Automatic Identity Verification Using Face Images

Sabry F. Saraya and John F. W. Zaki
Computer & Systems Eng. Dept.
Faculty of Engineering
Mansoura University.

Abstract

This paper presents two types of identity verification systems based on face images. In the first system principle component analysis (PCA) is used for dimensionality reduction and feature extraction whereas in the second system wavelet transform is used for dimensionality reduction and (PCA) for feature extraction. Two types of classifiers, the Euclidean distance and Angle distance, are used with both systems. Comparative study by computer simulation showed that the addition of wavelet transform before (PCA) provides better performance in the case of Euclidean distance classifier. Moreover, the results obtained by (PCA) are in agreement with those reported in literatures.

1. Introduction

The field of face recognition can be divided into two areas: face identification and face verification (also known as authentication). A face verification system verifies the claimed identity based on images of the claimant's face, this is in contrast to an identification of a given person out of a pool of N people.

Verification systems pervade out everyday life, for example, automatic teller machines (ATM) employ simple identity verification where the user is asked to enter their password (known only to the user), after inserting their ATM card; if the password matches the one prescribed to the card, the user is allowed access to their bank account. However, the verification system such as the one used in the ATM only verifies the validity of the combination of a certain possession (in this case the ATM card) and certain knowledge (the password). The ATM card can be lost or stolen, and the password can be compromised. In order to avoid this problem, biometric verification methods have been proposed where the password can be either replaced by, or used in addition to, biometrics [1, 2].

Biometrics being investigated include fingerprints [3], speech [4], signature dynamics [5], and face verification [6]. Face verification has the benefit of being a passive, non-intrusive system for verifying personal identity.

A central issue in face recognition in general and in face verification in particular, is the well-known problem of dimensionality reduction. Face images are highly redundant, since every individual has one mouth, one nose, two eyes and so on. Instead of using n intensity values for an n pixel images, it is generally possible to characterize an image instance by a set of "p" features for "p<< n". The set of face images of the same individual defines a class. The features must be chosen in such a way, that it is possible to identify the right class of a face image based only on those features [7].

In face verification, as in most image processing problems, features are extracted from the images before processing. Working with rough images is not efficient: in face verification, several images of a single person may be dramatically different, because of changes in viewpoint, in color and illumination, or simply because the person's face looks different from day to day. Therefore, extracting relevant features, or discriminant ones, is a must. Nevertheless, one hardly knows in advance which possible features will be discriminant or not. For this reason, one of the

methods often used to extract features in face verification is the principle component analysis (PCA) [8]. Other methods used are the local feature-based methods such as linear discriminant analysis [9] and independent component analysis (ICA) [10].

One method of identifying images is to measure the similarity between images. This may be accomplished using the L1 norm, L2 norm, correlation and Mahalanobis distance measures. The similarity measures can be calculated on the images in their original space or on the images projected into a new space.

2. Face Verification

A face is a surface of three dimensional solid having partially deformable parts. The images obtained from it depend upon pose, illumination conditions and expression. In these respects, face recognition/verification is paradigmatic for machine intelligence systems.

The face modality is very important for real world applications because it has many advantages over other biometric modalities. The most important advantage is that face modality is very well accepted by the users. Also, people use mainly face to identify each others in everyday life. The modality is non-intrusive and contactless, in the sense that there is no need to interfere with a sensor as for other modalities. Verification can be done without disturbing too much the user: the user only needs to be present in front of a camera. Another advantage of face modality is the low sensor costs. A cheap camera like a web-cam easily provides 25 frames/sec. at a resolution of 350×720 pixels.

Given a face image $X \in R^n$, the central task consists of devising a score function S(X) which leads to the best verification performance, that is the lowest False Acceptance Rate (FAR) and False Rejection Rate (FRR). Up to now, the problem of face recognition has received most of the attention from research community. As face verification and recognition have a lot in common, face verification algorithms are very often inspired by recognition algorithms and adapted to take into account of the particularities of the verification problem. Approaches to face recognition/verification are usually divided into two families: local feature based methods and holistic feature based methods.

1- The local feature based methods rely on a feature set small in comparison to the number of pixels in image. The success of these methods relies highly on the accuracy of the feature extraction process which requires good quality images (high resolution, good illumination) and may lack robustness.

2- In holistic or appearance based methods, the face image pixels are used directly as features. Images are seen as elements of a vector space called the image space. Template matching techniques work directly in the image space. The image to be tested is compared to the template using similarity measures. Template matching is quite effective when the images to compare have the same illumination and same pose.

Because of the high dimensionality of the image space and the limited data set sizes, a transform from the image space onto a low dimensional space is often performed with the hope that a decision boundary is easier to find in the low dimensional space. These very successful methods are called subspace methods. Kirby and Sirovitch [11] proposed the use of Karhunen-Loève Transform or principle component analysis (PCA) to represent faces in a low dimensional space. The technique has been applied to face verification by Sadeghi et. al [12].

2-1. Feature Extraction Using PCA

Suppose a face image consists of N pixels, so it can be represented by a vector Γ of dimension N. let $\{\Gamma i, i = 1, 2, 3 \dots M\}$ be the training set of face images. The average face of these M images is given by:

$$\Psi = \frac{1}{M} \sum_{i=1}^{M} \Gamma_i \tag{1}$$

Each face Γ_i differs from the average face Ψ by Φ_i given as:

$$\Phi_i = \Gamma_i - \Psi \qquad (2)$$

A covariance matrix of the training images can be constructed as:

$$C = AA^T \qquad (3)$$

Where $A = [\Phi_1 \ \Phi_2 \ \Phi_3 \ ....\Phi_M]$ are the basis vector of the face space, i.e., the eigenfaces are then the orthogonal eigenvectors of the covariance matrix C.

Finding the eigenvectors of the N×N matrix C is computationally expensive for typical image sizes. Hence, a simplified way of calculation has to be adopted. Since the number of the training images is usually less than the number of pixels in an image, there will be only M-1, instead of N, meaningful eigenvectors. Therefore, the eigenfaces are computed by first finding the eigenvectors, V_i (i=1, 2, 3… M) of the M×M matrix L:

$$L = A^T A \qquad (4)$$

The eigenvectors U_i (i = 1, 2, 3 …M) of the matrix C are then expressed by a linear combination of the difference face images Φ_i (i=1, 2, 3…M), weighted by V_i (i=1, 2, 3 ….M).

$$
\begin{aligned}
U &= [U_1 \ U_2 \ U_{3.......} \ U_M] \\
&= [\Phi_1 \ \Phi_2 \ \Phi_3 \ ....\Phi_M] \ [V_1 \ V_2 \ V_3 \ ....V_M] \\
&= A \cdot V \qquad (5)
\end{aligned}
$$

In practice, a smaller set of M ($M' < M$) eigenfaces is sufficient for face verification. Hence, only M' significant eigenvectors of L, corresponding to the largest M' eigenvalues, are selected for the eigenfaces computation, thus resulting in a further data compression.

2-2. Wavelet Transform

The wavelet transform is probably the most recent solution to overcome the short comings of the Fourier transform. In wavelet analysis a collection of time-frequency representations of the signal, all with different resolutions emerges. Because of this collection of representations we speak of a multi-resolution analysis. Now, let's formulate the wavelet transform (WT) in mathematical language. For a function $f(t)$, the wavelet transform is defined as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int f(t) \Psi^* (\frac{t-b}{a}) dt \qquad (6)$$

Where the mother wavelet function Ψ is defined as:

$$\Psi_{(a,b)}(t) = \frac{1}{\sqrt{a}} \Psi(\frac{t-b}{a}) \quad , \qquad (7)$$

"a" and "b" are scaling and translation parameters respectively. The inverse wavelet transform is given as:

$$f(t) = C_\Psi^{-1} \iint_{a\ b} W(a,b) \Psi(\frac{t-b}{a}) \frac{dadb}{a^2} \qquad (8)$$

To make digital computations possible, the signal is sampled and the continuous WT must be discretized. In discrete WT the function is scaled and translated in discrete steps. This is achieved by modifying the mother wavelet function Ψ as:

$$\Psi_{j,k} = a_o^{j/2} \Psi(a_o^j t - k), \quad j,k \in z \quad , \quad a_o = 2 \qquad (9)$$

Where "j" and "k" are integer scaling and translation factors. The one dimensional (1-D) discrete wavelet transform (DWT) is a repeated filtering processing using quadrature mirror filters, one is a low-pass filter, and the other is a high-pass filter. The output of each filter is decimated, that is, every second value is removed, halving the length of the output. The output of each filter stage is made up of transform coefficients and each filter stage represents a level of the transform. The low-pass result is then transformed by the same process and this is repeated until either the output of a stage is of length 1 or the desired depth of processing has been achieved. The 2-D wavelet transform is simply the application of the 1-D repeatedly to first the horizontal data of

the image, then the vertical data of the image. At the end of each stage, four regions are produced in the result, a High-High region, High-Low region, Low-High region, and a Low-Low region, which is then continually processed as for 1-D wavelet transform. A block diagram of this process is shown in Fig.1.
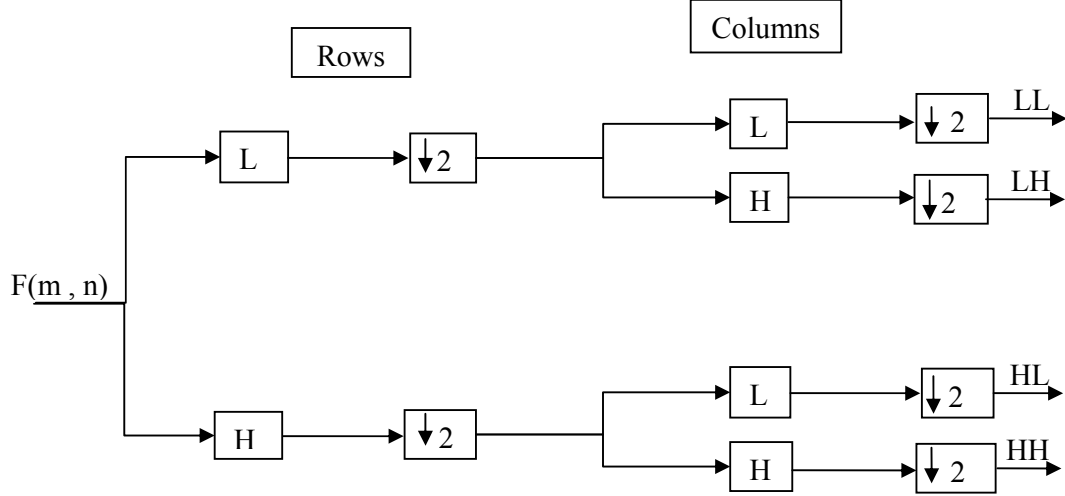

Fig.1. Block diagram for 2-D discrete wavelet transform (L is a low pass filter, H is a high Pass filter) and ↓2 is down sampling by 2

In the experimental work reported here, the face images are one-level wavelet transformed so that the 92×92 pixels image becomes 46×46 pixels image that is one quarter of the original image size.

2-3. Eigenvectors Selection

Up to this point, all eigenvectors associated with non-zero eigenvalues are used in creating the eigenspace. The computation time of eigenspace projection is directly proportional to the number of eigenvectors used to create the eigenspace. Therefore, removing some portion of the eigenvectors, computation time and storage capability are decreased. Furthermore, removing additional eigenvectors that do not contribute to the classification of the image, performance may be improved. Some of the selection methods are now considered.

1- Standard eigenspace projection:
All eigenvectors corresponding to non-zero eigenvalues are used to create the (M-1) subspace.

2- Remove the last 40% of the eigenvectors:
Since the eigenvectors are sorted by the corresponding descending eigenvalues, this method removes the eigenvectors corresponding to the least amount of variance among the images [13]. Specifically, 40% of the eigenvectors that find the least amount of variance are removed.

3- Energy dimension:
Rather than use a standard cutoff for all subspaces, this method uses the minimum number of eigenvectors to guarantee that energy (e) is greater than a certain threshold. A typical threshold is "0.9". The energy of the ith. eigenvector is defined as [14, 15]:

$$e_i = \frac{\sum_{j=1}^{i} \lambda_j}{\sum_{j=1}^{M} \lambda_j} \qquad (10)$$

4- *Stretching dimension:*

Another method of selecting eigenvectors based on the information provided by the eigenvalues is to calculate the stretch "S" of an eigenvector. The stretch of the ith eigenvector is defined as [14]:

$$s_i = \frac{\lambda_i}{\lambda_1} \qquad (11)$$

A common threshold for the stretching dimension is "0.01".

5- *Class eigenvector:*

This method suggests taking the eigenvectors number to be equal to the number of the face classes used during the training process. Each class means a different person with all the images used in training process of that person averaged to obtain only one eigenvector.

2-4. Face Verification Using Distance Measures

The eigenfaces-based face verification procedure is composed of two stages: a training stage and a verification stage. In the training stage, the face of each known individual Γ_k is projected into the face space and an M-dimensional vector

$$\Omega_k = U^T(\Gamma_k - \Psi) \; ; \; K=1,2,\ldots.N_c \qquad (12)$$

Where N_c is the number of face classes.

The face class in the face space is obtained by averaging the projected vectors from the training images of the corresponding individual. A global distance threshold that defines the maximum allowable distance from the face space is set up by computing half the largest distance between any two face classes, that is

$$\theta_c = \frac{1}{2} \max \{ \| \Omega_j - \Omega_k \| \} ; \quad j, k=1, 2, 3, \ldots\ldots N_c \qquad (13)$$

In the verification stage, a new claimant image Γ, is projected into the face space to obtain a vector Ω as

$$\Omega = U^T(\Gamma - \Psi) \qquad (14)$$

The distance of Ω to each face class is defined by

$$E_k = \| \Omega - \Omega_k \|, \, k=1, 2, 3\ldots N_c \qquad (15)$$

The distance is compared with the threshold given in equation (13) and the claimant image is classified by the following rules:
If

$$E_k < \theta_c \qquad (16)$$

Then the claimant is a genuine claimant
If

$$E_k > \theta_c \qquad (17)$$

Then the claimant is an imposter.

Another well known distance classifier is the covariance measure which is also known as the angle measure. It is defined as the angle between two normalized vectors so that it is calculated as the dot product of the normalized vectors [13]. The covariance between images A and B is therefore given as:

$$\text{cov}(A, B) = \frac{A}{\|A\|} \bullet \frac{B}{\|B\|} \qquad (18)$$

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Covariance is a similarity measure. A distance measure may be obtained by using the negative value of the covariance.

3. Error Estimation

In order to assess the performance of an identity verification system, two types of error have to be analyzed

1- An identity claim is rejected although it is genuine. This type of error is referred to as False Rejection (FR).
2- An identity claim is accepted although it is false. This type of error is usually referred to as False Acceptance (FA).

The False Rejection Rate (FRR) and False Acceptance Rate (FAR) should be as low as possible, ideally zero. These two error rates have to be distinguished because the cost incurred by false acceptances may be very different from the false rejection cost. It must be emphasized that there is a trade-off between FAR and FRR by varying the threshold Θ_c one can make one of the rates arbitrarily small while increasing the other. The rate at the operating point leading to equal FAR and FRR is called equal error rate (EER). Because it is a single number for a given identity verification system and dataset, the EER allows a coarse assessment of the identity verification system. An assessment measure also used is called half total error rate given as:

$$HTER = \frac{FAR + FRR}{2} \tag{19}$$

4. Experimental Results

In this work, the ORL (Olivetti Research Laboratory in Cambridge) database is used. In this database, there are 10 different images for each of the 40 distinct subjects. There are variations in facial expression (open/ closed eyes, smiling/ non-smiling), and facial details (glasses/ no glasses). All images were taken against a dark homogeneous background with the subjects in an up-right, frontal position, with tolerance for some tilting and rotation of up to about 20 degrees. The images are in grayscale with a resolution of 92×112 pixels. Some of the images are shown in Fig.2. The images were cropped to 92×92 pixels for convenience of simulation.

Two sets of computer simulation experiment were performed with 8 training images and 2 test images for 36 subjects. The four remaining subjects were used for test only as imposters. In the first simulation experiment set, PCA was applied to the face images directly and the PC features corresponding to the largest eigenvalues were used. Fig.3. shows the 8 eigenfaces corresponding to the largest 8 eigenvectors. The reconstructed images corresponding to Fig. 2 using eigenfaces are shown in Fig.4.

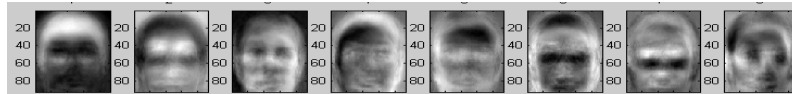**Fig.2.**First 8 images from the ORL database

Fig.3. First 8 eigenfaces corresponding to the largest 8 eigenvalues

Fig.4. Reconstructed faces of the above 8 images using PC.

In the second simulation experiment set, the wavelet transform is applied upon the database images for dimensionality reduction and the PCA was applied to the compressed images. Euclidean distance and angle distance classifiers were used with each set of the simulation experiments mentioned above. In each case, FAR, FRR, HTER were estimated and recorded in Table.1. The results in Table.1 show a comparison between five different values of eigenvectors namely: all eigenvectors, remove last 40% of the eigenvectors, eigenvectors corresponding to 90% energy (minimum energy), stretch i^{th} eigenvectors, and the number of eigenvectors equals the face classes. At the same table, verification results at low resolution (after wavelet) are also shown for the same cases mentioned above.

It can be seen that in the case of Euclidean distance classifier, the FRR decreases as the number of eigenvectors decreases. However, the FAR increases as the number of eigenvectors decrease. This is occurred for PCA and wavelet plus PCA methods. For angle distance classifier the results are reversed. That is, the FAR decreases as the number of eigenvectors decreases and the FRR increase as the number of eigenvectors decreases. In all cases of Euclidean distance, the dimensionality reduction using wavelet before PCA improves the performance in general. However, in the case of angle distance, PCA alone provides better performance than wavelet plus PCA. Note that the results provided by PCA are in agreement with those reported in literatures. However, to the knowledge of the authors, wavelet and PCA have not been seen in the literatures.

Table.1.

			FAR	FRR	HTER
Euclidean Distance Measure	All Eigenvectors	PCA	0.069	0.0472	0.058125
		Wavelet + PCA	0.05715	0.0444	0.050775
	Removing last 40%	PCA	0.0808	0.0389	0.05987
		Wavelet + PCA	0.0675	0.0389	0.0532
	Minimum Energy	PCA	0.101	0.0167	0.059
		Wavelet + PCA	0.09475	0.0139	0.0543
	Stretch ith Vector	PCA	0.1252	0.0056	0.0654
		Wavelet + PCA	0.1252	0.0111	0.060975
	Eigenvectors equal face classes	PCA	0.1432	0.0056	0.0744
		Wavelet + PCA	0.14555	0.0	0.072775
Angle Distance Measure	All Eigenvectors	PCA	0.0044277	0.3222	0.1633
		Wavelet + PCA	0.0007	0.3333	0.167
	Removing last 40%	PCA	0.004507	0.2944	0.149453
		Wavelet + PCA	0.00105	0.3111	0.156075
	Minimum Energy	PCA	0.005557	0.2361	0.120828
		Wavelet + PCA	0.001470	0.2722	0.136839
	Stretch ith Vector	PCA	0.00695	0.2139	0.110425
		Wavelet + PCA	0.001829	0.2444	0.1231168
	Eigenvectors equal face classes	PCA	0.00745	0.2194	0.113425
		Wavelet + PCA	0.001908	0.2528	0.12735

5. Conclusion

This paper introduced a new identity verification system based on wavelet transform for dimensionality reduction and PCA for feature extraction. This technique reduced the number of features required for storage significantly and provided better performance than PCA alone. The results showed also that Euclidean distance classifier provides lower FRR whereas the angle distance classifier provides lower FAR. This suggests that one may use a hybrid classifier

consisting of both Euclidean and Angle in succession to improve both FAR and FRR. Experiments on such a system are in progress and the results will be published later.

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