On Modeling Variations For Face Authentication

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Abstract

In this paper, we present a scheme for face authentication by using applying principal component analysis (PCA) to model variations. To deal with variations, such as facial expressions and registration errors, with which traditional appearance-based methods do not perform well, we propose the eigenflow approach. In this approach, the optical flow and the optical flow residue between a test image and a well-registered image in the training set are first computed. The optical flow is then fitted to a model that is pre-trained by applying PCA to optical flows resulting from facial expressions and registration errors for the subjects. The eigenflow residue, optimally combined with the optical flow residue using linear discriminant analysis (LDA), determines the authenticity of the test image. Experimental results show that the proposed scheme outperforms the traditional methods in the presence of facial variations.

1. Introduction

For decades human face recognition has drawn considerable interest and attention from many researchers [1]. A general statement of this problem can be formulated as follows. Given still or video images of a scene, identify one or more persons in the scene using a stored database of faces [2].

Face authentication [3] is a research field related to face recognition. The difference between face recognition and face authentication is that, in the former, the system has to determine the identity of the subject, while in the latter, the system only needs to verify the claimed identity of the user. Usually similar algorithms can be used for both recognition and authentication.

A comprehensive survey of human and machine recognition techniques can be found in [2][5][6]. There are mainly two kinds of face recognition systems: one is based on feature matching; the other is based on template matching. In the latter, applying PCA in the pixel domain (also known as eigenface approach [7]) plays a fundamental role. Several papers propose revised eigenface approaches to dealing with face image variability [8]. Some researchers have noted that applying PCA to image pixels directly is very sensitive to shift, rotation, scale, expression or lighting variations of face [4], which is because the eigenface method is basically an appearance based approach.

In this paper, we propose a general approach to performing face authentication by modeling different kind variations, such as facial expression variations and shift, rotation, scale type of registration errors. Optical flow is used to capture face appearance motion when there is variation in facial expression. For example, the optical flow between the neutral and happy expression of one subject tells us how this subject smiles. After we apply PCA to optical flows, we obtain an eigenspace spanned by its eigenvectors, that we call *eigenflow* in this paper. This eigenspace models possible expression variations. Optical flow and eigenflow can also be used to model other variations, such as registration error, shift, scale, and rotation. As a general framework, we can also model the illuminant variations by computing the features for images under different lighting conditions, and performing PCA on these features.

Optical flow methods are generally used for motion analysis. Some researchers have used optical flow in the analysis of human expression for the purpose of expression recognition [9][10]. Also Kruizinga and Petkov [11] proposed to utilize optical flow in person identification. However, they only considered the optical flow residue as the measurement of classification, while we propose to make use of the eigenflow residue, which appears to exhibit more classification ability than the former.

Essentially optical flow can provide us the visual motion information about face images. Moghaddam et. al also proposed modeling visual motion in [12]. They determine pixel difference between images, and utilize the Bayesian approach to modeling the pixel difference for all the subjects. In our case, first the optical flow is used to obtain motion field between images and then PCA is applied to model facial motion for individual subject.

This paper is organized as follows. In Section 2, we introduce the individual eigenspace. In Section 3, we present the individual eigenflow based approach in detail. Experiments based on different sets are presented in Section 3. Finally in Section 4, we provide the conclusions.

2. The individual eigenspace

Turk and Pentland [7], introduced the eigenface approach to performing face recognition. While constructing an eigenspace, face images from all training subjects are used. We call the resulting eigenspace a *universal eigenspace*. We can see that this eigenspace represents not only the personal identity, the inter- variation between different training subjects, but also the intra- variation of each subject, such as due to expression changes, illumination variability, age, etc. However, what we need for the authentication is robustness to expression and illumination variations within a single subject, not robust recognition for all the subjects. This observation suggests one potential metric for face authentication. The residue of a test vector to that vector's individual eigenspace, (i.e., the squared norm of the difference between a test vector and its representation in the eigenspace) is a good measure for authentication.

Throughout the rest of this paper, we will focus for simplicity on one specified subject. So for a training set of K subjects and M images for each subject, the same approach can be repeated K times. In the individual eigenspace approach, one eigenspace is constructed for each training subject. As the following equation indicates, the average face will be different for each subject.

$$\mathbf{g}_i = \frac{1}{M}\sum_{j=0}^{M-1}\mathbf{f}_{ij} \tag{1}$$

Now each face differs from the average by the vector $\mathbf{s}_{ij} = \mathbf{f}_{ij} - \mathbf{g}_i$. Also the $\mathbf{A}$ matrix is different for each subject, i.e., $\mathbf{A}_i = [\mathbf{s}_{i,0}, \mathbf{s}_{i,1}, ..., \mathbf{s}_{i,M-1}]$. Here we denote the eigenvector of each space as $\mathbf{u}_{i,n}$, and each face is projected to its own eigenspace as follows:

$$w_n = \mathbf{u}_{i,n}^T(\mathbf{f} - \mathbf{g}_i) \quad \textit{if } \mathbf{f} \textit{ belongs to Subject } i \tag{2}$$

So far we have suggested an individual eigenspace for each subject, and each training face (with its claimed identity) has corresponding projected eigencoefficients, w_n, in its own eigenspace. From these projected vectors, the face image can be reconstructed by:

$$\hat{\mathbf{s}} = \sum_{n=0}^{Q-1} w_n \mathbf{u}_{i,n} \tag{3}$$

Where Q is the number of eigenvectors in the eigenspace. Since this eigenspace is only an idealized representation for one subject, it cannot represent all manifestations of that subject's face perfectly, i.e. there will be a residue (i.e., difference or squared error) between the test image and its reconstructed version.

The residue is defined as the squared distance between the mean-adjusted test input image $\mathbf{s} = \mathbf{f} - \mathbf{g}_i$ and reconstructed image $\hat{\mathbf{s}}$, i.e.,

$$e = \|\mathbf{s} - \hat{\mathbf{s}}\|^2 \tag{4}$$

In the next section, we will call e the *eigenflow residue* since it characterizes how well the eigenspace can model the unknown sample.

2. Individual Eigenflow Based Face Authentication

The traditional eigenface approach is not as robust as needed to expression variations and to shift, rotation, and scale changes. Because PCA is an appearance-based approach, its authentication performance will degrade quickly when the appearance of a subject's face changes significantly, which occurs in the presence of expression changes and registration errors. In this section, we propose a new method based on optical flow to deal with such variations in face images.

2.1 Optical flow for face images

Essentially optical flow [15] is an approximation of the velocity field. It characterizes approximately the motion of each pixel between two images.

If two face images, which show different expressions of the same subject, are fed into the optical flow algorithm, the resultant motion field will emphasize the regions of facial features, such as eyes and mouth. This is illustrated in Figure 1. The left half of the figure shows two face images from the same subject, but with different expressions. The resulting optical flow is shown below these figures. Also by using the first image and the optical flow, we can construct a predicted image that is close to the second image. The third figure in the top row is the difference between prediction obtained via the optical flow and the second image. We call it *optical flow residue* image. For the correct subject, this residue image would have low energy because the motion of most pixels can be modeled well by the optical flow. The second set shows the same except that the two input images are from two different subjects. Obviously, the optical flow looks more irregular when the two images are from different subjects. Also the residue image of motion prediction has more "error". These two clues can help discriminating these two cases, which is the task of authentication.

The same idea can be applied to images with registration errors. Because the traditional eigenface approach is unacceptably sensitive to registration errors, even small shifts in input images can make the system performance degrade significantly. However, face images are usually difficult to register precisely, especially in a live authentication system. So here we want to use the optical flow to build a system that is tolerance to different kinds of registration errors. The second image in the left column of Figure 2 is an up-shifted version of the first image. The optical flow shown below captures most of its motion around facial features, and also the residue image has small intensity. The right column shows images of different subjects leading to an optical flow that appears to be random, and the residue image has larger intensity.

2.2 The training of eigenflow

Since the optical flow provides a useful pattern for classifying personal identity, we propose to use PCA to model this pattern.

Given two face images, there are some recommended preprocessing steps prior to the optical flow determination. Since some regions of face images will always contain background, it is better to crop the image before the optical flow computation.

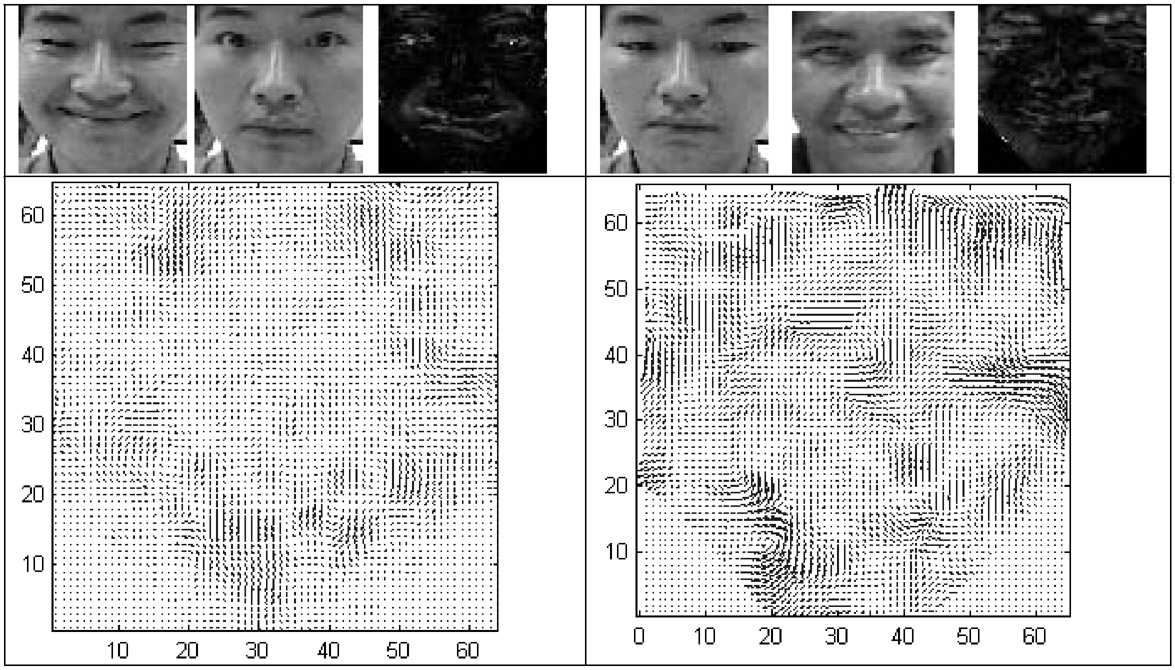

Figure 1 Application of optical flow to cases of different expressions

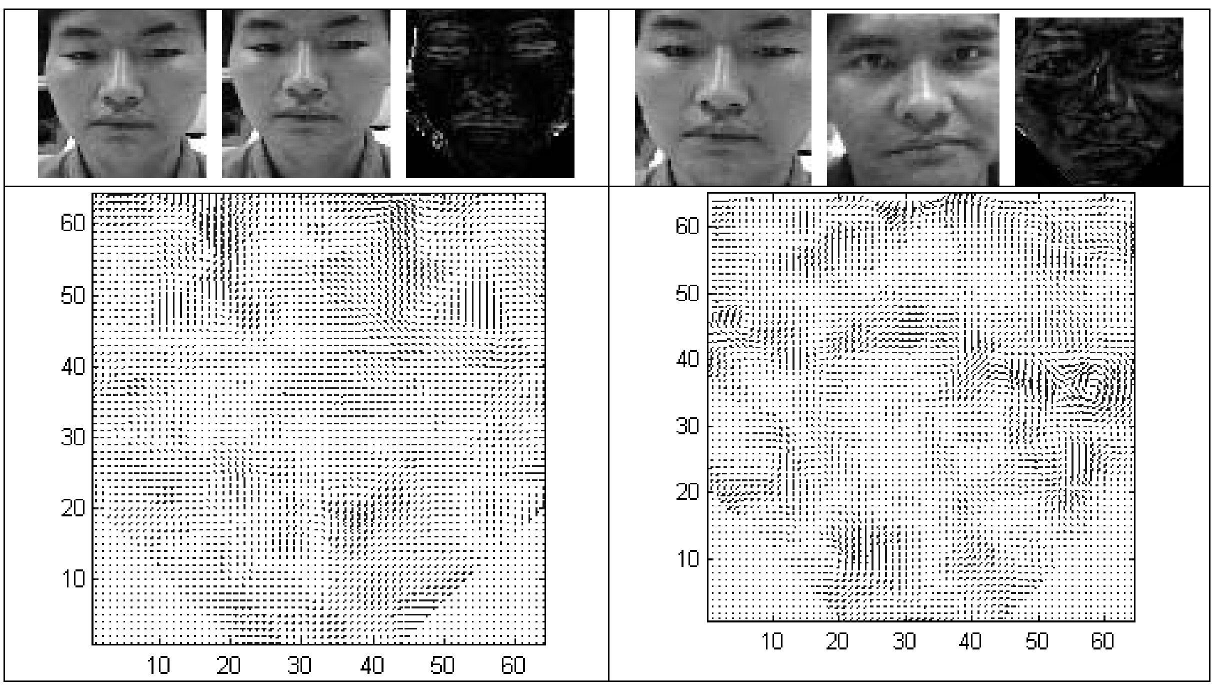

Figure 2 Application of optical flow to two cases of different registration.

Figure 3 Five expression images used for training eigenflow.

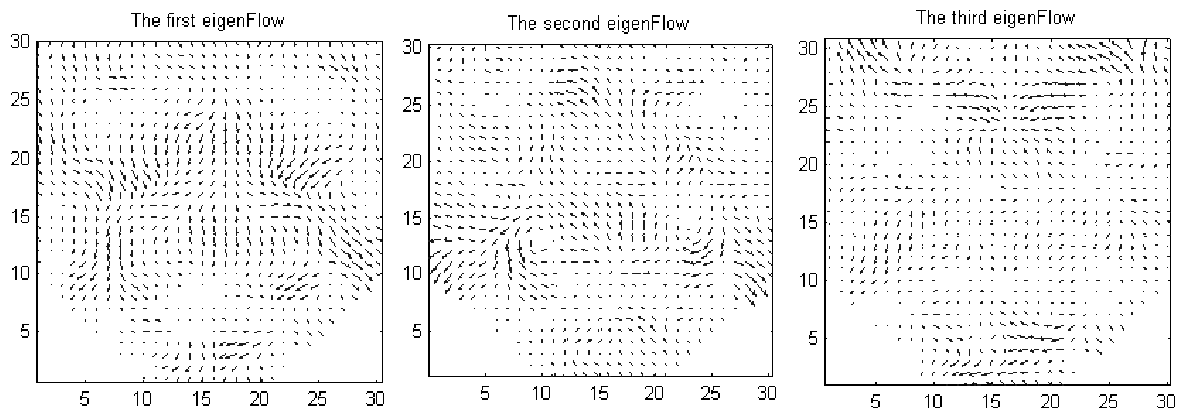

Figure 4 The first three eigenflows trained from expression images of one subject. Some prominent movement of facial features, such as mouth corner, eyebrow, scale, nasolabial furrow, can be seen from them.

Following the traditional PCA approach, optical flow vectors are regarded as sample vectors for training. Suppose that in the training dataset, there are a few images with different expressions for each subject, such as five images shown in Figure 3. Using these images, twenty optical flow images (corresponding to twenty pairs) can be obtained. The three principal eigenflow images of twenty optical flow images are shown in Figure 4. Obviously large motion can be observed in the region of facial features, such as mouth corner, eyebrow, nasolabial furrow. So all the expression variations occurring in a single subject can be represented by a space spanned by these eigenflows. In contrast, the optical flow between this subject and other subjects cannot be represented well by this space.

Similarly eigenflows can be used to model the optical flow caused by image registration errors. In the live application of face authentication, face region needs to be registered from a whole frame. Usually it is done via a crop operation based on the location of two eyes. In our approach, we synthesize images with registration errors from one well-registered image. Again the eigenflows can indicate the actual motion pattern appearing in the training set.

In the testing stage, both the optical flow residue and the eigenflow residue will be used for authentication, where the optical flow residue is computed in determining optical flow between the testing image and training images, and the eigenflow residue is obtained in projecting the optical flow into the eigenflow space. Eventually linear discriminant analysis [13] will combine these two residues and obtain the final measurement for authentication.

3. Experiment Results

Experiments and evaluations are important parts of any face authentication system. In order to isolate the effects of facial expression variations and registration errors, we assume that all the training and test images are captured under the same lighting condition.

Before discussing the results, we will present some details about our algorithm. Given any two training images, we generate the optical flow using four steps. First the background regions below the cheek in the face image are removed because the background seems to affect the optical flow calculation, and thus interferes with the authentication. Zero is filled into the two triangle regions in the lower part of the face square. Next, we determine the optical flow using Lucas-Kanade algorithm[20]. Third the optical flow is down sampled to be half its original size in order to speed up the PCA training and to clean up the noisy motion vectors. Finally within this smaller-size optical flow, the background and four side boundaries are removed because usually the boundary does not result in accurate motion estimation in the optical flow algorithm. Now the down-sampled optical flow image can be scanned into a vector, whose dimension is much lower than the unsampled one.

The first data set has only expression variations. 13 subjects are included in this set. Each has 5 images for training, and 70 images for testing. The reason we use more test images than training images is that we want to get a smother ROC curve. Also, only a few images may be available for training in a practical setup. Each of the five training images represents different expressions, such as neutral, happy, angry, sad, and surprise. All of these images are well registered by the location of the eyes. Here we implement three algorithms: the individual PCA approach on image domain, the universal PCA approach, and the individual eigenflow approach. From the result, we can see that for most part of the curve, our approach yields better performance. Also the improvement is significant compared to the universal PCA approach.

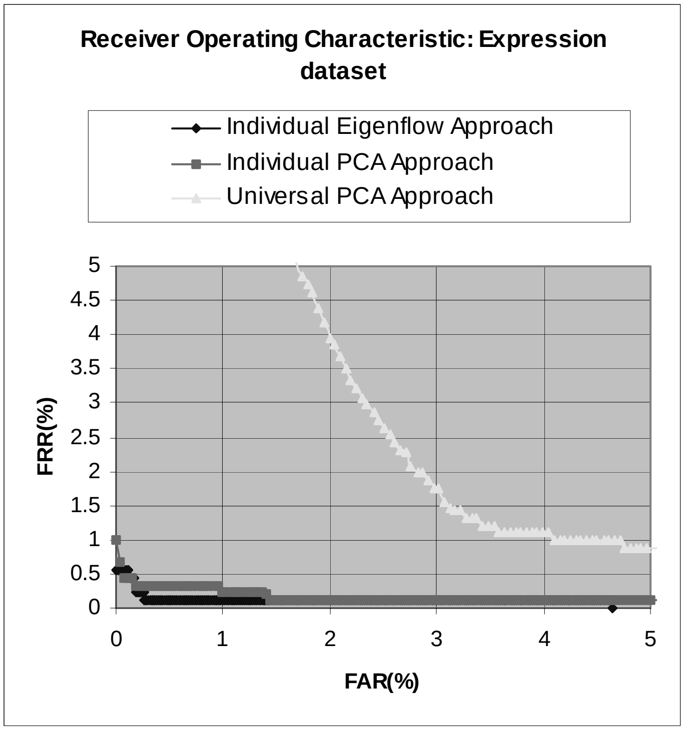

Figure 5 The experiment results on the expression dataset.

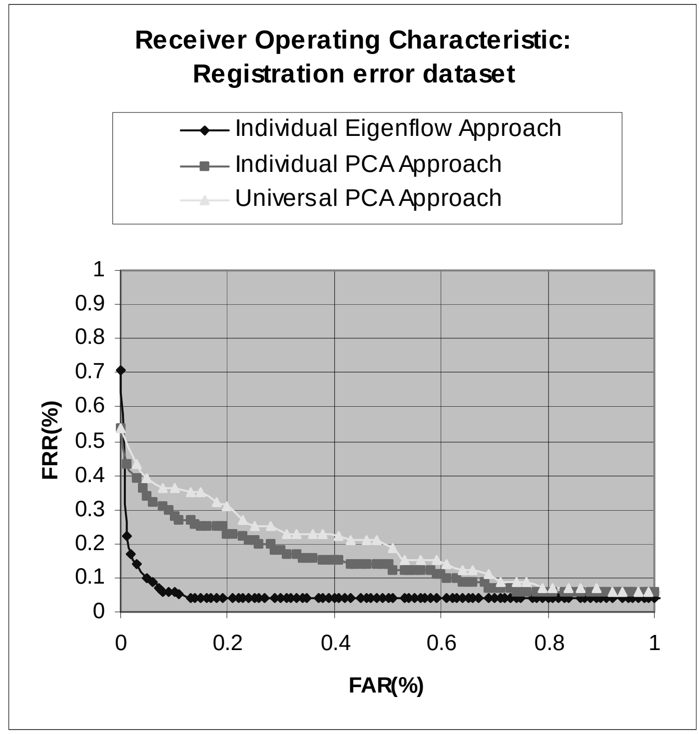

Figure 6 Experiment results on the data set with registration errors.

The second data set has the registration variation for each subject. Given one well-registered face image, we synthesize 625 images by cropping face region based on 25 points around the eye locations. These images are used for training one subject. The same method is used to generate the 625 test images except there is larger offset while selecting the eye neighbors, which means test images have larger registration errors than training one. So all these synthesized training images can represent different kinds of registration errors. Based on this set, the eigenflow-based approach has shown much better performance than the PCA approach.

The third data set has both expression variations and registration errors. First, for each one of the 13 subjects, 5 expression images are obtained to be the reference images. Then, for each reference image, 624 images can be synthesized to include all kinds of registration errors. Thus, 3125 images are collected for each subject. We also generate 3120 test images for each subject using the same approach, but there are two differences. One is that all the test images have different expressions compared to the reference images. The other is that the testing images have larger registration errors than the training one.

Since in this experiment, we have many more test images than in the previous two experiments, the denominator in computing *FAR* and *FRR* will be much larger. That is why a much smoother ROC curve can be observed from Figure 7.

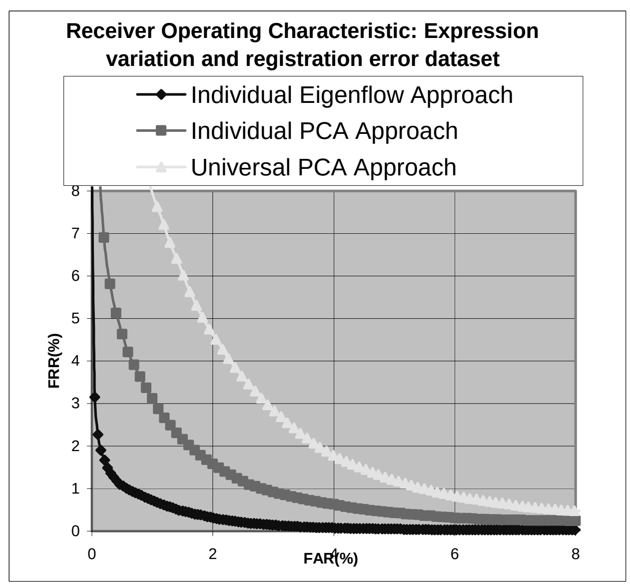

Figure 7 Experiment results on the data set containing both expression variations and registration errors.

5. Conclusions

In this paper, we present a scheme for face authentication by modeling variations via applying principal component analysis (PCA). To deal with variations, such as facial expressions and registration errors, with which traditional appearance-based methods do not perform well, we propose the eigenflow approach. In this approach, the optical flow and the optical flow residue between a test image and a well-registered image in the training set are first computed. The optical flow is then fitted to a model that is pre-trained by applying PCA to optical flows resulting from facial expressions and registration errors for the subjects. The eigenflow residue, optimally combined with the optical flow residue using linear discriminant analysis (LDA), determines the authenticity of the test image. Experimental results show that the proposed scheme outperforms the traditional methods in the presence of facial variations.

The advantage of this proposed approach is its tolerance to different kinds of variations, such as expression variations and registration errors, because all these variations have been modeled by PCA. As a general framework, our method can also been extended to model other variations that appear in faces, such as illuminants, poses.

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