitoring area do not overlap that the distance between two cameras is longer than wireless communication connection radius.

3) The density of nodes is large enough so that the adjacent set of common nodes deployed randomly in the area of wireless communication is not empty.

On the basis of the above assumption, the DMCN model for image compression and transmission can be designed as follows:

1) Common nodes in the connected region of the camera constitute a cluster.

2) Select a best node as the cluster head node according to energy, stability and link quality from the common nodes in the cluster.

3) Cluster head node broadcasts to surrounding nodes as a cluster head node, then inform them its own id number and the camera's id number.

4) Common nodes choose the cluster which belong to, and inform camera node and cluster head node their id numbers.

5) Cluster head node saves a list which records the id numbers in the cluster.

6) Repeat the step 1 to 5 indefinitely.

DMCN aims to construct a cluster structure where the set of common nodes is not empty which is shown in Fig. 1. The establishment of DMCN is an important step in cooperative image compression scheme.

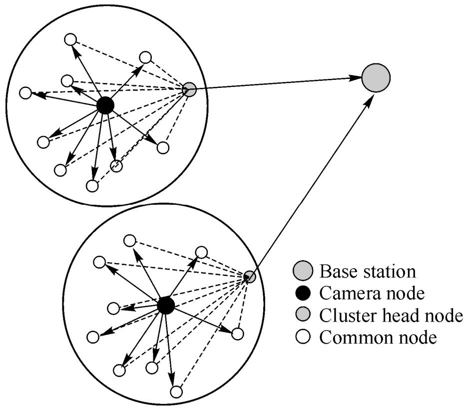

Fig. 1 Example of DMCN

3.2 NDIC-PCA algorithm

In this chapter, we propose a noise-tolerant distributed image compression algorithm based on PCA called NDIC-PCA which is based on the DMCN model in Sect. 3.1.

In order to reduce the cost of computation when dealing with large image, the block method is introduced. First, we divided the large image into blocks, then we rebuild each block matrix and compress the blocks by using NDIC. The combination of original image blocking method and block matrix regrouping method can effectively reduce the time of image compression by using NDIC-PCA algorithm, and we can obtain higher image quality in less time. Furthermore, the termination condition of our algorithm can be selected according to actual situation. The NDIC-PCA algorithm can be summarized as follows:

1) Divide the image ($m \times n$) captured by camera into blocks, the size of each block is $p \times q$.

2) Rebuild the block matrix.

3) Compress the rebuilt block matrix by using NDIC-PCA algorithm.

The processing time can be effectively reduced when the block matrix ($p \times q$) is small, and the processing time can be further reduced by rebuilding the blocking matrix. The block matrix rebuilding algorithm is as follows:

Algorithm 1: Block matrix rebuilding

Input: Matrix divided from the original grayscale image: $\boldsymbol{V}$, parameters u, v.

Output: Rebuilt block matrix $\boldsymbol{G}$

1) $\boldsymbol{V} = \text{Block(OriginFigure)}$; // $\boldsymbol{V}$ is one of blocks divided from original image

2) $[x, y] = \text{size}(\boldsymbol{V})$; //Get the number of rows and columns of the matrix $\boldsymbol{V}$

3) $s = x / u, t = y / v, h = 0$; //Calculate the number of blocks and

initialize t, h
4) for $i = 1:u:s$
5) for $j = 1:v:t$
6) $h = h+1$
7) $\boldsymbol{M}_{\text{block}} = \boldsymbol{V}\left(i:i+u-1, j:j+v-1\right)$;
8) $\boldsymbol{G}(:,h) = \boldsymbol{M}_{\text{block}}(:)$;
9) end for
10) end for
11) Output rebuilded block matrix: $\boldsymbol{G}$.

After the preparation of rebuilding the block matrix, we propose a NDIC-PCA algorithm in algorithm 2. Then the image compression ratio can be given by:

$$\rho' = \frac{\dfrac{mn}{pq}}{\displaystyle\sum_{i=1}^{\frac{mn}{pq}} \frac{\lambda_i \dfrac{pq}{uv} + uv\lambda_i + \dfrac{pq}{uv}}{pq}} \tag{12}$$

Algorithm 2 NDIC-PCA algorithm

Input: Block image matrix $\boldsymbol{V}$, threshold value η.
Output: Grayscale image matrix after recovery $\hat{\boldsymbol{A}}$.
1) $\boldsymbol{G} = \text{SecondBlock}(\boldsymbol{V})$; // $\boldsymbol{G}$ is rebuilded block matrix
2) $\bar{\boldsymbol{A}} = \text{mean}(\boldsymbol{G})$, //averaging
3) $\boldsymbol{G}' = \boldsymbol{G} - \bar{\boldsymbol{A}}$; //standardized
4) $\boldsymbol{C} = \text{cov}(\boldsymbol{G}')$; //solving the covariance matrix
5) $[\textbf{vec}, \lambda] = \text{eig}(\boldsymbol{C})$; //eigenvalues and eigenvectors
6) $[\lambda, \text{tr}] = \text{sort}(\text{val}, \text{'descend'})$; //eigenvalues in descending order
7) $\textbf{vec} = \textbf{vec}(:, \text{tr})$; // eigenvectors change order corresponding to eigenvalues
8) for $k = 1:\text{length}(\text{diag}(\text{val}))-1$ do
9) if $\dfrac{\sum_{i=1}^{k}\lambda_i}{S} \geqslant \eta$ then //chose eigenvalues
10) $k_\eta = k$;
11) break;
12) end if
13) end for
14) $\boldsymbol{Y}' = \boldsymbol{Y}(1:k_\eta, :)$; //save transformation matrix
15) $\boldsymbol{U}' = \boldsymbol{U}(:, 1:k_\eta)$; //save projection matrix
16) Rebuild matrix $\hat{\boldsymbol{G}} = \boldsymbol{U}'\boldsymbol{Y}' + \bar{\boldsymbol{A}}$, convert the column vector $\hat{\boldsymbol{G}}$ into a matrix $\hat{\boldsymbol{A}}$, return $\hat{\boldsymbol{A}}$.

We can adjust the number of rows and cols of block matrix by using algorithm 1 in order to effectively reduce the time of solving eigenvalues and eigenvectors in algorithm 2. Because the row number is much less than the column number of the rebuilt block matrix, so the size of the covariance matrix in algorithm 2 can be greatly reduced. Furthermore, we can compress the each block in accordance with respective threshold value η in algorithm 2. Therefore, NDIC-PCA algorithm can achieve higher peak signal to noise ratio without decreasing image compression ratio by taking full advantage of the characteristics of each image block.

3.3 Description of specific program

In this section, we describe the distributed multi-node cooperative image compression scheme based on NDIC-PCA algorithm in detail. The implementation process of the scheme can be given by:

1) The camera node is responsible for image acquisition and original data transmission. The camera node captures images and calculate the image size and number of blocks, then send the blocks to common nodes according to the established cluster structure.

2) After receiving image blocks from camera nodes, the common nodes rebuild the blocks according to algorithm 1, and compress the rebuilt blocks by using NDIC-PCA algorithm. Then the common nodes send compressed data to the cluster head node and monitor whether new blocks are transmitted from the camera node at the same time, if new data arrives, then continue to compress.

3) The work of the cluster head node is just to receive data from common nodes and send them to base station. Since each packet contains location information, so the cluster head node doesn't integrate data in order to save energy. Finally, the compressed data is integrated in base station.

4 Simulation experiment

4.1 Experiment setting and relevant parameters

4.1.1 Experiment setting

In this chapter, we use MATLAB 2009a to build a simulation environment according to the proposed DMCN model. It is assumed that we deploy 15 camera nodes for covering the monitoring area in 100 m$\times$100 m rectangular region. The sensing radius of camera node is 11 m, and we deploy 11 common nodes randomly in the connected area of each camera node. Then we chose a common node which is nearest to base station as the cluster head node. The base station is deployed in the center of rectangular area. The simulation network structure is shown in Fig. 2.

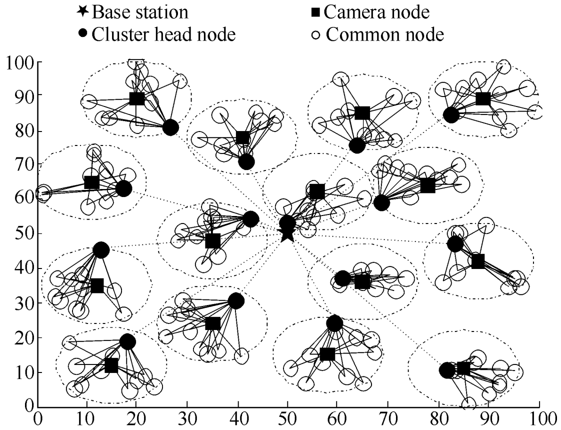

Fig. 2 Entire network topology

4.1.2 Energy consumption model and relevant parameters

The camera node collects $512\times512\times8$ bit grayscale images periodically. The size of blocking image is $128\times128\times8$ bit and the number of blocks is 16, and the total image compression ratio ρ is 4. Furthermore, we adopt classical Heizelman model to compute communication energy consumption [19]. The energy consumption of WMSNs can be divided into three parts: data acquisition energy consumption, wireless transceiver energy consumption and data processing energy consumption. Since the data acquisition energy consumption of camera nodes is only determined by camera configuration and has nothing to do with our algorithm, we mainly consider the latter two.

Suppose a node transmits 1 bit packet in its slot, the transmission distance is d, then the energy consumption of its transmitter module can be given by the following equation [19]:

$$E_s(J,d)=\begin{cases}E_{\text{elec}}+\mu_{\text{fs}}d^2; & d<d_0\\ E_{\text{elec}}+\mu_{\text{ump}}d^4; & d\geqslant d_0\end{cases} \tag{13}$$

The energy consumption of its receiver module can be given by the following equation [19]:

$$E_{\text{R}}(J)=E_{\text{elec}} \tag{14}$$

Where $E_{\text{S}}(J,d)$ is the energy consumption of transmitter module, $E_{\text{R}}(J)$ denotes the energy consumption of receiver module, E_{elec} is the energy consumption of transmitting circuit and receiving circuit. The energy consumption of the amplifier $\mu_{\text{fs}}d^2$ and $\mu_{\text{ump}}d^4$ depend on the transmission distance.

The relevant parameters in above formula are set as follows [19]: $E_{\text{elec}}=50\ \text{nJ/bit}$, $d_0=87\ \text{m}$, $\mu_{\text{ump}}=0.001\,3\ \text{pJ/(bit}\cdot\text{m}^2)$, $\mu_{\text{fs}}=10\ \text{pJ/(bit}\cdot\text{m}^2)$.

In this paper, the main data processing work is to solve the covariance matrix, the eigenvalues and eigenvectors. The energy consumption of data processing can be obtained by using the following formula [20]:

$$E=NCV_{\text{DD}}^2 \tag{15}$$

where N represents the number of clock cycles occupied by a processing task. C denotes the cycle switched capacitor which is set as 0.67 nF and V_{DD} is supply voltage of processor which is set as 3.3 V [20].

An energy consumption test was carried out at StrongARM SA-1100 processor platforms with the operating frequency of 206 MHz. As is shown in Table 1, we estimate the average number of clock cycles by executing NDIC-PCA algorithm is 40 (clock/bit). Then we can get that the energy consumed by processing 1 bit data is about 291.9 nJ according to the Eq. (15). Obviously, the proposed algorithm achieves less energy consumption compared with adaptive method based on SVD in literature [4].

Table 1 Energy consumption of the proposed algorithm and adaptive method based on SVD by processing 1 bit data

Method	Clock cycles/ (clock $\cdot$ pixel $^{-1}$)	Energy consumption/(nJ $\cdot$ bit $^{-1}$)
NDIC-PCA algorithm	40	291.9
Adaptive method based on SVD	50	364.8

4.2 Simulation results analysis

4.2.1 Energy consumption analysis

As the camera node plays a more important role than common nodes in the whole monitoring area, we first analyzes the energy consumption of camera node in the case of different network depths in the following three schemes:

Scheme one: The camera node transmits the original images directly to the base station without image compression.

Scheme two: The camera node compresses images and transmits the compressed data to the base station.

Scheme three: The camera node adopts the proposed working scheme, the image blocks are sent to the common nodes in the cluster, then common nodes are responsible for image compression and transmission.

Fig. 3 shows the comparison of energy consumption of the camera node by transmitting a $512\times512\times8$ bit image in the three schemes above. For scheme one, the energy consumption is lowest when the base station is in the connected region of the camera node, but it increases significantly with increasing of distance from the camera node to the base station. For scheme two, the main source of energy consumption is from image compression whether the camera node is near or not from the base station. However, as a key node in the network, the camera node is the basis of the network to survive. As the task of image compression is decomposed effectively in scheme three, the camera node is only responsible for communication with common nodes in the cluster, and its energy consumption is independent of the distance from the base station. Therefore, scheme three can greatly ensure the survival of the camera node.

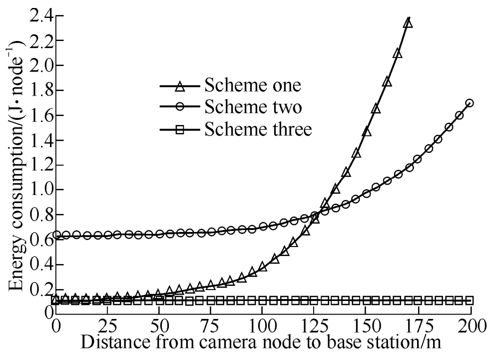

Fig. 3 Comparison of energy consumption of the camera node

Fig. 4 and Fig. 5 shows the distribution of energy consumption of centralized image compression and cooperative image compression by transmitting a $512 \times 512 \times 8$ bit image respectively.

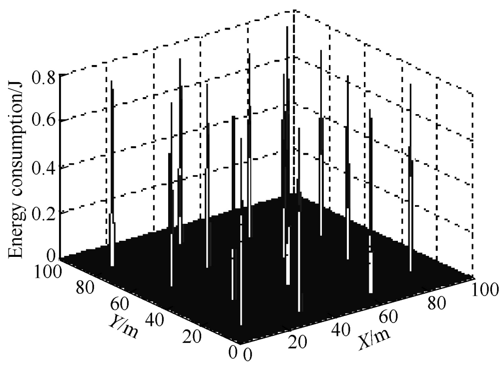

Fig. 4 Distribution of energy consumption of centralized image compression

Fig. 4 adopts the centralized method where there is only a camera node and the camera node compresses images and transmits the compressed data to the base station. Fig. 5 adopts the proposed method, the image compression and transmission are completed cooperatively by camera node, common nodes and cluster head node. The simulation results show that the average energy consumption decreases by one order of magnitude and has a strong balance in the proposed method. As the balance of energy consumption is helpful to prolong network lifetime, the proposed method greatly extends the network lifecycle.

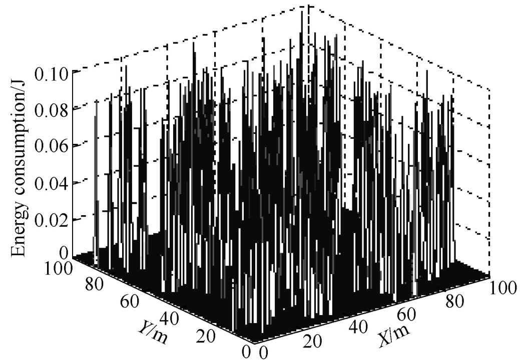

Fig. 5 Distribution of energy consumption of cooperative image compression

In the simulation experiment, we also conducted a comparison between the proposed method and other distributed compression methods. Fig. 6 shows the comparative relationship of the cluster head node energy consumption between improved JPEG2000 block adaptive method in Ref. [7] and the proposed method.

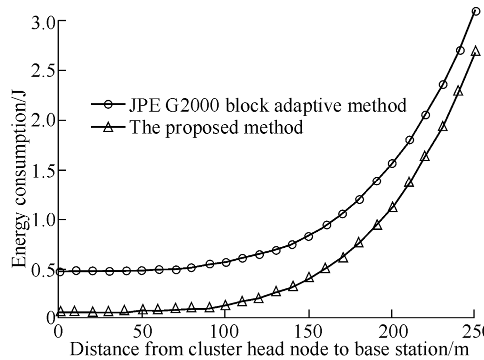

Fig. 6 Comparison of the cluster head node energy consumption

As is shown in Fig. 6, the cluster head node energy consumption in the proposed method is significantly less than that in the Ref. [7]. The reason for this result is that the energy consumption of cluster head node includes data receiving energy consumption from camera node and common nodes, wavelet transform and quantization energy consumption and data sending energy consumption to base station in Ref. [7]. However, the energy consumption of cluster head node in the proposed method only includes data receiving energy consumption from common nodes and data sending energy consumption to base station. Thus the proposed method achieves less cluster head node energy consumption compared with the method in Ref. [7].

For the energy consumption of camera nodes, the camera node in the proposed method is only responsible for sending images to common nodes in the cluster, but in Ref. [7], the energy consumption of camera node includes image sending energy consumption to common nodes, image gradient computing energy consumption and data receiving energy consumption. Therefore, the proposed method achieves less camera node energy consumption compared with the method in Ref. [7].

The average energy consumption of common nodes in the proposed method is obviously less than that in Ref. [7] by processing 1 bit data according to the former chapter. In a word, the proposed method achieves less total energy consumption compared with the method in Ref. [7].

4.2.2 Reconstructed image quality

Fig. 7 shows the comparative results of improved JPEG2000 block adaptive method in literature [7], adaptive method based on SVD in literature [4] and NDIC-PCA algorithm. Obviously, NDIC-PCA algorithm achieves higher peak signal to noise ratio compared with the former two, which means that NDIC-PCA algorithm has a considerable advantage. Moreover, we found that the distort rate of recovered image rises with the increase of the number of blocks by using the methods in Refs. [4,7]. However, the experimental results show that the number of blocks is not the more, the better, but has a limitation in the proposed method. We can find a stable point where our method achieves a superb recovery image quality without decreasing compression ratio.

In real application, the images collected by camera are often contaminated by noise, thus the set of experiments assumes that the images are affected by Gaussian noise with zero mean and variance of 0.05. Fig. 8 shows the comparative results between the adaptive method based on SVD in Ref. [4] and the proposed method. NDIC-PCA algorithm achieves higher peak signal to noise ratio compared than the method in Ref. [4]. The experiment result shows that NDIC-PCA algorithm is very efficient and robust to noise.

(a) Cooperative JPEG2000 PSNR=32.15 dB (b) Block cooperative SVD PSNR=37.03 dB (c) Block adaptive PCA PSNR=38.84 dB

1) Comparison of different image compression methods when block size is 64×64, number of blocks are 64 and compression ratio is 4.

(d) Cooperative JPEG2000 PSNR=34.38 dB (e) Block cooperative SVD PSNR=34.86 dB (f) Block adaptive PCA PSNR=36.54 dB

2) Comparison of different image compression methods when block size is 128×128, number of blocks are 16 and compression ratio is 4.

Fig. 7 Comparison of different image compression methods

(a) Image affected by Gaussian noise with zero mean and variance of 0.05 (b) Block cooperative SVD PSNR=23.56 dB (c) Block adaptive PCA PSNR=30.07 dB

Fig. 8 Comparison of different image compression methods for noise reduction

5 Conclusions

This paper focuses on the problem of distributed image compression in WMSNs. In combination of the characteristic of the network architecture of WMSNs, we design a DMCN model. In order to achieve high image compression ratio and high image quality, we propose a NDIC-PCA algorithm. Simulation results demonstrate that, DMCN can effectively balance the energy consumption of network and largely extend the network lifecycle. In addition, NDIC-PCA algorithm achieves higher peak signal to noise ratio without decreasing compression ratio compared with previous algorithms.

Acknowledgement

This work was supported by the National Natural Science Foundation of China (61300239, 61373139, 61572261), China Postdoctoral Science Foundation (2014M551635), Postdoctoral Fund of Jiangsu Province (1302085B), and Jiangsu Government Scholarship for Overseas Studies (JS-2014-085).

References

1. Luo W S, Zhai Y P, Lu Q. Study on wireless multimedia sensor networks. Journal of Electronics and Information Technology, 2008, 30(6): 1511−1516 (in Chinese)
2. Fu Y X, Jiang H, Liu H T. Cross-layer CSMA multi-user access based on spreading communication system in wireless sensor network. Optics and Precision Engineering, 2008, 16(2): 325−332 (in Chinese)
3. Margi C B, Petkov V, Obraczka K, et al. Characterizing energy consumption in a visual sensor network testbed. Proceedings of the 2nd International Conference on Testbeds and Research Infrastructures for the Development of Networks and Communities (TRIDENTCOM'06), Mar 1−3, 2006, Barcelona, Spain. Piscataway, NJ, USA: IEEE, 2006: 332−339
4. Han C, Sun L J, Xiao F, et al. Image compression scheme in wireless multimedia sensor networks based on SVD. Journal of Southeast University: Natural Science Edition, 2012, 42(5): 814−819 (in Chinese)
5. Wu H M, Abouzeid A A. Energy efficient distributed image compression in resource-constrained multihop wireless networks. Computer Communications, 2005, 28(14): 1658−1668
6. Lu Q, Luo W S, Wang J D, et al. Low-complexity and energy efficient image compression scheme for wireless sensor networks. Computer Networks, 2008, 52(13): 2594−2603
7. Lu Q, Luo W S, Hu B. Multi-node cooperative JPEG2000 implementation based on neighbor clusters in wireless sensor networks. Optics and Precision Engineering, 2010,18(1): 240−247 (in Chinese)
8. Mowafi M Y, Awad F H, Aljoby W A. A novel approach for extracting spatial correlation of visual information in heterogeneous wireless multimedia sensor networks. Computer Networks, 2014, 71: 31−47
9. Yu Z X, Wang R, Zhang H Y, et al. Distributed compressed sensing for image signals. Proceedings of the 2014 IEEE International Conference on Multimedia and Expo Workshops (ICMEW'14), Jul 14−18, 2014, Chengdu, China. Piscataway, NJ, USA: IEEE, 2014: 5p
10. Kountchev R, Kountcheva R. Decorrelation of multispectral images based on hierarchical adaptive PCA. WSEAS Transactions on Signal Processing, 2013, 9(3): 120−137
11. Du Q, Ly N, Fowler J E. An operational approach to PCA+JPEG2000 compression of hyperspectral imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 2014, 7(6): 2237−2245
12. Yang W K, Wang J, Guo J. A novel algorithm for satellite images fusion based on compressed sensing and PCA. Mathematical Problems in Engineering, 2013: ID 708985/1−10
13. Liu B S, Zhang Y, Zhang W L. Improved principal component analysis based hyperspectral image compression method. Proceedings of the 2013 IEEE International Geoscience and Remote Sensing Symposium (IGARSS'13), Jul 21−26, 2013, Melbourne, Australia. Piscataway, NJ, USA: IEEE, 2013: 147 8−1480
14. Turk M, Pentland A. Eigenfaces for Recognition. Journal of Cogntive Neuroscience, 1991, 3(1): 71−86
15. Yuan H D, Ma H D, Liao H Y. Coordination mechanism in wireless sensor and actor networks. Proceedings of the 1st International Multi-Symposiums on Computer and Computational Sciences (IMSCCS'06): Vol 2, Jun 20−24, 2006, Hanzhou, China. Piscataway, NJ, USA: IEEE, 2006: 627−634
16. Wang C G, Sohraby K, Li B, et al. A survey of transport protocols for wireless sensor networks. IEEE Network, 2006, 20(3): 34−40
17. He T, Huang C D, Blum B M, et al. Range-free localization schemes for large scale sensor networks. Proceedings of the 9th Annual International Conference on Mobile Computing and Networking (MobiCom'03), Sep 14−19, 2003, San Diego, CA, USA. New York, NY, USA: ACM, 2003: 81−95
18. Li Q, Rus D. Global clock synchronization in sensor networks. Proceedings of the 23rd Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM'04): Vol 1, Mar 7−11, 2004, Hong Kong, China. Piscataway, NJ, USA: IEEE, 2004: 574
19. Heizelman W R, Chandrakasan A, Balakrishnan H. Energy-efficient communication protocol for wireless microsensor networks. Proceedings of the 33rd Annual Hawaii International Conference on System Science (HICSS'00): Vol 2, Jan 4−7, 2000, Maui, HI, USA. Los Alamitos, CA, USA: IEEE Computer Society, 2000: 10p
20. Wang A, Chandrakasan A. Energy-efficient DSPs for wireless sensor networks. IEEE Signal Processing Magazine, 2002, 19(4): 68−78

(Editor: Lu Junqiang)