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REGION OF INTEREST BASED MEDICAL IMAGE COMPRESSION USING BLOCK-TO-ROW BI-DIRECTIONAL PRINCIPAL COMPONENT ANALYSIS

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Abstract. *Region of interest (ROI) based compression techniques are more considerable in medical field for the sake of reducing the storage space and shortening the transmission time. This is due to the fact that the only small part of a medical image is more useful out of the whole image. This paper presents an ROI based medical image compression algorithm using block-to-row bi-directional principal component analysis (PCA). The algorithm first segments the image into the ROI and the non-ROI using the segmentation method based on the level set. Then, general PCA is applied to non-ROI region whereas block-to-row bi-directional PCA is applied to ROI region in order to achieve desired image quality while improving compression ratio. After that, image reconstruction of ROI and non-ROI is carried out respectively. Finally, the final reconstructed image is obtained by image fusion. Experimental results show that the performance of the proposed method is superior to those of ROI based block-by-block PCA and ROI based block-to-row PCA in terms of compression ratio and peak signal to noise ratio.*
Keywords: Medical image compression, ROI, Block-to-row bi-directional PCA, Image segmentation

1. **Introduction.** Medical image is very important in grayscale images and has an excellent impact on the diagnosis and surgical planning of diseases. Hospitals and medical centers produce an enormous amount of digital medical images every day. For telemedicine applications, these medical images need to be transmitted to different destinations. Large storage space is required to store the information. Although there is greater improvement in transmission storage space and communication technologies, there is still a high demand for medical image compression [1-6]. Medical image has the same characteristics as general grayscale image, while it is very sensitive and cannot tolerate any illegal change. And its reconstructed image cannot affect normal medical diagnosis and so on [3,7].

PCA transformation called K-L transformation is an optimal linear transformation [8], whose function is the variance information condensation and the data information compression. It is a powerful multidimensional data compression method [9,10]. The main content of PCA is to calculate the eigenvalues and eigenvectors of the input data vector correlation matrix. Then, the original vector is projected onto the subspace generated by the eigenvectors corresponding to the dominant eigenvalues, and the part with the smallest eigenvalue is discarded to achieve the purpose of subtracting the dimension [11]. The main problems that need to be solved in image compression based on PCA are the covariance matrix construction and the extraction of principal components [12].

Image compression method based on PCA has been extensively studied in the field of image compression [13]. [14] proposed two kinds of PCA-based medical image compression methods, which are block-to-row PCA and block-by-block PCA. They achieve good compression effect in terms of image quality and compression ratio. ROI based coding techniques are more considerable in medical field for the sake of efficient compression and transmission [15,16]. ROI-based medical image compression algorithm separates the region into ROI and non-ROI. Then, they are processed respectively. This ensures ROI accuracy and at the same time, it improves the compression ratio and algorithm speed as far as possible [17]. This paper proposes an ROI based medical image compression method using block-to-row bi-directional PCA and experimental results show it improves the performance of medical image compression. Compared with previously proposed methods, the proposed algorithm improves the compression ratio and meanwhile, it ensures that the quality of the reconstructed image is desired

The rest of the paper is organized as follows. Block-to-row bi-directional PCA algorithm is described in Section 2. ROI based block-to-row bi-directional PCA is described in Section 3. The experimental results and performance analysis are discussed in Section 4 and Section 5 concludes the work.

2. **Block-to-Row Bi-Directional PCA Algorithm.** In the proposed method, an image is first divided into blocks of size $n \times n$. Each sub-block consists of intensity values $f(x, y)$ and $X_{i\text{th}}$ represents the ith sub-block of the image X.

$$X_{i\text{th}} = \begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,n-1) \\ f(1,0) & f(1,1) & \cdots & f(1,n-1) \\ \cdots & \cdots & \cdots & \cdots \\ f(n-1,0) & f(n-1,1) & \cdots & f(n-1,n-1) \end{bmatrix}_{(n \times n)} \tag{1}$$

Then, each block is concatenated into row to obtain a transformed matrix D.

$$D = [X_1, X_2, X_3, \ldots, X_{block}]_{(n^2 \times block)} \tag{2}$$

where X_i contains all elements within a block.

$$X_i = \begin{bmatrix} f(0,0) \\ f(1,0) \\ \cdots \\ f(n^2-1,0) \end{bmatrix}_{(n^2 \times 1)} \tag{3}$$

The mean vector m of transformed matrix D is calculated and the matrix D is adjusted by the mean on the line to obtain matrix $\overline{D}$. The covariance matrices C_r and C_c of matrix $\overline{D}$ are computed from the row and column directions respectively by Equations (4) and (5).

$$C_r = \overline{D}^T \overline{D} \tag{4}$$

$$C_c = \overline{D}\,\overline{D}^T \tag{5}$$

Then, the eigenvalues and eigenvectors of matrices C_r and C_c are calculated. The eigenvector with the highest eigenvalue is the principal component of the image. After the number of principal components is determined, the feature matrices V and U containing all the selected principal components are formed as follows:

$$V = [\lambda_{r1}, \lambda_{r2}, \lambda_{r3} \ldots \lambda_{rk}]_{\left(\frac{M \times N}{n^2} \times k\right)} \tag{6}$$

$$U = [\lambda_{c1}, \lambda_{c2}, \lambda_{c3} \ldots \lambda_{ck}]_{(n^2 \times f)} \tag{7}$$

where λ_r and λ_c are the selected principal components from the row and column directions respectively. The k and f are the number of chosen principal components from the row and column directions respectively.

The transpose of the feature matrix U is multiplied with the transformed matrix D and the feature matrix V to obtain the final compressed data Y.

$$Y = \left[U^T \times D \times V\right]_{(f \times k)} \tag{8}$$

The image X is reconstructed by the feature vector set.

$$X = U \times Y \times V^T + m \tag{9}$$

The compression ratio [2] is calculated based on the size of compressed data Y. It is calculated by Equation (10).

$$CR_{rb} = 1 - \frac{f \times k}{M \times N} \tag{10}$$

3. **ROI Based Block-to-Row Bi-Directional PCA.** In this method, the image is first divided into ROI and non-ROI by the segmentation algorithm based on the level set. Then, the general PCA algorithm is used in the non-ROI whereas block-to-row bi-directional PCA method is applied to the ROI. Afterwards, the ROI and non-ROI are reconstructed respectively by the feature vector sets. At last, the final reconstructed image is obtained by image fusion. The flow chart of the algorithm is shown in Figure 1.

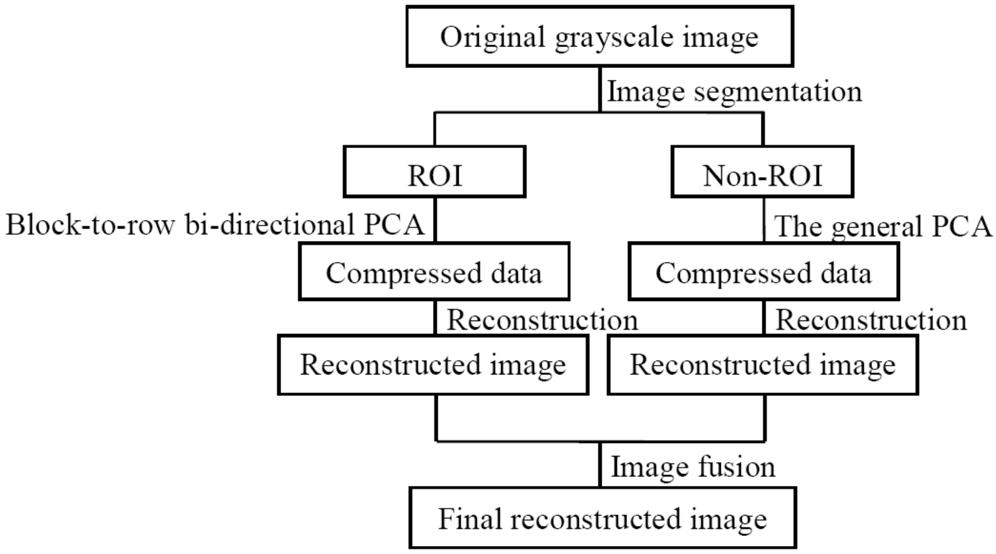


Figure 1. The flow chart of the proposed algorithm

Since the algorithm divides an image into the ROI and non-ROI, the final compression ratio is related to the size of the ROI and non-ROI. The compression ratio [2] is calculated as follows:

$$ROI\ area = \frac{Size\ of\ ROI\ image}{Size\ of\ original\ image\ (M \times N)} \tag{11}$$

$$ROI\ CR\ (\%) = CR_{rb} \times ROI\ area \tag{12}$$

$$Non\ ROI\ area = \frac{Size\ of\ non\ ROI\ image}{Size\ of\ original\ image\ (M \times N)} \tag{13}$$

$$Non\ ROI\ CR\ (\%) = CR \times Non\ ROI\ area \tag{14}$$

$$Total\ CR\ (\%) = ROI\ CR + Non\ ROI\ CR \tag{15}$$

Peak signal to noise ratio (PSNR) is the most common and the most widely used objective image evaluation index. Therefore, PSNR is used to evaluate the quality of reconstructed images. The larger PSNR value represents the less distortion, and at the same time, the quality of reconstructed image is better. PSNR is computed by Equation (16).

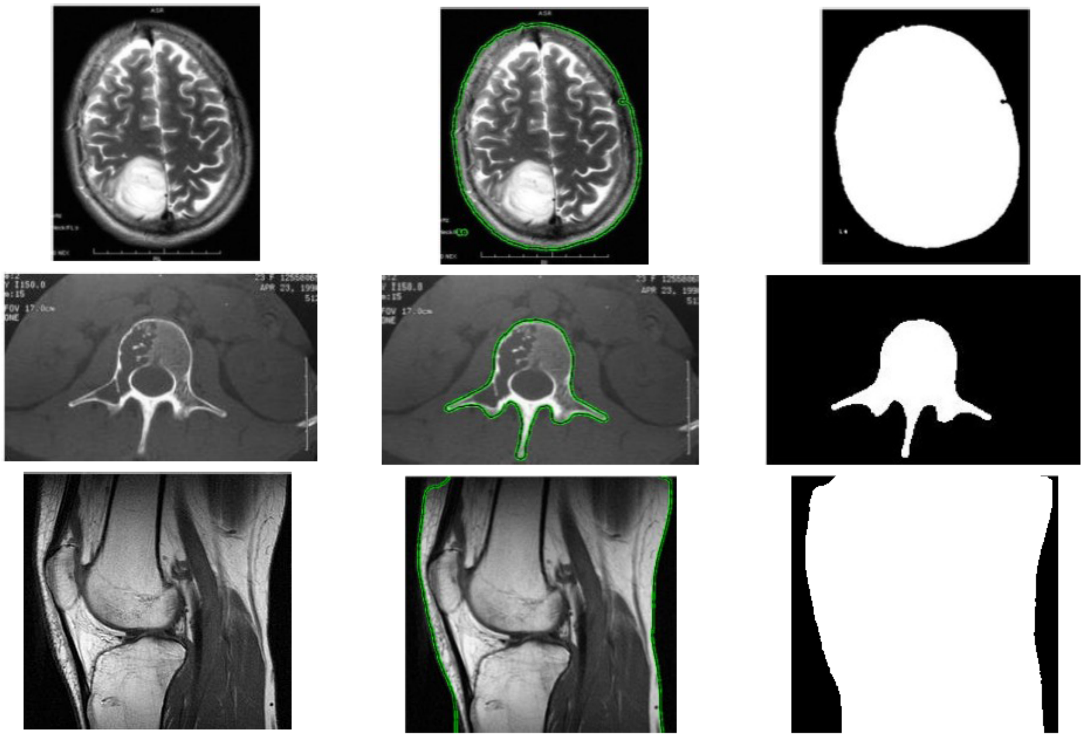
$$PSNR = 10 \times \log_{10}\left(\frac{255^2}{MSE}\right) \tag{16}$$

In Equation (16), MSE is the mean square error and it is calculated by Equation (17).

$$MSE = \frac{1}{MN} \sum_{0}^{M-1} \sum_{0}^{N-1} \|f(i,j) - g(i,j)\|^2 \tag{17}$$

where f represents the original image pixel value, g represents the reconstructed image pixel value, M and N represent the number of rows and columns of the images, and i and j represent the index of the row and column respectively.

4. **Experimental Results and Analysis.** Different medical images are used for the experiments including brain, spine and knee images. The experiments are carried out on the Intel i5-3230M, 2.6GHz, RAM 4GB PC using MATLAB R2010a. To verify the performance of the proposed algorithm in PSNR and compression ratio, we compare the proposed method with the ROI based block-by-block PCA and ROI based block-to-row PCA. The size of the original brain, spine and knee images is respectively 374×280, 151×239 and 230×230. First, the original medical images are divided into ROI and non-ROI by the segmentation technique based on the level set. The results of the segmentation are given in Figure 2.



(a) (b) (c)

Figure 2. The segmentation based on the level set ((a) original images, (b) the results of the segmentation based on the level set, (c) the final mask images). The first row shows brain images, the second row shows spine images, and the third row shows knee images.

PSNR is used to evaluate the quality of the reconstructed image varying with compression ratio. Tables 1-3 respectively show the experimental results of three algorithms using block size of 8×8 on the brain spine and knee images. As seen from Table 1, when the PSNR values of the proposed algorithm, the ROI based block-to-row PCA and the ROI based block-by-block PCA are respectively 37.8141, 37.0754 and 37.7008, the total compression ratios of three methods are respectively 0.9843, 0.9830 and 0.8354. This means that the performance of the proposed method is superior to the ROI based block-to-row

Table 1. The experimental results of three algorithms using block size of 8×8 on the brain image

The compression method of ROI	PSNR dB	Compression Ratio		
Block-by-block PCA		ROI (PC = 2)	Non ROI (PC = 8)	CR total
	37.7008	0.4607	0.3748	0.8354
		ROI (PC = 4)	Non ROI (PC = 8)	CR total
	38.5234	0.3071	0.3748	0.6819
		ROI (PC = 6)	Non ROI (PC = 8)	CR total
	38.5320	0.1536	0.3748	0.5283
Block-to-row PCA		ROI (PC = 16)	Non ROI (PC = 8)	CR total
	37.0754	0.6082	0.3748	0.9830
		ROI (PC = 32)	Non ROI (PC = 8)	CR total
	38.4997	0.6022	0.3748	0.9770
		ROI (PC = 64)	Non ROI (PC = 8)	CR total
	38.5321	0.5902	0.3748	0.9650
Block-to-row bi-directional PCA		ROI (PC_r = 20 PC_c = 40)	Non ROI (PC = 8)	CR total
	37.8141	0.6095	0.3748	0.9843
		ROI (PC_r = 40 PC_c = 40)	Non ROI (PC = 8)	CR total
	38.5824	0.6048	0.3748	0.9796
		ROI (PC_r = 60 PC_c = 40)	Non ROI (PC = 8)	CR total
	38.5824	0.6001	0.3748	0.9749

Table 2. The experimental results of three algorithms using block size of 8×8 on the spine image

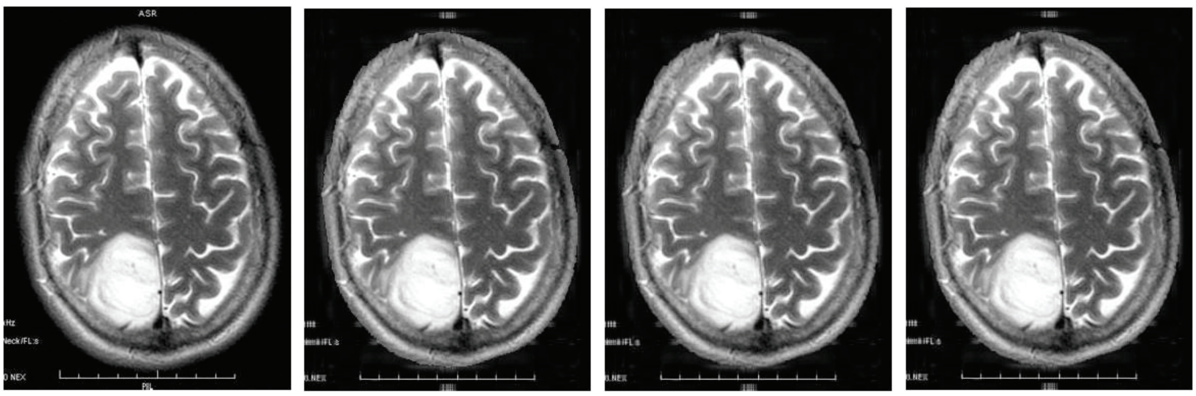
The compression method of ROI	PSNR dB	Compression Ratio		
Block-by-block PCA		ROI (PC = 2)	Non ROI (PC = 4)	CR total
	32.8848	0.0985	0.8541	0.9526
		ROI (PC = 4)	Non ROI (PC = 4)	CR total
	32.9022	0.0657	0.8541	0.9198
		ROI (PC = 6)	Non ROI (PC = 4)	CR total
	32.9025	0.0328	0.8541	0.8869
Block-to-row PCA		ROI (PC = 6)	Non ROI (PC = 4)	CR total
	32.6550	0.1300	0.8451	0.9841
		ROI (PC = 12)	Non ROI (PC = 4)	CR total
	32.8040	0.1286	0.8541	0.9827
		ROI (PC = 18)	Non ROI (PC = 4)	CR total
	32.8857	0.1272	0.8541	0.9813
Block-to-row bi-directional PCA		ROI (PC_r = 12 PC_c = 24)	Non ROI (PC = 4)	CR total
	32.8040	0.1303	0.8541	0.9844
		ROI (PC_r = 18 PC_c = 24)	Non ROI (PC = 4)	CR total
	32.8857	0.1298	0.8541	0.9839
		ROI (PC_r = 24 PC_c = 24)	Non ROI (PC = 4)	CR total
	32.9202	0.1293	0.8541	0.9834

PCA and the ROI based block-by-block PCA in both PSNR and compression ratio. In addition, it is also seen from Table 1 that the PSNR value increases as the compression ratio decreases. The same conclusions can be obtained from Tables 2 and 3.

Table 3. The experimental results of three algorithms using block size of 8×8 on the knee image

The compression method of ROI	PSNR dB	Compression Ratio		
Block-by-block PCA		ROI (PC = 2)	Non ROI (PC = 5)	CR total
	36.6676	0.6242	0.1640	0.7883
		ROI (PC = 4)	Non ROI (PC = 5)	CR total
	38.8195	0.4162	0.1640	0.5802
		ROI (PC = 6)	Non ROI (PC = 5)	CR total
	39.0171	0.2081	0.1640	0.3721
Block-to-row PCA		ROI (PC = 32)	Non ROI (PC = 5)	CR total
	37.4218	0.8001	0.1640	0.9641
		ROI (PC = 38)	Non ROI (PC = 5)	CR total
	38.2839	0.7940	0.1640	0.9581
		ROI (PC = 44)	Non ROI (PC = 5)	CR total
	38.7940	0.7880	0.1640	0.9520
Block-to-row bi-directional PCA		ROI ($PC_r = 40$ $PC_c = 60$)	Non ROI (PC = 5)	CR total
	38.4770	0.7945	0.1640	0.9586
		ROI ($PC_r = 50$ $PC_c = 60$)	Non ROI (PC = 5)	CR total
	39.0100	0.7851	0.1640	0.9492
		ROI ($PC_r = 60$ $PC_c = 60$)	Non ROI (PC = 5)	CR total
	39.0272	0.7757	0.1640	0.9397

Figure 3 is an original brain image and its reconstructed images obtained using three compression algorithms. As can be seen from Figure 3, compared with the other two methods, the ROI based block-to-row bi-directional PCA has high compression ratio. At the same time, the PSNR of the algorithm is better than the other two methods. It can be seen from Figure 3(d) that the ROI part of the image is still clear in the case of high compression ratio. This ensures the quality of the lesion part in the medical image with high compression ratio, and it does not affect the doctor's medical diagnosis.



(a) (b) (c) (d)

Figure 3. The original brain image and its reconstructed images obtained by three compression methods ((a) original brain image, (b) block-by-block PCA, total CR = 0.8354, PSNR = 37.7008, (c) block-to-row PCA, total CR = 0.9830, PSNR = 37.0754, (d) block-to-row bi-directional PCA, total CR = 0.9843, PSNR = 37.8141)

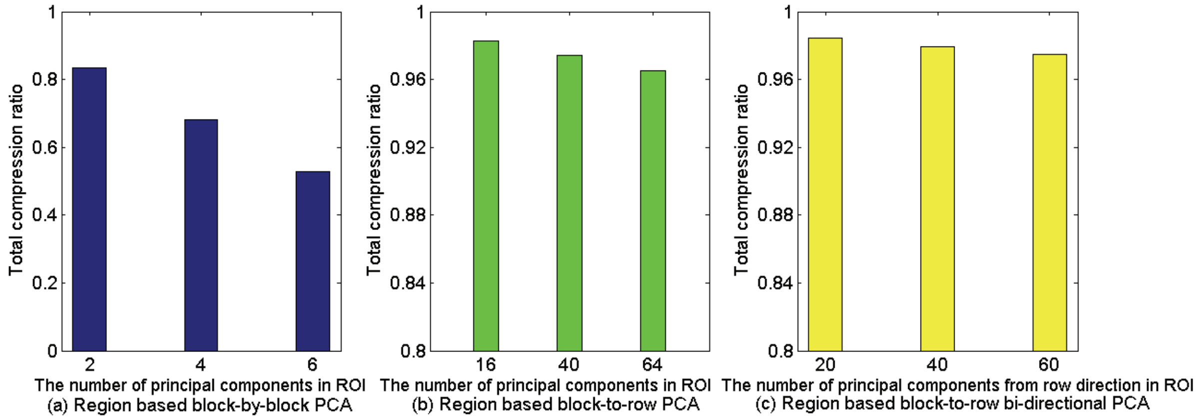


Figure 4. The compression ratio varying with the number of chosen principal components in the ROI by three algorithms

Figure 4 shows the experimental results of compression ratio varying with the number of selected principal components in the ROI by three compression methods. It can be seen from Figure 4 that as the number of selected principal components increases, the compression ratio decreases. This indicates that the more principal components are selected, the more original image information is retained. And the quality of the reconstructed image is higher. At the same time, the compression ratio is sacrificed.

5. **Conclusions.** In the paper, the ROI based medical image compression algorithm using block-to-row bi-directional PCA is presented. In the algorithm, the block-to-row bi-directional PCA compression method is employed in the ROI. This ensures that the quality of the ROI in the reconstructed image is desired and the PSNR value is high. Thus, the diagnosis of medical images is not affected by the reconstructed images. Meanwhile, the proposed method compresses images from the row and column directions, so the compression ratio is improved. The results of experiments on brain, spine and knee images show that the performance of the proposed algorithm is superior to the ROI based block-by-block PCA and the ROI based block-to-row PCA in both compression ratio and PSNR. At present, we study the compression algorithm for medical images. In the future work, we will improve the algorithm to make it applicable to a variety of other types of images.

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