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Improving Face Recognition Rate by Combining Eigenface Approach and Case-based Reasoning

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***Abstract*—There are many approaches to the face recognition. This paper presents an approach that combines advantage of generalization ability of Principal Component Analysis (PCA) and specialization ability of Case- based reasoning (CBR). CBR is expected to improve the generalization ability of PCA in the recognition process. By using PCA the new image is projected into its eigenface components. The projected vector represents a description component of a new face case. The CBR module compares the similarity of the new face case and previously stored face cases in the face casebase and retrieves the most similar case. The solution component of the retrieved case represents the results of the recognition process.**

***Index Terms* — case based reasoning, face recognition, eigenvalues, eigenvectors, principal component analysis.**

I. Introduction

As one of the most successful applications of image analysis and understanding, face recognition has recently received significant attention. The problem of face recognition can be formulated as follows [1] :

„For a given image of scene, identify or verify one or more persons in the scene using a stored database of faces“.

The input to the face recognition system is an unknown face, and the system determines identity from a database of known individuals. In verification problems, the face recognition system needs to confirm or reject the claimed identity of the input face.

In general, the human face recognition system utilizes a broad spectrum of stimuli obtained from many of the senses: visual, auditory, olfactory, etc. In recognition process contextual knowledge is also used [2]. However, the human brain has its limitations in the total number of persons that it can remember. A main adventage of a computer face recognition system is its capacity to handle large image databases. Some psychological studies have pointed out that the internal facial features, such as eyes, nose, and mouth, are very important for human beings to recognize familiar faces.

A complete face recognition system should includ two stages. The first stage is detecting the location and size of a face. This task is difficult because of the unknown position and orientation of faces in image. The second stage involves recognizing the faces obtained in the first stage. It is very important to emphasize that there are many problems that has to be solved for complete success of face recognition systems. The following two problems are the most important: the ilumination problem and the pose problem [3]. The illumination problem can be described as the problem where same face appears differently due to the change in lighting. The changes produced by illumination could be larger than the differences between individuals. The pose problem can be described as a problem where the same face appears differently due to changes in viewing condition.

Face recognition approaches can be broadly grouped into geometric and template matching techniques. In the first case, geometric characteristics of faces to be matched, such as distances between different facial features, are compared. In the second case, face images represented as a two-dimensional array of pixel intensity values are compared to a single or several templates representing the whole face. More successful template matching approaches are: Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA).

Template matching approaches to face recognition use the concept of image space. A two-dimensional image $I(x,y)$ may be viewed as a point in a very high dimensional space, called image space, where each coordinate of the space corresponds to a sample of the image. For example, an image with 32 rows and 32 columns describes a point in a 1024-dimensional image space. In general, an image of N rows and N columns describes a point in N^2-dimensional image space. All the faces look like each other. They all have two eyes, a mouth, a nose, etc. Therefore, all the face vectors are located in a very narrow cluster in the image space [4].

II. The Eigenface Approach

Different eigenspace-based approaches have been proposed for the face recognition. They differ mostly in the kind of projection method been used and in the similarity matching criterion employed. Principal Component Analysis (PCA) is a general method to identify the linear directions in which a set of vectors are best represented and after that to make a dimensional reduction of them. Turk and Pentland used the PCA for dimensionality reduction to find the vectors which best account for the distribution of face images within the entire image space [5], [6].

Let S denote the training set of M face images [6]:

$$S = \{\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M\}. \quad (1)$$

The mean image of the set if defined by:

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad (2)$$

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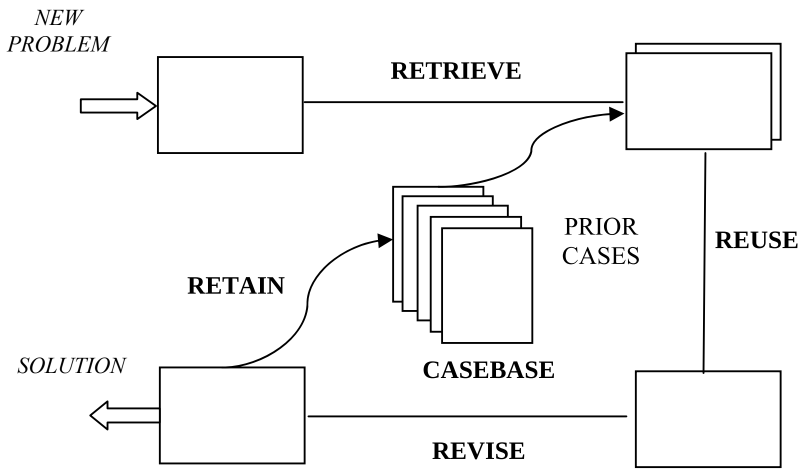


Fig. 1. The CBR cycle. Adapted from [9]

The set of deviation-from-mean vectors, $\{\Phi_1, \Phi_2, \Phi_3, \ldots, \Phi_M\}$ contains the individual difference of each training image from the mean vector Ψ. Individual differences are defined as:

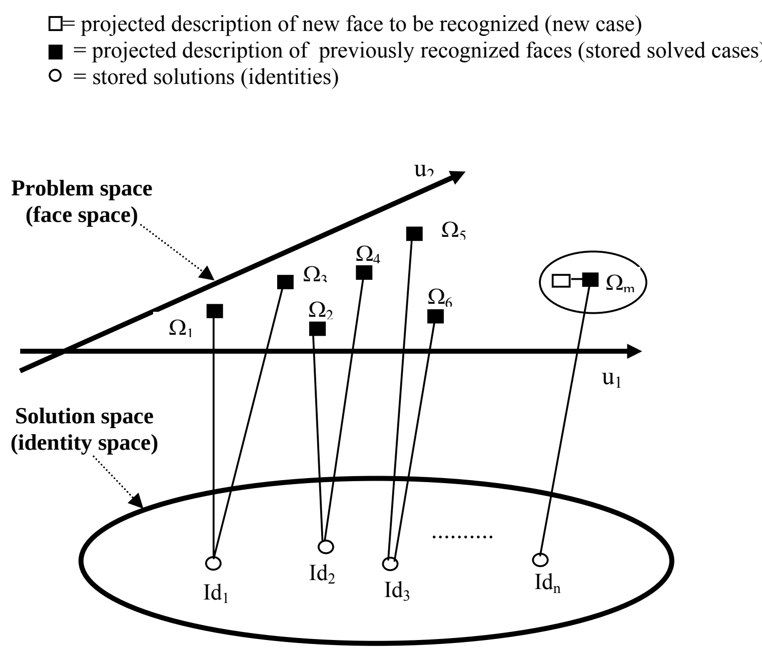
$$\Phi_i = \Gamma_i - \Psi\ ,\ i=1,2,\ldots M \tag{3}$$

To obtain the eigenface description of the training set, the training images are subjected to PCA, which seeks a set of M orthonormal vectors u_n and their associated eigenvalues λ_k which best describes the distribution of the data. The vectors u_k and scalars λ_k are the eigenvectors and eigenvalues, respectively, of the covariance matrix. The covariance matrix is given by [6]:

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T \tag{4}$$

where the matrix A is $A=[\Phi_1\ \Phi_2 \ldots \Phi_M]$

The matrix C is a N^2 by N^2 matrix and would generate N^2 eigenvectors and eigenvalues. With image sizes like 256 by 256, or even lower than that, such a calculation would be



$CB_f=\{(\Omega_1, Id_1), (\Omega_3,Id_1), (\Omega_2,Id_2), (\Omega_4,Id_2), (\Omega_5,Id_3), (\Omega_6,Id_3),\ldots,(\Omega_m,Id_n)\}$

Fig. 2. Simplified representation of problem description (face space) and solution (identity) space

impractical to implement. A computationally feasible method was suggested to find out the eigenvectors [5]. If the number of images in the training set is less than the number of pixels in an image (i.e $M < N^2$), there will be only $M-1$, rather than N^2, meaningful eigenvectors. The remaining eigenvectors will have associated eigenvalues of zero. Thus, we can solve an M by M matrix instead of solving a N^2 by N^2 matrix [5], [6].

A. Standard Recognition Procedure

The M' significant eigenvectors of the matrix $L=A^TA$ are chosen as those with the largest associated eigenvalues. The eigenfaces span an M'-dimensional subspace of the original N^2 image space.

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

$$w_k = u_k^T (\Gamma - \psi), \ \ k=1,2,....M'. \tag{5}$$

The weights obtained as above form a vector [6]:

$$\Omega^T = [w_1, w_2, w_{3,....} w_{M'}] \tag{6}$$

that describes the contribution of each eigenface in representing the input face image. The standard 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 Euclidian distance

$$\varepsilon_k^2 = || \Omega - \Omega_k||^2 \tag{7}$$

where Ω_k is a vector describing the k^{th} face class. The new face is considered to belong to a class if ε_k is bellow an established threshold θ_ε. Then the face image is considered to be a known face. If the difference is above the given threshold, but bellow a second threshold, the image can be determined as an unknown face. If the input image is above these two thresholds, the image is determined not to be a face.

III. THE EIGENFACE-CBR APPROACH

In this section we will describe the eigenface-CBR approach to face recognition. The main purpose of eigenface-CBR approach is to take advantage of generalization ability of PCA and specialization ability of CBR. CBR is expected to improve the generalization ability in the recognition process. CBR ability of a given approach should be manifested in the experiments as the ability to improve a recognition rate when increasing the number of retained previously face recognition cases. In order to evaluate this approach, we compared the approach with the standard eigenface approach.

A. Case-based reasoning

Case-based reasoning (CBR) is able to utilize the *specific* knowledge of previously experienced, concrete problem situations (cases). A new problem is solved by finding a similar past case, and reusing it in the new problem situation [7]. There are two main ways to reuse past cases: reuse the past case solution and reuse the past method that constructed the solution [8]. In CBR terminology, a *case* usually denotes a *problem situation*. A previously experienced situation, which has been captured and learned in a way that it can be reused in the solving of future problems, is referred to as a previous case, stored case, or retained case. Correspondingly, a new case or unsolved case is the description of a new problem to be solved.

Fig. 1 shows the model of the problem solving cycle in CBR. Solving a problem by CBR involves obtaining a problem description, measuring the similarity of the current problem to previous problems stored in a case base with their known solutions, retrieving one or more similar cases, and attempting to reuse the solution of one of the retrieved cases, possibly after adapting it to account for differences in problem descriptions [9]. The solution proposed by the system is then evaluated (e.g.., by being applied to the initial problem or assessed by a domain expert). Following revision of the proposed solution if required in light of its evaluation, the problem description and its solution can then be retained as a new case, and the system has learned to solve a new problem [9].

CBR is founded on the premise that similar problems have similar solutions. Thus, one of the primary goals of a CBR system is to find the most similar, or most relevant, cases for new input problems. The effectiveness of CBR depends on the quality and quantity of cases in a casebase. In some domains, even a small number of cases provide good solutions, but in other domains, an increased number of unique cases improve problem-solving capabilities of CBR systems because there are more experiences to draw on. Case-based reasoning systems can also be viewed as continuous knowledge acquisition and learning systems.

B. Case Representation for Eigenface-CBR Approach

In this section, we describe case representation used for the eigenface-CBR approach. Case representation is generally regarded as one of the most important problems and is crucial to success of case-based reasoning system. The case representation problem is primarily the problem of deciding what to store in a case, and finding an appropriate structure for describing case contents. In general, a case consists of a problem description component and a solution component. In this work, face cases C_f are represented as two-tuples (see Fig. 2):

$$C_f=(\Omega^T, Id)$$

where:

- Ω^T is a face case description component that represents projected image vector Γ,
- Id is a face case solution component that represents identity.

C. CBR Recognition Procedure

Let CB_f denotes the face casebase:

$$CB_f = \{C_1, C_2,....,C_{|CB|}\},$$

where

$C_i=(\Omega_i^T,Id_j)$, $i=1,2,...|CB|$, $j=1,2,...|ID|$ and where ID is the set of all previously recognized persons.

Fig. 3 shows the block diagram of the eigenface-CBR recognition system. It is used PCA and the new image Γ_n is

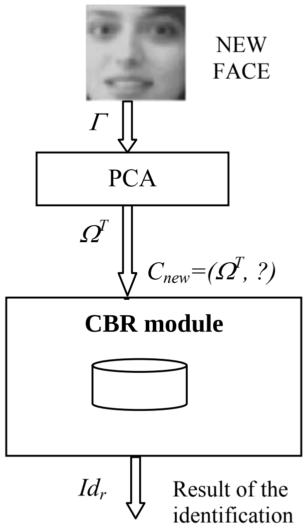


Fig. 3. Block diagram of the eigenface-CBR approach

transformed into its eigenface components. The resulting weights form the weight vector $\Omega_n^T = [w_1, w_2, w_3, \ldots w_M]$. Task of the CBR module is create the new face recognition case, find a prior case similar to the new one, use that case to suggest a solution to the current face recognition problem, and update the system by learning from this experience. The projected vector Ω_n^T represents the description component of the new face case $C_n=(\Omega_n^T, ?)$. The symbol *?* denotes that the solution component (identity) is unknown. The CBR module compares the similarity of the description component Ω_n^T of the new face case and previously stored description components Ω_i, $i=1,2,\ldots|CB|$, of face cases in the casebase CB_f. The Euclidean distance between two description components $d(\Omega_n^T,\Omega_i)$, $i=1,2,\ldots|CB|$, provides a measure of similarity between the new case C_n and previously stored cases $C_i, i=1,2,\ldots|CB|$. By using the criterion of similarity based on Euclidian distance, CBR module determines and retrieves the most similar case $C_r=(\Omega_r^T, Id_r)$ in the case base. The solution component Id_r of the retrieved case C_r represents the results of the recognition process.

The input face is considered to belong to an identity if distance $d(\Omega_n^T, \Omega_r^T)$ is bellow an established threshold θ_r. If the distance $d(\Omega_n^T, \Omega_r^T)$ is above the given threshold, but bellow a second threshold θ_f, the image can be considered as an unknown face. If the distance $d(\Omega_n^T, \Omega_r^T)$ is above these two thresholds, the new face case is determined not to be a face. A very important characteristic of the eigenface-CBR approach is incremental learning, since a new experience is retained each time a new face has been recognized, making it immediately available for future face recognition problems.

IV. Recognition Experiments

This section is focused on the comparison of standard eigenspace based face recognition using the PCA projection method and the eigenface-CBR approach previously presented in this paper. In order to compare the standard eigenface recognition procedure and the eigenface-CBR recognition procedure, we applied both procedures to the same 90 images, obtained in good illumination conditions. All presented results were obtained with one processing for each amount of eigenvectors (5, 15, and 30).

Table I presents the results obtained with the standard eigenfaces recognition procedure. Table II presents the results obtained with the eigenface-CBR recognition procedure, working with the same 90 well illuminated images and with the three different casebase sizes: 60, 120, and 180.

We can see that the experimental results obtained using the eigenface-CBR approach increases its recognition rate. The recognition rates increases with increasing number of previously experienced face recognition cases.

Table I. Standard eigenface results

Eigenv-ectors	Errors		Success	
	Quantity	Rate	Quantity	Rate
5	19	21,1%	71	78,9%
15	6	6,7%	84	93,3%
30	3	3,3%	87	96,7%

Table II. Eigenface-CBR results

Num. of stored cases	Eigen vect.	Errors		Success	
		Quant.	Rate	Quant.	Rate
60	5	16	17,8%	74	82,2%
	15	6	6,7%	84	93,3%
	30	2	2,2%	88	97,8%
120	5	13	14.4%	77	85,6%
	15	4	4,4%	86	95,6%
	30	2	2,2%	88	97,8%
180	5	8	8,9%	82	91,1%
	15	3	3,3%	87	96,7%
	30	1	1,1%	89	98,9%

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V. CONCLUSIONS AND FUTURE WORK

In this paper we have presented an approach that combines eigenface approach and case-based reasoning. The case based approach to face recognition was motivated by the desire to combine the advantage of generalization ability of Principal Component Analysis (PCA) and the advantage of specialization ability of case-based reasoning (CBR). The preliminary experimental results show that using the eigenface-CBR approach increases the recognition rate. The recognition rate increases with increasing number of previously experienced face recognition cases. As future work we are focusing on the extension of the research, considering other kind of eigenspace-based approaches. Also, we are interested in development of algorithms for more efficient case retrieval from the casebase.

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