A Different Approach to Appearance –based Statistical Method for Face Recognition Using Median

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Abstract

Different statistical methods for face recognition have been proposed in recent years. They mostly differ in the type of projection and distance measure used. The aim of this paper is to effectively identify a frontal human face with better recognition rate using appearance-based statistical method for Face Recognition. We used Median instead of mean and with different distance measures like city block, Euclidean and Chess board. Our approach produces better recognition rate when more complex images are used. Our experimental result shows that Median with City block distance measure gives better results for face recognition.

Key words: image processing and analysis, face recognition, eigenfaces, principle component analysis, distance measures.

1. Introduction

The face is our primary focus of attention in social intercourse, playing a major role in conveying identity and emotion. Although the
ability to infer intelligence or character from facial appearance is suspect the human ability to recognize thousands of faces at a glance even after years of separation. This skill is quite robust, despite large changes in the visual Stimulus due to viewing conditions, expression, aging, and distractions such as glasses or changes in hairstyle or facial hair. As a consequence the visual processing of human faces has fascinated philosophers and scientists for centuries.

Computational models of face recognition, in particular, are interesting because they can contribute not only to theoretical insights but also to practical applications. Computers that recognize faces could be applied to a wide variety of problems, including criminal identification, security systems, image and film processing, and human-computer interaction.

The scheme is based on an information theory approach that decomposes face images into a small set of characteristic feature images called "eigenfaces", which may be thought of as the principal components of the training set of face images. Recognition is performed by the eigengaces ("face space") and then classifying the face by comparing its position in face space with the position of known individuals. The approach has advantages over other face recognition schemes in its speed and simplicity, insensitivity to small or gradual changes in the face image and performed under different distance measures.

The rest of this paper is organized as follows: Section 2 deals with background and related work, Section 3 deals with appearance-based statistical method for face recognition, Performance evaluation and experimental results presented in Section 4, and conclusion is given in Section 5.

2. Background and related work

Much of the work in computer recognition of faces has focused on detecting Individual features such as the eyes, nose, mouth, and head outline, and defining a face model by the position, size, and relationship among these features. Such approaches have proven difficult to extend to multiple views, and have often been
Quite fragile, requiring a good initial guess to guide them.

Bledsoe [1966a.b] was the first to attempt semi automated face recognition with a hybrid human-computer system that classified faces on the basis of fiducial marks entered on photographs by hand. Parameters for the classification were normalized distances and ratios among points such as eye corners, mouth corners, nose up, and chin point. Later work at Bell Labs (Goldstein, Harmon, & Lesk. 1971) developed a vector of up to 21 features, and recognized faces using standard pattern classification techniques. The chosen features were largely subjective evaluations (e.g. shade of hair, length of ears, lip thickness) made by human subjects, each of which would be quite difficult to automate. An early paper by Fischler and Elschlager (1973) attempted to measure similar features automatically.

Kohonen (1989) and Lahtio (1981) describe an associative network with a simple Learning algorithm that can recognize face images and recall a face image from an incomplete or noisy version input to the network. Fleming and Cottrell (1990) extend these ideas using nonlinear units, training the system by back propagation. Stonham's WISARD system (1986) is a general-purpose pattern recognition device based on neural net principles. It has been applied with some success to binary face images, recognizing both identity and expression.

Others have approached automated face recognition by characterizing a face by a set of geometric parameters and performing pattern recognition based on the parameters (e.g., Kaya & Kobayashi, 1972; Cannon, Jones, Campbell & Morgan, 1986; Craw. Ellis, & Lishman, 1987; Wong. Law, & Tsaug, 1989). Kanade's (1973) face identification system was the first systems in which all steps of the recognition process were automated, using a top-down control strategy directed by a genetic model of expected feature characteristics. His system calculated a set of facial parameters from a single face image and used a pattern classification technique to match the face from a known set, a purely statistical approach depending primarily on local histogram analysis and absolute gray-scale values.

Recent work by Matthew Turk and Alex Pentland (1991a) "Eigenfaces for recognition" based on principal component analysis method [1].

3. Appearance –Based Statistical Method Face Recognition

The task of facial identification is discriminating input image data into several classes (persons). The input signals are highly noisy (e.g. the noise is caused by differing lighting conditions, pose etc.,), yet the input images are not completely random and in spite of their differences there are patterns which occur in any input image data. Such patterns, which can be observed in all images, could be in the domain of facial recognition. The presence of some objects (eyes, nose, mouth) in any face as well as relative distances between these objects. These characteristic features are called eigenfaces in the facial recognition domain (or principal component generally). They can be extracted out of original image data by means of mathematical tool called Principal Component Analysis (PCA) [3].

By means of PCA one can transform each original image of the training set into a corresponding eigenface [12]. An important feature of PCA is that one can reconstruct any original image from the training set by combining the eigenvectors. Each eigenface represents only certain features of the faces, which may or may not be present in the original image. If the feature is present in the original images to a higher degree, the share of the eigenface is the "sum" of the eigenfaces should be greater.

If contrary, the particular feature is not (or almost not) present in the original image, then the corresponding eigenface should contribute a smaller (or not at all) part to the sum of eigenfaces [16]. So, in order to reconstruct the original image from the eigenfaces, one has to build a kind of weighted sum of eigenfaces. That is, the eigenfaces, with each eigenface having a certain weight. This weight specifies, to what degree the specific feature (eigenface) is present in the original image.

If one uses all the eigenfaces extracted from original images, one can reconstruct the original images from the eigenfaces exactly. But one can also use only a part of the eigenfaces. The reconstructed image is an approximation of the original image.(See in Fig.5.) However, one can ensure that losses due to omitting some of the eigenfaces can be minimized. This happens by choosing only the most important features (eigenfaces). Omission of eigenfaces is necessary due to scarcity of computational resources. How does this relate to facial recognition? The clue is that it is possible not only to extract the face from the eigenfaces given a set of weights, but also to go the opposite way. This opposite way would be to extract the weights from eigenfaces and the face to be recognized. These weights tell as the amount by which the face in question differs from "typical" faces represented by the eigenfaces.

This approach to face identification involves the following initialization operations:

1. Acquire an initial set of face images (the training set)
2. Calculate the eigenfaces from the training set, keeping only the M images that Correspond to the highest eigenvalues. These M images define the face space. As new faces are experienced, the eigenfaces can be updated or recalculated.
3. Calculate the corresponding distribution in M-dimensional weight space for each Known individual, by projecting their face images onto the "face space".

Having initialized the system, the following steps are then used to recognize new face images.

a) Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the eigenfaces.
b) Determine if the image is a face at all (whether known or unknown) by checking to see if the image is sufficiently close to "face space".
c) If it is a face, classify the weight pattern as either a known person or as unknown.

3.1. Face Recognition using Median

Let a face image I(x, y) be a two-dimensional N by N array of (8-bit) intensity values. An image may also be considered as a vector of dimension N^2, so that a typical image of size 256 by 256 becomes a vector of dimension 65,536, or, equivalently, a point in 65,536 –dimensional space. Images of faces, being similar in overall configuration will not be randomly distributed. In this huge space and thus can be described by a relatively low dimensional subspace. The main idea of the PCA is to find the vectors that best account for the distribution of face Images within the entire image space [8]. These vectors define the subspace of face images, which we call "face space". Each vector is of length N^2, describes an N by N image, and is a linear combination of the original face images. Because these vectors are the eigenvectors of the covariance matrix corresponding to the original face images, and because they are face like in appearance, we refer to them as eigenfaces. (See in Fig.1.b)

Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$. The median face of the Set is say ψ. Each face differs from the median by the vector
$\Phi i = \Gamma_i - \psi$. An example training set is shown in Figure 1a.with the median face Ψ shown in Figure1b. This set of very large vectors is then subject to principal Component analysis, which seeks a set of M orthonormal vectors u_n, which best describes the distribution of the data. The Kth vector, u_k is chosen such that

$$\lambda_k = 1/M \sum (u_k^T \Phi n)^2 \quad , n = 1, 2\ldots M \qquad (1)$$

is a maximum, subject to

$$u_l^T u_k = \quad \delta = \begin{cases} 1, & \text{if } l = k \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

The vectors u_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix

$$C = 1/M \sum \Phi n \, \Phi n^T , n = 1, 2\ldots M \qquad (3)$$

$$= AA^T$$

Where the matrix $A = \{\Phi_1, \Phi_2, \Phi_3 \ldots \Phi_4\}$. The matrix C however, is N^2 by N^2 and determining the N^2 eigenvectors and eigenvalues is an intractable task for typical image sizes. We need a computationally feasible method to find out these eigenvectors [20].

If the number of data points in the image space is less than the dimensions of the Space ($M< N^2$), there will be only M = 1, rather than N^2, meaningful eigenvectors. (The remaining eigenvectors will have associated eigenvalues of zero). Fortunately we can solve for the N^2 dimensional eigenvectors in the case by first solving for the Eigenvectors of an M by m matrix – e.g., solving 16 x 16 Matrix rather than a 16,384 x 16,384 matrix, and then taking appropriate linear combinations of the face
Image Φ_i. Consider the eigenvector v_i of AA^T such that

$$A^TA\, v_i = \mu_i\, v_i \qquad (4)$$

Pre-multiplying both sides by A, we have

$$A\, A^TA\, v_i = \mu_i A\, v_i \qquad (5)$$

From which we see that Av_i are the eigenvectors of $C = AA^T$

Following this analysis, we constructed the M by M matrix $L = A^TA$, where
$L_{mn} = \Phi m^T \Phi n$, and find the M eigenvectors,
v_i of L. These vectors determine Linear combinations of the M training set of face images to form the eigenfaces u_l

$$U_l = \sum v_{lk}\, \Phi_k , \quad l = 1, 2\ldots M \qquad (6)$$

With this analysis the calculations are greatly reduced from the order of the number of pixels (N^2) to the order of then number of images in the training set (M). In Practice, the training set of face images will be relatively small ($M < N^2$), and the calculations become quite manageable. The associated eigenvectors allow us to rank the eigenvectors according to their usefulness in characterizing the variation among the image. Figure1 (b) shows the top 20 eigenfaces derived from the input images of Figure 1(a).

(a) (b)

Fig.1. (a) Input Training Images (b) Eigen faces

3.2. Using Eigenvectors to Classify a Face Image

The eigenface image calculated from the eigenvectors of L span a basis set with which to describe face images [19]. In practice, a smaller M' is sufficient for identification, since accurate reconstruction of the image is not a requirement. In this framework, identification becomes a pattern recognition task. The eigenfaces span an M'dimensional subspace of the original N^2 image space. The M' significant eigenvectors of the L matrix are chosen as those with the largest associated eigenvalues. In many of our test cases, based on M = 20 face images, M'= 20 eigenfaces were used.

A new face image (Γ) is transformed into its eigenface components (projected into "face space") by a simple operation,

$$w_k = w_k^T(\Gamma - \psi) \qquad (7)$$

for $k = 1, 2,\ldots, M'$.

The weights form a vector $\Omega^T = (w_1, w_2, \ldots, w_{M'})$ that describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images. The simplest method for determining which face class provides the best description of an input face image is to find the face class k that minimizes the Euclidean distance

$$\epsilon_k = \|\Omega - \Omega_k\|^2 \qquad (8)$$

where Ω_k is a vector describing the kth face class. The face classes Ω are calculated by averaging the results of the eigenface representation over a small number of face images of each individual. In our approach we also used Chess board distance measure and City block distance measure. Out of these distance measures city block distance distance provides the accurate, better and effective results than Euclidean distance and Chess board distance results are effective and accurate.

A face is classified as belonging to class k when the minimum ϵ_k is below some chosen threshold $\theta_{\epsilon 1}$ and maximum ϵ_k is below some chosen threshold $\theta_{\epsilon 2}$. Otherwise the face is classified as "unknown", and optionally used to create a new face class.

4. Performance Evaluation and Experimental Results

A Performance Evaluation

Most detection methods require a training data set of face images and the databases originally developed for face recognition experiments can be used as training sets for face detection [4]. We used two face databases. The Yale face database (available at http://cvc.yale.edu/) contains 10 frontal images per person, each with different facial expressions, with and without glasses, and under different lighting conditions [16]. The other face database AT&T(Olivetti) (available at http:/www.uk.research.att.com/facedatabase.html) contains 10 different images and each of 40 distinct subjects of varying the lighting, facial expressions (open/closed eyes, smiling/not smiling) and facial details (glasses/no glasses) [17]. Our approach accepts input training images as BMP or PGM images with all images must have same size. The test image will be BMP or JPG image. The above mentioned databases are designed mainly to measure performance of face recognition methods and, thus, each image contains only one individual. Therefore, such databases can be best utilized as training sets rather than test sets.

B Experimental Results with Eigenfaces

Table 1: Experimental Results on Images from Test Set 1 (16 Images with 160 Faces) and Test Set 2 (40 Images with 400 Faces)

Distance Measures	Test Set 1		Test Set 2	
	Detection Rate		Detection Rate	
	Mean	Median	Mean	Median
Euclidean Distance	89.30%	90.36%	88.23%	90.20%
City Block Distance	90.10%	92.50%	91.41%	92.64%
Chess Board Distance	79.21%	80.10%	78.34%	80.57%

We have used two training sets of faces in our experiments. The first set includes 20 face images (see Fig.1a) and is used to compute the face recognition based on eigenfaces using median with different distance measures. The second set includes 20 face images

We have tested our approach on several frontal face images with variant facial expressions and lighting conditions. From the above table it is evident that city block distance measure works more accurately for face recognition than the other two distance measures. In our approach, the time complexity mainly depends on size of input images. The compilation time of our approach roughly takes 9 seconds for images with size 10 kb

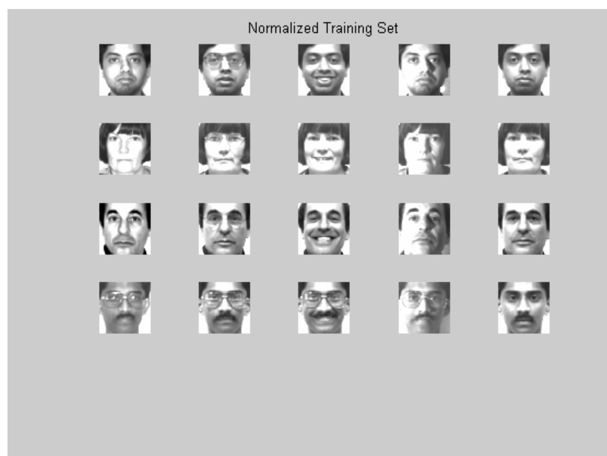

Fig.2. Normalized Training Images

It is evident that (see Fig. 6) the input test face image is not a recognized face by using Euclidean distance and not a face (see Fig. 7)by using Chess board distance measure, and (see Fig. 8) the input test image is a recognized face by using City block distance measure with median..

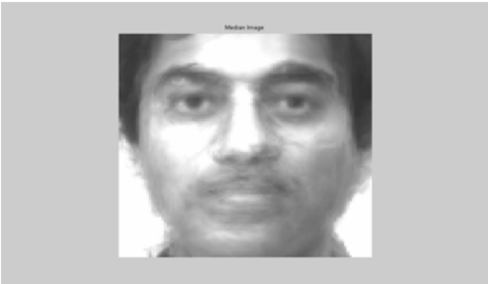

Fig3. Median Image

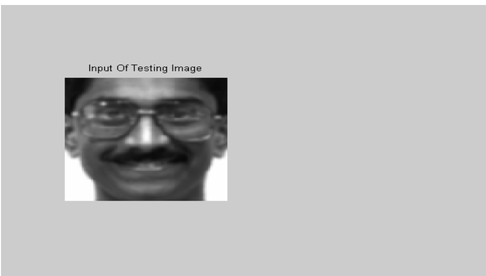

Fig.4. Input of Test Image Image

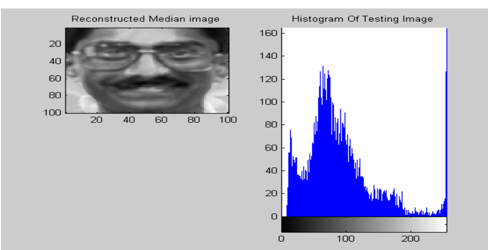

Fig.5. Reconstructed Image and Histogram of test Image

Fig.6. Recognized Face: City Block Distance

Fig.7. Unrecognized Face: Euclidean distance

Fig.8. Not a Face: Chess board distance

5. Conclusions

The Eigenface approach to face recognition was motivated by information theory, leading to the idea of basing face recognition on a small set of image features that best approximates the set of known face images, without requiring that they correspond to our intuitive notions of facial parts and features. Although it is not an elegant solution to the general recognition problem. The eigenface approach does provide practical solution that is well fitted to the problem of face recognition. It is fast, relatively simple, and has been shown to work well in a constrained environment.

It is important to note that many applications of face recognition do not require

Identification, although most require a low false positive rate. In searching a large database of faces, for example, it may be preferable to find a small set of likely matches to present to the user. For applications such as security systems of human-computer interaction, the system will normally be able to “view” the subject for a few seconds or minutes, and thus will have a number of chances to recognize the person. Experimental results shows that our technique is the simplest and effective method for face recognition using Median with various distance measures, and we obtained the best accuracy using City Block distance. Our approach works only for images with same size.

We are currently investigating in more detail about the issues of robustness to changes in lighting, head size, head orientation, various angles of face views and to apply in real-time systems.

References

[1] M.Turk and A.Pentland, "Eigenfaces for recognition", Journal of Cognitive Neuroscience, vol.3, no.1, pp. 71-86, 1991a.

[2] M.Turk and A.Pentland, "Face recognition using eigenfaces", In. Proc. of Computer Vision and Pattern Recognition, pp.586-591, IEEE, June 1991b.

[3] W.Zhao, R. Chellappa, and A. Krishnaswamy, "Discriminant Analysis of Principal Components for Face Recognition", Proc. Third Int'l Conf. Automatic Face and Gesture Recognition, pp. 336-341, 1998.

[4] R. Chellappa, C.L.Wilson, and S. Sirohey, "Human and Machine Recognition of Faces: A Survey", Proc.IEEE, vol.83, no.5, pp. 705-740, 1995.

[5] Ming-Hsuan Yang, David J. Kriegman, and Narendra Ahuja, "Detecting Faces in Images: A Survey", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol.24, no.1, Jan. 2002.

[6] R.C.Conzalez and P.A. Wintz, "Digital Image Processing: Reading", Addison Weslay, 1987.

[7] K. Etemad and R. Chellappa, " Discriminant analysis for recognition of human faces", in Proceedings of the International Conference on Acoustics ,Speech and Signal Processing (IEEE, New York,1996), pp. 2148-2151.

[8] I.T. Jolliffe, "Principal Component Analysis (Springer-Verlag, New York, 1986).

[9] G.Yang and T.S. Huang, "Human Face detection in Complex Background", Pattern Recognition, vol.27, no.1, pp.53-63, 1994.

[10] G.Burel and D. Carel, "Detection and Localization of Faces on Digital Images", Pattern Recognition Letters, vol.15, no.10, pp. 963-967, 1994.

[11] A.Pentland and T. Choudhury, "Face Recognition for Smart Environments", IEEE Computer, pp.50-55, 2000.

[12] D.L.Swets and J. Weng, "Using Discriminant Eigen Features for Image Retrieval" , IEEE Trans. Pattern Analysis and Machine Intelligence, vol.18, no.8, pp.891-896, Aug. 1996.

[13] P.J. Phillips, H. Moon, S.A. Rizvi, and P.J. Rauss, "The FERET Evaluation Methodology for Face Recognition Algorithms", IEEE Trans. Pattern Analysis and Machine Intelligence, vol.22, no.10, pp. 1090-1094, Oct. 2000.

[14] K.C. Yow and R. Cipolla, "Feature-Based Human Face Detection", Image and Vision Computing, vol.15, no.9, pp. 713-735, 1997.

[15] A. Martinez and A. Kak, "PCA versus LDA", IEEE Trans. Pattern Analysis and Machine Intelligence, vol.23, no.2, pp.228-233, Feb. 2001.

[16] P. Belhumeur, J. Hespanha, and D. Kriegman, "Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection", IEEE Trans. Pattern Analysis and Machine Intelligence, vol.19, no. 7, pp. 711-720, 1997.

[17] F.S.Samaria, "Face Recognition Using Hidden Markov Models", PhD thesis, Univ. of Cambridge, 1994.

[18] Marian Stewart Bartlelt, Javier R. Movellan, and Ferrence J. Sejnowski, "Face Recognition by Independent Component Analysis", IEEE Trans. on Neural Networks, vol.13, no. 6, Nov'2002.

[19] Ming_Hsusan Yang, David Kriegman, and Narendra Ahuja, "Detecting Faces in Images", IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 24, no. 1, pp. 34-58, 2002.

[20] "Recent Advances in Face Detection", IEEE ICPR 2004, Tutorial, Cambridge, United Kingdom, Aug'2004.