Face recognition under Varying views

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ostract

this paper "EIGENFACES» are used to recognize human faces. We have developed a method that uses three enspaces. The system can identify faces under different angles, even if considerable changes were made in the entation. First of all we represent the face using the Karhunen-loeve transform. The face entered is automatically ssified according to its orientation. Then we applied the rule of decision of the minimal distance for the identification. e system is simple, powerful and robust.

ywords

ntification, Recognition, Face, Eigenface, Principal Component Analysis, Karhunen-loeve transform.

Introduction

e recognition is not a simple problem since a new image of object (face) seen in the recognition phase is usually erent from the images previously seen by the system in the ning phase. There are several sources for the variations ween images of the same face. The image depends on wing conditions, device characteristic and environment. s including viewing position which determines the entation, location and size of the face in the image; imaging lity which influences the resolution, blurring and noise in picture; the light source which influences the reflection. other source for differences between images take in nges of the faces over time. The face is a dynamic object: it nges according to expressions, mood and age. In addition, face image may also contain features that can change gether as hairstyle, beard or classes.

automatic face recognition system should be able to solve e problems. Thus, developing a computational model of recognition is quite difficult. But such systems can ribute not only to theoretical insights but also to practical lications.

nputers that recognize faces could be applied to a wide ety of problems, including criminal identification, security ems and human-computer interaction.

ny researches in this field have been done and several ems were developed. In the beginning, much of the work omputer recognition of faces has focused on detecting vidual features. In these models, faces are represented in s of distances, angles and area between the features such e eyes, the nose, the chin…etc. [1][2][3].

Recent research on computational modeling of faces has found it useful to employ a simpler representation of faces that consists of a normalized pixel-based representation of faces. One of the thoroughly approach in this field is extraction of a global features using PCA (Principal Component Analysis). In this approach, a set of faces is represented using a small number of global eingenvectors known as " eigenfaces".

Much of the effort going into the face recognition problem has been concentrated on the processing of frontal (or nearly frontal) 2D pixel-based face representation. Consequently, their performance is sensitive to substantial variations in lighting conditions, size and position in the image. To avoid these problems a preprocessing of the faces is necessary. However, this can be done in a relatively straightforward manner by using automatic algorithms to locating the faces in the images and normalizing them for size, lighting and position. Most face recognition systems operate under relatively rigid imaging conditions: lighting is controlled, people are not allowed to make facial expressions and facial pose is fixed at a fall frontal view.

In this paper we explore the eigenface technique of TURK & PENTLAND [4][5][6] to generalize face recognition under varying orientations.

2. Eigenfaces

The idea of using the eigenfaces was motivated by a technique developed by SIROVICH & KIRBY (1987) for efficiently representing pictures of faces using principal component analysis (PCA) [7][8]. TURK & PENTLAND used this method for face detection and recognition.

A simple approach to extracting the information contained in an image of face is somehow to capture the variation in collection of face images, independent of any feature judgement, and use this information to encode and compare individual face images. In mathematical terms, we consider the principal components of the face distribution or the eigenvectors of the covariance matrix of the set of face images and we treat an image as a point (or vector) in very high dimensional space. These eigenvectors can be thought of as a set of features that together characterize the variation between face images. Each image location contributes more or less to each eigenvector, so that we ca display the eigenvector as a sort of ghostly face called "**eigenface**". An example of an eigenface is shown in figure (Fig.1).

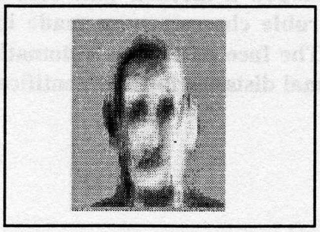

Fig.1. Example of an eigenface.

Each individual face can be represented exactly in terms of a linear combination of the eigenfaces. (Fig.2.)

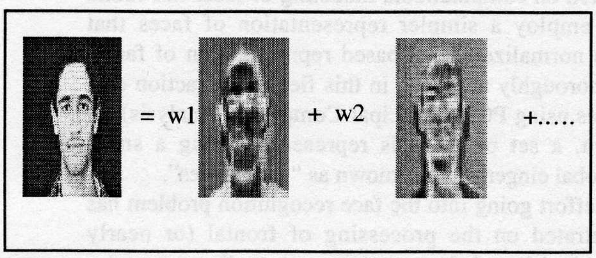

Fig.2. A face as combination of eigenfaces

Given the eigenfaces, every face in the database can be represented as a vector of weights (w_i). The weights are obtained by projecting the image into eigenface components by a simple product operation. When a new test image whose identification is required is given, the new image is also represented by its vector of weights. The identification of the test image is done by locating the image in the database whose weights are the closest to the weights of the test image. By using the observation that the projection of a face image and a no face image are quite different, a method for detecting the presence of a face in a given image is obtained. It is reported that this approach is fairly robust to changes in lighting condition but degrades as the scale or the orientation change. In this work we generalize this method to deal with the problem of the head orientation in the image.

3. Eigenfaces and multi-views

As discussed in the previous section, not much work has taken face recognizers beyond the narrow imaging conditions of expressionless and frontal views of faces with controlled lighting. More research is needed to enable automatic face recognizer to run under less stringent imaging conditions. Our goal is to build a face recognition system that work under varying orientations of the face. Our system is a particular application focussed on the use of the eigenfaces in face recognition. It is built with an architecture that allow to recognize a face under most viewing conditions.

First, we have to take the face under a compact representation. So we apply a compact representation of a face image using Karhunen-Loeve Transform. The result of this transformation is a weight vector called " **feature vector**". This is performed by building a projection space called "**Face space**". The extraction of the features vector consists then on the projection of the face on the face space. Therefore, the recognition is done by using feature vector and decision rule of the minimum distance.

To solve the problem of the orientation of the face in the image, we have thought of building three spaces of projection. Each space characterizes one possible orientation of a face. Three fundamental orientations had been chosen: frontal face (90°), **diagonal face** (45°) and **profile face** (0°). The others orientations will be brought to a nearest mentioned classes of orientation. The achieved spaces of projection are Space of frontal faces, space of diagonal faces and space of profile faces. Figures (Fig.3), (Fig4) and (Fig.5) illustrate examples of eigenfaces of each space.

Fig.3. Example of diagonal

Fig.4. Example of frontal

Fig.5. Example of profile

. The general configuration of the system

he system encloses the two following processes: ***the itialization process and the classification and identification rocess.*** Its architecture is presented in figure (Fig.6.)

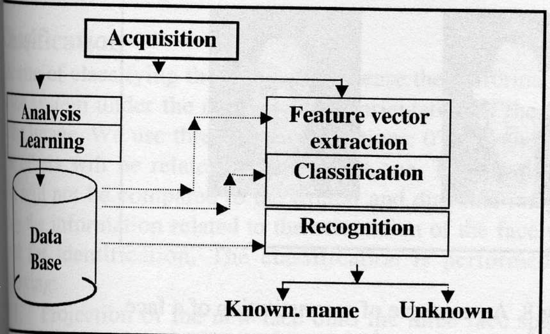

Fig.6. system configuration

e initialization process

e initialization process includes the following steps:

acquire an initial set of face images (the training set)

Calculate the eigenfaces of this set, keeping only the M' images that correspond to the highest eingenvalues.

Extract the feature vectors of known faces.

For each class (person) determine the class vector by averaging the eigenface vectors.

Choose the threshold for each class and faces space.

sults of steps 2, 4 and 5 are stored in the system. This ocess is executed for the three face spaces.

e classification and identification process

ce the system is initialized, it is ready for the identification. e classification and identification process includes:

Projection of the new face onto the three face spaces.

Classification of the face following its orientation (choose the closest orientation).

Identification of the face using the feature vectors and determine if the face is known or not.

Initialization process

a face image *I(x,y)* be a two-dimensional *N* by *N* array of nsity values. An image may also be considered as a vector dimension *N_*. This vector represents a point in a N_ ensional space. A set of images maps a collection of points this huge space (*N_* =128*128=16384). Images of faces, g similar in overall configuration, will not be randomly rbed in this huge image space and thus can be described relatively low dimensional subspace. The main idea of principal analysis component is to find vectors that best unt for the distribution of face images within the entire image space. These vectors define the subspace of face images which is called "face space". Each vector is of length *N_*, *describes* an *N* by *N* image, 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".

Let the training set of the face images be $\Gamma_1, \Gamma_2, \ldots, \Gamma_M$:

Average face:

The average face of the set is defined by:

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \qquad (1)$$

M: number of images used for each orientation.

An example of an average face is shown in figure (Fig .7.) It represents the original of the face space.

Fig.7. Example of an average face

Each face differs from the average by the vector:

$$\Phi_i = \Gamma_i - \Psi, \qquad i = 1,\ldots,M \qquad (2)$$

This set of very large vectors is then subject to principal component analysis. Thus, we obtain a set of M vectors U_n which best describes the distribution of the data.

$$u_l^T \, u_k = \begin{cases} 1 & \text{if } l=k \\ 0 & \text{else} \end{cases} \qquad (3)$$

The vectors U_k are the eigenvectors of the covariance matrix:

$$C = \sum_{n=1}^{M} \Phi_n \Phi_n^T = A.A^T, \qquad (4)$$

where $A = [\Phi_1, \Phi_2, \ldots, \Phi_m]$

The matrix C, however is *N_* by *N_* and determining the *N_* eigenvectors is an intractable task for typical image sizes. We need a computationally method to find these eigenvectors.

We know that if the number of data points in the image space is less than the dimension of the space (M< *N_)*, so there will be only M rather *N_* meaningful eigenvectors. Fortunately we can solve for the *N_* dimensional eigenvectos in this case by first solving for the eigenvectors of an M by M matrix, and then taking appropriate linear combination of the face images ϕ_i.

Consider the eigenvectors V_i *of* $L= A^T.A$ such that :

$$A^T.A.V_i = \lambda_i . Vi \qquad (5)$$

Pre multiplying both sides by A we have :

$$A.A^T.A.V_i = \lambda_i .A. Vi$$

From which we see that $A .Vi$ are the eigenvectors of $C= A.A^T$.

Following this analysis, we construct the M by M matrix $L= A^T.A$ where

$$L_{m,n} = \Phi^T_m.\Phi_n \qquad (6)$$

and find the M eigenvectors V_i of L. These vectors determine linear combinations of the M training set face images to form the eigenfaces U_l

$$U_l = \sum_{k=1}^{m} V_{lk}\Phi_k \qquad l = 1,...,m \qquad (7)$$

With this analysis, the calculations are greatly reduced from the order of the number of pixels in the image ($N\_=128*128=16384$) to the order of the number of images in the training set (M=40).

In practice, a smaller set of eigenvectors (M') is sufficient for identification. These M' eigenvectors are chosen at those with the largest associated eigenvalues.

Feature vector extraction

A new face image Γ_i is transformed into eigenface components (projected onto face space) by a simple operation:

$$w_k^{(i)} = u_k^T(\Gamma_i - \Psi) = u_k^T\Phi_i , \qquad (8)$$
$$i = 1,\ldots, M;\ k = 1,\ldots, M'.$$

Where $w_k^{(i)}$ represents the projection of the i^{th} face image into k^{th} eigenface. Thus, the feature vector of the i^{th} face image will be :

$$\Omega^{(i)} = \{w_1^{(i)}, w_2^{(i)}, \ldots, w_{M'}^{(i)}\} \qquad (9)$$

Each face is represented by a feature vector as shown in figure (Fig.2.)

We can reconstitute the initial face image using the feature vector. The ratio of reconstitution is given by

$$\gamma = \frac{\sum_{i=1}^{M'} \lambda_i}{tr(L)} = \frac{\sum_{i=1}^{M'} \lambda_i}{\sum_{i=1}^{M} \lambda_i} \qquad (10)$$

where λ_l : l^{th} eigenvalue.

$tr(L)$: represents the sum of the L diagonal components. Figure (Fig.8.) shows a projection of a face and its reconstitution.

Fig.8. An example of reconstitution of a face image

Learning

In this phase, we compute the feature vectors of all the known faces and determine the thresholds of each class and those of the face space.

A class feature vector

To each person corresponds one class. In our case, each class is composed by 4 images of the same person taken under different lighting and expressions conditions. Hence the class feature vector is defined by :

$$\Omega classe^{(k)} = \frac{1}{4}\sum_{i=1}^{4} \Omega_i^{(k)} \quad , k = 1,..., NI \qquad (11)$$

NI: number of persons.

The class threshold $DCI^{(k)}$:

The threshold of each class (person) is defined by:

$$DCI^{(k)} = \max_{i=1,..,4}(\|\Omega_i^{(k)} - \Omega classe^{(k)}\|^2) \qquad (12)$$

$$k = 1,..., NI$$

The face space class threshold 'DEV'

The DEV represents the maximum allowed distance from the face space:

$$DEV = \max_{i=1,...,m}(d_i) \qquad (13)$$

$$d_i = \|\Phi_i - \Phi f_i\| \qquad (14)$$

$$\Phi f_i = \sum_{i=1}^{M'} w_k^{(i)} u_k \qquad (15)$$

$$i = 1,..m$$

lassification and identification process

e projection of a new face

fore classifying a new face into one of the three orientation sses (0°, 45° & 90°), we compute the following feature ctors: ΩF(frontal), ΩD(diagonal) and ΩP(profile).

lassification

e aim of classifying the face is to increase the performances the system under the changes in the orientation of the face the image. We use three basic orientations: 0°, 45° and 90°. e others will be related to the nearest one. Thus, a profile e will not be compared to the frontal and diagonal images. ly the information related to the orientation of the face will ed for identification. The classification is performed as lowing:

1. Projection of the new face onto the three face spaces (frontal, diagonal and profile), thus we obtain Φ_{fF} , Φ_{fD} and Φ_{fP} . (using equation (15)).
2. Determine the nearest orientation (or class) to attribute to the face. We compute:

$$DistFrontal = \left\|\Phi_F - \Phi_{fF}\right\|$$

$$DistDiagonal = \left\|\Phi_D - \Phi_{fD}\right\|$$

$$Dist\,\mathrm{Pr}ofil = \left\|\Phi_P - \Phi_{fP}\right\|$$

Distfrontal: means the distance between the new face and the frontal face space.

e classification is then done by the following algorithm:

```
ar= min(DistFrontal, DistDiagonal, DistProfil);

itch (Near) {
e Distfrontal:    write(" frontal face ");
                  Lancer_Identification( Frontal );
                  Break;

e DistDiagonal:   write(" diagonal face ");
                  Lancer_Identification( Diagonal );
                  Break;

e DistProfil:     write(" face of profile ");
                  Lancer_Identification( Profile );
                  Break;

ault:             Break;
       }
```

ntification

r classifying the face into one orientation, we compare the ure vector of this face to these of the faces in the sponding orientation class. This is done by :

1. Compute the distance which separates the feature vector of the new face $\Omega^{(p)}$ with feature vectors of each class $\Omega CLASSE^{(p)}_{(k)}$:

$$d_k = \left\|\Omega^{(p)} - \Omega classe^{(p)}_{(k)}\right\|^2 \qquad (16)$$

with k : k[th] class or k[th] person.
p∈ {frontal, diagonal, profile}

2. Choose the closest class (person) K' that minimizes the distance d_c . thus

$$d_c = \min_{i=1,\dots,NI}(d_i) \qquad (17)$$

3. Identification :

$$\begin{aligned}&if \quad d_{k'} > DCI^{p}_{k'} \quad then \quad unknown\ face\\ &else \quad known\ face(k'^{th}\ person)\\ &end\end{aligned}$$

7.Results

We have tested our system in a face database which contains variations in scale, in expressions and in orientation. The first step is to classify the face into the appropriate class orientation (profile, frontal and diagonal). The system performs well this phase, among the entire test set, only three incorrect classifications have been detected. Figure (fig.9.) shows an example of an incorrect classification (a diagonal face classified as a face of a profile)

«Fig.9. An example of an incorrect classification »

The following table (Tab.1.) illustrate the results of the classification step.

	Familiar Faces		Unfamiliar faces
	Learned faces	No learned faces	
Classific ation	120/120	37/39	8/9
rate	100%	94,87%	88,88%

Tab.1. : results of classification

After classification, a new face will be identified in its corresponding class of orientation. The following tables show the results of the identification process.

	frontal Faces			
	familiar			unfamiliar
	learned	No Learned		Same scale
		Same scale	Different scale	
Recognition	40/40	8/10	2/3	
Discrimination	-	-	-	3/3

Tab.2. : results of the identification of frontal faces.

	diagonal Faces			
	Familiar			unfamiliar
	learned	no Learned		Same scale
		Same scale	Different scale	
Recognition	40/40	6/10	1/3	-
Discrimination	-			2/3

Tab.3. : results of the identification of the diagonals faces.

	Faces of Profile			
	familiar			unfamiliar
	learned	No Learned		Same scale
		Same scale	Different scale	
Recognition	40/40	7/10	1/3	-
Discrimination	-	-	-	3/3

Tab.4.: results of the identification of the faces of profile

Thus we have obtained a rate of 91,1 % of a correct identification and a rate of 88,88% in the discrimination case

8.Conclusion

We have developed a system based on eigenfaces. We have generalized this technique to deal with the problem of the orientation of the face in the image.

It seems to be that more the number of classes of orientation increases more the system is efficient, but it is not the case. Because by increasing the number of classes, we will have difficulties to discriminate between classes and easiness to identify faces in one class. While decreasing this number, we will have more easiness for the discrimination between classes but also more difficulties to identify faces in one class. Therefor, it is necessary to find a compromise. In our case, we have used three classes what gives variations of about 20% in each class.

However, it is necessary to signal that the performance of the system decrease quickly as soon as changes in scale and inclination are signaled. The following figure (Fig.10.) shows a case of failure recognition due to the change in scale.

Our approach treated the problem of the face orientation in the image. In the first stage, the face is assigned to a certain class of orientation according to its orientation in the image. Identification is then launched in the appropriate class. We can improve the system by introducing others treatments in the second stage which consider the scale and inclination changes.

Fig.10. An example of a failure recognition due to changes in scale

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