Hybrid Technique to Improve Face Recognition Using Principal Component Analysis and Singular Value Decomposition

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Abstract: This paper present a hybrid technique between two of the most popular face recognition methods, Principal Component Analysis (PCA) and singular value decomposition (SVD), and attempts to offer a study for all its mathematical equations in detail and concentrate on the hybrid place between equations in order to focus on the way of processing the hybrid method. Dot product used in mathematical equations and for testing the proposed method used Olivetti Research Laboratory (ORL) data set images were used with different number of images for training set and used various number of Eigen faces and used also dissimilar number for test images and Manhattan distance was used to measure the distances between image vectors in this system, the result shows that the recognition rate using this hybrid technique is higher than the recognition rate using PCA or SVD separately and each time increase the threshold value the accuracy rate increased and conclude that when increase the threshold value and the chosen number of Eigen faces then recognition rate increased.

Keywords: Face recognition, Principal Component Analysis (PCA), singular value decomposition (SVD), and Manhattan distance.

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1. Introduction

During the three past decades, face recognition which is a subpart of pattern recognition became the most known biometric technique used in various applications. Applications used to recognize the faces which was depends on biometric have been improved where it was in the past years depend on different individual portion from human body which could be accessed to its biometric easily in order to prove general approbation and provide high level of security [1]. Systems which use face recognition in its security allow only for authorized user to be passed and enter him to the system [2] [3].

Two essential aims found in face recognition there are verification and identification. Verifying user tries to enter a system processed by matching one image with only one image copy saved in a file while Identifying user in a system processed by matching the user face to a database of multiple faces and gave a ranked number of most similar faces [4].

Face recognition has three methods, Firstly holistic method which depends on extract the face portion and uses it as input face to system used as face recognizer and compares it with database of multiple faces, its contain two approaches statistical which based on two dimension array and artificial intelligence approach which based on neural network and machine learning algorithms, it has another names which called photometric or template approach and its used in face recognition and as example for this method is Eigen faces [5][6] [7]. Secondly feature based method is more successful and less critical than holistic with face expression and difference in lighting and occlusion. It extracts local features of face like mouth, nose or eyes for recognize faces and take in consideration the size and place of those features and it's also known as geometric method and best use for it in image restoration. Lastly, hybrid method it represents a merge method between feature based method and holistic methods and its used in 3D images [8][9] [10].

The main disadvantage in the prior works is the researches didn't present some of PCA operations in detail, how get the threshold value and the way of choosing the best Eigen faces. The aim of this paper is gain best recognition rate with the use for various threshold values and eigen faces.

Section 2 will view several prior research works as a literature survey; section 3 describes hybrid between PCA and SVD algorithms in detail, section 4 displays result and discussion and section 5 shows the conclusion.

2. Literature Review

In 2011, Hussein R. published a paper [11] in face recognition using PCA method with several distances measurement where introduced results of accuracy rate from use Euclidean distance where identified 80 object and obtain 95.2% while in using city-block distance identified 78 objects and obtain 94.3% and shows that PCA method with Euclidean distance gives higher rate than city-block distance but it was less efficient in processing.

In 2012, Bahurupi and Chaudha produced PCA method for Face Recognition. They introduce that the noise in training set images head to decrease in the accuracy ratio and higher number of trained images helps in increase the variance and the result will be higher for recognition rate [12].

In 2014, Israa A. A., et. al. was written a research to enhance face recognition rate by applying wavelet de-noising filters such as Haar at different levels on ORL dataset and after that enhance the contrast of images and finally “Laplacian of Gaussian filter” used to detect the images edges all these techniques used in order to rising recognition rate to 10% from the original rate when 400 images used .In this paper they did not remind the threshold value or expended time [13].

In 2015, Aluko et. al. presented a research about the evaluation performance for principal component analysis depending on different techniques and showed original PCA has accuracy rates equal to 91%,75% and 56% respectively when 75,150 and 300 Eigen faces selected respectively. They were showed that hybrid PCA with Artificial Neural Network (ANN) techniques provided accuracy rates 94%,93% and 93% respectively when 75,150 and 300 Eigen faces selected respectively. The PCA ANN hybrid method has more execution time than original PCA The threshold value was not mentioned in there research [14].

In 2016, Thamizharasi and Jayasudha made a research to rise the face recognition using a combination between two methods to manage the

lighting pre-processing problem. First 2D discrete wavelet transform which applied on the ORL dataset and others by got the coefficient for the images then multiply it with a specific scale then save the resulted dataset to prepare it to the second stage and treated it as training set. Second method was Contrast Limited Adaptive Histogram Equalization which applied on the resulted dataset and computes the recognition ratio by used Gabor wavelet and showed the hybrid method work effectively with images which has lighting problem. They got accuracy rate equal to 98.50% on ORL database and applied on Yale database by used a ratio of trained to tested images on the database by (3:8) and got 100% ratio. Unfortunately they did not show the tools they used in this paper like number of selected eigenvectors, threshold value and time execution [15].

3. Hybrid technique between (PCA) and (SVD):

3.1 Principal component analysis (PCA):

PCA is a useful statistical approach and one of holistic method which used in face recognition, coding and compression. The main advantage of PCA is the dimensionality reduction. PCA grants better results in varying poses but it expends a lot of time in execution [16]. Dimensionality reduction is the main purpose for the powerful of PCA which processed to have the useful data in images by remove the noise so in PCA redundant data removed by find the variance between image vectors using covariance matrix which give information about how much these vectors are in the same direction, if these vectors are not in the same direction means they are orthogonal on each other. Dot product is the used mathematical operation for the proposed system.

PCA method is described in the next steps [16] [18] [19] [20]:

- Construct A matrix for training set images, each image represent a vector with size M=(row*column).

$$\text{Matrix } (A) = (\overrightarrow{a_1}, \overrightarrow{a_2}, \ldots\ldots \overrightarrow{a_M}) \quad (1)$$

- Compute the average mean face $\bar{A}$ as in figure (1).

$$\text{Matrix } (\bar{A}) = \frac{1}{M-1} \sum_{i=0}^{M-1} A_i \quad (2)$$

- Average face vector subtracted from each image vector

$$\Phi = A - \bar{A} \quad (3)$$

- Reduce dimension by Compute covariance matrix $= \bar{A}A$.

$$C = \frac{1}{M-1} \sum_{i=0}^{M-1} A^T A \quad (5)$$

- Compute eigenvalue and eigenvectors from covariance matrix and sort eigenvectors according to its eigenvalues descending.

$$eig(C)=V\alpha \quad (6)$$

- Compute eigenfaces (U) matrix by change (V) matrix from small space to large space

$$U= AV \quad (7)$$

(U) matrix size is equal to (x*y, K), where K is a number of taken eigenvectors [6633]. eigenfaces are shown in figure (2).

The first eigen values (α) associated with its corresponding eigenvectors (V) have the high energy comprised from the according eigenvectors in small eigen space so choose eigenvectors happened by take the largest eigenvalues to get the eigenfaces in large space.

- Sort eigenvectors in descending based on its corresponding eigenvalue.
- Compute eigenvectors projection weights matrix which represents the original image weight in each eigenvectors

$$\Omega_{(K,K)} = U^T \Phi \quad (8)$$

- Compute the distance between the weights of all vectors

$$£_K = \|\Omega_i - \Omega_K\| \quad (9)$$

Manhattan distance was used in this work which get absolute difference between vectors of weight for training images.

$$\text{Manhattan Distance}(x,y)= \sum_{i=0}^{k} | x_{i-} y_i | \quad (10)$$

Where k= higher values of eigenvalues

- Compute threshold value which acts as the maximum distance between all the vectors and then a proportion value used equal to some values like (0.3,0.5,0.8).

$$\text{Threshold=t* max } \|\Omega_i - \Omega_K\| \quad (11)$$

Following steps applied on test images:

- Input test image and transform it into vector $[X_p]$ where p is the size of test image.
- Compute average test image

$$\bar{X}=\sum_{i=0}^{P-1} x_i \quad (12)$$

- Subtract the X vector from the average test image

$$\phi_p=X_p - \bar{X}_p \quad (13)$$

- weight test image computed in each eigenface

$$\Omega_K = U^T \phi \quad (14)$$

- Minimum distance computed between the weight test image and all weights of the training image in the dataset

$$£ =\text{min } \|\Omega - \Omega_K\| \quad (15)$$

Where Ω is test image weight and Ω_k the weight of all database images

- If min ≤ threshold then the unknown image is a face; else it is not a face.

3.2 Singular value decomposition

In statistic principal component analysis (PCA) and in order to reduce data of two dimensions from high data space to low data space, singular value decomposition (SVD) plays role in this process. SVD applied on two

dimension images matrix to obtain three matrices which are orthogonal on each other [20]. Computing singular value decomposition for matrix$A_{(n,m)}$, where n=x*y and $n > m$ has the decomposing form:

$$\mathrm{SVD(A)} = \mathrm{U\Lambda V^T} \tag{16}$$

Where $\mathrm{U_{(n,m)}}$ matrix with orthogonal columns, $\mathrm{V_{(m,m)}}$ is orthogonal matrix and $\Lambda_{(\mathrm{m,m})}$ is diagonal matrix contain the singular values and the other matrix element are zeros. From eq. (16) can reconstruct two symmetric matrices $\mathrm{AA^T}$ and $\mathrm{A^TA}$ as follow:

$$\mathrm{AA^T} = \mathrm{U\Lambda V^T V\Lambda U^T} = \mathrm{U\Lambda^2 U^T} \tag{17}$$
$$\mathrm{A^TA} = \mathrm{V\Lambda U^T U\Lambda V^T} = \mathrm{V\Lambda^2 V^T} \tag{18}$$

(U) matrix in eq. (17) represents eigenvectors in large image space while (V) in eq.(18) represents eigenvector in small image space. (Λ^2) represents the root square of eigenvalue that associated with its corresponding eigenvectors in the other space [21].

$$\alpha = \sqrt{\Lambda^2} \tag{19}$$

SVD algorithm

Input: N training set images
Output: Recognition rate
Begin
Step1: Convert N training set of images into A matrix with image vectors of size $\mathrm{M} = (\mathrm{rows} * \mathrm{columns})$.
Step2: Compute mean average face $\overline{\mathrm{A}}$.
Step3: Subtract mean face from matrix A.
Step4: Compute the coordinate vector $\mathrm{Y} = \mathrm{A^T}/(\mathrm{N}-1)$.
Step5: Compute singular value by SVD for matrix Y, $\mathrm{SVD(Y)} = \mathrm{U\Lambda V}$.
Step6: Project the test image onto eigen faces to classify input image [22].
End

3.3 The proposed hybrid system

The combination of singular value decomposition (SVD) method with principal component analysis (PCA) method rise the accuracy rate to 100% and that processed by using the most benefit equations in both of these methods. Figure (3) describes the block diagram for the proposed

system. In PCA dimensionality reduction is very useful in order to compute covariance matrix in less time.

$$C = A^T * A$$

$$(400 * 400) \quad (400 * 10304) \ (10304 * 400)$$

The height of matrix A is 10304 which it refers to the size of each image where 92 for width and 112 is for height so, 92*112 equal to 10304. The width of matrix A is 400 which refer to the number of images used for training. After computing the covariance matrix with smaller size (400*400) then it is easier to compute the eigenvalue and eigenvectors for covariance matrix. Computing eigenvalue and eigenvectors for image vectors in small space allowing in extract the best features from images vectors in order to increase the effectivity of recognition. The singular value decomposition method hybrid with PCA method by using the benefit of PCA in dimensionality reduction for the covariance matrix and the speed of processing for SVD for the covariance matrix in the small space ecause the original SVD get the eigenvalue and eigenvectors for the coordinate matrix vectors Y which has size (400*10304) as follow:

$$Y = A^T / (N - 1)$$

$$(400 * 10304) \quad (400 * 10304)$$

which slower the processing process because each vector has size 10304 and that needs a lot of mathematical operation to get the determinant and eigenvalues for them and because the SVD considered as fast in processing so when it process a vector with size 400 rather than 10304 that is will be faster and give a good result in typical time. The other difference between the two methods is the PCA sort the eigenvectors according to the related eigenvalues and choose the highest eigen vectors and use them while in the SVD method all the eigenvectors used without take in the consideration the best eigenvectors and that take a lot of time too so using this part of PCA method is better. The other reason is with SVD when using all eigenvectors computing the distance between face vectors will take a lot of time because it take all eigenvectors while in the PCA method compute the distance only between the best eigenvectors. Table (1) shows the difference between both methods in equations part and how that merge happened between the equations in their original

methods and how their programmed in the proposed work and where the merge happened.

In hybrid PCA SVD method tried to get best output with different recognition ratio by getting highest eigenfaces for all 400 images in ORL database to recognize test input image. The recognition rate depends on the number of faces are recognized true from the 400 faces and dividing the gained number over 400. In this paper all the 400 images are tested over the 400 images so the hybrid method algorithm repeated 400 times, the time expended in execution for this method was computed and registered that its be higher in some seconds when the chosen number of Eigen faces and threshold values are rise but recognition rate was increased.

Hybrid (PCA SVD) algorithm

Input**:** N Training set images
Output**:** Recognition face ratio
Begin
Step 1: Load training images data set;
Step 2: Read m=number of training image;
Step 3: Read x=image_width , y= image_height;
Step 4: Convert each training image to vector
Step 5:Normalize all images vector in matrix A.
Step 6: Compute average face image $\phi = \mathrm{A} - \overline{\mathrm{A}}$.
Step 7: Compute covariance C=$\frac{1}{\mathrm{M}-1}\sum_{\mathrm{i}=0}^{\mathrm{M}-1} \mathrm{A}^{\mathrm{T}}\,\mathrm{A}$.
Step 8: Compute $SVD(C) = U\Lambda V$.
Step 9: Compute weight for each eigen face $\Omega_{\mathrm{K}} = \mathrm{U}^{\mathrm{T}}\phi$.
Step 10: Compute distance between eigen face vectors; £ =min $\|\Omega - \Omega_{\mathrm{K}}\|$ .Step 11: Load test image.
Step 12: Compute sum=$\sum_{\mathrm{i}=0}^{\mathrm{M}-1} P_i$
Step13:Compute average test image vector pixels= $each\ image\ pixel - sum/(x * y)$.
Step 14: Compute the minimum distance.
Step 15: Recognize test image is face or not.
End

Figure (1): Average image

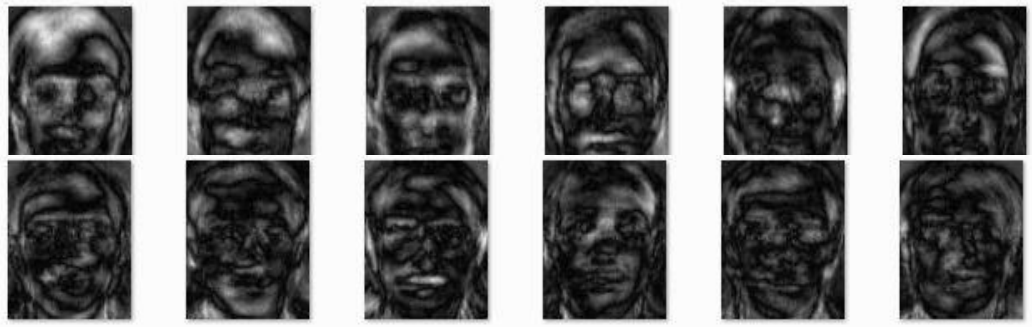

Figure (2): Eigen faces

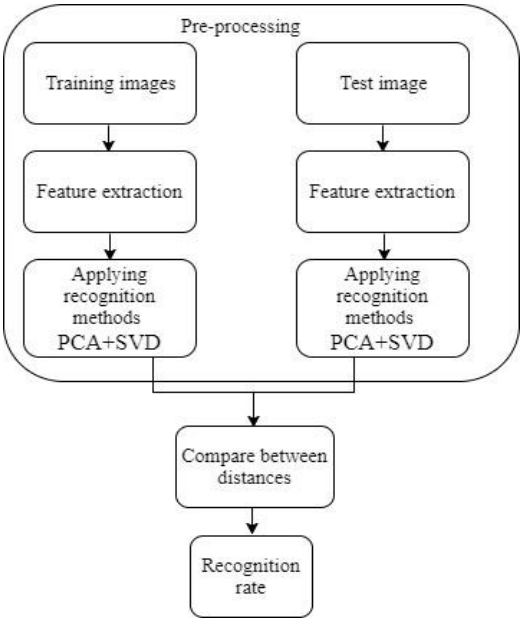

Figure (3): Proposed system diagram

Table (1) Difference between PCA and SVD with the hybrid between them

PCA	SVD
$C=\frac{1}{M-1}\sum_{i=0}^{M-1} A^T A$	$Y = A^T/(N-1)$
eig(C)=Vα	$SVD(Y) = U\Lambda V$
Covariance matrix (C) size=(400*400)	Coordinate matrix (Y) size=(400*10304)
Hybrid PCA+SVD	
$C=\frac{1}{M-1}\sum_{i=0}^{M-1} A^T A$	
Covariance matrix (C) size=(400*400)	
$SVD(C) = U\Lambda V$	

4. Experimental Results and Discussion

The proposed system merges two methods which mentioned before; these methods are PCA and SVD. During programming these methods in hybrid way and getting their results by use various values used for threshold value, the number of training set and the number of taken Eigen faces in order to have the best results.

The training set size parameter which plays a very powerful role in recognition process because when the number of images in the training set decreased the ratio of recognition increased as described in table (2) and using the same number of training set but increase the number of chosen eigen faces will increase the recognition rate also as described in table (3).

One of the most important factors is the time expended in execution. During the execution was observed that time expended in execution rising with the grow in the number of training set. The number of Eigen faces uses in recognition and rise the threshold value makes the accuracy rate higher as shows in table (4). The hybrid PCA SVD gained best results in recognition than using each method of PCA and SVD Separately. Results in table (4) uses 400 training image in recognition process.

Table (2): Results of proposed work based on training set number of images

Distance method	Training set number	Number of taken eigenvectors	Threshold	Recognition Rate
Manhattan distance	400	100	0.3	96.75
	300	100	0.3	98
	200	100	0.3	98.5
	100	100	0.3	99

Table (3): Results of proposed work based on the number of Eigen faces

Distance method	Training set number	Number of taken eigenvectors	Threshold	Recognition Rate
Manhattan distance	400	40	0.3	94
	400	60	0.3	97.5
	400	100	0.3	97.5
	400	200	0.3	97.5
	400	40	0.5	99
	400	60	0.5	99.75
	400	100	0.5	99.75
	200	60	0.5	100
	100	60	0.5	100

Table (4): Results of proposed work with various threshold values and time and 400 training set

Distance method	Number of taken eigenvectors	Threshold	Recognition Rate	Execution time In seconds
Manhattan distance	100	0.3	97.5	50.605338
	100	0.5	99.75	47.480996
	100	0.8	100	52.594938
	200	0.3	97.5	70.206857
	200	0.5	99.75	69.953542
	200	0.7	100	71.719915
	200	0.8	100	74.760243
	342	0.3	99.5	115.817706
	342	0.5	100	131.228688
	342	0.8	100	134.899615
	60 from 400	0.3	97.5	38.415091
	40 from 400	0.3	94	31.465255
	60 from 200	0.3	97	16.631629
	40 from 200	0.3	97	14.866826

5. Conclusions

In this paper realized that the combination between face recognition methods (PCA and SVD) provides the advantage of the two techniques to have a very integrated system that can give best performance. Decreasing the number of trained images led to increase the accuracy rate and its decrease the time expended in execution and concluded that using higher threshold value and higher number of chosen eigenfaces gave higher recognition ratio. The size of images effect also on recognition rate and the smaller image give better and faster result.

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تقنية هجينة لتحسين التعرف على الوجه باستخدام تحليل المكونات الرئيسية وتحلل القيمة المفردة

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المستخلص: هذا البحث يقوم بتقديم نظرية هجينه بين اثنين من طرق التعرف على الوجوه واحد من اهم طرق تمييز الوجوه الإحصائية المُسماة (تحليل العنصر الاساسي) و(تحلل القيمة المفردة) ومحاولة لعرض جميع المعادلات الرياضية المستخدمة في هاتان الطريقتان وابراز المكان الذي تم فيه التهجين في كلتا الخوارزميتين والتركيز على طريقة المعالجة الرياضية باستخدام الضرب النقطي، لاختبار الطريقة المقترحة تم استخدام صور مجموعة بيانات أورل مع عدد مختلف من الصور لمجموعة التدريب، وعدد مختلف من الوجوه إيجن المختار واستخدامها أيضا عدد غير متباينة لصور الاختبار وتم استخدام مسافة مانهاتن لقياس المسافات بين ناقلات الصور في هذا النظام، فإن النتيجة تبين أن معدل الاعتراف باستعمال هذه التقنية الهجينة أعلى من معدل التعرف باستخدام (تحليل العنصر الاساسي) أو (تحلل القيمة المفردة) بشكل منفصل، وفي كل مرة تزيد قيمة العتبة وزيادة عدد وجوه الايكن المأخوذة يزيد من معدل دقة تمييز الوجوه.

الكلمات المفتاحية: تمييز الوجه، تحليل العنصر الاساسي، تحلل القيمة المفردة، مسافة منهاتن.

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