ISSN: 0067-2904
GIF: 0.851

The Design of Efficient Algorithm for Face Recognition Based on Hybrid PCA-Wavelet Transform

Matheel E. Abdulmunem[1*], Fatima B. Ibrahim[2]
[1] Department of Computer Science, University of Technology, Baghdad, Iraq
[2]Information and Communication Engineering Department, Al-Khawarizmy College of Engineering, Baghdad University, Baghdad, Iraq

Abstract

In modern times face recognition is one of the vital sides for computer vision. This is due to many reasons involving availability and accessibility of technologies and commercial applications. Face recognition in a brief statement is robotically recognizing a person from an image or video frame. In this paper, an efficient face recognition algorithm is proposed based on the benefit of wavelet decomposition to extract the most important and distractive features for the face and Eigen face method to classify faces according to the minimum distance with feature vectors. Faces94 data base is used to test the method. An excellent recognition with minimum computation time is obtained with accuracy reaches to 100% and recognition time decreases to 87.5%.

Keywords: Face Recognition, PCA, DWT.

تصميم خوارزمية تتسم بالكفاءة للتعرف على الوجوه بالاعتماد على طريقة هجينة لطريقة تحليل المكونات الاساسية و تحويلة المويجات

مثيل عماد الدين عبد المنعم[1]*، فاطمة بهجت ابراهيم[2]
[1]قسم الحاسبات ، الجامعة التكنلوجية ، بغداد ، العراق
[2]قسم هندسة المعلومات و الاتصالات ، كلية هندسة الخوارزمي ، جامعة بغداد ، بغداد ، العراق

الخلاصة

في الوقت الحاضر تميز الوجوه يعتبر احد الجوانب الحيوية في رؤى الكمبيوتر وذلك يرجع الى عدة اسباب منها تواجد التكنلوجيا و التطبيقات التجارية و سهولة الوصول اليها و استعمالها .باختصار تميز الوجوه يميز الشخص تلقائيا من صورة او مقطع فيدو. في هذا البحث أُقترح خوارزمية كفؤة لتميز الوجوه معتمدة على الاستفادة من خواص تحليل المويجات بإستخلاص اهم الصفات المميزة للوجه و طريقة القيم الذاتية للوجه و تصنيف الوجوه حسب أقل مسافة مع متجهات الصفات المميزة. قاعدة البيانات العامة (Faces94) قد استعملت لإختبار الخوارزمية و تم الحصول على نتائج تميز ممتازة بأقل وقت حسابات حيث وصلت الدقة الى 100% بينما قل الوقت ال 87.5 %.

1.Introduction

Face recognition has extensive applications in security, authentication, surveillance, and criminal identification. Conventional identification methods based ID card and password are no more trustworthy as before, even it is very popular, due to the use of various advanced techniques of fake and password-hacking. As an option, biometric, which is well-defined as an essential physical or behavioral signature of human beings, is being utilized for identity access management [1].

*Email: Matheel_74@yahoo.com

Identifying the uniqueness of a person from a database of well-known individuals is the focus of face recognition. Face Recognition will manage limitless unpretending systems like access control for airport security, smart environments at home, buildings and vehicles like monitoring and surveillance for building and car, and for intelligent human computer interaction and perception interfaces. In the near past, face recognition has instituted a widespread application fields, from authentication and identification to the interaction and communication of the human and computer devices through face based video applications [2].

The standing face recognition algorithms are commonly categorized into three groups depending on the nature of features applied [3]:

1. Holistic methods: These techniques symbolize the whole facial area as a high-dimensional vector which will be an input to a classifier. It is retain the global (universal) trait of a face. Principle Component Analysis (PCA) is an operative method for holistic face recognition method [4], Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) also are popular and effective holistic methods.

2. Local methods: These techniques express local traits from facial areas, such as the eyes, mouth, nose and cheeks, and then use these traits to classify faces. Template matching methodology [5] provides a worthy matching accuracy. As well as a geometric-based method, which the distances between manually located traits are used [6], is another popular local method.

3. Hybrid methods: In these techniques, both the holistic and local traits are used to recognize and identify a face. A method motivated by the human recognition manner that employ both holistic and local features providing work for a dual stage holistic (PCA) and local feature-based recognition (Gabor Wavelet) algorithms is invoked in [3].

The main gain of biometric features is their immunity from stealing, losing and damaging. As well as these features have no reliability on the memory of their owners. Among physical biometrics, face has the most attractiveness due to its tendency to not encroach the privacy with great amount of security. Furthermore, unlike iris or finger-print recognition, face recognition dose not have need of high precision devices and user contract, when the image is picked up, which estimate face recognition plain more widely held for video surveillance [1].

2. Principle Component Analysis (PCA)

PCA is a dimensionality reduction performance method that is making the most of compression and recognition difficulties. It is also known as eigenspace projection or Karhunen-Loeve transformation.[7] The chief knowledge of the principal component is to catch the vectors that best description for the distribution of face images contained by the entire image regions. These vectors satisfy the eigenvectors of the covariance matrix consistent with the original face images, and because they are face like in presence [8].

Fundamentally, eigenface is the eigenvector acquired from PCA. In face recognition, each training image is converted into a vector by series of connected rows. The covariance matrix is assembled from a prepared set of training images [9]. This is the idea which is proposed and developed by Turk and Pentland [4] for face recognition system using PCA.

Using the PCA technique, the feature vectors for facial image can be found as follows [10]:

(i) Assume having N face images of$(m \times m)$. The images are symbolized in column vectors with $(m^2 \times 1)$ dimension as the symbols $\Gamma_1, \Gamma_2, \ldots, \Gamma_N$. Then the mean face image(Ψ) is calculated from the vectors by

$$\boldsymbol{\Psi} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{\Gamma_i} \quad \textbf{(1)}$$

(ii) Next to the mean face image calculation, the distance of each face image to the mean face image is calculated as $\Phi_i$column vector,

$$\boldsymbol{\Phi_i} = (\boldsymbol{\Gamma_i} - \boldsymbol{\Psi}) \quad \textbf{(2)}$$

(iii) The Φ_i column vectors are assembled to form the matrix $D = [\Phi_1, \Phi_2, \ldots, \Phi_N]$ its dimension is $(m^2 \times N)$ then the covariance matrix C is molded as,

$$\boldsymbol{C} = \boldsymbol{D}.\boldsymbol{D^T} \quad \textbf{(3)}$$

Where D^T is D transport.

An enormous computational complexity is grounded by the calculation of the covariance matrix C of m^2 eigenvalues and m^2 eigenvectors. To moderate this complexity as stated in [4] the dimension $(N \times N)$ is chosen for the covariance matrix C as,

$$\boldsymbol{C = D^T . D} \quad \textbf{(4)}$$

(iv) Then the eigenface space is calculated from N eigenvalues (λ_K)and N eigenvectors (υ_K) of C. $V = [\upsilon_1, \upsilon_2, \dots, \upsilon_N]$ denotes a matrix counting eigenvectors of C with dimension of$(N \times N)$. Eigenface space $U = [u_1, u_2, \dots, u_N]^T$ is obtained by,

$$\boldsymbol{U = V . D^T} \quad \textbf{(5)}$$

Each row of U represents the ‘‘eigenfaces” of each face image in the training set. The face images that have greater eigenvalues have more influence to the eigenface space. This is the reason that the system tends to sort the eigenvector for the face images in a descending order and chosen the first Z eigenvector to produce a smaller eigenface space that accomplish a low computational capability system.

(v) Obtain the matrix $W = [w_1, w_2, \dots, w_N]$ in $(N \times N)$ dimension, which contains N columns each is equivalent to a face image in the training set. Each column vector is known as ‘‘feature vectors” and they symbolize the image’s specific traits. W is obtained by,

$$\boldsymbol{W = U . D} \quad \textbf{(6)}$$

Now, after the training complete and eigenface space and feature vectors are gained, testing can be down for any test face image by comparing the test image with the faces in the training set. This is achieved by next steps [10]:

(a) Γ_T is the column vector that represents the face tested image in dimension $(m^2 \times 1)$. So the column vector Φ_T is obtained to represent the distance of the face tested image from the mean face image by,

$$\boldsymbol{\Phi_T = (\Gamma_T - \Psi)} \quad \textbf{(7)}$$

(b) After the distance Φ_T is calculated, it is projected to the eigenface space so that to obtain the feature column vectors w_T in dimension $(N \times 1)$for the face image by,

$$\boldsymbol{w_T = U . \Phi_T} \quad \textbf{(8)}$$

(c) Finally the matching of the face testing image to the images in the training set; Similarity of w_T to each $w_i$in matrix W is needed to be calculated. A number of classifiers and classification techniques can be used in this step.

However, in spite of PCA's popularity, it suffers from large computational load [9].

3. Discrete Wavelet Transform (DWT)

Generally face recognition system, involves two main modules, a feature extraction module and a classification module. The accuracy of the system is influenced hardly by features extracted to characterize the face images and classification methods used to differentiate among the faces. The aim of feature extraction is to supply valuable information which professionally embodies the face images devoid of redundancy. At the same time, it can significantly reduce the dimensionality of the involved image representation [11].

The DWT decomposes a signal into a set of elementary functions called wavelets; decomposition is distinct as the “resolution” of a signal. The DWT then executes a multi-resolution analysis of a signal with responsiveness in frequency and time domains. DWT can be mathematically illustrated as follows:

$$\boldsymbol{DWT_{x(n)}} = \begin{cases} \boldsymbol{d_{j,k} = \sum x(n) h_j^*(n - 2^j k)} \\ \boldsymbol{a_{j,k} = \sum x(n) g_j^*(n - 2^j k)} \end{cases} \quad \textbf{(9)}$$

Where coefficients $d_{j,k}$, $a_{j,k}$ mention to the detail components and the approximation components respectively in the signal $x(n)$. The parameters j and k state to the scale of the wavelet and the factor of translation respectively. The functions $h(n)$ and $g(n)$ exemplify the coefficients of the high-pass filter and low-pass filters in that order [7].

The DWT has a gigantic amount of implementations in mathematics, engineering and science. It is used in the most cases in signal coding for representing the discrete signal in the more redundant form for data compression. Practical and useful applications can also be bringing into being in signal processing for stepping up to signal analysis, in communications and voluminous others. DWT as it is known is efficaciously applied in many cases like analog filter in biomedical signal processing and in Ultra-Wideband (UWB) wireless communication [2].

In mathematics, the Haar wavelet is a confident arrangement of rescaled "square-shaped" functions which composed together a wavelet family or basis [12]. Haar wavelet is simple and fast. It is memory efficient, that it can be computed in place without temporary array [13]. Haar wavelet is defined by the formula [2]:

$$\boldsymbol{\Psi(t)} = \begin{cases} \mathbf{1} & \boldsymbol{for\ t\epsilon[0,\frac{1}{2}]} \\ \mathbf{-1} & \boldsymbol{for\ t \in [\frac{1}{2},1]} \\ \mathbf{0} & \boldsymbol{otherwize} \end{cases} \quad \textbf{(10)}$$

4. Algorithmic Complexity

Algorithmic complexity is concerned about how fast or slow particular algorithm performs. The goal of computational complexity is to classify algorithms according to their performances. The "big-O" notation expresses an algorithm runtime complexity. It defines the upper bound of a function. Its most common types can be Constant time O(1) if it requires the same amount of time regardless of the input size, Linear time O(n) if its time execution is directly proportional to the input size, i.e. time grows linearly as input size increases, or Quadratic Time $O(n^2)$ if its time execution is proportional to the square of the input size.

To describe lower bounds the big-omega notation Ω is used. The big Theta notation Θ is used to find upper and lower bounds. [14]

5. The Proposed algorithm for face recognition

A combination method for face recognition system is suggested using statistical and frequency domain approaches depending on wavelet transform and PCA. First of all the face image is compressed by DWT then classified the compressed face by PCA.

Minimum Euclidian distance is used as a classifier. Figure-1 and Figure-2 represent the flowcharts for both the training phase and testing phase respectively.

In this paper, the Eigen vectors are sorted and eliminate which has a corresponding Eigen value less than $1 \times e^{-4}$ to reduce the Eigen face space.

The threshold value is selected by studying the system to be low False Acceptance Rate FAR. This is due to the tendency of the work to be suitable for security and access control systems. FAR is the percentage of incorrect input to be accepted incorrectly, and False Rejection Rate FRR is the percentage of correct input be rejected incorrectly. FAR and FRR are the most common performance measures for biometric recognition systems [15]. The tradeoff between FAR and FRR depends on the application sort and usage [4]. As threshold decrease the system becomes more robust.

6. Experimental Results

The software to implement and test the proposed method is Matlab® 2010a. The database FACES94 is used in testing. The database has images of 123 individuals grouped to male, female and male_staff each has 20 image taken while he/she is spoken with a little variation to positon. The image is colored with resolution of 180×200.

Different subsets from the database are used with different number of training images. The system complexity is $O(n^2)$, where n is the data size and the input is two dimensional array, this array is reduced using DWT level by level so the computations of Eigen faces and Eigen values is decreased significantly level by level, the facial image size is 200×180 with the PCA method the Eigen values and Eigen vectors is computed for 36000 values which is a high computational complexity. Using the approximation compressed values by DWT level by level reaching to level 5 the facial values will be 7×6 which means that the Eigen value and Eigen vectors is computes for 42 values only. The Reduction details is shown in table 1 with the time needed to compute the Eigen faces for each level and the recognition rate that reach to 100% in level 3 decomposition. Although the time is decreased significantly in level 5 decomposition. The results above obtained from 10 individuals each has 10 images and tested by 60 different images.

Figure-3 shows the mean image in different levels. It is clear that as level increased the image become chopped in appearance and smaller but has the most concentrate information for the trained faces.

Figure-5 shows the Euclidean distance for the tested facial image in Figure-4 with the Eigen faces generated at different decomposition level of DWT as well as to the PCA only method.

Y-axis represents the Euclidean distance with the x-axis that represents the Eigen faces. The observation of Figure-5 shows that the distance is decreased in number level by level and become more discriminatory to the classes. This is due to the accuracy of the trained data which is extremely extracted by the hybrid method proposed.

Figure-6 shows the correctly recognition for tested facial image in Figure-6a which has a closed eyes and soft smile.

Figure-7 shows the correctly recognition of the rejection of an unauthorized individual shown in Figure-7a.

The threshold value is small enough to enforce the system to reject unauthorized individuals. Authorized individuals with strong shifting or rotation facial images i.e. uncomplete face is rejected. By trail and observation and as observed in the examples in Figure-5, Figur-6 and Figure-7 that the threshold value depending on the Euclidean distance as a similarity measure and for level 5 DWT method that value of 100 is an appropriate value to reject any doubtful face.

Table 1- data size and training time for different levels of Decomposing

	Data size	Time to compute the Eigen faces	Recognition Rate
Original Image	200X180	≅ 30.02 sec.	98%
After level 1 DWT	100X90	≅ 12.01 sec.	98.8%
After level 2 DWT	50X45	≅ 10.3 sec.	98.8%
After level 3 DWT	25X23	≅ 9.87 sec.	100%
After level 4 DWT	13X12	≅ 9.07 sec.	100%
After level 5 DWT	7X6	≅ 2.89 sec.	100%

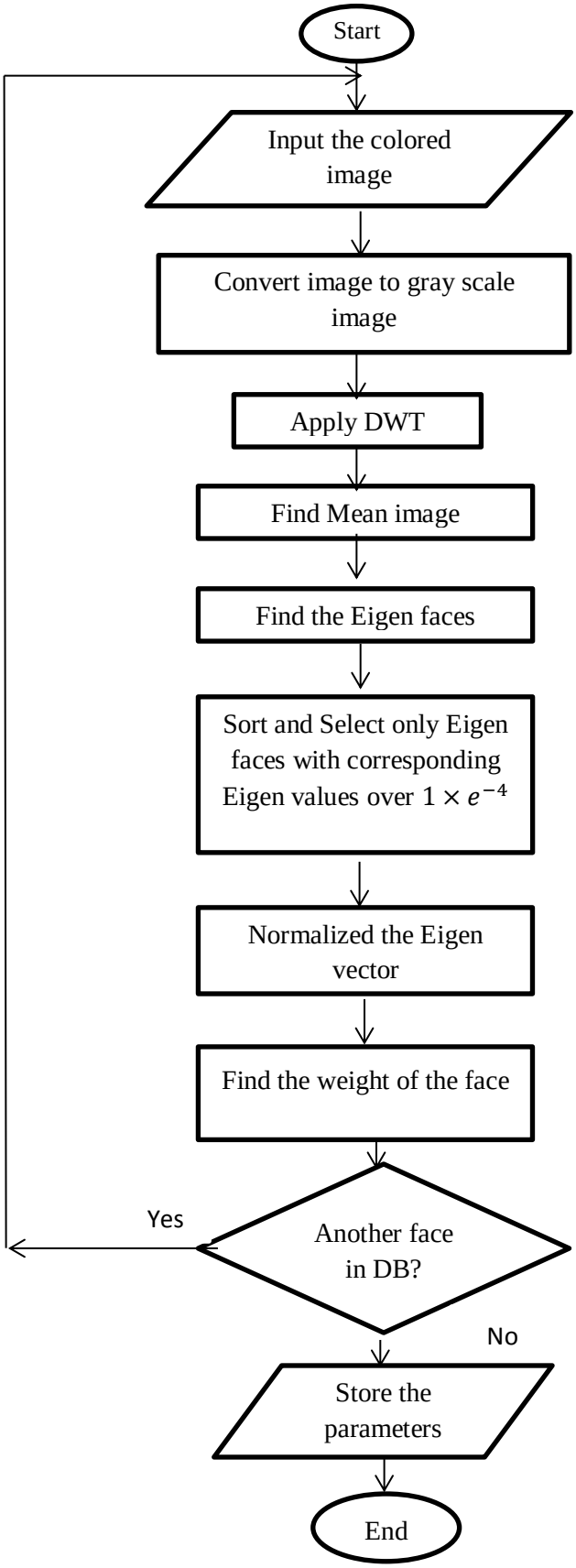

Figure 1- Training phase flowchart

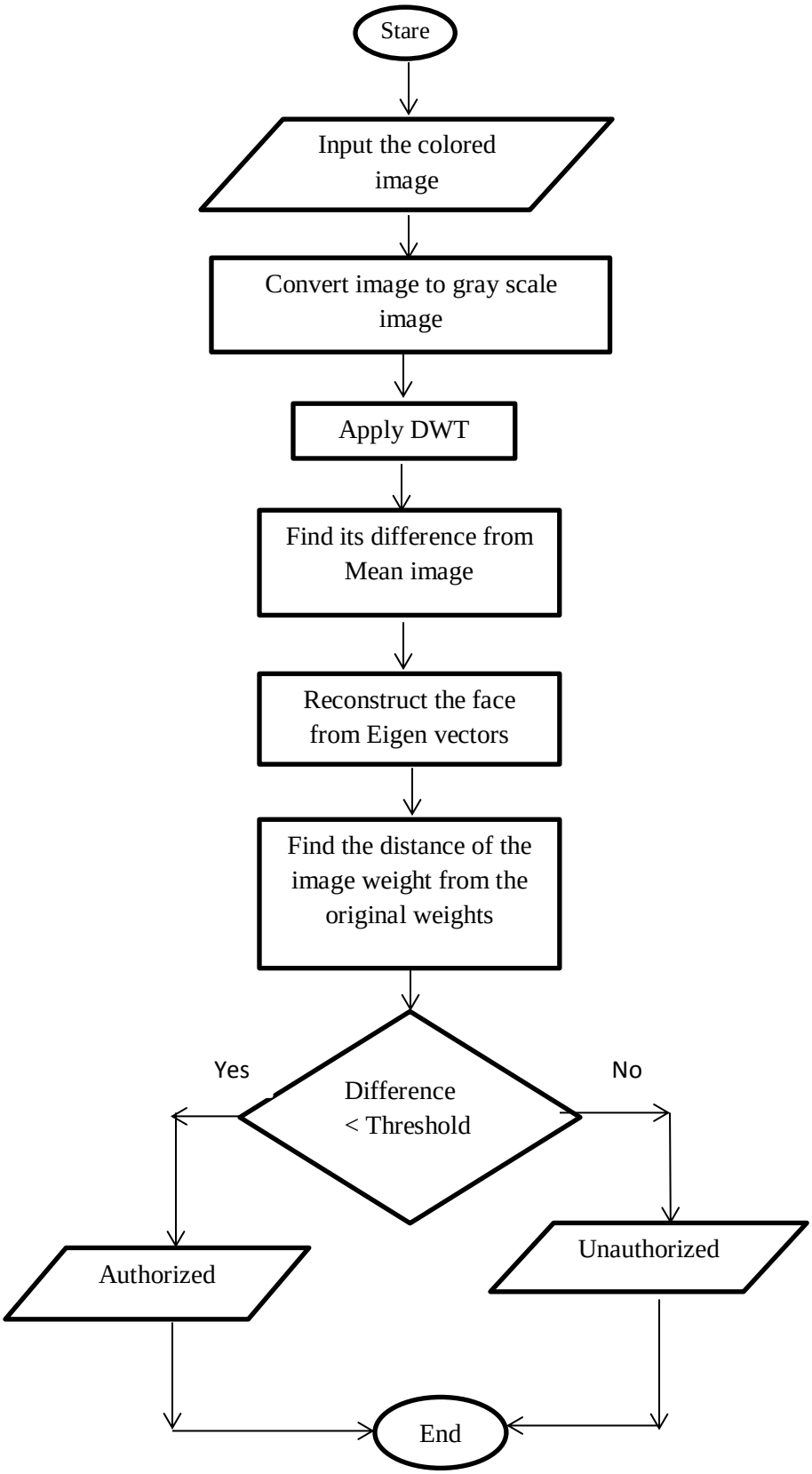

Figure 2- Testing phase flowchart

Figure 3-a Mean image for PCA only method with 10 classes 10 training images

Figure 3-b Mean image for PCA with level 1 DWT method with 10 classes 10 training images

Figure 3-c Mean image for PCA with level 2 DWT method with 10 classes 10 training images

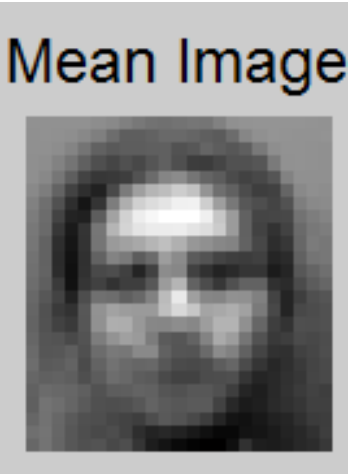

Figure 3-d Mean image for PCA with level 3 DWT method with 10 classes 10 training images

Figure 3-e Mean image for PCA with level 4 DWT method with 10 classes 10 training images

Figure 3-f Mean image for PCA with level 5 DWT method with 10 classes 10 training images

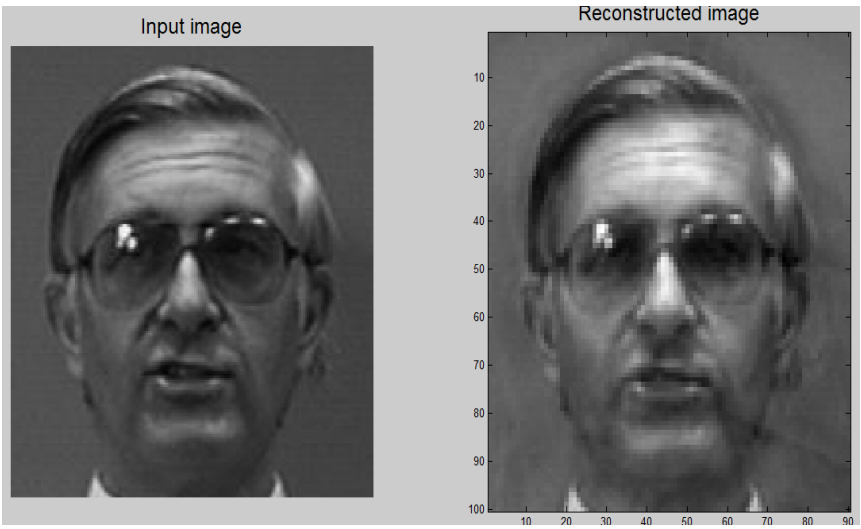

Figure 4- An input tested image with the reconstructed image obtained with level 1 DWT (choppy).

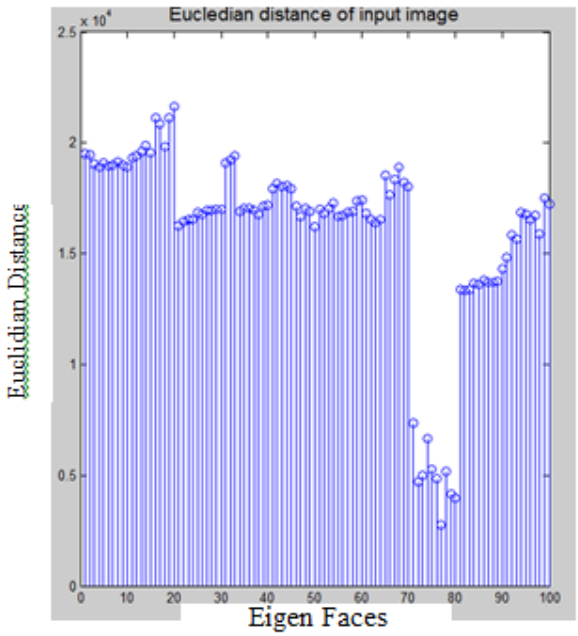

Figure 5-a Euclidean distance of the testing image with Eigen faces of PCA only method

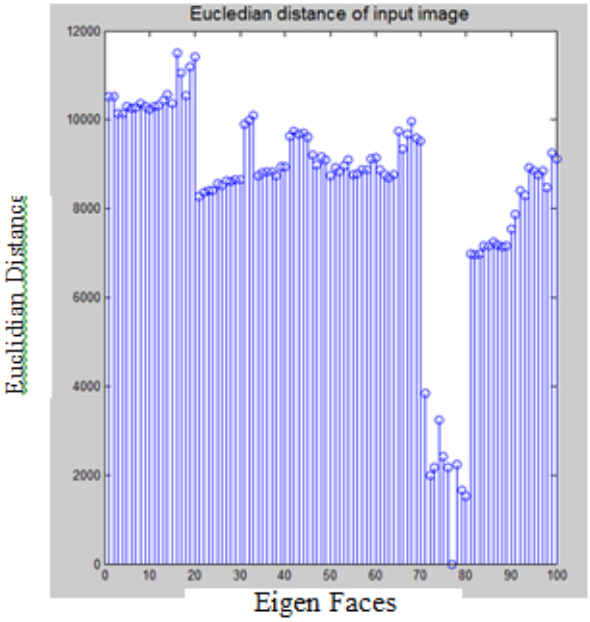

Figure 5-b Euclidean distance of the testing image with Eigen faces of PCA with level 1 DWT method

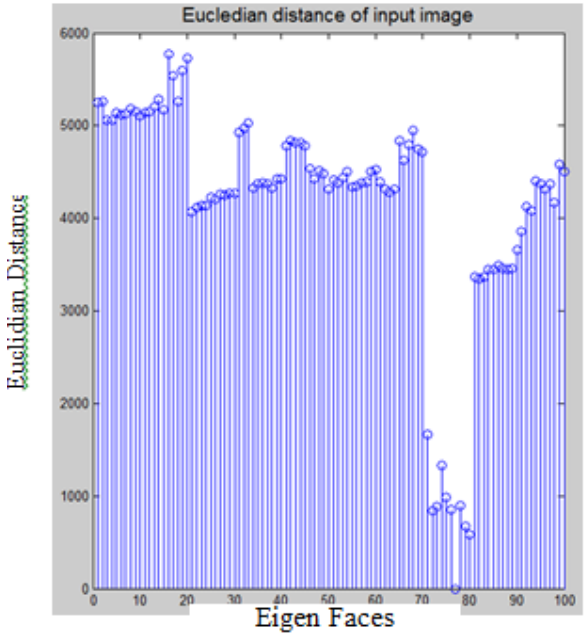

Figure 5-c Euclidean distance of the testing image with Eigen faces of PCA with level 2 DWT method.

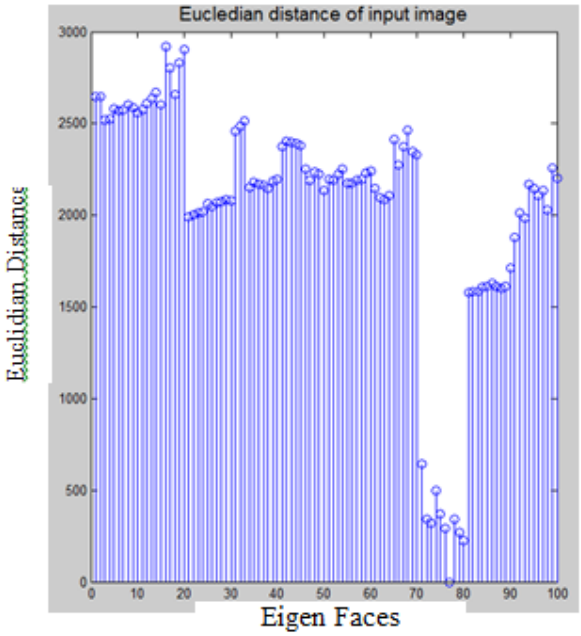

Figure 5-d Euclidean distance of the testing image with Eigen faces of PCA with level 3 DWT method

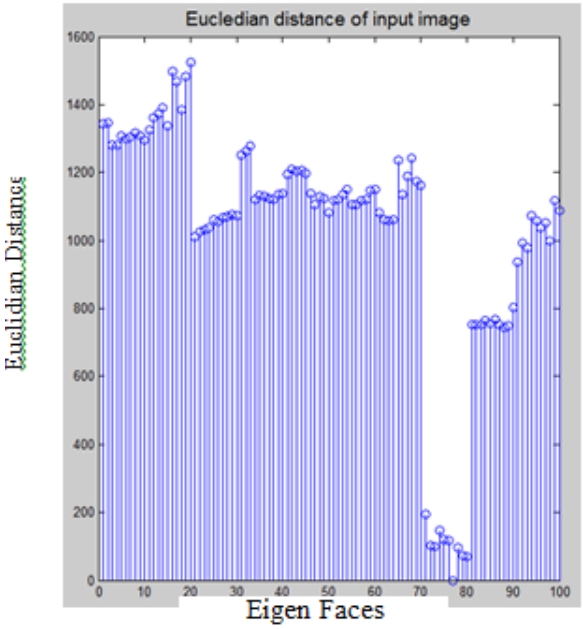

Figure 5-e Euclidean distance of the testing image with Eigen faces of PCA with level 4 DWT method

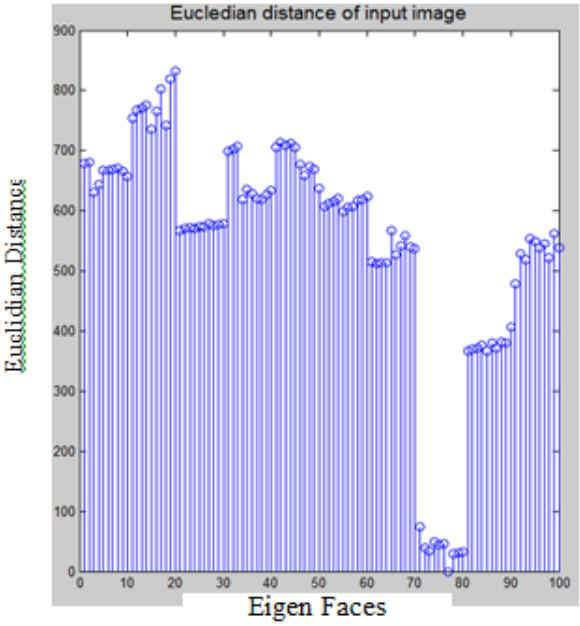

Figure 5-f Euclidean distance of the testing image with Eigen faces of PCA with level 5 DWT method

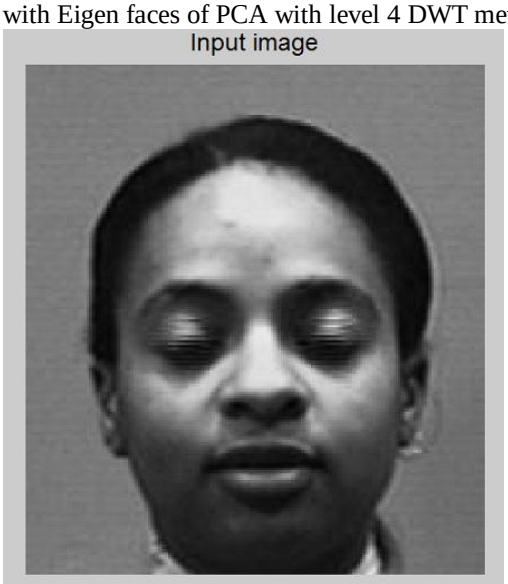

Figure 6-a input tested facial image of authorized individual

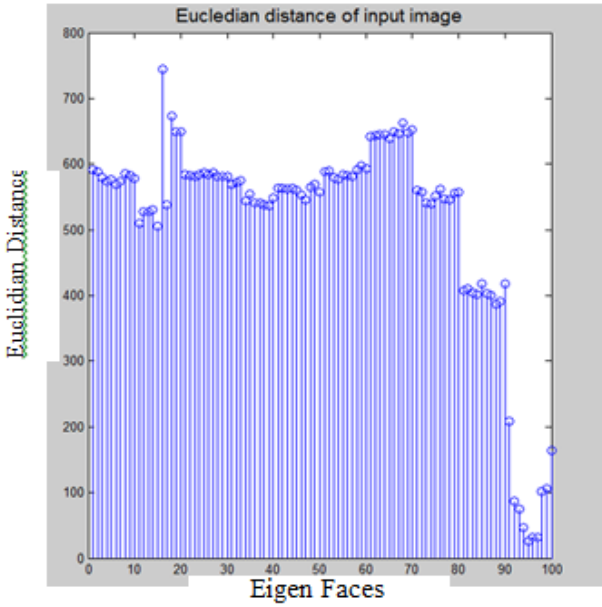

Figure 6-b Euclidean distance of the testing image in a with Eigen faces of PCA with level 5 DWT method

Figure 7-a input tested facial image of unauthorized individual

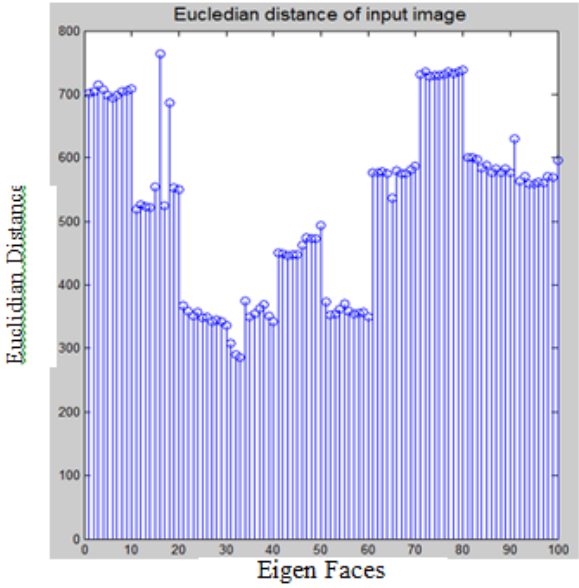

Figure 7-b Euclidean distance of the testing image in a with Eigen faces of PCA with level 5 DWT method

This paper has presented face recognition technique that uses DWT and PCA as a compression and recognition method. The experiments show that as the number of training images increased, the accuracy is increased. When the number of training images for less than 5 classes the accuracy reaches to 90%. Raising the number to 10 the accuracy reaches to 100%.

The system is fast with less computational requirements reaches to about 87.5% faster than ordinary PCA method. The speed, low computation and good accuracy reaches to 100% give the method the aptitude to be used with low cost hardware implementations. As well as it is suitable for real time applications and network communication applications including networks with bandwidth and energy limitations challenges and for multimedia network implementations as it reduce useful image data for recognition.

As a future work different transform techniques can be evaluated and developed to strengthen the compression facility and speed up of the system.

References:

1. Imtiaz, H. and Fattah,S. **2011**. A Face Recognition Scheme Using Wavelet based Dominant Features. *Signal & Image Processing: An International Journal (SIPIJ)*, 2(3), pp: 69-80.
2. Jain,S. and Bhati,D. **2013**. Face Recognition Using ANN with Reduce Feature by PCA in Wavelet Domain. *International Journal of Scientific Engineering and Technology*, 2(6), pp: 595-599.
3. Cho, H. Roberts, R. Jung,B. Choi,O. and Moon,S. **2014**. An efficient Hybrid Face Recognition Algorithm Using PCA and Gabor wavelets. *International Journal of Advanced Robotic Systems*.
4. Turk,M. Pentland,A. **1991**. Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, 3(1), pp:71-86.
5. Sharma, S. **2013**. Template Matching Approach for Face Recognition System. *International Journal of Signal Processing Systems*, 1(2), pp: 284-289.
6. Pouli, T. **2007**. Implementation and Comparison of Face Recognition Algorithms. BSc (Hons) Computer Software Theory of the University of Bath. England, UK.
7. Kaur, A. Singh,S. and Taqdir. **2015**. Face Recognition using PCA (Principle Component Analysis) and LDA (Linear Discriminant Analysis) Techniques. *International Journal of Advanced Research in Computer and Communication Engineering*, 4(3), pp:308-310.
8. Aswis,A. Morsy,M. and Abo-Elsoud, M. **2015**. Face Recognition based on PCA and DCT combination technique. *International Journal of Engineering Research & Technology*, 3(6), pp: 1295-1298.
9. Mazloom,M. and Kasei, S. **2005**. Face Recognition using Wavelet, PCA, and Neural Networks. proceeding of the First International conference on Modeling Simulation and Applied Optimization, Sharjah, U.A.E. Feb. 1-3.

10. Gumus, E. Kilic, N. Sertbas, A. and Ucan,O. **2010**. Evaluation of face recognition techniques using PCA, wavelets and SVM. *Expert Systems with Applications*, 37, pp: 6404-6408.

11. Satone, M. and Kharate, G. **2013**. Comparative Study of multiresolution Analysis and Distance Measures for face recognition. *International Journal of Signal Processing Systems*, 1(1), pp: 34-38.

12. Nagil, J. Ahmed, and Nagif, S. **2008**. Pose Invariant Face Recognition using Hybrid DWT-DCT frequency features with Support Vector Machines. Proceeding of the 4th International conference on Information Technology and Multimedia UNITEN, Malaysia. 17th – 19th November, pp: 99-104.

13. Tamboli, S. and Udupi, V. **2013**.Image Compression Using Haar Wavelet Transform. *International Journal of Advanced Research in Computer and Communication Engineering*, 8(2), pp:3166-3170.

14. Cormen, T.H. Leiserson, C.E. Rivest, R.L. and Stein, C. **2001**. *Introduction to algorithms*. McGraw-Hill Book Company.

15. Navaz, S. Dhevisri, T. and Mazumder, P. **2013**. Face Recognition using Principle Component Analysis and Neural Networks. *International Journal of computer Networking, Wireless and Mobile Communications*, 1(3), pp: 245-256.

16. TheDatabase of FACES94, http://cmp.felk.cvut.ci/space lib/faces/faces94.html.