ISSN 2320-9984

Volume 2 Issue 2 | June 2014 ISSN: 2320-9984 (Online)

International Journal of Modern Engineering & Management Research

Website: www.ijmemr.org

Performance Analysis of Principal Component Analysis Face Detection Algorithm

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Abstract:— *Recently face recognition is attracting much attention in the society of network multimedia information access. Areas such as network security, content indexing and retrieval, and video compression benefits from face recognition technology because "people" are the center of attention in a lot of video. Network access control via face recognition not only makes hackers virtually impossible to steal one's "password", but also increases the user-friendliness in human-computer interaction. Indexing and/or retrieving video data based on the appearances of particular persons will be useful for users such as news reporters, political scientists, and moviegoers. For the applications of videophone and teleconferencing, the assistance of face recognition also provides a more efficient coding scheme. In this paper, an introductory course of this new information processing technology is being discussed. The Principal Component Analysis face recognition algorithms, is explained in detail.*

Keywords:—*Face Recognition; Biometric Identification; Network Security and Surveillance, Principal Component Analysis.*

1. INTRODUCTION

In today's networked world, the need to maintain the security of information or physical property is becoming both increasingly important and increasingly difficult. From time to time we hear about the crimes of credit card fraud, computer breakin's by hackers, or security breaches in a company or government building. In the year 1998, sophisticated cyber crooks caused well over US $100 million in losses (Reuters, 1999).

In most of these crimes, the criminals were taking advantage of a fundamental flaw in the conventional access control systems: the systems do not grant access by "who we are", but by" what we have", such as ID cards, keys, passwords, PIN numbers, or mother's maiden name. None of these means are really define us.

Rather, they merely are means to authenticate us. It goes without saying that if someone steals, duplicates, or acquires these identity means, he or she will be able to access our data or our personal property any time they want. Recently, technology became available to allow verification of "true" individual identity. This technology is based in a field called "biometrics". Biometric access controls are automated methods of verifying or recognizing the identity of a living person on the basis of some physiological characteristics, such as fingerprints or facial features, or some aspects of the person's behavior, like his/her handwriting style or keystroke patterns. Since biometric systems identify a person by biological characteristics, they are difficult to forge.

Among the various biometric ID methods, the physiological methods (fingerprint, face, DNA) are more stable than methods in behavioral category (keystroke, voice print). The reason is that physiological features are often non-alterable except by severe injury. The behavioral patterns, on the other hand, may fluctuate due to stress, fatigue, or illness. However, behavioral IDs have the advantage of being non intrusiveness. People are more comfortable signing their names or speaking to a microphone than placing their eyes before a scanner or giving a drop of blood for DNA sequencing. Face recognition is one of the few biometric methods that possess the merits of both high accuracy and low intrusiveness. It has the accuracy of a physiological approach without being intrusive. For this reason, since the early 70's (Kelly,1970), face recognition has drawn the attention of researchers in fields from security, psychology, and image processing, to computer vision. Numerous algorithms have been proposed for face recognition since then.

While network security and access control are it most widely discussed applications, face recognition has also proven useful in other multimedia information processing areas. Chan et al. (1998) use faces recognition techniques to browse video database to find out shots of particular people. Li et al.(1993) code the face images with a compact parameterized facial model for low-bandwidth communication applications such as videophone and teleconferencing.

Recently, as the technology has matured, commercial products (such as Miros' True Face (1999) and Visionics' Face It (1999) have appeared on the market. Despite the commercial success of those face recognition products, a few research issues remain to be explored.

2. PRINCIPAL COMPONENT ANALYSIS

The Principal Component Analysis (PCA) is one of the most successful techniques that havebeen used in image recognition and compression. PCA is a statistical method under the broad title of *factor analysis*. The purpose of PCA is to reduce the large dimensionality of the data space (observed variables) to the smaller intrinsic dimensionality of feature space (independent variables), which are needed to describe the data economically. This is the case when there is a strong correlation between observed variables.

The jobs which PCA can do are prediction, redundancy removal, feature extraction, data compression, etc. Because PCA is a classical technique which can do something in the linear domain, applications having linear models are suitable, such as signal processing, image processing, system and control theory, communications, etc.

Face recognition has many applicable areas. Moreover, it can be categorized into face identification, face classification, or sex determination. The most useful applications contain crowd surveillance, video content indexing, personal identification (ex. driver's license), mug shots matching, entrance security, etc. The main idea of using PCA for face recognition is to express the large 1-Dvector of pixels constructed from 2-D facial image into the compact principal components of the feature space. This can be called eigenspac projection. Eigen space is calculated by identifying the eigenvectors of the covariance matrix derived from a set of facial images (vectors).

3. MATHEMATICS OF PCA

A 2-D facial image can be represented as 1-D vector by concatenating each row (or column) into a long thin vector. Let's suppose we have M vectors of size N (= rows of image £ columns of image) representing a set of sampled images. p_j's represent the pixel values.

The images are mean centered by subtracting the mean image from each image vector. Let m represent the mean image.

$$m = \frac{1}{M}\sum_{i=1}^{M} x_i$$

And let w_i be defined as mean centered image

$$w_i = x_i \text{ ¡ } m$$

Our goal is to find a set of e_i' s which have the largest possible projection onto each of the w_i' s. We wish to find a set of M ortho normal vectors e_i for which the quantity.

$$\lambda_i = \frac{1}{M}\sum_{n=1}^{M}(e_i^T w_n)^2$$

Is maximized with the orthonormality constraint

$$e_l^T e_k = \Delta_{lk}$$

It has been shown that the e_i's and ¸$_i$'s are given by the eigenvectors and eigenvalues of the covariance matrix

$$C = WW^T$$

Where W is a matrix composed of the column vectors w_i placed side by side. The size of C is $N \times N$ which could be enormous. For example, images of size 64 × 64 create the covariance matrix of size 4096 × 4096. It is not practical to solve for the eigenvectors of C directly. A common theorem in linear algebra states that the vectors e_i and scalars ¸$_i$ can be obtained by solving for the eigenvectors and eigenvalues of the $M \times M$ matrix W^TW. Let d_i and ¹$_i$ be the eigenvectors and eigenvalues of W^TW, respectively.

$$W^TWd_i = ¹_i d_i$$

By multiplying left to both sides by W

$$WW^T(Wd_i) = ¹_i(Wd_i)$$

which means that the first M- 1 eigenvectors e_i and eigenvalues ¸$_i$ of WW^T are given by Wd_i and ¹$_i$, respectively. Wd_i needs to be normalized in order to be equal to e_i. Since we only sum up a finite number of image vectors, M, the rank of the covariance matrix cannot exceed M - 1 (The -1 come from the subtraction of the mean vector m).

The eigenvectors corresponding to nonzero eigenvalues of the covariance matrix produce an orthonormal basis for the subspace within which most image data can be represented with a small amount of error. The eigenvectors are sorted from high to low according to their corresponding eigen values. The eigenvector associated with the largest eigenvalue is one that reflects the greatest variance in the image. That is, the smallest eigenvalue is associated with the eigenvector that finds the least variance. They decrease in exponential fashion, meaning that the roughly 90% of the total variance is contained in the first 5% to 10% of the dimensions.

A facial image can be projected onto M'' (<<M) dimensions by computing

$$\Omega = [v_1 v_2 : : : v_{M'}]^T$$

Where vi = $e^T_i w_i$. v_i is the i^{th} coordinate of the facial image in the new space, which came to be the principal component. The vectors e_i are also images, so called, *eigenimages*, or *eigenfaces* in our case, which was first named by. They can be viewed as images and indeed look like faces. So, Ω describes the contribution of each eigenface in representing the facial image by treating the eigenfaces as a basis set for facial images. The simplest method for determining which face class provides the best description of an input facial image is to find the face class k that minimizes the Euclidean distance

$$\epsilon_k = \|\Omega - \Omega_k\|$$

whereΩ_k is a vector describing the kth face class. If ²$_k$ is less than some predefined threshold µ₂, a face is classified as belonging to the class k.

4. FACE RECOGNITION

Once the Eigen faces have been computed, several types of decision can be made depending on the application. What we call face recognition is a broad term which may be further specified to one of following tasks:

- ***Identification*** where the labels of individuals must be obtained,
- ***Recognition*** of a person, where it must be decided if the individual has already been seen,
- ***Categorization*** where the face must be assigned to a certain class.

PCA computes the basis of a space which is represented by its training vectors. These basis vectors, actually eigenvectors, computed by PCA are in the direction of the largest variance of the training vectors. As it has been said earlier, we call them eigenfaces. Each eigenface can be viewed a feature. When a particular face is projected onto the face space, its vector into the face space describes the importance of each of those features in the face. The face is expressed in the face space by its eigenface coefficients (or weights). We can handle a large input vector, facial image, only by taking its small weight vector in the face space. This means that we can reconstruct the original face with some error, since the dimensionality of the image space is much larger than that of face space.

In this manuscript, each face in the training set is trans formed into the face space and its components are stored in memory. The face space has to be populated with these known faces. An input face is given to the system, and then it is projected onto the face space. The system computes its distance from all the stored faces. However, two issues should be carefully considered:

1. What if the image presented to the system is not a face?
2. What if the face presented to the system has not already learned, i.e., not stored as a known face?

The first defect is easily avoided since the first eigenface is a good face filter which can test whether each image is highly correlated with itself. The images with a low correlation can be rejected. Or these two issues are altogether addressed by categorizing following four different regions:

1. Near face space and near stored face =known faces
2. Near face space but not near a known face =unknown faces
3. Distant from face space and near a face class =non-faces
4. Distant from face space and not near a known class =non-faces

Since a face is well represented by the face space, its reconstruction should be similar to the original, hence the reconstruction error will be small. Non-face images will have a large recon struction error which is larger than some threshold μr. The distance ²*k* determines whether the input face is near a known face.

5. IMPLEMENTATION AND RESULT

There is a well-known face database which can be downloadable from the *AT&T Laboratories, Cambridge* at http:// www.uk.research.att.com/facedatabase.html It contains ten different images of each of 40 distinct subjects. For some subjects, the images were taken at different times, varying the lighting, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/ no glasses). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).

To ensure how well the eigenface system can identify each individual's face 12 images are considered. The system has been implemented by MATLAB. 10 subjects are selected as training set and other 2 subjects are the part of test set, which should be classified as unknown faces. There are 5 additional test images, each of which is the known face.

Figure 3 shows the eigenface images which are originally the eigenvectors $e_i$of the ovariance matrix. The first eigenface account for the maximal variation of the training vectors. The 10 original training images and their reconstructed versions are depicted in Figure 1 and 2. The result was very successful given the test images in Figure 4. Every test image was correctly classified. When two unknown faces in Figure 5 are input to the system, the ^{2}'s at Eq. 10 are larger than the predefined threshold. In the case of two non-face images in Figure 5, the reconstruction errors were larger than the reconstruction threshold, then they are not considered as face images. The MATLAB source codes are attached to the appendix in the end of this summary.

Figure-1:- Original Training Images

Figure-2:- Reconstructed images of training images- they are almost same as their original images.

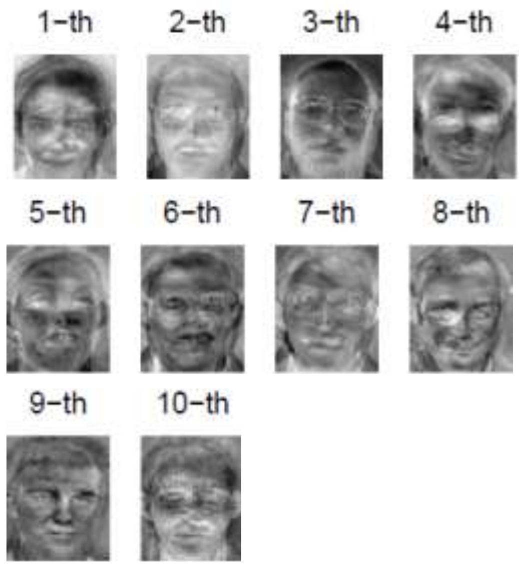

Figure-3:- The first eigenface account for the maximal variation of the training vectors, and the second one accounts for the second maximal variation, etc.

Figure 4: Test images - the number corresponds the order of the set of original training images in Figure 1. r means the reconstructed image.*

*Figure-5:- Unknown face and Non-face images - t11 and t12 are unknown faces. t13 and t14 are non-faces. r** means the reconstructed image*

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