Image Compression Effects on Face Recognition for Images with Reduction in Size

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ABSTRACT

In this research work, face recognition for the compressed images is evaluated when the images are stored at smaller sizes. When the images are stored at smaller sizes, the information is lost and sometimes it is not possible to recognize the faces successfully. The practical applications and need for storing the images at smaller sizes is explained. The results for successful recognition are presented along with the eigen values and coefficients of the some of the eigen vectors. Finally important conclusions are drawn and future scope for the research is outlined.

Index Terms—Face recognition, compression, image compression and face recognition, security.

1. INTRODUCTION

Face recognition has been considered as an important subject of research work over the last fifteen years. This subject has gained as much importance as the areas of image analysis, pattern recognition and more precisely biometrics [1-4], because it has become one of the identification methods to be used in e-passports and identification of candidates appearing in various national and international academic examinations**.** The resolution or the size of the image plays an important role in the face recognition. Higher the resolution the better it is. However, the image compression effects on the face recognition system are not given as importance it deserves in the recent years.

Images are compressed for different reasons like storing the images in a small memory like mobile devices or low capacity devices, for transmitting the large data over network, or storing large number of images in databases for experimentation or research purpose. This is essential due to the reason that compressed images occupy less memory space or it can be transmitted faster due its small size. Due to this reason, the effects of image compression on face recognition started gaining importance and have become one of the important areas of research work in other biometric approaches as well like iris recognition and fingerprint recognition. Most recent contribution were made in iris recognition [5, 6] and fingerprint recognition [7, 8]. In addition to paying importance to standard compression methods in recognition, researchers have focused in developing special purpose compression algorithms, e.g. a recent low bit-rate compression of face images [9].

One of the major drawbacks in the face recognition using compressed images is, the image has to in the decompressed mode. However, the task of decompressing a compressed image for the purpose of face recognition is computationally expensive and the face recognition systems would benefit if full decompression could somehow be eliminated. In other words, the face recognition is carried out while the images are in compressed mode and it would additionally increase computation speed and overall performance of a face recognition system.

The most popular compression techniques are JPEG [10, 11] and their related transformations are Discrete Cosine Transform and Discrete Wavelet Transform. It is treated that common image compression standards such as JPEG and JPEG2000 have the highest number of applications for actual usage in real life, since the image will always have to decompressed and presented to a human at some point.

It is required to store large number of images in a given space. For the image can be stored in the compressed form as well as in other forms like gray images etc. There various compression techniques available to achieve this objective but it affect the face recognition when the image is compressed with regular transformation techniques.

Also, some times the actual data set of a person need to be stored at a secret and secured place and only a representative image is stored in a computer which has access to people who are not in actual need of the real data. For example, a security guard at the airport need to identify only those people who are under surveillance and handover them to investigating agencies if the probe image and stored image matches. However, sometimes the security agencies do not want to store the real pictures of the people in the computers operated by security guards. This is a challenging task as the representative image may not be useful for the actual face recognition and some time it may lead to misses.

The solution for both these problems can be addressed with a single technique used in this research work. In order to address the problem of reducing the size of the file size by using regular transformation technique, one can use to reduce the frame size of the image. In this way, size of the image is reduced. However the image need to reconstructed back to its original size while doing face recognition. Since the quality of the image is altered when an image is reconstructed from lower frame size to higher frame size, it may affect its face recognition capability. In this work it is proven that face recognition technique will succeed in recognizing the faces even if the image are compressed to 10% of its original size. To address the issue mentioned in second point, the reconstructed images can be stored at the computers held by security agencies. These reconstructed images are not of good quality and the images are blurred to the maximum extent possible when reconstructed from 10% size back to its original size.

2. PCA

A 2D image made up of pixels arranged in the form of a matrix. Each pixel has three values represented for three basic colors red, green and blue. The color intensity of each pixel is represented by an integer and is usually in the range between 0 and 255. Hence, the image can be represented by a three matrices of size equal to the size of the image. For example if the image size 200 x 300 pixels, then it can be represented by 3 matrices of size 200 x 300. A gray image will have one matrix representing the pixels. A 2-D image can be transformed to 1D vector by concatenating all rows one after the other into a long thin vector. This operation can also be performed column wise to get a long thin vector. Let there are M vector of size. *N* is the product of number of rows and number of columns.

$$x_i = \begin{Bmatrix} p_1 \\ p_2 \\ \cdot \\ \cdot \\ p_N \end{Bmatrix}, i = 1,2,\ldots,M \quad (1)$$

Each image is represented by x_i and all the images can be averaged to get a mean image. The concept of mean image is only mathematical in the sense and so not carries any physical significance.

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i \quad (2)$$

The centered image c_i with respect to mean image can be found by subtracting mean image from each image

$$c_i = x_i - m \quad (3)$$

and let

W is the matrix composed by placing the column vectors c_i side by side. The covariance matrix can be defined by

$$Q = WW^T \quad (4)$$

Hence the size of covariance matrix becomes *N* x *N*. For example, for the image size of 200 x 300 pixels, the size of the covariance matrix *Q* becomes 60000 x 60000 which is huge for solving the covariance matrix for Eigenvalues and Eigenvectors. In order to determine the Eigen values and Eigen vectors of the covariance matrix, one can follow the common theorem proposed in linear algebra.
The procedure is mentioned below:
Let
λ_i = Eigen values of WW^T
Λ_i=Eigen vectors of WW^T
τ_i = Eigen values of W^TW
Γ_i=Eigen vectors of W^TW

$$W^TW = \tau_i \quad (5)$$

$$W^TW\Gamma_i = \tau_i\Gamma_i \quad (6)$$

By multiplying both the sides by W

$$WW^T(W\Gamma_i) = \tau_i(W\Gamma_i) \quad (7)$$

The above equation can be interpreted as the first *M-1* Eigen values $\lambda_i$and Eigen vectors $\Lambda_i$can be derived from $\tau_i$and$W\Gamma_i$. The *M-1* represents the number of degrees of freedom of the matrix considering the mean image. However, $W\Gamma_i$ needs normalization to make to equal to Λ_i.

The Eigen vectors can be computed for each no zero Eigen value and they are sorted out in descending order based on the Eigen values. This set of Eigen vector form the orthonormal basis for the subspace within which most image data can be represented, but a with a minimal amount of error. The Eigen vector corresponding to the largest Eigen value is the one with greatest variance among all images and the Eigen vector corresponding to the smallest Eigen value is the one with least variance.

3. EXPERIMENTAL RESULTS

Fig. 1 shows the image of 10 people whose images are considered for face recognition in this work. Two expressions of each face is taken as and stored in the database. Hence there are totally 20 images stored in the database which will be compared with the probe image to check if the probe image matches with any of the stored faces.

The stored images are considered in 10 different sizes and each size of all the 20 faces are stored in the database at a time for experimentation purpose. Fig.2 shows the image sets of the compressed images from 90% of the original size to 10% of the original size. The left most image represents the original size, the second image is of 90% of the size, third image is 80% of the size and so on; and last one is of 10% of the size. The original size of the image is 180 x 200 pixels and the images shown below are only representative. When the original image is compressed to 10% of its original size, the size of the image becomes 18 x 20. When the probe image, which is 180 x 200 is presented to compare with the store image which is of size 18 x 20, the dimension mis-match occurs for a the PCA algorithm, hence the stored image is reconstructed back to the size 180 x 200. However, though the compressed image is reconstructed back to original size, the original image quality is not recovered as the information is lost when it is compressed and stored at 10% of he original size. In this way, a high quality probe image of size 180 x 200 is compared with the poor quality stored image of size 180 x 200. It is the interest of this work to verify to what level of compression the face recognition is successful and that size of the image can be stored in the databases instead of the original size.

Figure 1: Images of persons considered for face recognition

Image Set 1

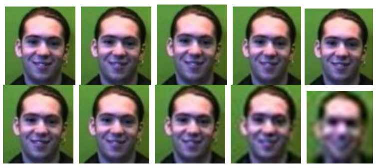
Image Set 2


Image Set 3


Image Set 4

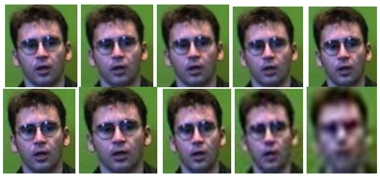
Image Set 5

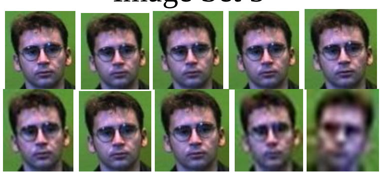
Image Set 6

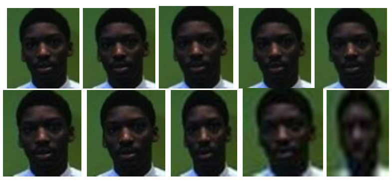
Image Set 7

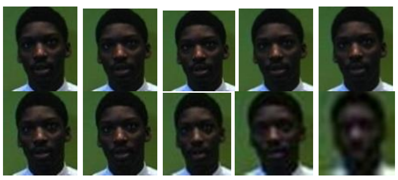
Image Set 8

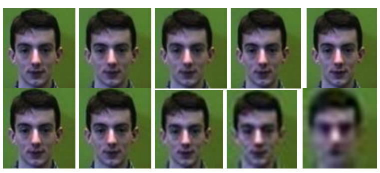
Image Set 9

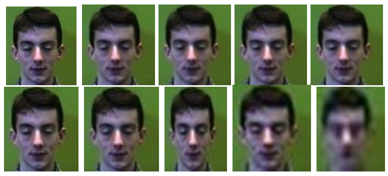
Image Set 10


Image Set 11


Image Set 12


Image Set 13


Image Set 14

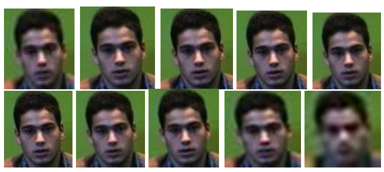
Image Set 15


Image Set 16

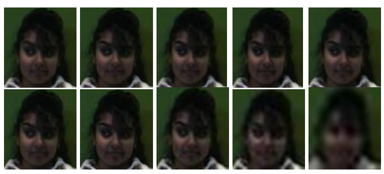
Image Set 17

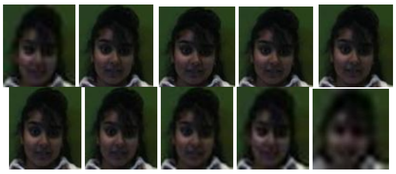

Image Set 18

Image Set 19

Image Set 20

Figure 2: Image sets original and compressed in size from 90% to 10% of the size from left to right.

The face recognition is successful when the probe images are presented to compare with the stored images. For all probe images, the face recognition was successful for compression sizes up to 10% of the original size. When the compression is carried out below 10%, the face recognition was not successful for some of the probe images. Hence the cases below 10% compression are not presented here.

Fig. 3 shows the distribution of Eigen values for the reconstructed images of original and compressed ones. We can notice that the original and compressed image Eigen values are almost same for all cases. When the compression approaches 10% of the size, there is very small difference in the Eigen values between the original images and 10% of the compressed size of the images. This shows that even if we compress the image to 10% of its size the information is available.

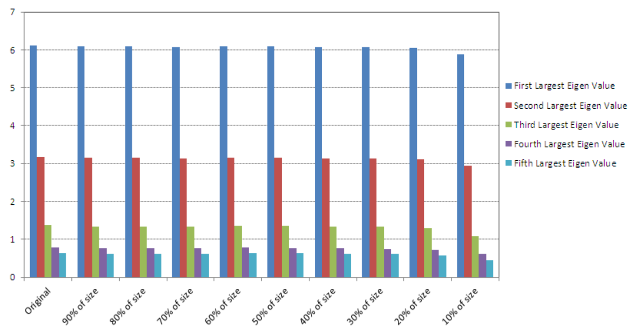

Figure 3: Distribution of Eigen Values for the reconstructed images

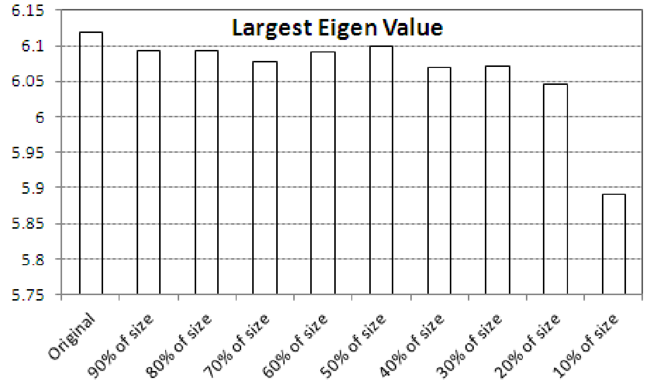

Figure 4: Distribution of Largest Eigen Values for the reconstructed images

Fig. 4 shows the distribution of largest Eigen values for the reconstructed images of original and compressed ones. The largest Eigen values of the different compression ratios show very minimal variation up to 20% of size and there is a relatively a dip when the image of 10% size is considered. However, the magnitude does not have much difference and the face recognition is successful.

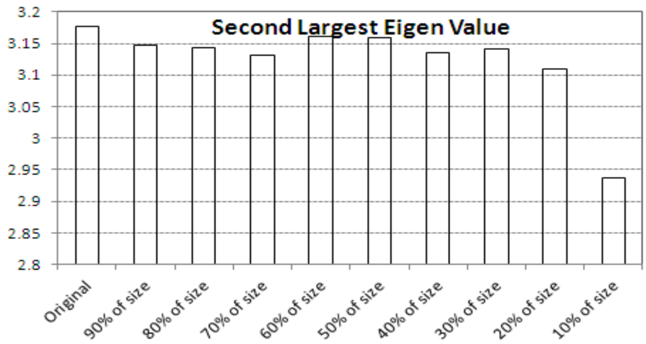

Figure 5: Distribution of Second Largest Eigen Values for the reconstructed images

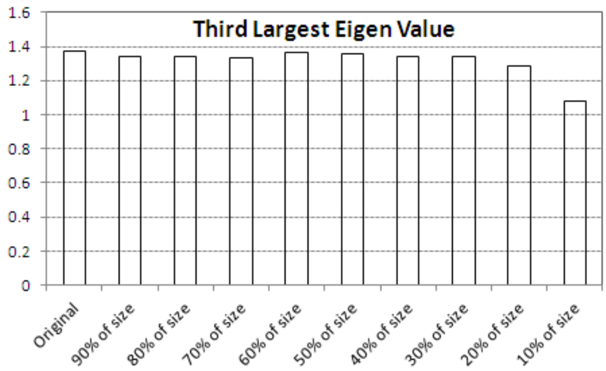

Figure 6: Distribution of Third Largest Eigen Values for the reconstructed images

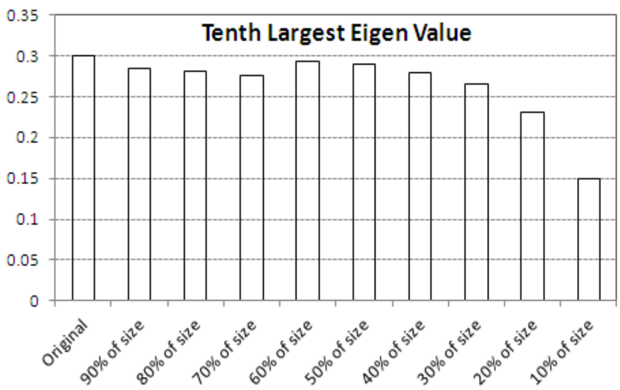

Figure 7: Distribution of Tenth Largest Eigen Values for the reconstructed images

Figs. 5 to 7 shows the distribution of second, third and tenth largest Eigen values for the reconstructed images of original and compressed ones. These Eigen values of the different compression ratios show very minimal variation up to 20% of size and there is a relatively a dip when the image of 10% size is considered. However, the magnitude does not have much difference and the face recognition is successful.

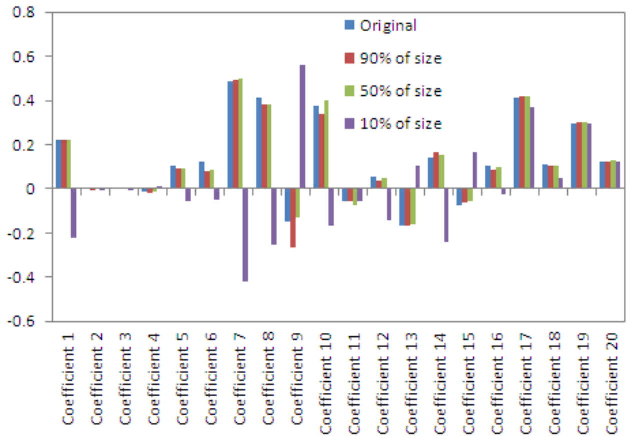

Figure 8: Coefficients of First Eigen vector

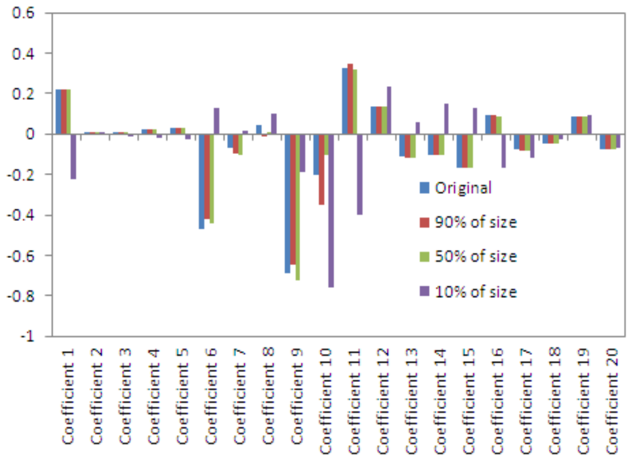

Figure 9: Coefficients of Fifth Eigen vector

Figs 8 and 9 show the coefficients of the first and fifth Eigen vectors of the reconstructed images. The coefficients have almost same sign as well the nearest magnitudes with respect to the original image. However, it is quite different at 10 of the size, the Eigen values and Eigen vector coefficients vary too much, and more research is required to understand this behavior, which is under progress.

4. CONCLUSION

In this work, the face recognition using PCA is tested for various sizes of compression and its suitability to store the images at smaller sizes is evaluated. It is proven that, when the images are compressed up to a size of 10 % of its original size, the face recognition is successful and the compression of images to sizes below 10% is not successful in all cases. By looking at the Eigen values and coefficients of Eigen vectors, it is concluded that, the values start to deviate from the Eigen values and Eigen vectors of original image at 10% of the size. Research is under progress to determine if it is possible to successfully recognize faces by modifying the Eigen values with suitable algorithms.

5. REFERENCES

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