Novel Face Recognition Based on Individual Eigen-subspaces

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Abstract:

In this paper, a novel method of face recognition based on Individual Eigen-subspaces is presented, which is expected to tackle such problems on face recognition as that available reference samples for each subject are enough at hand. In the proposed method, multiple face eigen-subspaces are created, with each one corresponding to one known subject privately, rather than all individuals sharing one universal subspace as in the traditional eigenface method. Compared with the traditional single subspace face representation, the proposed method captures the extrapersonal difference to the most possible extent, which is crucial to distinguish between individuals, and on the other hand, it throws away the most intrapersonal difference and noise in the input. Our experiments strongly support the proposed idea, in which 20% improvement of performance over the traditional "eigenface" has been observed when tested on the same face base.

Keywords: face recognition, eigenface, Individual Eigen-subspace

1. Introduction

Identity verification is vital to access control and credit card use. While traditional verification methods can not put an end to forging, in recent years biometric identification technologies has attracted much attention, among which automatic face recognition is one of the most important approaches. Such technologies can also be utilized in identity-based facial image retrieval, especially in mug shot searching.

Researchers have developed a number of face recognition techniques such as geometry-based recognition, template matching, principal component analysis (PCA), eigenface, ANN and elastic graph matching etc.[1], which can be categorized into two classes: feature-based and bitmap-based. Among these techniques, "eigenface" method[2] proposed by Turk and Pentland in 1991 remains popular internationally since then. Eigenface is essentially PCA, in which the principal components of the facial image distribution are estimated by a training facial image set. These principal components are face-like visually when displayed, for which Turk and Pentland called them "eigenface". And they span a low dimensional subspace in the whole image space, the so-called "face subspace". Any high dimensional input facial image can be approximately represented as a low dimension feature vector by projecting it to the subspace.

After "Eigenface" is proposed, the concepts such as view-based eigenspace and eigenfeatures (eigeneye，eigennose， eigenmouth) have been developed[3]. While in these methods all the subjects share one or several subspaces for different views or independent feature components, we propose to represent each subject with one private subspace, or even with several subspaces for different views or feature components.

We propose this method based on analyzing the essence of "eigenface" from the viewpoint of eigen-subspace theory. According to this theory, we know that face-subspace spanned by the "eigenfaces" is actually the signal subspace of the face image, which captures the common information that might be useless for the recognition of different subjects. The residual eigenvectors span an orthogonal complementary subspace, which is called noise subspace that contains three kinds of information: extrapersonal variance, intrapersonal variance and stochastic noise, among which the first one is vital for distinguishing different subjects while the next two are useless. From this analysis, we argue that single face subspace might throw away extrapersonal difference that is actually quite important for recognition. To avoid this kind of information loss, we propose the idea that each person has one private subspace, which preserves the common information for the specific person and throws away intrapersonal difference and noise.

The following parts of this paper are organized as follows: In section 2, eigenface technique is analyzed from the perspective of signal eigen-subspace. Section 3 describes our individual eigen-subspaces-based face recognition. In section 4 some experiments are set up to compare the performances of different algorithms.

2. Understanding "eigenface" from the viewpoint of "eigen-subspace" approach

In signal processing applications, useful low-rank information is often needed to be extracted from a stochastic broadband signal with noise. Eigenvalue decomposition of the covariance matrix can be used to achieve this goal. By using the magnitude of the eigenvalues, the eigen-subspace of the signal can be divided into two orthogonal subspaces: signal subspace and noise subspace, capturing the signal and the noise component respectively.

2.1 "Eigenface" face recognition

Let $\{\Gamma_1,\Gamma_2,\cdots,\Gamma_n\}$ be a facial image set, with each $\Gamma_i, i=1,\dots n$ being a n^2-D vector. Their mean vector is $\Psi=\frac{1}{m}\sum_{i=1}^{m}\Gamma_i$, and difference image is calculated by $\Phi_i=\Gamma_i-\Psi, i=1,2,\dots,m$ for each image. So its covariance matrix is $C=\frac{1}{m}\sum_{i=1}^{m}\Phi_i\Phi_i^T$. We can work out C's m non-zero eigen-values $\lambda_1\ge\lambda_2\ge\cdots\ge\lambda_m$ and corresponding eigenvectors: $\mu_1,\mu_2,\cdots,\mu_m$ respectively. The first d eigenvectors $U_f=[\mu_1\mu_2\cdots\mu_d]$ span a subspace, so called "face subspace", $span(U_f)=span(\mu_1\mu_2\cdots\mu_d)$. Any face image Γ can be projected to the subspace to obtain a low dimension description as:

$$W=U_f^T\Phi \tag{1}$$

Where $\Phi=\Gamma-\Psi$ is the difference image. W can be regarded as feature vector of the input image. Then recognition can be completed in the low dimension space. Note that if we let $W=[\omega_1\omega_2\cdots\omega_d]$ be d-D description of the input image Γ, we can reconstruct the input image as $\Phi_r=U_fW$. The Euclidean distance $\varepsilon=\|\Phi-\Phi_r\|$ measures the similarity of the input image as a "face", called distance from face-subspace (DFFS)[2].

2.2 Introduction of eigen-subspace approach

Considering a broad band harmonic signal $x(t)$, it can be expanded as the linear combination of the first d complex sinusoidal signals:

$$x(t)=\sum_{k=1}^{d}P_k\exp(j2\pi f_k t+\theta_k)+w(t) \tag{2}$$

Where θ_k and P_k are the initial phase and power of the k-th sinusoidal wave， θ_k is a stochastic variable ranging in $(-\pi,\pi)$ satisfying uniform distribution. Additive noise $W(t)$ is a Gaussian noise with zero-mean and σ^2 variance. The Toeplitz covariance matrix of $x(t)$ is:

$$R=\sum_{k=1}^{d}P_k s_k s_k^H+\sigma^2 I,\ \text{where}\ s_k=\begin{bmatrix}1\\ \exp(j2\pi f_k)\\ \vdots\\ \exp[j2\pi f_k(M-1)]\end{bmatrix} \tag{3}$$

Where s_k is a vector carrying the frequency information of the k-th sinusoidal wave. From the above formulation, we can rewrite R as the sum of signal covariance matrix S and noise covariance matrix W:

$$R=S+W,\ where\ S=\sum_{k=1}^{d}P_k s_k s_k^H, and\ W=\sigma^2 I \tag{4}$$

S and ***W*** are both $M\times M$ matrices, and $rank(S)=d, rank(W)=M$. Let S's eigevalue decomposition be: $S=\sum_{i=1}^{M}\lambda_i v_i v_i^H$. Since $d<M$ and S has （$M-d$） zero eigenvalues, thus $S=\sum_{i=1}^{d}\lambda_i v_i v_i^H$, and formulation (4) can be converted to:

$$R=\sum_{i=1}^{d}\lambda_i v_i v_i^H+\sigma^2\sum_{i=0}^{M}v_i v_i^H=\sum_{i=1}^{d}(\lambda_i+\sigma^2)v_i v_i^H+\sum_{i=d+1}^{M}\sigma^2 v_i v_i^H \tag{5}$$

So, ***R***'s non-incremental ordered eigenvalues are $\lambda_1+\sigma^2,\lambda_2+\sigma^2,\cdots,\lambda_d+\sigma^2,\underbrace{\sigma^2,\cdots,\sigma^2}_{M-d}$.

Mathematically, the first d maximal eigenvalues are called dominant eigenvalues and the others are called subeigenvalues, corresponding eigenvectors are dominant eigenvectors and subeigenvectors. In signal processing, they are called signal eigenvalues/eigevectors and noise eigenvalues/eigevectors respectively. Signal eigenvectors $V_s=[v_1,v_2,\dots,v_d]$ span signal subspace $Span\{V_s\}=span\{v_1,v_2,\dots,v_d\}$, while noise eigenvectors $V_n=[v_{d+1},v_{d+2},\dots,v_M]$ span noise subspace $Span\{V_n\}=span\{v_{d+1},v_{d+2},\dots,v_M\}$.

2.3 Analysis of "eigenface" method

All faces have common features. We can describe the common face as Ψ . Any face image Φ can be regarded as a stochastic observed data with an expectation of Ψ . According to the eigen-subspace theory, the useful information in the stochastic signal vector can be extracted by estimating the signal subspace and the noise subspace. It is obvious that the eigenface is just eigen-subspace decomposition, in which signal and noise subspaces are $S_{signal}=S_{face}=Span\{V_{face}\}=span\{v_1,v_2,\dots,v_d\}$ and $S_{noise}=Span\{V_{noise}\}=span\{v_{d+1},v_{d+2},\dots,v_M\}$ respectively.

While the signal (/face) subspace has been studied exhaustively, the residual noise subspace has rarely been pondered by now. It can be concluded that the signal subspace depicts the common information, while the “noise” subspace represents the distribution of three kinds of information: extrapersonal variance, interpersonal variance and stochastic noise, among which extrapersonal difference is essential for distinguishing different individuals, whereas interpersonal difference and stochastic noise are useless for recognition. Unfortunately, the extrapersonal difference crucial for recognition is blended inseparably with the intrapersonal difference and noise information in the “noise” subspace. So we argue that “eigenface” technique might be more favorable for face detection rather than face recognition. Based on this notion, we propose the following individual eigen-subspaces-based face recognition technique.

3. Individual eigensubspaces-based face recognition

Extrapersonal difference is the most crucial factor for distinguishing different persons. In order to capture the key information and at the same time throw away the disturbances (i.e. interpersonal variance and noise), we propose to describe each subject with a private face eigensubspace. The private face eigensubspace can best represent the common character of the subject while at the same time throw away interpersonal difference and noise.

Let a class set with p subjects is $C=\{\Omega_1,\Omega_2,\cdots,\Omega_p\}$. Each class $\Omega_k, k=1,2,\cdots,p$ in C is analyzed by eigensubspace:

$$\begin{aligned} R_k &= \sum_{i=1}^{d_k}\lambda_i^{(k)} v_i^{(k)} v_i^{(k)H} + \sigma_k^2 \sum_{i=0}^{M_k} v_i^{(k)} v_i^{(k)H} \\ &= \sum_{i=1}^{d_k}(\lambda_i^{(k)}+\sigma_k^2) v_i^{(k)} v_i^{(k)H} + \sum_{i=d+1}^{M_k}\sigma_k^2 v_i^{(k)} v_i^{(k)H} \end{aligned} \tag{6}$$

Then the face signal subspace and corresponding noise subspace for the k-th person are:

$$S_{face}^{(k)} = Span\{U_{face}^{(k)}\} = span\{v_1^{(k)}, v_2^{(k)}, ..., v_{d_k}^{(k)}\} \tag{7}$$

$$S_{noise}^{(k)} = Span\{U_{noise}^{(k)}\} = span\{v_{d+1}^{(k)}, v_{d+2}^{(k)}, ..., v_{M_k}^{(k)}\} \tag{8}$$

They are called individual face eigensubspace and individual noise subspace respectively. Then the distance from individual face subspace (DFSFS) can measure the similarity between one input face image and the eigensubspace. DFSFS is calculated as follows:

Any face image Γ can be projected to the k-th individual face eigensubspace $S_{face}^{(k)}$ by:

$$W^{(k)} = U_{face}^{(k)\,T}\Phi^{(k)} \tag{9}$$

Where $\Phi^{(k)} = \Gamma - \Psi^{(k)}$ is the difference image. Then the input image can be reconstructed by:

$$\Phi_r^{(k)} = U_{face}^{(k)} W^{(k)} \tag{10}$$

So, DFSFS of the input image to the k-th individual face subspace $S_{face}^{(k)}$ is:

$$\varepsilon^{(k)} = \left\| \Phi^{(k)} - \Phi_r^{(k)} \right\| \tag{11}$$

A minimal DFSFS recognition strategy is as follows:

$$\Gamma \in \Omega_l \ \text{ if } \ \varepsilon^{(l)} = \min_{1\le k\le p}\{\varepsilon^{(k)}\} \tag{12}$$

4. Experiments

There are 10 subjects in our face-base, including 3 females and 7 males. Each subject has 35 facial images, in which total 200 images (each subject 20 images) constitute the training set. All the training images are quasi-frontal, with uniform luminance, neural expression, no ornament such as glasses, as illustrated in Fig.1. All testing facial images are taken at different time, with large variances in luminance, background, expression, pose, hairstyle and accouterments compared with those in the training set, as shown in Fig.2. We must note that our testing images are quite different from their training counterparts, which results in the relatively low recognition ratio. Since our experiments are designed to evaluate the performance of different approaches, recognition ratio is not so critical.

Fig.1 Training images for one subject in the training set

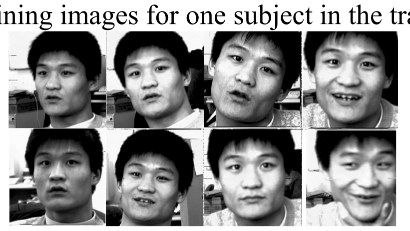

Fig.2 Some test images of the subject in Fig.1

Due to the randomness of the face location, pose, illumination and scale, normalization is necessary in order to achieve robust recognition. In our system, we first detected the face using a multi-level face detection model based on skin model, template matching and eigen-features. Then based on the localization of the two irises, facial region is warped by affine transformation, luminance normalization, scale normalization and masking. Details of face normalization can be found in [4]. Some normalized faces are illustrated in Fig.3.

In order to compare the two different approaches, a single "face subspace" is created according to the method in section 2.1, using all the 200 images in the training set. And 10 individual eigen-subspaces for 10 subjects are generated using our proposed approach with 20 images for each subject. The following two experiments are set up.

Fig.3 Some normalized face images

Experiment 1:

Recognition test is performed on the training set. The performances of eigenface and our novel approach are as in Table-1 and Table-2 respectively, among which the noise is a stochastic uniform one within specified range.

From Table-1 and Table-2, we can find that both of the approaches have good performances, especially they are both quite robust to the noise. Little change is observed on the recognition performance when noise is added to the input image. And our proposed approach is better than the "eigenface".

Table-1 Performance of the proposed approach tested on the training set including 200 samples

Samples	Performance under stochastic uniform noise(%)				
	none	10	20	30	40
200	100%	100%	100%	100%	100%

Table-2 Performance of the "eigenface" tested on the training set including 200 samples

		Performance under stochastic uniform noise %				
eference sam es erson	test sam es erson	None	5	10	15	20
8	120	97.5	97.5	97.5	97.5	97.5
9	110	98.2	98.2	98.2	98.2	98.2
10	100	99.0	99.0	99.0	99.0	99.0

Experiment 2:

Recognition test is performed on the 150 test samples in the test set. The performances of both approaches are illustrated in Table-3 and Table-4 respectively. From Table-3 and Table-4 we find that our approach has an impressive 20% improvement than the traditional "eigenface" in recognition performance when tested on the same test set, in which our approach has a maximal recognition ratio of 80.7% while the eigenface's peak of recognition ratio is only 60.7%. Fig.4 illustrates the recognition curve of the two approaches, whose abscissa is the number of eigenfaces used and y-axis is the corresponding recognition ratio.

Table-3 Performance of the proposed approach testing on the test set

performance under stochastic uniform noise				
None	[-5,+5]	[-10,10]	[-15,+15]	[-20,20]
80	80	80	80	80 0

Table-4 Performance of the "eigenface" testing on test set

Samples per person	Performance under stochastic uniform noise				
	one		[-10,10]	[-15,15]	[-20,20]
8	60.7	60	60	60.7	60

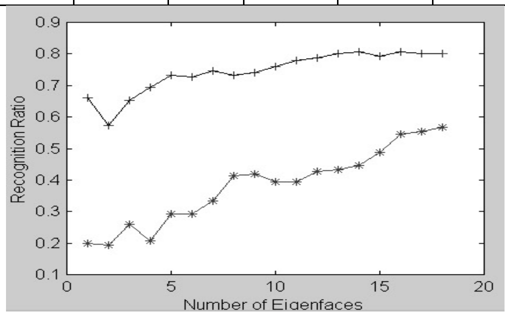

Fig.4 Recognition ratio curve of the two approaches, '*': eigenface, '+': our proposed method

5. Conclusion

In this paper, we have analyzed the traditional "eigenface" algorithm from the viewpoint of eigen-subspace analysis. According to the descriptive power of eigen-subspace approach, we argue that the subspace spanned by the traditional eigenfaces keeps mainly the common properties of the images in the training set while throws away the most extrapersonal difference. To extract the extrapersonal difference, we proposed a novel face recognition approach based on individual face eigen-subspaces. Experiments have strongly indicated that our approach has much better performance in recognizing testing face images that are quite different in appearance from those in the training set.

Reference

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