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Image Compression Transmission Algorithm Based on the Singular Value Decomposition Applied in the Wireless Multimedia Sensor Networks

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Abstract

There are many shortcomings in traditional JPEG2000 image compression transmission algorithms in the wireless networks, such as, large energy consumption of resources in the network, large stress and energy consumption of the compressed image acquisition node and long transmission time, the image compression algorithm based on singular value decomposition is proposed. Block adaptive compression algorithm based on singular value decomposition is used in image compression processing, through the analysis of singular value decomposition and network energy consumption model. Meanwhile, the task of the network data processing and long-distance data transmission is assigned to different roles node to complete to balance the distribution of the network energy consumption. Finally, detailed experimental simulation have done, and the experimental results show that compared with the traditional compression algorithm (JPEG2000 image compression), the image compression algorithm based on singular value decomposition greatly alleviates the network camera key node energy consumption, and improves the speed of multimedia data transmission in wireless multimedia sensor network, and quality.

Keywords: *network energy consumption, camera node, distributed collaboration, adaptive compression*

1. Introduction

Wireless multimedia sensor networks (*WMSNs*) are developed on the basis of the traditional sensor network. It can sense the large amount of data such as audio, video, images and multimedia information, and has broad application prospects in the environmental monitoring, the battlefield monitoring, and intelligent household and other fields [1-3]. Images, however, as one of the most important sensory information to *WMSNs*, has a large amount of data and high complexity and demanding memory requirement, and resources serious limitations of a single node is difficult to achieve image processing and transmission, we need to compress the original image before transmission [4-6]. Therefore, *WMSNs* can percept the rich information multimedia to finish the environmental monitoring task of fine-grained and accurate information. How to make use of *WMSNs* node collaboration features for image compression processing is a hot topic in the field of *WMSNs* research [7].

According to the problems of the distributed collaborative image compression, Wu H M put forward a multi-node distributed image compression method based on wavelet transform. This method uses the cluster structure, to decompose and finish the multi-level wavelet tasks in different clusters and balance energy consumption [8-10]. However, because of the

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complexity of the wavelet transform and the excessive energy consumption of wireless transceiver, the method is not ideal to apply in *WMSNs*. Wang Pu et al. put forward image compression coding agreement framework based on the information entropy difference measurement scheme and distributed clusters to maximize the overall compression of *WMSNs* visual information [11]. Nasri M put forward image compression mechanism, which focused on achieving a best balance between the image reconstruction quality and node energy consumption [12-14]. Lu Q etc based on camera node and ordinary node in the network situation, put forward using the camera node to acquire images and the around ordinary nodes clustering for collaborative coding transmission scheme to balance the network energy consumption and prolong network life time. Huu P N *et al.* put forward a node role transformation plan to prolong network life to avoid the uneven problems of the node energy consumption when use the Lu Q's overlap transform methods to compress images, the collaborative node is too little [14-18].

In image compression method, the image compression method based on singular value decomposition (SVD) has received extensive attention of the researchers. The method is suitable for block. Based on this, this paper puts forward a *WMSNs* image compression collaboration mechanism, which is based on singular value decomposition. We block the image obtained by the camera and adopt to the adaptive singular value decomposition method to improve the compression of each block. Meanwhile, the camera node of image compression and transmission tasks effectively decompose into multiple ordinary nodes surrounding the camera node by using the collaboration features of *WMSNs* nodes, so as to realize the goal of energy saving and maximize the network life cycle.

This paper mainly in the following aspects as the development and innovative work:

(a) On the basis of analyzing the singular value decomposition method and the model of network energy and the transmission image compression algorithm based on singular value decomposition in the compression and transmission, wireless multimedia sensor networks was studied based on singular value decomposition of the block image adaptive compression algorithms to balance the network energy consumption. According to the different roles of the camera node and ordinary node, they will complete the image acquisition, compression and transmission work, and the camera node is responsible for collecting the image information, and then send image block to ordinary nodes in the cluster; the ordinary nodes in the clusters will adaptive compress the block image and send the data to cluster head node; and then, the cluster head node will send the compressed data to the base station. The image compression algorithm based on singular value decomposition greatly alleviates the network camera key node energy consumption, and improves the speed of multimedia data transmission in wireless multimedia sensor network, and quality.

(b) To further verify the correctness and validity of compression and transmission of the transmission image compression algorithm based on singular value decomposition in wireless multimedia sensor networks, we carried a detailed experimental simulation and compared with JPEG2000 image compression algorithm. The experimental results show that compared with the traditional compression algorithms, it greatly reduces the energy consumption of network camera key node, and can effectively balance the network energy consumption and prolong the network life cycle.

2. Proposed Method

From the perspective of linear algebra, a digital image can be seen as a nonnegative matrix. Given the basic principle and related properties of singular value decomposition, performance on the digital image watermarking has several notable characteristics: (a) the embedded watermark has better robustness when the image is to small perturbations, its singular value won't have big change; (b) the singular value reflects the intrinsic characteristics of image characteristics (energy), embedding watermark image singular value, the image of the visual effect will not have too big effect, and it ensures the good image quality; (c) digital image can effectively resist geometric attacks to enhance the robustness of the watermark for the singular value of geometric distortion invariance. Therefore, using singular value decomposition as a digital image watermark embedding and extraction method has good practicability. For example, we use $A \in RM * N$ matrix to represent the image. The singular value decomposition (SVD) of matrix A is defined as follows: A = USVT. In the formula, $u \in RM * M$, $V \in RM * N$ are orthogonal matrix; $s \in RM * N$ is diagonal matrix and its non diagonal elements are zero, on the diagonal elements of the [$\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_r \geq \lambda_r + 1 = \lambda_m (i,1,2,...,m)$] is the rank of matrix and it is equal to the number of non-zero singular value, λ_i is the singular values of A.

A. Method of the Singular Value Decomposition

Singular value decomposition is to use the characteristic value or singular value as orthogonal basis in spatial orthogonal decomposition of signal characteristics to enhance the coherence energy and suppress interference signals. Let us set the two-dimensional record section for X, word number is m and the sampling points is n, the m * n order the singular value decomposition (SVD) of matrix X can be turned into m * m order orthogonal array U and m * n order diagonal matrix Σ and n * n order orthogonal array of V. The singular value decomposition is a kind of analysis tool commonly used in numerical matrix. For any m * n matrix B, it can be resolved in the following:

$$B = u \sum v^p \tag{1}$$

In the formula, U is consists of the characteristic value of the XXT vector; V is composed of the characteristic value of the XTX vector; Σ consists of singular values, singular values by the order of the matrix on the main diagonal and the number of non-zero singular values is the same as the matrix of rank and the rest of the location of the elements is zero, so the 2D data matrix X of the covariance matrix $p = kk^y$ can be represented by the correlation matrix e_r, i, e .

$$p = e_r = kk^y \tag{2}$$

Obviously, the diagonal elements of the matrix are the autocorrelation values of zero. If $e_1^2, e_2^2, ..., e_n^2$ is the energy or the variance of each word and each unrelated, r = e, the above matrix can be simplified into diagonal matrix

$$kk^y = \begin{bmatrix} e2_1 & & 0 & \\ & e_2^2 & & \\ & & \ddots & \\ 0 & & & e2_n \end{bmatrix} \tag{3}$$

If the square root of the characteristic value of matrix is the singular value of matrix, which indicates that the strength of the energy related to the size of the singular value e_i , or the sum of characteristic value e_1^2 reflects the sum of signal energy

$$E_x = \sum_{i=1}^{n} e_i^2 \tag{4}$$

In the formula $\sum 1 = diag(sigma\,1, sigma\,2, ..., sigma\,r)$, $e_1 \succ e_2 \succ ... e_r \succ 0$,r = rank(A). The Singular value σ likes the characteristic value, and e_i decreases rapidly. In most cases, the top

10% (or 1%) of the sum of singular value accounted for more than 99% of the total sum of the singular value, therefore we can use singular value1 to k to approximately describe the matrix. The principle of SVD was applied to image compression for the digital image has the nature of matrix structure. Thus, the rate of image compression is

$$p = \frac{mr}{l(m+r+1)} \tag{5}$$

B. Topology Structure

Image compression in *WMSNs* energy limited is the use of *WMSNs* features and the collaboration method to decompose the work of high computational complexity and high energy consumption. This paper adopts the cluster type layer of network topology model to realize the image compression. First of all, we will divide the nodes in the network into the camera node and ordinary node, and carry on the following assumptions:

(a) Each node in a network has a unique ID number and all the nodes in the network time synchronization.

(b) Camera node is a particular node in the network, and it is deployed to determine deployment. In order to save cost and save energy consumption, the region of interest using the camera nodes in network monitoring, and different camera monitoring area do not overlap.

(c) Ordinary nodes in the network are randomly deployed for the center around the camera node and node density is large enough to make the camera node in the wireless communication link connecting area adjacent normal node is not null. The establishment of the network topology structure is the important step in collaborative image compression model. The steps of the image compression transmission mechanism of the network topology structure based on collaboration are as follows:

a) With the camera node as the center, we will make the ordinary nodes in the camera node connected region form a cluster.

b) In the cluster of the ordinary nodes, we choose the node with abundant energy and best link quality of the distance to the base station node. Under the condition of the initial energy is equal, we usually choose the base station nearest node as the cluster head.

c) The cluster node tells the around nodes its ID number and the ID number of the camera node in the cluster.

d) The common nodes in the cluster will tell the camera node and the cluster head nodes its own ID.

e) The camera nodes and the cluster node save a ID list of a cluster node. Using the network topology structure method, we can ensure that the common node set of the camera node connected area is not empty, so as to form a cluster with involved in image compression transmission structure.

C. Energy Consumption Model

This paper adapts to the classic Kaizeman model as the proposed energy consumption model of communications. The node energy consumption of communication is decided by the energy consumption of emission module and receiving module. Assume that a node sends 1 bit of data in the time slot and the transmission distance is d, the energy consumption of nodes launch module are as follows:

$$t_r(c,d) = \begin{cases} t_{eler} + \eta_{rs} p^2 & p \prec p_0 \\ t_{eler} + \eta_{ars} p^4 & p \geq p_0 \end{cases} \tag{6}$$

In the formula, $Eeler$ is the energy consumption of launch and receiving circuit; η_{rs} and η_{ars} is the model parameters the slow fading model and fast fading respectively; d0 is the distance threshold for sending and receiving ends.

Data receiving module receives 1 bit on the node energy consumption as follows:

$$t_r(d) = t_{Eeler} \tag{7}$$

The design of network topology in section 2.2, between the camera node and cluster in common nodes and between the cluster head node and ordinary node in the cluster communication adopts single jump model. Assuming that the number of the cluster head nodes within the cluster is a, these nodes are within the camera node communication radius, and set the distance between the camera node and ordinary node of the cluster for $t_1, t_2, ...t_n$,la, the distance between the common nodes and the cluster head node of the cluster for $d_1, d_2, ..., d_a$, the distance between the cluster head node and base station node for d_{ch} -s. make camera to collect picture size for e * f, block the image size of the p * q. Ordinary nodes at the same initial energy consumption, the camera node sent the probability of each ordinary node data within the same cluster, and the probability as follows:

$$\beta = \frac{tr/(pq)}{e} \tag{8}$$

When the number of image blocks is larger than that of ordinary nodes within the cluster $\beta \succ 1$.

Set c the bits of image which is transmitted from camera nodes to each ordinary node within cluster. W is the energy consumption when camera nodes collect image. The total consumption of energy of camera nodes is:

$$r_{ed} = p + \beta t\left(\alpha r_{elec} + \sum_{j=1}^{i} \gamma_{is} k_i^2\right) \tag{9}$$

Energy consumption of common nodes within the cluster can be divided to energy consumption of receiving, compressing image and sending. If we assume r_{ed} to the required compression ratio that a certain image restore the quality, E_{cp} to energy consumption of compressing a image of 1 bit, the total energy B_t of single common node in cluster is:

$$B_t = \beta c\left(E_{cp} + \left(1 + \frac{1}{p_{ri}}\right)E_{eler} + \frac{1}{p_{ri}}\gamma_{is} e_i^1\right) \tag{10}$$

Ordinary nodes within the cluster send compressed data to cluster head node which will transmit the received data to the base station node. Energy consumption E_{cp} of cluster head node is the total energy consumption of the ordinary cluster node receiving data and sending data to base station.

$$E_{cp} = \begin{cases} \frac{a\eta r}{p'}\left(2E_{eler} + \gamma_{is} e_{chs}^2\right) & e_{chs}^2 \prec \beta_0 \\ \frac{a\mu r}{p'}(2E_{eler} + \gamma_{rmu} e_{chs}^2) & e_{chs}^2 \geq \beta_0 \end{cases} \tag{11}$$

In formula, ρ 'is the compression ratio of the restored image.

Compared with the energy consumption of compressing and transmitting image, that of camera nodes collecting image is less, so the energy in the network is mainly consumed in data processing and transmission. The data processing in this paper is mainly the decomposition work of matrix SVD. We use H (12) to calculate the energy consumption of 1 bit of data processing, that is

$$H = FVG_{dy}^{2} \quad (12)$$

In formula, N is number of clock cycles required to handle a task; C is cyclic switched capacitor, and its value is general $0.65 n_t$; VDD is supply voltage of the processor. We assume that the node uses the Strong ARM SA-1100 processor to test energy consumption at the operating frequency of 206MHz. According to running time of the CPU, we can estimate that it average needs to spend 50 of clock cycles in handling 1 bit of data in the algorithm of testing SVD. When we put it into equation (10), we can calculate out the energy consumption of handling 1 bit of data. That is approximately $363.9 n_j$.

D. SVD blocks'Self-adaptive Compression Algorithm

When handling the large image, volume of computation of SVD method is large, so we can adopt the idea of separating the large image into small blocks, and then use method of adaptive selection value of k to compress each block. In the singular value $\sum 1 = diag(e_1, e_2, ..., e_r)$ of the complete decomposition $_{cp}$ of SVD, the proportion "e_i"of a singular value"e_n "in all singular values can be calculated as follow:

$$\vartheta_i = \frac{e_i}{\sum_{j=1}^{n} e_1} \quad (13)$$

From the characteristics of singular values, we can know that the function of singular value on information of image restoration is proportional to the size of the singular value. According to the proportion "ϑ_i"of the singular value, we can calculate out the value k which is required for a quality of image restoration, and then conduct adaptive singular value decomposition in the image of block. If we divide the original image with the size of e×f into a number of small pictures with the size of $p \times q$, then the compression ratio after image restoration is:

$$p' = \frac{\sum_{j=1}^{tft(pq)} \frac{pq}{e_i(p+q+1)}}{\frac{tft}{pq}} \quad (14)$$

Block adaptive compression algorithm of SVD is as shown in Algorithm 1.

Algorithm 1 block adaptive compression algorithm of SVD:

A = block (Origin Figure)
$[R, \Sigma, S] = SVD(A)$;
$d_{iag}(\Sigma)$;
For $k = 1 : length(d_{iag}(\Sigma)) - 1${
If $(\Sigma_{i=1}^{r} e_i) \succ = \vartheta)${
$k_i = k$;
break;
}
}
$R' = R(:, 1 : K_i)$;
$\Sigma' = \Sigma(1 : k^{\varepsilon}, 1 : k_i)$;
$S' = S(1 : e_i, 1 : k_i)$;

$A = R' \times \Sigma' \times S'^{T}$

Different blocking images can get different number of singular values on the same singular value thresholds. During the original image reconstruction, this method can match on characteristic of each blocking image, so the quality of the reconstructed image (expressed in PSNR) is higher. Related experiments show that compared with the method of the blocks of the same singular value used to reconstruct image, block adaptive matching method does not significantly reduce the compression ratio.

In the 512 × 512 × 8 bit of the Lena image, we use the improved JPEG2000 compression method proposed by Lu Qin and SVD block adaptive compression algorithm for simulation experiment. The results is shown in Figure 1 and Figure 2. In images, T is the size of image block, M is the number of blocks. The figure shows that, at the same compression ratio, SVD block adaptive compression algorithm has certain advantages.

(a)JPEG2000 Collaborative compression method (b)SVD block adaptive compression algorithm

($q_{smt} = 33.01DB$) ($q_{smt} = 37.05DB$)

Figure 1. Reconstructed Image Contrast based on Two Kinds of Image Compression Method (T=64*64,M=64, Error! Reference source not found.**)**

(a)JPEG2000 Collaborative compression method (b)SVD block adaptive compression algorithm

($q_{smt} = 34.41DB$) ($q_{smt} = 3.88DB$)

Figure 2. Reconstructed Image Contrast based on Two Kinds of Image Compression Method (T=128*128,M=16,Error! Reference source not found.**)**

E. Collaborative Image Compression Scheme

The following proposes SVD-based Distributed multi-node collaborative compression and transmission schemes of *WMSNs* network image. Realization process of its compression and transmission is as follows

a) The camera node is the key node in the network, and it is responsible for the original image acquisition and data transmission. After the camera node collects the image, it will calculate the size and number of blocks that the image should be block according to the established cluster structure, and then successively send image blocks to the ordinary nodes within a cluster according to a certain probability.

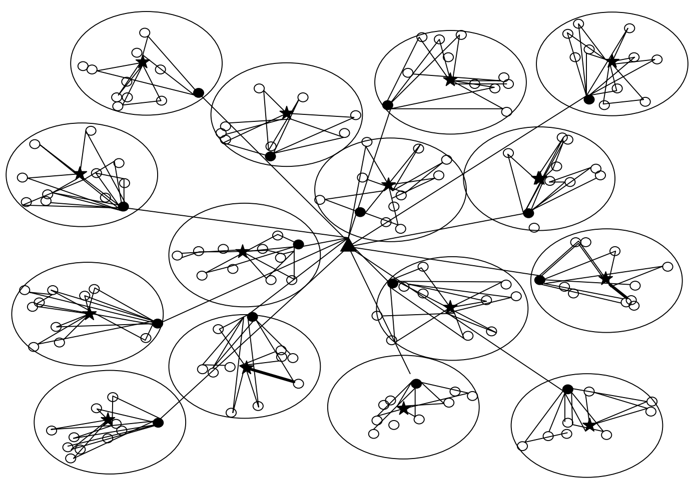
b) After common nodes within the cluster receive image blocks transmitted from the camera node, it conducts SVD adaptive compression. According to Algorithm 1, after it conducts the block adaptive compression for this blocking image, it will be sent to the cluster head node, while monitoring whether a new image block is sent from the camera over. If there is a new image block sent here, it will continue to compress.

c) The work of the cluster head node is to receive data which is sent from ordinary nodes within the cluster and forward it to the base station. Since each compressed data packet contains location information, the cluster head node does not need to integrate data, and images are integrated at the base station node.

4. Experiments and Analysis

A. Relevant Parameters

We use *Matlab* to establish the network energy consumption simulation environment. Let us assume that we identify 15 of camera nodes to cover the monitoring area of interest point in the 100 m × 100 meter region, and the sensing radius of camera nodes is 11 meter. Let us randomly deploy 11 of ordinary nodes in the connective area around the each camera node. We choose the deploy the base station node in the center of the rectangular area. Figure 3 is the network structure diagram.



▲ Base station;★the Camera node;●Cluster head node;○Ordinary nodes in the cluster

Figure 3. The Network Structure Diagram of Collaborative Image Compression Processing

Figure 3 is the network structure diagram of collaborative image compression processing. The camera node periodically collect 512 × 512 × 8 bit of gray scale image. The size of image blocks is 128 × 128; the number of blocks is 16. Let us set the overall compression ratio ρ = 4. When calculating network energy consumption, the relevant parameters' values in the equation (4) are set as follows: $E_{eler} = 51n_j$ / bit, $\mu_{fs} = 10p_j$ / (bit·m2), $\mu_{amp=0.0014}p_j$ / (bit·m2), $d_0 = 87$ m.

B. Simulation Results and Analysis

The camera node is the key node in transmission of *WMSNs* network image. In order to research what influence changes of distance from the camera node to the base station has on image compression and transmission energy consumption, we use the following three kinds of programs for simulation: a) the camera node does not compress images and directly transmits images to the base station; b) the camera node compresses images, and then transmits the compressed image to the base station; c)the camera node uses SVD-based distributed compression mechanism to transmit the image block to the cluster nodes in the connected region, and then it collaborates to conduct image compression and transmission.

Figure 4 is the comparative chart of three kinds of programs about the energy consumption that is required for the camera node to transmit a 512 × 512 × 8 bit of image and the distance relationship from the camera node to the base station. In chart, D is the distance between the camera and the base station node; E is the energy consumption of the camera node. The figure shows: when it adopts the program 1, the primary energy consumption of the camera node is the energy consumption of communication, and communication power consumption increases rapidly with increase of distance from the camera node to the base station, when it uses the program 2, the image compression is the primary energy consumption of the camera node; when it adopts program 3, the camera node is only responsible to communicate with ordinary nodes in cluster within the connected radius, and its energy consumption has nothing with the distance between the camera node and the base station node, so this scheme can greatly ensure the viability of camera nodes.

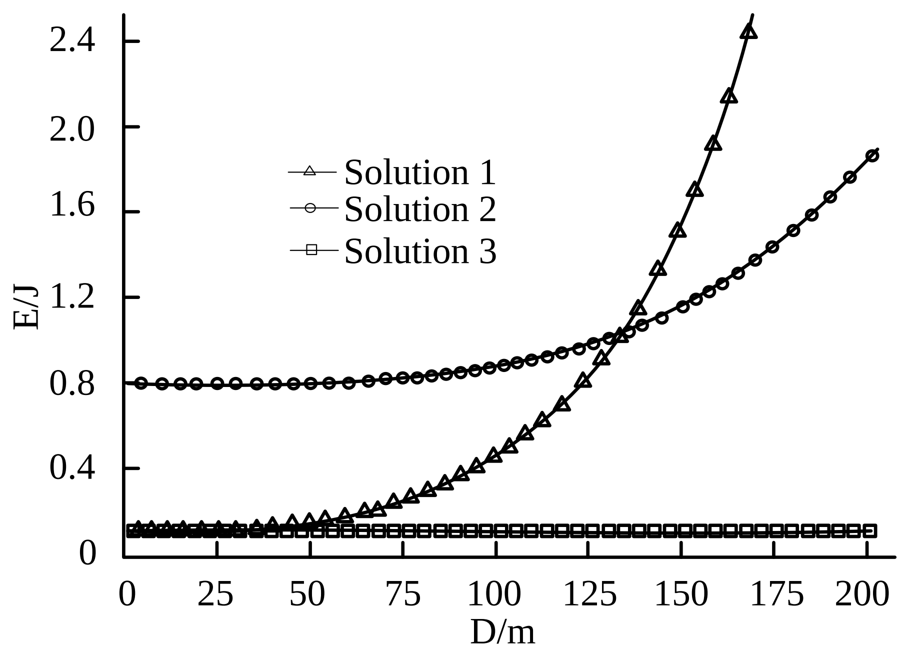
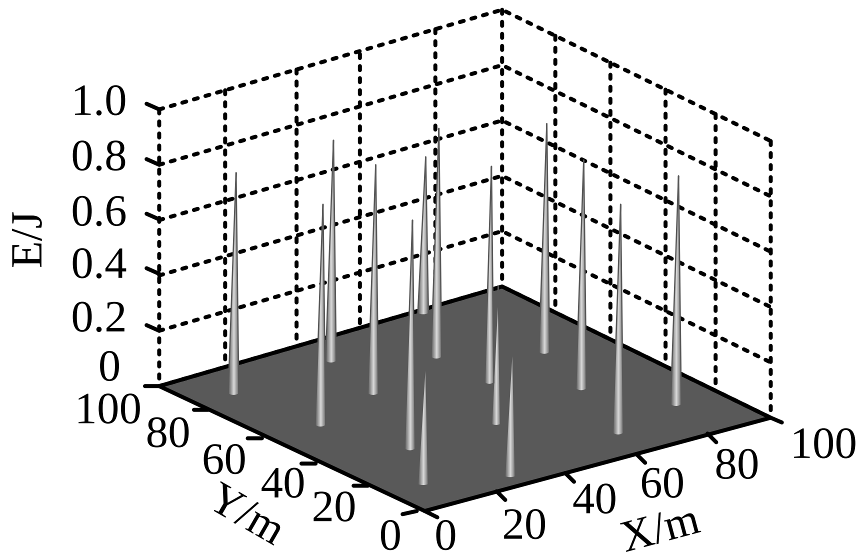


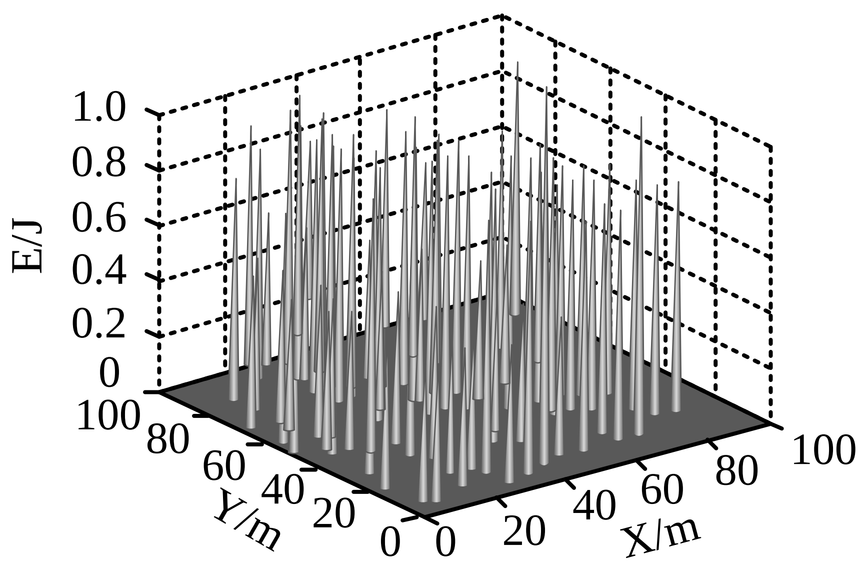
Figure 4. Comparison of Camera Node's Energy Consumption

Let us respectively adopt centralized and distributed image compression and transmission scheme to transmit a 512 × 512 × 8 bit of image to the base station. The distribution diagram of network nodes' energy consumption in the scene is shown in Figure 5.

When using a centralized image compression scheme, the camera node directly conducts image compression, and sends the compressed data to the base station; when using SVD-based image compression method of distributed collaboration, the camera node, common node and the cluster head node carry on the division of labor, and they collaborate for image compression and transmission. Compared Figure 5 (a) and (b) it can be seen, we can see that the average energy consumption of the latter camera node is reduced by nearly an order of magnitude than the former. As the energy consumption of nodes in the network has a strong ability of balance, lifetime of the network will be greatly prolonged.



(a) Centralized image compression



(b)Distributed Image Compression

Figure 5. Energy Consumption Distribution Chart of Image Compression Node

Figure 6 is the comparison of energy consumption of cluster head nodes at the same image compression ratio when we respectively adopt JPEG2000 compression method proposed by Lu Qin and SVD-based block collaborative compression method. From the compared results in the figure, we can see that energy consumption of cluster head node is less when we adopt the latter approach. The reason is: when using JPEG2000 compression methods together, the energy consumption of the cluster head node includes the energy consumption of receiving block images from the camera node, the energy consumption of wavelet transform and quantization of the blocking image data, the energy consumption of transmitting the quantized image data to the surrounding common node and the energy consumption of receiving compressed code stream of the surrounding ordinary nodes, organizing then and transmitting them to the base station; when it uses SVD-based image block cooperative compression method, the energy consumption of the cluster head node contains only the energy consumption of receiving data from the common node and of forwarding the received data to the base station, so its energy consumption is less.

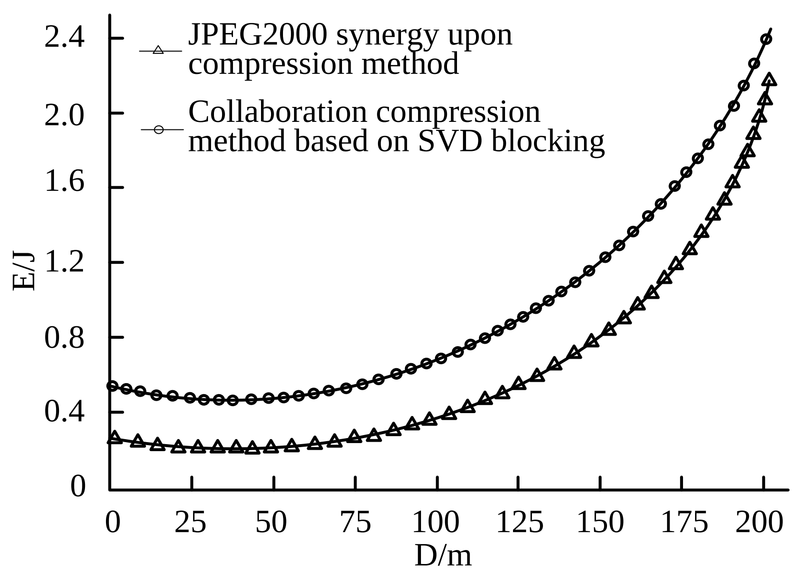


Figure 6. Comparison of Cluster Head Node Energy Consumption

On comparison of the energy consumption of the camera node and ordinary nodes, the camera node is only responsible for sending the image block to the ordinary node within the connected region at a certain probability SVD-based block collaborative compression method and the camera node is responsible for pre-processing image blocks, calculating gradient amplitude value of the image edge information, and sending the image block to the cluster head node in JPEG2000 collaborative compression method; when it transmits the same size of images, the camera node in this scenario consumes less energy. On the comparison of energy consumption of common nodes within the cluster, common nodes in JPEG2000 collaborative compression method are responsible for receiving the quantized image data from the cluster head node, running EBC algorithm and then sending the compressed data to the cluster head, but common nodes in the SVD block collaboration compression method are responsible for receiving block image data sent from the camera node and conducting SVD compression for them, and then transmitting the compressed data to the cluster head node. As the energy consumption of EBC algorithm is more than that of SVD algorithm at the same amount of data, theoretically the energy consumption of common nodes in this scheme is less than that in JPEG2000 collaborative compression methods. To sum up, the total energy consumption of network in this program is less than that in JPEG2000 collaborative image processing method.

4. Conclusion

Aiming at the feature of basic balance of data processing and transmission energy consumption in *WMSNs* application, this paper starts from collaboration features of the network node, adopts SVD-based block adaptive compression algorithms for image compression disposal, and assigns the tasks of data processing and long-distance data transfer in network to different roles to complete them in order to balance the network energy distribution. Simulating results show that the SVD-based image distributed collaboration compression mechanism greatly eases energy consumption of the key node of the network or the camera node, and it can effectively balance the network energy consumption and prolong the network life-cycle.

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