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A Novel Approach for Arbitrary-Shape ROI Compression of Medical Images Using Principal Component Analysis (PCA)

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ABSTRACT

PCA-based image compression is inherently limited by its matrix form and thus being restricted to work on block information only. In this study a novel approach is proposed to apply PCA technique on arbitrary shape ROI instead of rectangular or square ROI only. Based on factorization, this method successfully compresses arbitrary-shape ROI of an MRI brain image with different compression ratios using PCA. Simulation results show that no visible distortion were apparent on test image for total compression ratio as high as 80%.

Key words: Principal component analysis, medical image compression, region-of-interest

INTRODUCTION

For over the past 30 years, medical imaging technologies offer the invaluable means for physicians in disease detection, diagnosis and treatment planning. To ensure highest accuracy, medical images produced by the imaging modalities are in high resolution, typically in the size of Mbytes. Hence, the large storage space occupied by the images raises the need to compress the images with high compression ratio, at the same time, preserving the diagnostic value of the images especially in some diagnostically important areas, called Regions of Interest (ROIs).

There are few compression schemes for instance the MAXSHIFT, the EZW-based and the ROI-VQ methods that have incorporated ROI in the algorithms, allowing ROI to be compressed at different quality levels (Doukas and Maglogiannis, 2007). However, only a few of the algorithms support arbitrary ROI coding. Principal Component Analysis (PCA) is a data reduction techniques used in image recognition and compression (Costa and Fiori, 2001). Its purpose is to reduce the high dimensionality of the data space to a smaller dimensionality, resulting in a smaller set of uncorrelated variables. Taur and Tao (1996) was the first to propose a PCA coding scheme that incorporated ROI. In their study, the images were partitioned into blocks with means and variances being computed within the blocks. ROI were distinguished and compressed according to the class belonged by the blocks. In this study, ROI segmented based on mean thresholding yield oversegmentation or undersegmentation problems and may not reflect the real boundary of the ROI. Similarly, abdomen CT images were divided into blocks and ROI were segmented based on mathematical morphology (Gokturk *et al*., 2001). In the mentioned studies, PCA were applied only on block information because standard PCA can only define for matrices.

In this study, the first attempt to apply PCA technique on arbitrary shape ROI instead of block information only was proposed. The new algorithm will serve to faithfully extract the ROI desired by the user and compress the selected ROI with different degree of compression ratio.

MATERIALS AND METHODS

Simulation of the proposed method was done using MATLAB R2013a Image Processing Toolbox on a Dual Core 2.6 GHz PC. The test image, as shown in Fig. 1, is an MRI brain image obtained from the Osirix† public dataset, with a size of 512×512. The test image will then undergo series of operation as summarized in Fig. 2.

Manual segmentation: To test the robustness of the proposed system, the ROI of the image was interactively selected by the user using imfreehand. By placing the mouse over the image, the user is free to outline the contour of the desired arbitrary ROI, regardless of any shape. A mask for the ROI is created to locate and extract the pixel values contained within the ROI.

ROI reshaping: Prior to applying PCA, the segmented ROI will be reshaped to form a matrix. Initially, the arbitrary ROI will first be converted into a row, resulting in a vector of 1×k, as shown in Eq. 1:

$$h(x) = (h(0)\ h(1)\ \ldots\ h(k-1))_{(1\times k)} \quad (1)$$

where, k represents the total number of pixel values contained within the ROI. With the purpose of constructing a matrix from a row vector, the divisors of k were found using factorization.

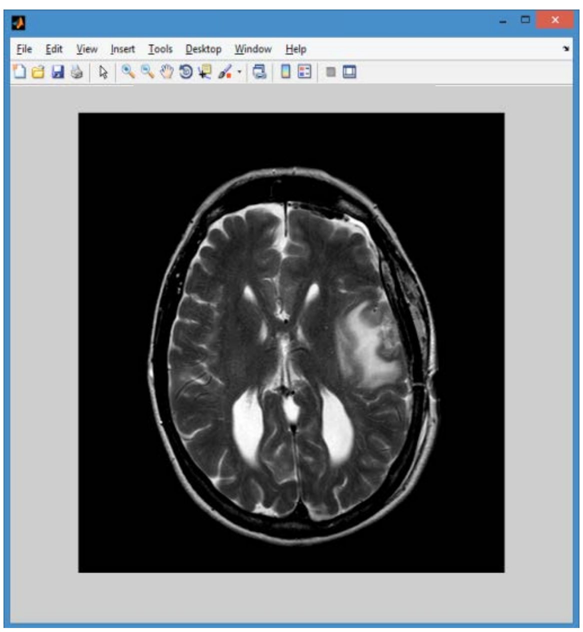

Fig. 1: A slice of brain image (IM-0001-0011) obtained from Osirix brain dataset†, BRAINIX

†http://www.osirix-viewer.com/datasets

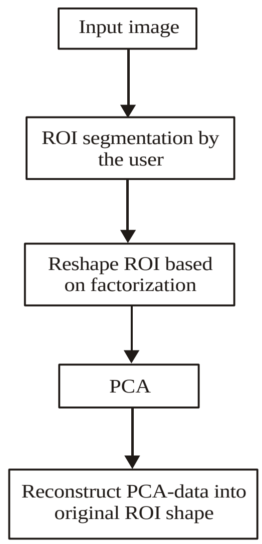

Fig. 2: Flowchart of the proposed method in compressing arbitrary ROI using PCA

However, to have a standardize algorithm in this study, there is only one divisor to be used. Assume that the total number of divisors of k is found to be t, the divisor will be selected based on the following statements given $d(0) \le d(t/2) \le d(t)$:

- If t is even, then d is selected from position (t/2)
- If t is odd, then d is selected from position ((t+1)/2)

The formulated matrix that carries the ROI information by now has the size of ($d \times k/d$) that is ready to be compressed using PCA algorithm.

PCA algorithm: PCA is a sophisticated statistical tool that linearly transforms a large set of correlated variables into a lower dimension of uncorrelated variables. In pattern recognition, PCA is used to reveal hidden trends and patterns from complex data sets. Image compression can then be achieved by removing variables with smaller eigenvalues or lower data significance (Pandey *et al.*, 2011). PCA has been developed based on Eigen Decomposition (ED), Singular Value Decomposition (SVD) and neural networks. In this study, PCA based on ED is used because of its simplicity and its comparable compression performance with SVD and neural network for single image computation (Kumar *et al.*, 2008). Assume now that the ROI data, g(x,y) has a size of m×n with its pixels values represent the gray level at each coordinates, its expression can be defined as:

$$g(x,y) = \begin{bmatrix} g(0,0) & g(0,1) & \dots & g(0,n-1) \\ g(1,0) & g(1,1) & \dots & g(1,n-1) \\ : & : & : & : \\ g(m-1,0) & g(m-1,1) & : & g(m-1,n-1) \end{bmatrix}_{(m\times n)} \quad (2)$$

To apply PCA by ED, the first step required is to compute the mean from each of the data dimension (n):

$$\text{mean} = \frac{1}{n}\begin{bmatrix} \sum_{i=0}^{m-1} g(i,0) \\ \sum_{i=0}^{m-1} g(i,1) \\ \vdots \\ \sum_{i=0}^{m-1} g(i,n-1) \end{bmatrix}_{(n\times 1)} = \begin{bmatrix} m_1 & m_2 & \cdots & m_n \end{bmatrix}_{(1\times n)} \tag{3}$$

To prepare a dataset with zero mean, ROI data is subtracted with the mean computed above, resulting in mean ROI data ($\bar{g}$):

$$\overline{g(x,y)} = \begin{bmatrix} g(0,0)-m_1 & g(0,1)-m_2 & \dots & g(0,n-1)-m_n \\ g(1,0)-m_1 & g(1,1)-m_2 & \dots & g(1,n-1)-m_n \\ \vdots & \vdots & \vdots & \vdots \\ g(m-1,0)-m_1 & g(m-1,1)-m_2 & \vdots & g(m-1,n-1)-m_n \end{bmatrix} \tag{4}$$

Next, covariance matrix of $\bar{g}$ is determined so that the eigenvectors and eigenvalues for the ROI data can be found. The value of covariance matrix intuitively conveys the relationships between the dimensions. A positive non-diagonal element in the covariance matrix indicates a positive correlation between the variables and vice versa. The resulting covariance matrix is a square matrix. Given a matrix with size m×n, the computed covariance matrix size will be n×n. The covariance matrix can be expressed as:

$$C(x,y) = \begin{bmatrix} C(0,0) & C(0,1) & \dots & C(0,n-1) \\ C(1,0) & C(1,1) & \dots & C(1,n-1) \\ \vdots & \vdots & \vdots & \vdots \\ C(n-1,0) & C(n-1,1) & \vdots & C(n-1,n-1) \end{bmatrix}_{(n\times n)} \tag{5}$$

The interesting part of PCA lies in its ability to linear transform the data to a new coordinate system by the manipulation of the eigenvectors and eigenvalues. An eigenvector is a transformation matrix when it is multiplied with a matrix, the resulting matrix is the multiple of the eigenvector itself. It should be noted that eigenvectors can only be found from square matrix but not every square matrix has eigenvectors. There will be n eigenvectors for n×n matrix that does have eigenvectors and all eigenvectors for a matrix are orthogonal to each other. Eigenvalues indicate by how much the matrix is being scaled by their corresponding eigenvectors such that the higher the eigenvalue, the more significant of the eigenvector in representing the data dimensions. The eigenvalues with their corresponding eigenvectors are then sorted based on their significance as shown in Table 1.

Once obtaining the eigenvalue-eigenvector pairs, data compression is achieved by only selecting the first p eigenvectors and excluding the least important eigenvectors. The resulting orthogonal matrix V contains only the chosen p eigenvectors:

$$V(x,y) = \begin{bmatrix} V(0,0) & V(0,1) & \dots & V(0,p-1) \\ V(1,0) & V(1,1) & \dots & V(1,p-1) \\ \vdots & \vdots & \vdots & \vdots \\ V(n-1,0) & V(n-1,1) & \vdots & V(n-1,p-1) \end{bmatrix}_{(n\times p)} \tag{6}$$

Table 1: Eigenvalue-eigenvector pairs storage in a specific way as $\lambda_1 \geq \lambda_2 \geq ,..., \lambda_n$

Eigenvalue-eigenvector pair	λ_1	λ_2	...	λ_n
1	V_{11}	V_{12}	...	V_{1n}
2	V_{12}	V_{22}	...	V_{2n}
⋮	⋮	⋮	⋮	⋮
n	V_{n1}	V_{n2}	...	V_{nn}

In this case, the compression rate and image quality is dependent on the number of eigenvectors that are being selected. The compressed data is finally achieved by taking the transpose of V and multiply it with the transposed mean ROI data.

$$R = V^T \times (\underline{g})^T \tag{7}$$

$$R(x,y) = \begin{bmatrix} R(0,0) & R(0,1) & ... & R(0,m-1) \\ R(1,0) & R(1,1) & ... & R(1,m-1) \\ \vdots & \vdots & \vdots & \vdots \\ R(p-1,0) & R(p-1,1) & \vdots & R(p-1,m-1) \end{bmatrix}_{(p \times m)} \tag{8}$$

At this stage, the dimensionality of the ROI data has been reduced from n to p columns. The compression rate of the ROI is therefore defined as:

$$\begin{aligned} CR\_ROI &= 1 - \frac{\text{Size of compressed ROI data}}{\text{Size of originalROI data}} \\ &= 1 - \frac{m \times p}{m \times n} \\ &= 1 - \frac{p}{n} \end{aligned} \tag{9}$$

The ROI data is now being compressed but it will not serve meaningful purpose without transforming it back to the original axes. The reconstructed ROI can be obtained by using Eq. 10:

$$G = (V \times R)^T + \overline{g} \tag{10}$$

$$G(x,y) = \begin{bmatrix} G(0,0) & G(0,1) & ... & G(0,n-1) \\ G(1,0) & G(1,1) & ... & G(1,n-1) \\ : & : & : & : \\ G(m-1,0) & G(m-1,1) & : & G(m-1,n-1) \end{bmatrix}_{(m \times n)} \tag{11}$$

Reform PCA-data: Subsequently, the reconstructed ROI is reformed back into its previous arbitrary shape by replacing the original pixels with the 'new' pixels as shown in Fig. 3. The performance of the proposed method will be evaluated based on compression ratio and Peak Signal Noise Ratio (PSNR).

The total compression ratio for an image is calculated based on the total pixels encompassed by the arbitrary ROI:

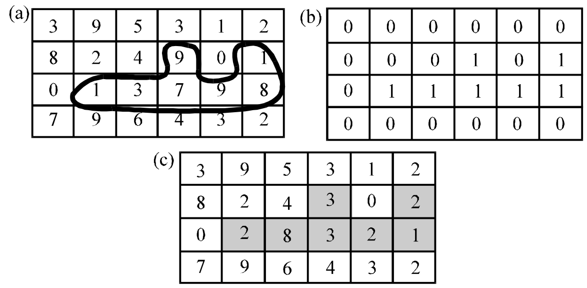

Fig. 3(a-c): (a) Arbitrary ROI selected, (b) Mask created to mark the position of the ROI and (c) Masked pixels replaced by reconstructed data (shaded area)

$$\text{Total CR} = \left(\frac{\text{Total pixels in ROI}}{\text{Total pixels in image}}\right)\% \times \left(1 - \frac{p}{n}\right) \tag{12}$$

PSNR is an objective indicator for image quality and it is based on the Mean Square Error (MSE):

$$\text{PSNR} = 10\log_{10}\left(\frac{255}{\sqrt{\text{MSE}}}\right) \tag{13}$$

$$\text{MSE} = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\left\| f(i,j) - g(i,j) \right\|^2 \tag{14}$$

Where:
f = Pixel value of the original image
g = Pixel value of the compressed image
m = Number of rows of the images and i represents the index of that row
n = Number of columns of the image and j represents the index of that column

RESULTS AND DISCUSSION

The ROI drawn in this study is shown in Fig. 4. The ROI comprises a total of 4270 pixels and all the divisors of 4270 were found to be 1, 2, 5, 7, 10, 14, 35, 61, 70, 122, 305, 427, 610, 854, 2135 and 4270. According to the selection criterion that have defined earlier, 61, being situated mid-way of the divisors, is chosen as the divisor and the reshaped ROI thus has the matrix size of 61×70. The ROI was then compressed at CR of 50, 60, 70, 80 and 90%. As seen from Fig. 5, no distortion is visible on the reconstructed image at CR up to 80% while ROI was slightly blurred out on the image at CR of 90%. This finding is consistent with the objective evaluation of the image quality as shown in Table 2 in which PSNR value decreases when higher CR is applied to the ROI. However, the algorithm failed when the total number of pixels in a ROI is a prime number because the divisors of a prime number are only 1 and the prime number itself. This limitation of the algorithm will be addressed an overcome in future study. Based on the results presented, the proposed method supersedes the existing PCA algorithm (Taur and Tao, 1996; Gokturk *et al.*, 2001) by incorporating an arbitrary ROI that suit the need of each users. This study provides insights into the possibility of performing partial compression for image compression efficiency. Future study will also take in the factor of ROI size and the evaluation of the expert panels.

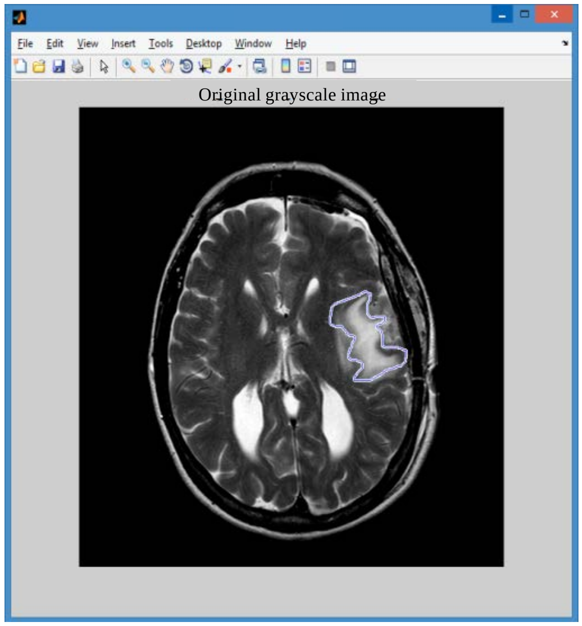

Fig. 4: Arbitrary ROI drawn by holding the mouse and the contour is shown in blue line

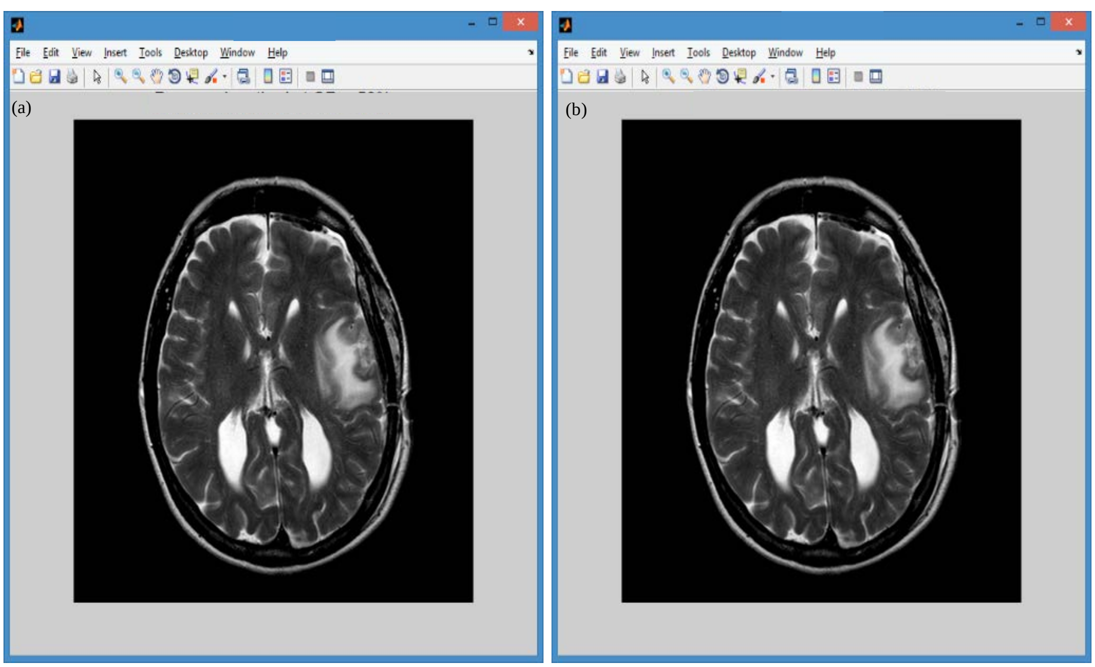

Fig. 5(a-e): Continue

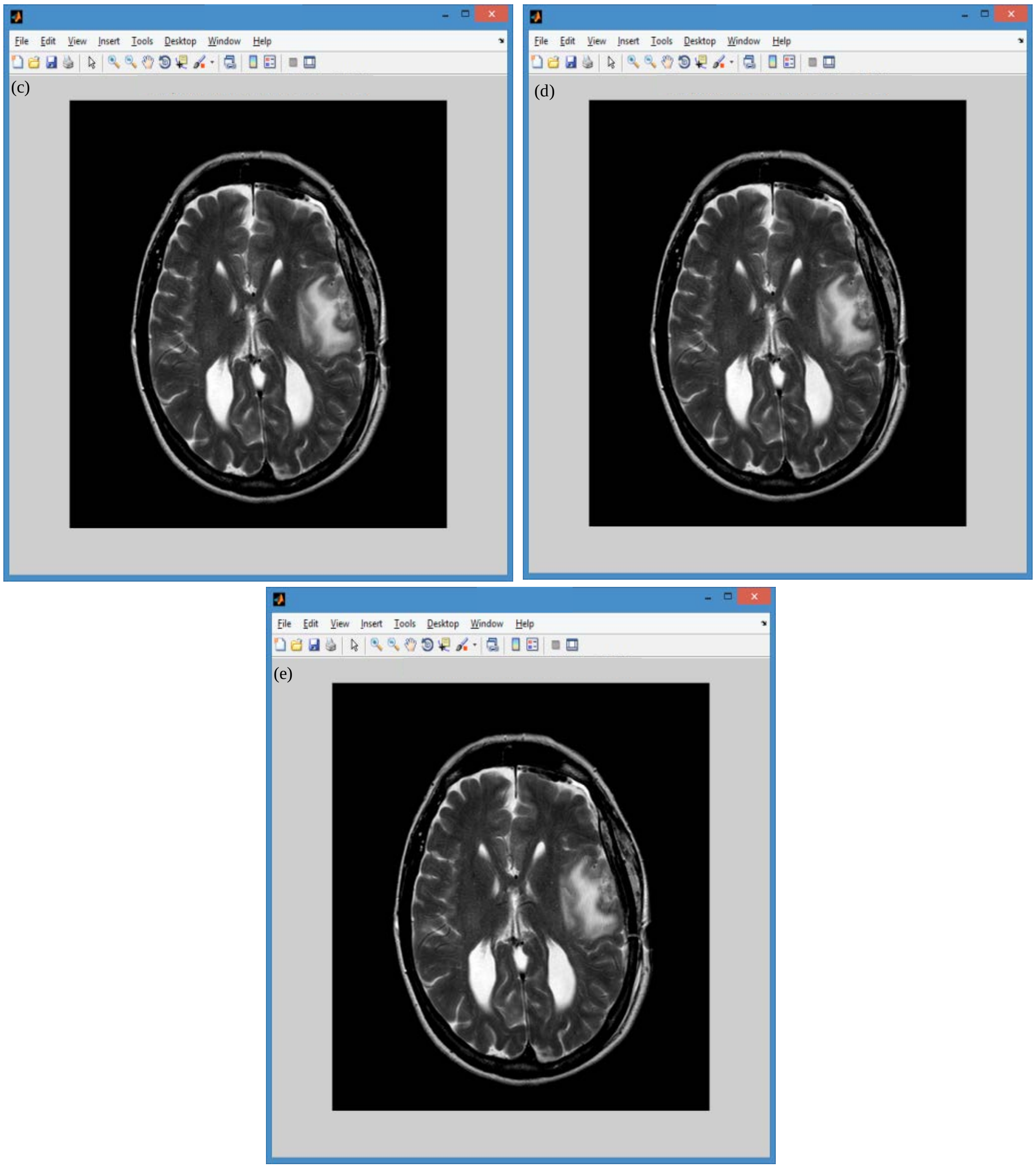

Fig. 5(a-e): Comparison of output images obtained with compression rate of (a) 50, (b) 60, (c) 70, (d) 80 and (e) 90%

Table 2: Simulation results achieved by the proposed method

CR (%)	PSNR (dB)
50	63.44
60	60.12
70	57.12
80	53.89
90	50.49

CONCLUSION

This study took the initiative to present a method that applies PCA compression on arbitrary ROI. The initiative of developing the algorithm comes from having a compression scheme that compresses the ROI in various shapes, without restricting it to block information as what is being adopted by previous research. Normal or abnormal features exhibited on medical images are in arbitrary shapes and inclusion of only the exact contour of the ROI will not only improve the compression ratio but also increase the efficiency of the algorithm in preserving the diagnostically important area.

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