Biometric Identification of an Individual Using Eigenface Method

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Abstract-Authentication is a key challenge to ascertain effectively, in present era. Many techniques have been introduced so far, but most of them fail due to certain shortcomings. Face recognition has bloomed as robust face recognition based technique among other biometric based authentication approaches. This paper aims at effectively recognizing a given face using eigenface and eigenvector method. The proposed work can be used as an effective means of authentication technique to drive real time applications.

Keywords-Authentication, face recognition, eigenvector, eigenface, biometric.

I. INTRODUCTION

Authentication is the most crucial aspect nowadays and it is being accomplished using PIN numbers, user ids, magstripe magnetic cards, etc. However these techniques are susceptible to many liabilities. They can be shared unknowingly or could be forgotten, or they can be assessed either by stealthy monitoring or can get disclosed. Even maintaining same passwords for all the accounts is highly risky. This can be avoided by using different sets of passwords. Nevertheless, this creates an overhead of remembering them. Therefore, all these methods are very prejudicial and alternative methods to tackle these issues are of paramount importance.

Biometric authentication involves uniquely identifying a person which is dependent on the user's physiological or behavioral characteristics. As a result, this technique bestows true user authentication. Physiological aspects used here are iris matching, finger-print, fingergeometry, voice, palms, hand geometry, hand veins, face, etc [1]. Behavioral biometric can be a speech, gait, and keystroke and signature analysis. Such a technique is of great help for illiterates. However, these techniques are prone to errors, i.e. voice matching is vulnerable. Iris verification requires high end devices for data collection and compilation since it is sensitive to bodily motions. In case of hand geometry or finger printing, cracks or bruises on these organs can cause errors in authenticating a person. Signature based authentication can be subjected to modification or forgery. Face recognition on the other hand is a convenient form of biometric authentication involving lesser intricacy both in terms of hardware and software.

During data acquisition in other biometric techniques, the sensor devices get accumulated by germs and impurities and get transmitted among its users. However, face recognition is devoid of this as the camera is placed at a considerably far distance and is not in contact of the user.

Face recognition uses face as an authentication paradigm by matching a given face against an assortment of faces in the database [2]. Faces are complex, multidimensional and meaningful visual stimuli. Face recognition tasks can be grouped into three categories, namely closed-universe face identification, open-universe face identification, and open-universe face verification [3]. Based on the application, the selection of face recognition technique is based. Static images and videos are the two types of inputs given to the face recognition system. Such systems are usually built in two phases: Artifact removal and feature acquisition; and classification of the images.

Face recognition can effectively be used for both verification and identification of an individual. It finds wide applications in seaports, ATMs, security in computer networks [4]; identity verification in passports, reconstruction of the face of the witness [5]; airports, forensics, ecommerce, driver license, missing children, recognition of expression, assessment of behavior, surveillance in CCTVs; gender classification, stress and exhaustion detection in drivers [6] and thus alarm him to drive cautiously, etc.

II. EIGEN METHODS

Face recognition is the technique of identifying a specific fixed face amidst an assortment of faces. The input signals to such model are images. High degree of noise is prevalent in these input signals culminating as a result of variances in poses [7], lighting, appearance, gender, race, goggles, facial hair, cosmetics, changes due to age and health, face occlusions, etc [8]. In spite of these impediments, there exist patterns which serve the purpose of face recognition. The patterns of interest in the face recognition domain are the nose, eyes, mouth, skin color, etc. These are better known as principal components or eigen faces. Principal Component Analysis (PCA) is often used to excavate the above mentioned patterns [9,10,11]. PCA transforms a given image into a set of eigenfaces

(also called Karhunen-Loeve transform). Eigen faces are the characteristic features of an image. Also, the original image can be reconstructed from these eigenfaces. Each eigenface represents only a specific characteristic of the face. The feature may or may not be present in the original image. Reconstructing the original image using eigenfaces requires the building of weighted sum of all eigenfaces. The degree to which the specific feature is inherent in the original image is determined by the weight. PCA is generally used to classify faces based on the distance between feature vectors. Euclidean distance, distance criterion and nearest mean classification are the standard classifiers used in this regard. In [12], an enhanced version of eigenface approach was applied by maximizing the intersubject variation and minimizing the intrasubject variation.

A. A review on the mathematical background of Eigen faces method

Eigen face method uses PCA to determine the eigenvectors of the sample covariance matrix, C

 $C = \sum_{k=1}^{N} (x_k - \mu) (x_k - \mu)^T$, where mean of all face samples is given by $\mu = \frac{1}{N} \sum_{k=1}^{N} x_k$.

Let A denote $(x_k-\mu)$, where k=1,..., N. Then C can be represented as,

$$C = AA^{T}$$
.

The first n eigen vectors μ_i , i=1,..., n. corresponding to the nth largest eigenvalues are forming the eigenspace $U=\{u_1,\ldots,u_n\}$ in the standard eigenface approach.

Each face differs from the average by a vector,

 $r_i = x_i - m$

If v is a nonzero vector and λ is a number such that

 $Av = \lambda v$, then v is said to be an *eigenvector* of A with *eigenvalue* λ .

Consider the eigenvectors v_i of $A^T A$ such that

 $A^{\mathrm{T}}A\mathbf{v}_{\mathrm{i}} = \boldsymbol{\mu}_{\mathrm{i}}\mathbf{v}_{\mathrm{i}}$

Premultiplying both sides by A, we have

$$AA^{\mathrm{T}}(A\mathbf{v}_{\mathrm{i}}) = \mu_{\mathrm{i}}(A\mathbf{v}_{\mathrm{i}})$$

The eigenvectors of the covariance matrix are

$$\mathbf{u}_i = A \mathbf{v}_i$$

u_i resemble facial images which look ghostly, hence called Eigenfaces. A face image can be projected into this face space by

$$p_k = U^1(x_k - m)$$
 where k=1,...,m

The test image x is projected into the face space to obtain a vector p:

 $p = U^{T}(x - m)$ The distance of p to each face class is defined by

$$\mathbb{E}_{k}^{2} = ||\mathbf{p} - \mathbf{p}_{k}||^{2}; k = 1,...,m$$

A distance threshold Θ_{c} , is half the largest distance between any two face images:

$$\Theta_{c} = \frac{1}{2} \max_{j,k} \{ \|p_{j} - p_{k}\| \}; j,k = 1,...,m$$

Find the distance ε between the original image x and its reconstructed image from the eigenface space, x_f,

$$C^{2} = || x - x_{f} ||^{2}$$
, where $x_{f} = U * x + m$

Recognition process: IF $\in \geq \Theta_c$ then input image is not a face image; then input image contains an unknown face; IF $\in \Theta_c$ AND $\in_k = \min_k \{ \in_k \} < \Theta_c$ then input image contains the face of individual k.

B. Advancements in PCA based approaches

Many inclusions have been deployed to foster the PCA approach, they are; symmetrical PCA [13], multi-linear subspace analysis [14], eigen bands [15], weighted modular PCA [16], two-dimensional PCA [17,18], diagonal PCA [19] and kernel PCA [20,21] and adaptively weighted subpattern PCA [22].

III. IMPLEMENTATION AND METHODOLOGY

The usage of eigenvectors and eigenfaces to recognize faces is explained through the following steps: 1) Initialization: Acquire the training set and calculate eigenfaces (using PCA projections) which define eigenspace. 2) Calculate the weight of the new face encountered. 3) Find out whether the image is a face. 4) If yes, classify the weight pattern as known or unknown. 5) If the same unknown face is seen several times, incorporate it into known faces.

The software used to develop the program was Matlab(2011) 7.13 run on a 64-bit machine. Two databases of faces were maintained, training database and the other, test database. The user was provided with a provision to select the image to test for authentication. After reading the images, it was converted from 2D to 1D array. Euclidean distances between various geometric points on the face were calculated which forms the core parameter in identification schemata. Then a near match face was displayed from the training database.

A. Details of the face database

The AR Face Database was used exclusively in this study [23]. The face database was created by Aleix Martinez and Robert Benavente in the Computer Vision Center (CVC) at the U.A.B. It contains over 4,000 images corresponding to 126 people's faces (70 men and 56 women). Images feature frontal view faces with different facial expressions, illumination conditions, and occlusions (sun glasses and scarf). The pictures were taken at the CVC under strictly controlled conditions. No restrictions on wear (clothes, glasses, etc.), make-up, hair style, etc. were imposed to participants. Each person participated in two sessions, separated by two weeks (14 days) time. The same pictures were taken in both sessions. From these 50 people's faces were considered for experimentation.

The implementation of the proposed method can be summarized using the following flowchart:





IV. RESULTS AND DISCUSSIONS

Figure 2 shows the three faces stored in the training database. The program implementing the proposed technique was tested for correctness by randomly picking an image from the test database. Figure 3 shows the three faces in the test database. Figure 4 a, b shows the results obtained after running the program using second face (from left) from Figure 3 as the testing face. On similar grounds, other images were also tested and it was found that the program could effectively identify a given face for a near match face in the training database. Out of 50 faces, 45 were correctly recognized; and from 2 non-faces, both were recognized as non-faces. Therefore accuracy gained is (45+2)/(50+2) i.e. 90.38%.



Figure 2 Set of images in the training database.



Figure 3 Set of images in the testing database.



Nearly Matching With Face



Figure 4a. Test image Figure

4b. Nearly matching face

V. CONCLUSION

A PCA based face recognition program was developed using eigenvector and eigenfaces scheme. The proposed technique was capable of effectively removing the artifacts from the face under test and matching it correctly with the one in the database.

VI. FUTURE SCOPE

The proposed methodology can be enhanced as per the type of applications so as to enable it to run in real world applications. Images other than the ones used from the standard database must be used to make the technique more robust and increase the accuracy.

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