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A novel image compression method using PCA algorithm for a telemedicine network

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Abstract: Image compression is important in the transfer and storage of medical images especially in telemedicine network. Although image compression using standard PCA algorithm were seen as promising in its potential in reducing image dimension, the actual size of the decompressed image still remains the same. To ensure that a reduction of memory space take place; a new way to employ PCA algorithm to image compression is proposed. In this study, a model image is carefully selected to serve as a key to compress and decompress the image using PCA and hence eliminate the need to transfer all image components across the transmission link. Two ophthalmologist were asked to rate two sets of retinal fundus images and results shown that for compression rate of 70% and below, images compressed using proposed method achieve comparable performance as those compressed using standard PCA method, with a total memory save of 60%.

Key words: Principal Component Analysis (PCA); Medical image compression**;** Image quality

1. Introduction

With an increasing advancement in telemedicine technology, the demand to store and transfer medical images between health professionals within or beyond healthcare institutional has grown by leaps and bounds. In teleradiology, high resolution medical images such as CT and MRI scans are shared among medical professionals in a universal server called the Picture Archive and Communication System (PACS). Teleradiology not only does facilitate the diagnostic interpretation on the images, it also allows the doctors to provide consultation for patients located at remote places via telecommunication link that further improve the quality of care of a healthcare system. Telepathology can only be done when colour microscopic images of the patients are readily available. As the volume of pixel data grows, the need for a larger storage space increases, so as the speed requirement of a communication link. Therefore, the compression and decompression scheme play an important role in telemedicine to achieve sufficient reduction of image file size and at the same time maintain maximum information carried by the image.

The common and well-established loss compression techniques include Joint Photographic Expert Group (JPEG), Moving Picture Experts Group (MPEG), wavelets and fractals (Yanek et al., 2000). Relatively uncommon, Principal Component Analysis (PCA) is a loss compression method that begins to receive attention in medical image compression. PCA method is also termed as Karhunen-Loeve (KL) transform in image compression (Carevic and Caelli, 1997). It is a statistical approach that transforms the image data to an orthogonal plane and discards principal components with smaller eigenvalues. However, since the transferred data must include both eigenvector matrix and mean matrix, standard PCA failed to achieve high compression ratio (Lv and Zhao, 2005). This limitation is apparent if a telemedicine setting is considered where the transferred data is to be transmitted over a link.

PCA applications in image compression have been documented in various papers (Clausen and Wechsler, 2000; Bonad and Bonad, 2012; Dwivedi et al., 2006; Santo, 2012; Doukas and Maglogiannis, 2007; Costa and Fiori, 2001; Taur and Tao, 1996; Gokturk et al., 2001; Kumar et al., 2011; Kumar et al., 2008) but the possibility of further reducing the memory space of the transferred data in a telemedicine setting is not considered in any of the study. The aim of this study was to propose a new method that reduces the amount of transfer data required to represent the image in a telemedicine setting. This new method differs from the standard PCA technique in a way that a standard, normal image is pre-selected to take part in both compression and decompression process. The detailed description of the algorithms can be found in Section II of this paper. The resultant compression results and performance evaluation of our proposed algorithm are presented in Section III. Finally, Section IV concludes the proposed approach.

2. Materials and methods

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PCA algorithm is first used in pattern recognition due to its ability to simplify a large group of variables, reducing less significant dimension to reveal the dominating pattern of the datasets. In image processing, the outcome of adopting PCA algorithm onto an image is a set of data with reduced number of dimension (column, in this case). Since the compressed data cannot represent the image therein, it is in practice coupled with the covariance matrix of the original image, X to represent the original image in a "compressed" form. Suppose that the original gray scale image is in the form of $m \times n$ matrix, the preliminary step in PCA algorithm is to minus all elements in the matrix with the mean obtained along each column. To access the relationships between the each variable, the covariance matrix of the mean-minus matrix will be calculated, followed by a computational of the eigenvectors and the eigenvalues. Eigenvectors that have higher eigenvalues, termed as the principal component of the image, will be used to derive the compressed data (CD):

$$C(X) == (SE)^T \times \bar{X}^T = CD_{[PC \times m]} \quad (1)$$

SE = Selected Eigenvectors of the covariance matrix

$\bar{X}$ = Mean-minus Matrix of the original image

The reduction of the original n dimension will be determined by the number of principal component (PC) selected. The lesser the number of eigenvectors being selected in SE, the lesser the information contained within the compressed data. However compressed, the compressed data itself serves no practical functions in image display. In order to reconstruct a viewable image in the compressed form, equation (2) is used:

$$D(X) = (SE \times CD)^T + \bar{m} = Y_{[m \times n]} \quad (2)$$

Y = Recovered Image using standard PCA

$\bar{m}$= Mean obtained along the row

The rate of compression (CR) in terms of dimension reduction is therefore defined in equation (3). CR values scale between 0 and 1 in which 0 indicates no compression and its values increases towards 1 when compression increases.

$$CR = 1 - \frac{PC}{n} \quad (3)$$

It is now obvious that the three components namely the SE, CD and $\bar{m}$ are necessary in order to reconstruct the image. Take a common setting in a telemedicine system as shown in Fig. 1, if the PCA-compressed medical image is to be transmitted via a network, these three components derived from the medical image are required to be sent to the recipient. The total memory size of these components altogether, M_r could be larger than the memory size of sending the original image alone, M_o depending on the number of PC chosen. In equation (4), M_r is the sum of the size of SE, CD and $\bar{m}$ whereas in equation (5), M_o is the size of the original image. In order to achieve image compression, the number of PC must be low below the threshold as shown in equation (6). Hence, the goal of image compression will not be achieved without a close scrutiny of the number of PC.

$$M_r = (m \times pc) + (pc \times n) + m \quad (4)$$

$$M_0 = mn \quad (5)$$

M_r = Total memory size of SE, CD and $\bar{m}$

M_0 = Memory size of the original image

$$PC \le \frac{m(n-1)}{(m+n)} \quad (6)$$

To overcome the aforementioned limitations, a novel way to compress and decompress the image using PCA algorithm is therefore proposed in this study in an attempt to optimize the bandwidth usage of a network in image transmission.

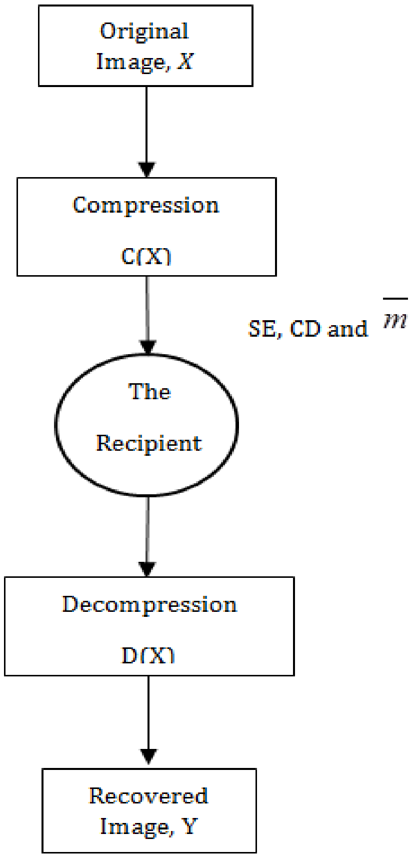

Fig. 1: Compression scheme using standard PCA algorithm where all three image components derived from the original image are required in decompression

The mainstay of the proposed method lies on the use of a model image for both compression and decompression process as shown in Fig. 2. A model image is pre-selected carefully by the sender and the recipient. Akin to the private-key encryption network in cryptography, the sender and the recipient hold the same common key in which the information carried by the model image will be used by the sender to compress the original image and the same model image will be used by the recipient to recover the compressed data closest to the original image.

The compressed data (CD_s) are acquired based on the function in equation (7) :

$$C_s(X) = (SE_s)^T \times \bar{X}^T = CD_{s[PC \times m]} \quad (7)$$

SE_s= Selected Eigenvector of the model image

In this case, the compressed data alone is transmitted to the recipient. On the receiver side, the mean and the selected eigenvector of the model image will be manipulated with the compressed data, as shown in equation (8) to form a recovered image represented by the compressed data.

$$D_s(X) = (SE_s \times CD_s)^T + \overline{m}_s = Y_{s[m \times n]} \quad (8)$$

Y_s = Recovered image using proposed method

$\overline{m}_s$= mean obtained along the row for the standard image.

By employing the same model image at both sides of the communication link, the need to transmit the image components SE and $\overline{m}$ required by standard PCA algorithm is therefore eliminated.

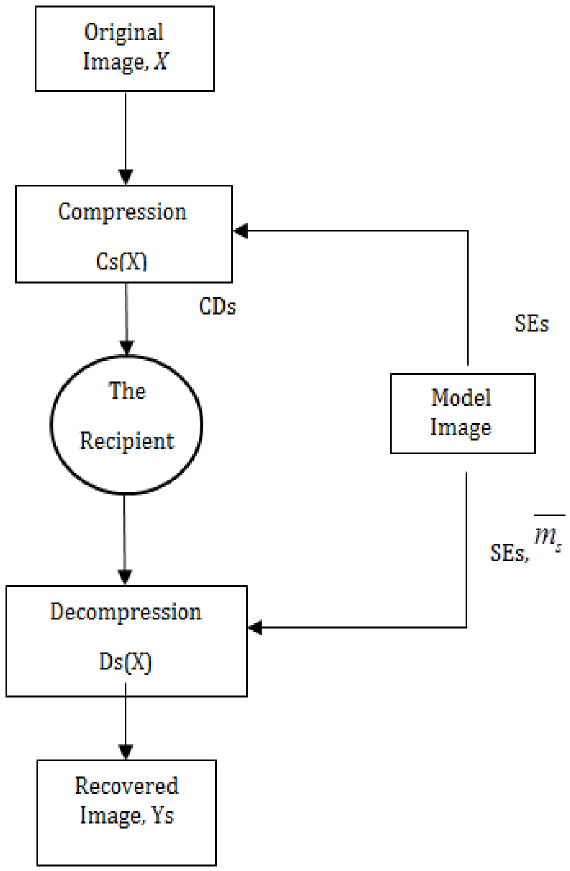

Fig. 2: Compression scheme using proposed method in which only one image component, CD_s is needed to be transferred to the recipient.

2.1. Data collection

High quality digital fundus images were obtained from MESSIDOR ["Methods to evaluate segmentation", 2008] public database to serve as the input images for the proposed algorithm. The image size is 1488 x 2240 pixels at 8 bits per colour plane and the images were stored in TIF image format file (.tif) without any prior compression. A normal fundus image without any disease indication as shown in Fig.3 was chosen as the model image and two other images, labelled as image I (Fig. 4) and II, were randomly selected as the test images ready to be compressed. The red, green and blue (RGB) space of the original image was first converted into gray level as it is the preliminary step for PCA algorithm. Two test images selected were either compressed by standard PCA algorithm or the proposed method in different compression ratio (i.e. without compression, 30%, 50%, 70%, 90% and 98%). Hence, the dataset for test images consisted of 24 retinal images altogether.

Objective evaluation

Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE) for all tested images were computed. The differences in PSNR values for standard PCA and proposed method was estimated using a paired-match t-test.

$$PSNR = 10log_{10}(\frac{255}{\sqrt{MSE}}) \quad (9)$$

$$MSE = \frac{1}{mn}\sum_0^{m-1}\sum_0^{n-1}\|f(i,j) - g(i,j)\|^2 \quad (10)$$

f: Pixel value of the original image

g: Pixel value of the compressed image

m: Number of rows of the images and i represent the index of that row

n: Number of columns of the image and j represents the index of that column

2.2. Subjective evaluation

To assess image quality to diagnostic utility, image quality for tested images were evaluated subjectively by an expert panel of two ophthalmologists (A and B). Each panel was presented independently with test images mixed randomly and anonymously. The 24 test images were shown on the computer screen and the panels were asked to rank the images based on the criteria as shown in Table 1. No time limit was placed on evaluating the images. To access intra-rater variability, the evaluations were done twice by one of the reviewers using the same criteria. Normality of the distribution of scores was tested using Shapiro-Wilk's W test. The differences in scores between two methods were compared using Wilcoxon's match-pairs signed rank test.

Table 1: Mean Opinion Score (MOS) for subjective evaluation

MOS	Description	Comments
5	Excellent (Imperceptible Distortion)	Useful for Diagnosis Purposes
4	Good (Perceptible Distortion but not Annoying)	Useful for Diagnosis Purposes
3	Fair (Slightly Annoying but acceptable)	Useful for Diagnosis Purposes
2	Bad (Annoying)	Not Useful for Diagnosis Purposes
1	Very bad (Very Annoying)	Not Useful for Diagnosis Purposes

3. Results and Discussion

The algorithms in this study were developed in Matlab environment R2010a and the statistical analyses were performed using SPSS Statistics 21.0.

The mean (±SD) PSNR values were 106.9 (±8.32) for standard PCA and 54.24 (±0.39) for proposed method. There was a significant decrease in PSNR values for proposed method (P<0.05) as illustrated in Fig. 5 (Figs. 3 and 4).

As shown in Table 2, there was a perfect inter-reviewer agreement of scoring for two different test images. The Friedman test did not report any difference in the distribution of scores obtained by the reviewer between two consecutive evaluation (P<0.05).

Fig. 3: A fundus image without abnormality is chosen as the model image

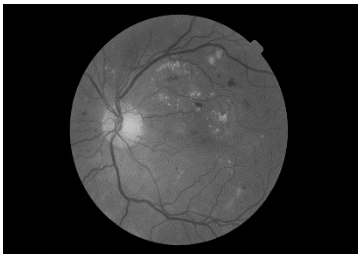

Fig. 4: Original image I

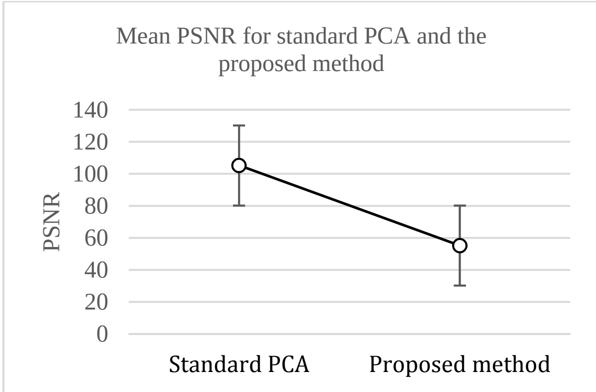

Fig. 5: Mean PSNR for standard PCA and the proposed method for test images. There was a significant decrease in values (P < 0.05)

Table 2: Details of scores attributed by the two reviewers (A and B)

Image		Standard PCA	Proposed method	Standard PCA	Proposed method
		Panel A	Panel A	Panel B	Panel B
I	Without Compression	3	3	3	3
	98%	1	1	1	1
	90%	3	2	3	2
	70%	3	3	3	3
	50%	3	3	3	3
	30%	3	3	3	3
II	Without Compression	3	3	3	3
	98%	1	1	1	1
	90%	3	2	3	2
	70%	3	3	3	3
	50%	3	3	3	3
	30%	3	3	3	3

As tabulated in Table 2 and Table 3, panel A and B gave lower rank to image compressed at 98% for both methods. Images compressed at 90% in the proposed method received lower rank than the one compressed using standard PCA. Out of the test images, 83.3% of images compressed using proposed method achieves same score as the images compressed using standard PCA. This result is promising as it suggested that the proposed method is capable to yield performance on par with the standard PCA for image compressed as high as 70%, only with a 60% save in memory space as tabulated in Table 4. Compared to images recovered from standard PCA, images recovered from the proposed method have increase in brightness level in all compression level tested as shown in Fig. 6.

Table 3: Contingency table of scores for both reviewers

	Proposed method			
	Scores	3	2	1
Standard PCA	3	16(66.67%)	4(16.67%)	-
	2	-	-	-
	1	-	-	4(16.67%)

Table 4: Comparison of memory space for image compressed at 70%

Compression scheme	Memory space	Memory space at CR = 70%
Proposed method	*PC*m*	1M
Standard PCA	*PC*m + PC*n + m*	2.5M

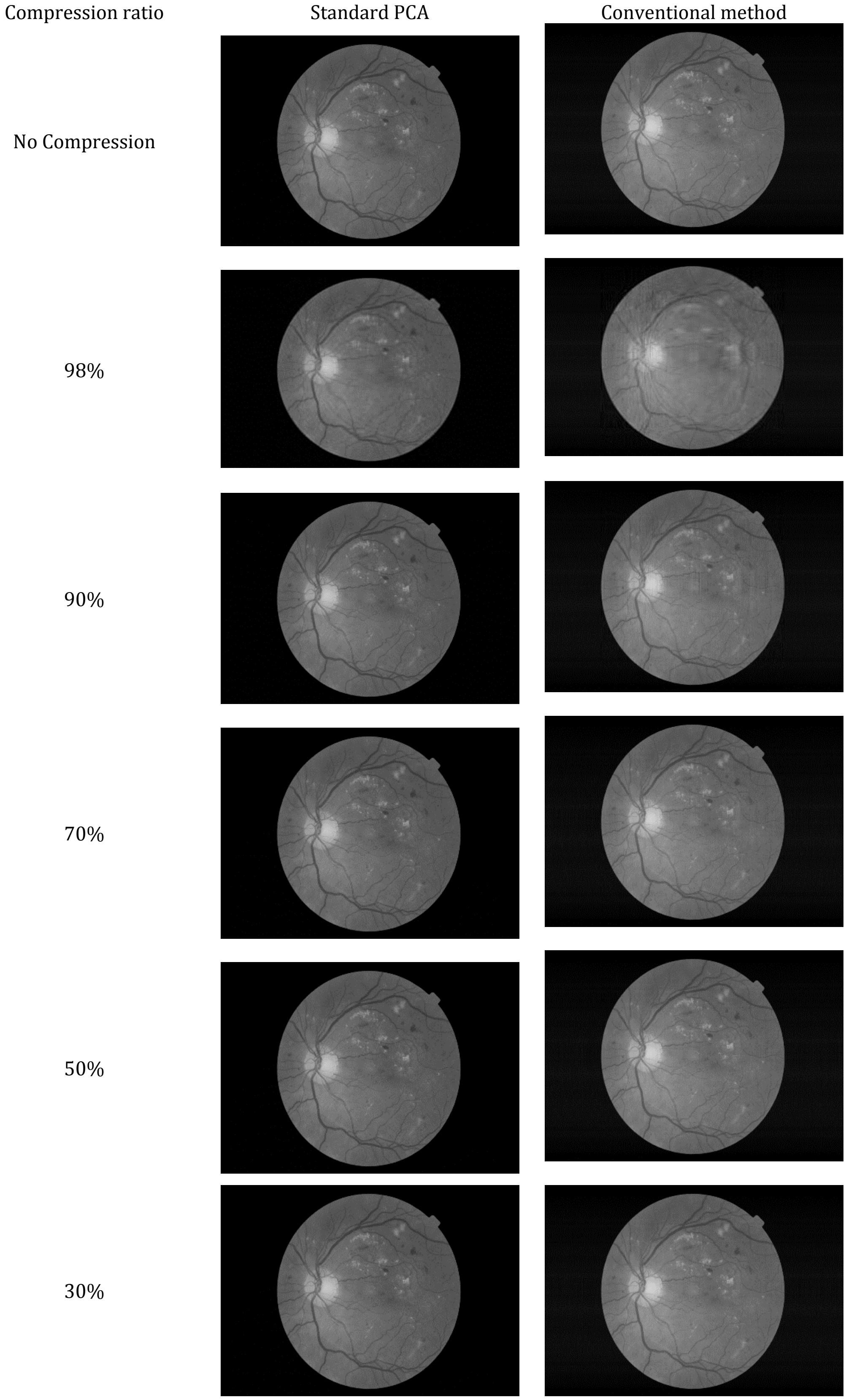

Fig. 6: Recovered images with respect to different compression levels for image I.

The increase in brightness value may contribute to the reduction in PSNR value although there are no blocking, non-uniform artifacts exhibited on images compressed below 70%. The idea that the images compressed as high as 70% were artifact-free were supported by the grading of two reviewers in which scores of 3 are given to images compressed at 70% and below. It is apparent that images compressed at 90% and 98% were blurred out and image artifacts were visible.

4. Conclusions

The need to transfer and store hundreds to thousands of radiological images per day drives the development of an efficient compression scheme.

The answer to its efficiency involves the amount of memory space that can be saved and how well information is retained. To the authors' knowledge, this is the first study reporting a new concept that employs a model image at both sides of a communication link to achieve image compression. Instead of transmitting the whole image, the information to be transferred across the network is only the image component of the image. Likewise, the image to be stored in the system is only the image component for each image and the model image.

This study has nonetheless several limitations. First of all, it is intuitive to understand that the results will be affected if different model image were to be used. Besides selecting a model image without any abnormalities, what are the criteria for selecting the model image? The answer to it will be probed in future studies.

Both panels gave the maximum score of three instead five due to the stripped off of colours from the images even though some images deserve a score of five in term of image quality. Hence to ensure the compressed images are fully ready for diagnosis purposes, colour image compression using proposed method will be considered in the future.

To conclude, a PCA image compression scheme based on a model image was realized and tested. The results show that for a fundus image compressed at 70%, the total memory space is saved by 60% if compared with a standard PCA. Image quality for the image is acceptable as rated by two reviewers. This concept is especially space-saving to medical images where structural similarity of the features lies across all images. Hence, a single model image was proposed to compress all images that share the same similarity. The true contribution of this approach shall be tested in a larger scale on a different image datasets.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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