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An Effective Approach to Frontal Face Recognition Using Distance Measures

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Abstract: Our method An effective approach to frontal face recognition using distance measures will detect and then recognize the face by comparing characteristics of the face to those of known individuals. Present approach treats the face identification problem as an intrinsically two-dimensional (2-D) identification problem rather than requiring recovery of three- dimensional geometry, taking advantage of the fact that faces are normally upright and thus may be described by a small set of 2-D characteristic views. The system functions by projecting face images onto a feature space that spans the significant variations among known face images. The significant features are known as eigenfaces, because they are the eigenvectors (principal components) of the set of faces, they do not necessarily correspond to features such as eyes, ears and noses. The projection operation characterizes an individual face in a weighted sum of the eigenface feature and so to recognize a particular face it is necessary only to compute these weights to those of known individuals. Some particular advantages of our approach are that using only a weighted sum of these eigenfaces, it is possible to reconstruct each face in the data set. At present existing method recognize faces using Euc lidean distance measure. But in present system we used various distance measures such as Euclidean, chess board a nd city block distanc e measures. In our method City block distance which gives better results as compared to Euclidean and chess board distance measures.

Key words: Image processing, analysis, face recognition, eigenfaces, principle component analysis

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 consequences 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.

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. However, face detection is not straight forward because it has lots of variations of image appearance, such as pose variation (front, non-front, occlusion, image orientation, illuminating condition and facial expression.

Many novel methods have been proposed to restore each variation listed above. For example, the template-matching methods[1,2] are used for face localization and detection by computing the correlation of an input image to a standard face pattern. The feature invariant approaches are used for face detection[3,4] of eyes, mouth, ears, nose, etc. The appearance-based methods are used for face detection with eigenface[5,7], neural network[8,9], and information theoretical approach[10,11]. Nevertheless, implementing the methods together is still a great challenge.

MATERIALS AND METHODS

The method of Eigenfaces: 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).

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[13]. 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 the reconstructed image is an approximation of the original image. 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:

- Acquire an initial set of face images (the training set)
- 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.
- 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.

- Calculate a set of weights based on the input image and the M eigenfaces by projecting the input image onto each of the eigenfaces.
- 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.
- If it is a face, classify the weight pattern as either a known person or as unknown.

Calculating eigenfaces: 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[14]. 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. Some examples are shown in Fig. 2a and b.

Let the training set of face images be $\Gamma_1, \Gamma_2, \Gamma_3, \ldots\ldots, \Gamma_M$. The average face of the Set is defined by $\psi = 1/M \, \Sigma \, \Gamma_n$ n=1, 2 ,……, M. (Fig. 3) Each face differs from the average by the vector $\Phi i = \Gamma_i - \psi$. An example training set is shown in Fig. 1a.with the average face Ø shown in Fig. 1b. 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

$$\lambda_k = 1/M \, \Sigma(u_k^T \, \Phi n)^2 \quad , n = 1,2,\ldots\ldots,M \tag{1}$$

is a maximum, subject to

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

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

$$C = 1/M\ ?\ \Phi n\ \Phi n^T,\ \ n = 1,2,\ldots\ldots,M \quad (3)$$
$$= AA^T$$

Where the matrix $A = \{\hat{O}_1, \hat{O}_2, \hat{O}_3, \ldots\ldots, \hat{O}_4\}$. 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
these eigenvectors[15].

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 $\hat{O}_i$. Consider the eigenvector v_i of AA^T such that

$$A^TA\ v_i\ = ì_i\ v_i \quad (4)$$

Premultiplying both sides by A, we have

$$A\ A^TA\ v_i\ = ì_iA\ v_i \quad (5)$$

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

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

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. Fig. 2a and 2b shows the top 20 eigenfaces derived from the input training images of Fig. 1a and 1b.

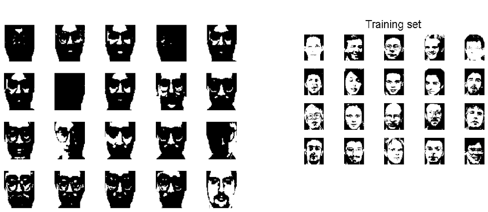


Fig. 1a: Input training images for test set 1
b: Input Training Images for test set 2

Fig. 2a: Eigenfaces for test set 1
b: Eigenfaces for test set 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[16]. 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 ($\tilde{A}$) is transformed into its eigenface components (projected into face space) by a simple operation,

$$w_k = w_k^T(\ \tilde{A} - ø) \quad (7)$$

for k = 1,2,………..,M'.

The weights form a vector $?^T = (w_1, w_2, \ldots\ldots, w_{M'})$ 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

$$\_\,_k = |?\ -\ ?_k|^2 \quad (8)$$

where $?_k$ is a vector describing the kth face class. The face classes ? 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 (Fig. 5 and 6). 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 $\_\,_k$ is below some chosen threshold $è_{\_1}$ and maximum $\_\,_k$ is below some chosen threshold $è_{\_2}$.

Otherwise the face is classified as unknown and optionally used to create a new face class.

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[12]. The other face database ATandT(Olivett)(availableathttp://www.uk.research.att.com) contains 10 different images of 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.

RESULTS

In Table 1 condition X refers to frontal view images taken with plain white background under relatively controlled lighting conditions and with different facial expressions. Condition Y images are those randomly taken from the set of images that were taken under worsening lighting conditions and some times with a black background.

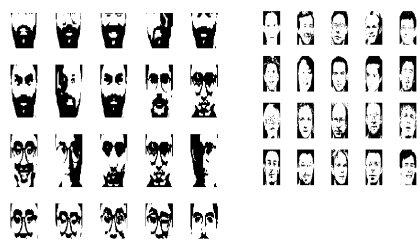
We have used two training sets of faces in our experiments. The first Test set includes 20 input training face images(BMP) (Fig. 1.a) and is used to compute the face recognition based on eigenfaces with different distance measures. The second Test set includes 20 input training face images (PGM) (Fig.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

Table 1: Results based on distance measures

Distance measures	Condition of images	Total tested	Successful detection	Failures
City Block	X	28	28 100%	0 0%
	Y	35	33 94.3%	2 5.7%
Eucli--dean	X	28	27 96.43%	1 3.57%
	Y	35	30 85.7%	5 14.3%
Chess Board	X	28	12 43%	16 57%
	Y	35	5 14.30%	30 85.70%

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.
From our results City block distance is fast, accurate and robust to the changes in illumination and background. The Factors ,which affect ed the recognition rate include: facial expressions, orientation, make-up,lighting condition, glasses, and beard etc.

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



(a) Test set 1 (b) Test set 2

Fig. 2: Normalized Training Images

(a) (b)

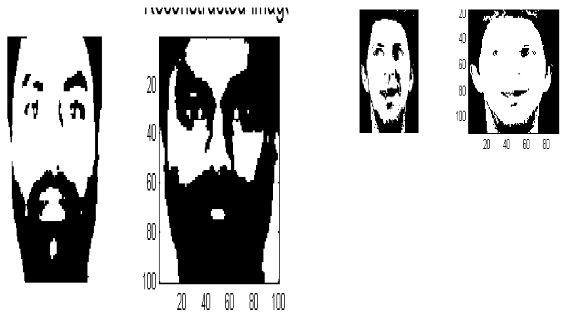
Fig. 3a: Mean Image for test set 1
b: Mean Image for test set 2

From the Fig 5 it is evident that both City block and Euclidean distance measures correctly recognize the face and while Chess board distance fails to recognize the face for test set 1.

Figure 6 clearly shows that both City block and Euclidean distance recognize the face while Chess board distance fails to recognize the face for test set 2.

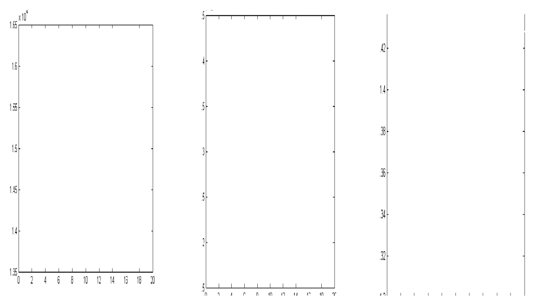
CONCLUSIONS

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



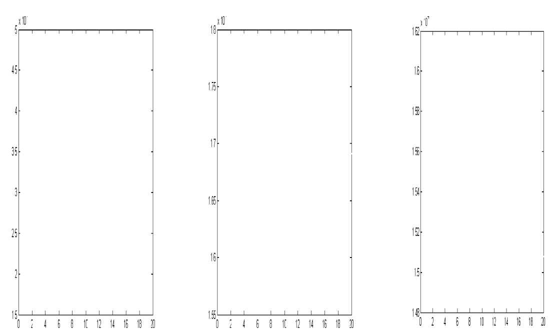
(a) (b)

Fig. 5a: Input Test Image and Reconstructed Image for test set 1
b: Input Test Image and Reconstructed Image for test set 2



(a) City block (b) Euclidean (c) Chess board

Fig. 6: Distance measure for test set 1



(a) City block (b) Euclidean (c) Chess board

Fig. 7: Distance measure for test set 2

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. Our results shows that our method is the simplest and effective method using city block distance measure, and we obtained the best accuracy. Our approach works better for images with same size.

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

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