Face Recognition using Weighted Modular Principle Component Analysis

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Abstract. *A method of face recognition using a weighted modular principle component analysis (WMPCA) is presented in this paper. The proposed methodology has a better recognition rate, when compared with conventional PCA, for faces with large variations in expression and illumination. The face is divided into horizontal sub-regions such as forehead, eyes, nose and mouth. Then each of them are separately analyzed using PCA. The final decision is taken based on a weighted sum of errors obtained from each sub-region.A method is proposed, to calculate these weights, which is based on the assumption that different regions in a face vary at different rates with expression, pose and illumination.*

1 Introduction

Biometry using face recognition is an increasingly important area today. Its applications are becoming more important, as in ATM machines, criminal identification, access restriction, monitoring public areas for known faces. The task of automated face recognition is very difficult due to the similarity of faces in general and large variations in the faces of same person due to expression, pose and illumination.

Various algorithms have been proposed for the automatic face recognition in last few decades, with varying degrees of success. Rama Chellappa et al.[1] gave a detailed survey of face recognition algorithms based on neural network models, statistical models, and feature-based models. Majority of the contributions are based on PCA [2], LDA [3] and SVM [4] techniques. Modular PCA [5, 6] is an improvement proposed over PCA. Most of these AFR algorithms evaluate faces as one unit which leads to problems due to variations in expression, illumination and pose. This neglects the important fact that few facial features are expression invariant and others are more susceptible to the expressions.

In this paper we propose a modified approach, where different parts of face (eyes, nose, lips) are separately analyzed and the final decision is based on the weighted sum of errors obtained from separate modules. We have also proposed a method to calculate these weights using the extent to which each sub-region, of a subject, is spread in the eigenspace. The weights are the measures of intra-person variance of the sub-region.

This paper is organized as follows: Section 2 gives an overview of PCA. Section 3 describes the proposed algorithm. In Section 4, we discuss the experiments and results. Finally Section 5 gives the conclusions and future scope of work.

2 Review of PCA

PCA is a dimensionality reduction technique. Usually a face image of size $N*N$, can be represented as a point in a N^2-Dimension space, termed as *image Space.* Since most faces are similar in nature, face images are not randomly distributed in the image space and fall in a small subspace, called *face Space.* The concept of PCA is to find vectors that best describe the distribution of these faces in the image subspace.

Let the training set be $\Gamma_1,\ \Gamma_2,\ \Gamma_3,\ \ldots,\ \Gamma_M$ where M is the number of faces in the training set. These faces are represented by using column vectors (N^2*1) instead of the usual matrix representation $(N*N)$. The average face of the training set, Ψ, is calculated as, $\Psi = \frac{1}{M}\sum_{m=1}^{M}\Gamma_m$. A vector that describes the difference of each face from average face is obtained, as $d_m = \Gamma_m - \Psi$, $m = 1. ..., M$. The covariance matrix is obtained as,

$$C = \frac{1}{M}\sum_{m=1}^{M} d_m d_m^T \tag{1}$$

The eigenvectors of this matrix are computed and the most significant S eigenvectors, $\mu_1, \mu_2, ..., \mu_S$ are chosen as those corresponding to largest corresponding eigenvalues. Given these eigenvectors, each face Γ_m can be expressed as a set of weights, $w_{m,s}$, which are obtained as,

$$w_{m,s} = \mu_s^T(\Gamma_m - \Psi), \qquad m = 1, 2, \ldots, M;\ s = 1, 2, \ldots, S; \tag{2}$$

The weights obtained in above equation form the weight vector for the corresponding face m, $\Omega_m = [w_{m,1}\ w_{m,2} \ldots w_{m,S}]^T$, where $m = 1, 2, \ldots,\ M$. Given a test face Γ_{test}, it is projected on the face space and the weights are obtained as in (2), $w_{test,s} = \mu_s^T(\Gamma_{test} - \Psi)$, where $s = 1, .., S$, which gives the corresponding weight vector, Ω_{test}. The error vector, which is the euclidean distance between the test face Ω_{test} and training faces Ω_m, is obtained as, $e_m = ||\Omega_{test} - \Omega_m||$, where $m = 1, 2, \ldots, M$.

The test face Γ_{test} is said to have best matched with a face, $\Gamma_{m'}$, for which the error vector e_m is minimum. Suitable threshold τ can be used for rejection as $\tau < min(e_m)$.

3 Proposed Methodology

We propose an algorithm based on modular PCA, which modularizes the face into sub-regions and performs recognition on each sub-region individually. Each face is horizontally split into a set of sub-regions such as forehead, eye, nose, mouth, chin. For each sub-region, ρ, of each face, we now compute average sub-region, calculate covariance matrix, eigenvectors and the weight set as mentioned in section 2. All these computations can be implemented in parallel. Finally net error is obtained as a weighted sum of the error vectors of individual sub-regions. The given face is classified as to belong to that class which is at nearest euclidean distance in the face space.

3.1 Training

Let the training set contain L subjects, where each subject is one person. Each person has N different faces. So the training set has $M = LN$ faces. All M faces are divided in to R regions. Hence, each r^{th} partition of n^{th} sample of l^{th} subject is, $\rho_{l,n,r}$, where $l = 1, 2, ..., L;\ n = 1, 2, ..., N;\ r = 1, 2, ..., R$. Thus entire training set can be represented as $T_{set} = \{\ \rho_{l,n,r} \mid \forall l, n, r\}$. The following steps are repeated for each sub-region $r = 1, 2, ..., R$. For each r^{th} sub-region, an average sub-region, ψ_r is computed over all faces as, $\psi_r = \frac{1}{LN}\sum_{l=1}^{L}\sum_{n=1}^{N}\rho_{l,n,r}$ This equation can be conveniently rewritten as,

$$\psi_r = \frac{1}{M}\sum_{m=1}^{M}(\Upsilon_m)_r, \qquad r = 1, 2, ..., R;\ M = LN;$$

where $(\Upsilon_m)_r$ is the r^{th} sub-region of m^{th} face.

The covariance matrix C_r of r^{th} sub-region is calculated as in (1) and its eigenvectors are computed. The most significant S eigenvectors, $((\mu_1)_r\ , ...,\ (\mu_S)_r)$, are considered for each sub-region r as mentioned in section 2. Then each sub-region r of face m can be expressed as a set of weights, $(w_{m,s})_r$, which are calculated as,

$$(w_{m,s})_r = (\mu_s)_r^T((\Upsilon_m)_r - \psi_r), \qquad m = 1, 2, ..., M;\ s = 1, 2, ..., S;\ r = 1, 2, ..., R; \tag{3}$$

Similarly weight vector of each sub-region $(\Omega_m)_r$ is generated from these weights as,$(\Omega_m)_r = [\ (w_{m,1})_r\ (w_{m,2})_r\ ...\ (w_{m,S})_r\ ],\ m = 1, 2, ..., M;\ r = 1, 2, ..., R$.

3.2 Intra-subject variance of each sub-region

As mentioned, the final decision is based on the weighted sum of error vectors obtained from each sub-region. These weights represent a measure of *the extent of variation in eigenspace for a sub-region of a subject across all samples.* For each sub-region r of each subject, l, average sub-region $(\Phi_l)_r$ is calculated. Then For each sub-region r, the measure of variance for l^{th} subject is,

$$(P_l)_r = \frac{1}{N}\sum_{n=N*(l-1)+1}^{l*N}[(\Omega_n)_r - (\Phi_l)_r]^2, \qquad l = 1, 2, ..., L;\ r = 1, 2, ..., R; \tag{4}$$

It may be noted that more compact sub-regions have lesser value of $(P_l)_r$.

3.3 Classification

Given a test face, Γ_{test}, it is split into R horizontal sub-regions as in the training phase. These regions can be represented as, $(\Upsilon_{test})_r$ where $r = 1, 2, ..., R$. These regions are then projected onto face space, weights are calculated as in (3), $(w_{test,s})_r = (\mu_s)_r^T((\Upsilon_m)_r - \psi_r)$. The corresponding weight vector is built as, $(\Omega_{test})_r = [(w_{test,1})_r \ (w_{test,2})_r \ \ldots \ (w_{test,S})_r]$, $r = 1, 2, ..., R$;

The error vector for a region r, is the euclidean distance between $(\Omega_{test})_r$ and $(\Omega_m)_r$. It is computed as $(E_m)_r = [(\Omega_{test})_r - (\Omega_m)_r]^2$, $m = 1, 2, ..., M$; $r = 1, 2, ..., R$. For each subject, the sub-region that is more invariant to expressions and illuminations is given more priority in the net error function. This is implemented by multiplying each error of the sub-region with the measure obtained in (4). The net error function for comparing a test image Γ_{test} with Γ_m is,

$$(F_{test})_m = \sum_{r=1}^{R}[(\Omega_{test})_r - (\Omega_m)_r]^2.(P_l)_r, \qquad m = 1, 2, \ldots, M; \tag{5}$$

where l is the subject of m^{th} sample. The test face is said to have matched with face m', for which $(F_{test})_{m'} = min(F_{test})_m, \forall m$. Suitable threshold is used to reduce false acceptance.

Reconstruction: The sub-regions of the test face can be reconstructed from the eigenvectors, the weight vectors of each sub-region and variance measure of each subject as, $(\rho_r)_{rc} = \psi_r + (P_l)_r[\sum_{i=1}^{\mathbf{S}}(w_{test,i})_r(\mu_i)_r]$, where $r = 1, 2, \ldots, R$ and l is the subject into which Γ_{test} is classified as. The test face can be obtained by concatenating these reconstructed sub-regions.

4 Experiments and Results

The algorithm was tested on the Yale Face Database. This database consists of 15 subjects each with 11 different samples with varying expressions and illumination. The training set consists of only 6 images of each subject whereas the other 5 images are used for testing. This choice was done such that both the sets had expression and illumination variations. Figure 1 shows the images used in testing and training phases of the experiment for a subject.

Fig. 1. *Some examples of faces used for training (top row) and testing (bottom row).*

The faces were first cropped horizontally (manually in this experiment), into three sub-regions containing forehead, eyes with nose and mouth as shown in Fig.

2. The method of training explained in section 3.1 was applied to all these sub-regions and the weight vectors were computed. Then measures of intra-person variance for all the sub-regions were calculated as in section 3.2. Figure 3 shows the distribution of average foreheads, eyes and mouths for all the subjects in 3-D eigenspace using the first three eigenvectors. A set of weights obtained using 20 eigenvectors, for 10 different subjects, are given in Table 1. These weights are normalized for each subject.

We performed PCA on the actual samples and modular PCA, weighted modular PCA (WMPCA) on the partitioned set with varying number of eigenvectors. The recognition rates obtained using PCA, MPCA and WMPCA, for 5, 10, 20, 30, 40 eigenvectors are illustrated in Fig. 4. It can be observed that WMPCA is able to achieve higher rates of recognition than PCA at lower number of eigenvectors itself.

WMPCA achieved an accuracy of over 87% while PCA achieved only 76%. Using modular PCA, described in [6], the recognition rate reached only 80%. There also has been significant improvement in the reconstruction of faces from weighted eigenvectors. Figure 5 shows a face reconstructed using PCA and WM-PCA. The recognition rate of WMPCA improved to 89%, if 7 images of each subject were used for training.

Fig. 2. *(a) Actual face and (b) the cropped modules of the face from the Yale database.*

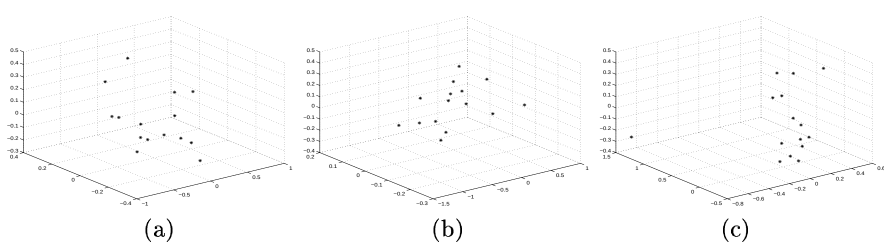

Fig. 3. *Distribution of average (a) foreheads (b) eyes and (c) mouths for all subjects in 3-D eigenspace using the first 3 eigenvectors.*

Table 1. *Intra-person variance of each sub-region, for 10 different subjects.*

Subject	1	2	3	4	5	6	7	8	9	10
Forehead	0.5357	0.8212	0.8415	0.8456	1.0000	0.7148	0.7089	0.7924	0.7697	0.6346
Eyes	0.8567	1.0000	0.9986	1.0000	0.9222	1.0000	1.0000	1.0000	1.0000	1.0000
Mouth	1.0000	0.5556	1.0000	0.9508	0.9204	0.7769	0.9810	0.9399	0.9455	0.8648

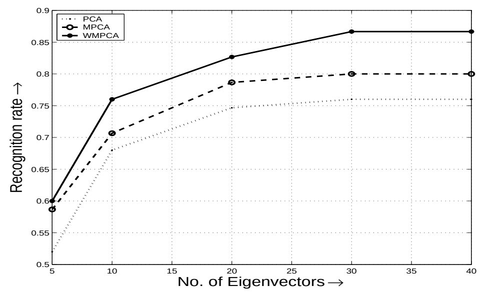

Fig. 4. *Results of PCA, MPCA, WMPCA for different number of eigenvectors used in the experiment.*

(a) (b) (c)

Fig. 5. *Reconstruction of faces: (a) Test face, (b) Reconstruction using PCA, (C) using WMPCA.*

5 Conclusions

In this paper we assume that different regions of the face vary at different rates due to variations in expression and illumination. We recognize all sub-regions of the face independently and the final decision is a weighted sum of the errors of each sub-region. We also calculate the intra-person variance of each sub-region, which is a measure of how each sub-region of a subject varies over various expressions and illuminations. The results were very promising and the method is suitable for real time applications. The recognition rate shows improvement over PCA and modular PCA in case of faces having variation in expression and illumination.

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