On Modeling Variations for Face Authentication

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Abstract

In this paper, we present a scheme for face authentication in the presence of 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 training image are computed first. The optical flow is then fitted to a model that is pre-trained by applying principal component analysis (PCA) to optical flows resulting from variations caused by facial expressions and registration errors. 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 expression variations and registration errors. The approach can be extended to model lighting and pose variations as well.

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 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][4]. 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 principal component analysis (PCA) in the pixel domain (also known as the eigenface approach [5]) plays a fundamental role. Some researchers have noted that applying PCA to image pixels directly is very sensitive to shift, rotation, scale, expression or lighting variations [6], because the eigenface method is basically an appearance-based approach. Several papers propose revised eigenface approaches to dealing with face image variations [7].

In this paper, we propose a general approach to performing face authentication by modeling variations, such as facial expression variations and registration errors. Optical flow is used to capture these variations. For example, the optical flow between the neutral and happy expressions of one subject tells us how this subject smiles. We propose to apply PCA to optical flows, and obtain an eigenspace spanned by its eigenvectors, which we call *eigenflows*. This eigenspace models all possible expression variations. Optical flow and eigenflow can also be used to model other variations, such as registration errors, including shift, scaling, 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 [8]. Also Kruizinga and Petkov [9] proposed to utilize optical flow in person identification. However, they only considered the optical flow residue as the measurement of classification without considering the statistics of the optical flow itself. We model the statistics of the optical flow using PCA, which exhibits more classification ability.

Moghaddam et al. also proposed modeling visual motion in [1]. They determined pixel difference between images, and utilized the Bayesian approach to model the pixel difference for all the subjects. In our case, we model the motion directly. First the optical flow is used to obtain motion field between images and then PCA is applied to model facial motion for the subject.

This paper is organized as follows. In Section 2, we introduce the individual eigenspace, the basic framework of our classification method. In Section 3, we present the eigenflow based approach. Experiments based on different sets are presented in Section 4. We conclude in Section 5.

2. The individual eigenspace

Turk and Pentland [5] 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. This observation suggests one potential metric for face authentication: the residue of a test image to a subject's individual eigenspace, i.e., the difference between a test image and its projection to the eigenspace. We proposed the individual eigenspace method in [11], which we outline as follows.

Throughout the rest of this paper, we will focus on authentication of one specific subject as opposed to all other subjects in the database. Suppose there are K subjects and M training images. In the individual eigenspace approach, one eigenspace is constructed for each training subject. The average face of Subject i is:

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

Now each face differs from the average by the vector $\mathbf{s}_{ij} = \mathbf{f}_{ij} - \mathbf{g}_i$. Based on $\mathbf{A}_i = [\mathbf{s}_{i,0}, \mathbf{s}_{i,1}, ..., \mathbf{s}_{i,M-1}]$, we can derive the eigenvectors of Subject i and denote them as $\mathbf{u}_{i,n}$. Given a test image $\mathbf{f}$, it is projected to the eigenspace of Subject i as follows:

$$w_n = \mathbf{u}_{i,n}^T(\mathbf{f} - \mathbf{g}_i)$$

The face image $\mathbf{f}$ can be reconstructed by:

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

where Q is the number of eigenvectors in the eigenspace. 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.,

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

based on which we can authenticate the test image $\mathbf{f}$.

Note that the above analysis can be applied to optical flows as well. In other words, $\mathbf{f}_{ij}$ and $\mathbf{f}$ can represent training optical flows and the test optimal flow, respectively, rather than images of pixel values. In this case, $\mathbf{u}_{i,n}$ represents the eigenflow of Subject i, and the residue e becomes the eigenflow residue. We will explain these in more detail in the following section.

3. 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 eigenface is an appearance-based approach, its authentication performance degrades 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 our approach based on optical flow to deal with such variations in face images.

3.1 Optical flow for face images

Optical flow [12] 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. On the left, two face images from the same subject, but with different expressions, are shown. The resulting optical flow is shown below them. Also, by using the first image and the optical flow, we can construct a predicted image for the second image. The difference between the predicted image and the second image is shown as the third image in Figure 1. We call it the *optical flow residue* image. For the same subject, this residue image would have low energy because the motion of most pixels can be modeled well by the optical flow. On the right of Figure 1, the two input images are from two different subjects. The resulting optical flow looks more irregular. Also the residue image has more energy. These two clues can help discriminating these two cases, which is the goal of authentication.

The same idea can be applied to images with registration errors. Because the traditional eigenface approach is sensitive to registration errors, even small shifts in input images can make the system performance degrade significantly. We propose to use the optical flow to build a system that is tolerance to registration errors. Figure 2 shows one example. On the left, the second image 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 energy. On the right, it shows images of different subjects leading to an optical flow that appears to be more irregular, and the residue image has larger energy.

3.2 The training of eigenflow

Optical flow provides a useful pattern for classifying personal identity. To capture the pattern, we propose to use PCA to model the statistics of the optical flow.

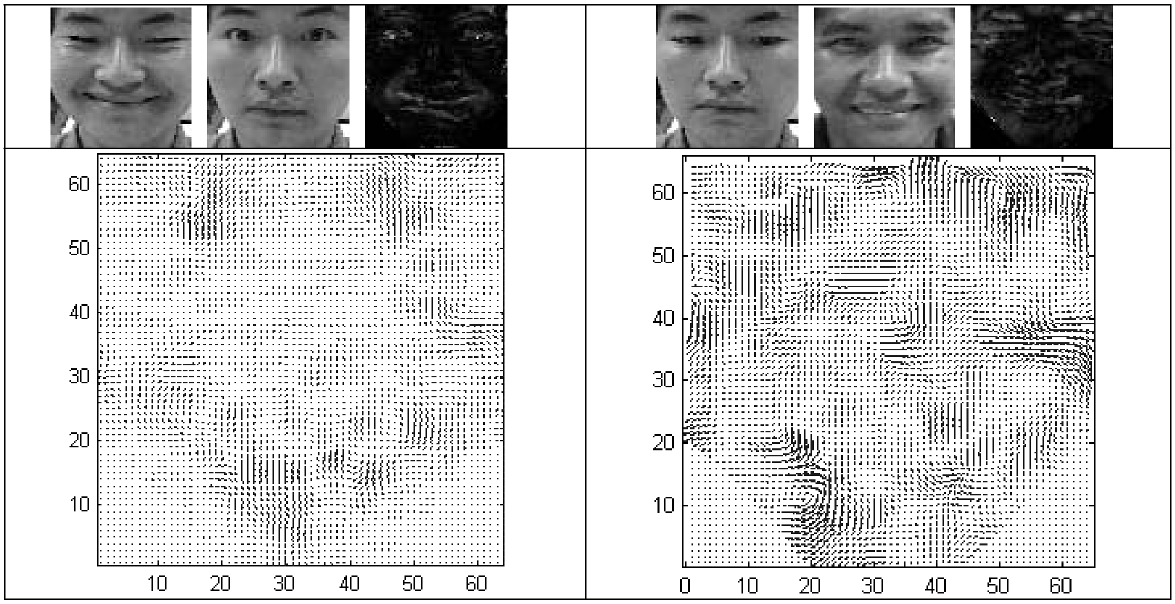

Figure 1. Application of optical flow to cases of different expressions

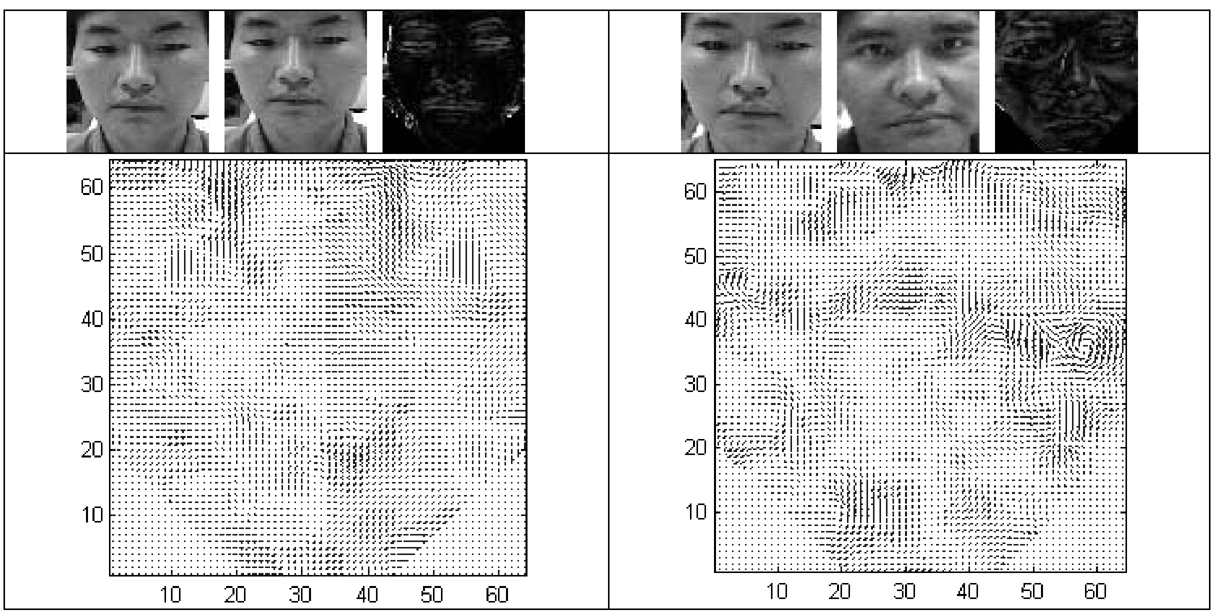

Figure 2. Application of optical flow to two cases of different registration.

Figure 3. Five expression images used for training eigenflows.

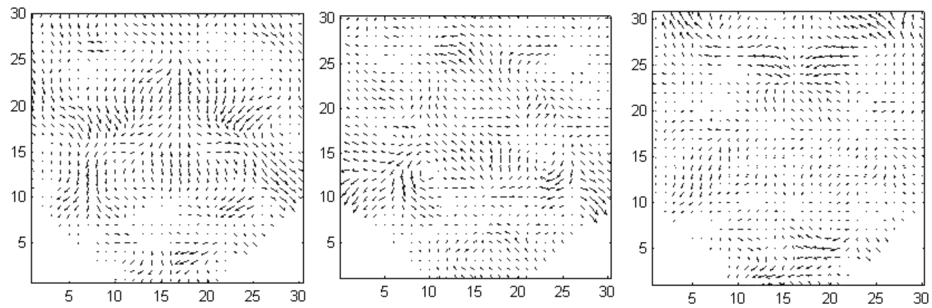

Figure 4. The first three eigenflows trained from expression images of one subject. Some prominent movement of facial features, such as mouth corner, eyebrow, nasolabial furrow, can be seen.

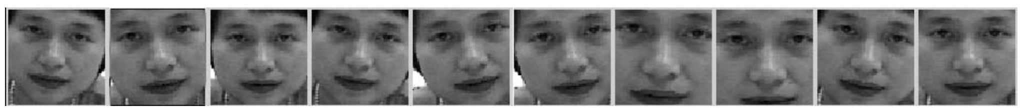

Figure 5. Training images with synthesized registration errors.

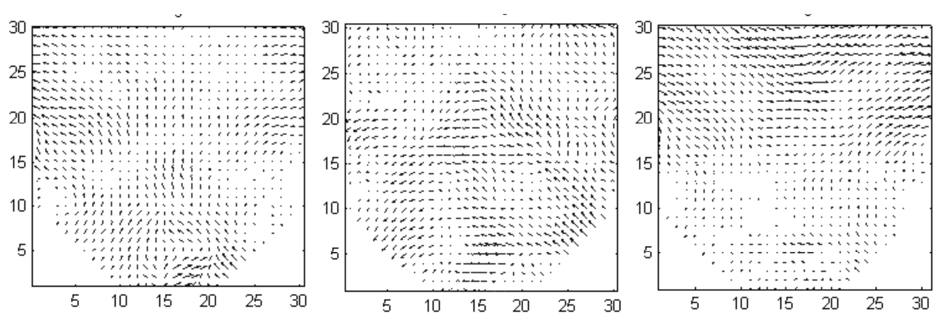

Figure 6. The first three eigenflows trained from synthetic images of one subject. Some prominent motions, such as shifts, rotations, scales, can be seen.

Following the traditional PCA approach, we treat optical flow vectors as sample vectors. Suppose that in the training dataset, there are a number of images with different expressions for each subject, such as the five images shown in Figure 3. Using these images, twenty optical flows (corresponding to twenty pairs) can be obtained. After applying PCA to the optical flows, the three principal eigenflows are shown in Figure 4. Obviously large motion can be observed in the region of facial features, such as mouth corner, eyebrow, and 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 these eigenflows. That is, the eigenflow residue will be large.

Similarly eigenflows can be used to model the optical flow caused by image registration errors as shown in Figure 5. We can see different kinds of registration errors, such as shifts, rotations, and scales. The resulting eigenflows are shown in Figure 6. Again the eigenflows model well the motion caused by registration errors.

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. Finally LDA [13] combines these two residues and obtain the final measurement for authentication.

4. Experiment results

Before discussing the results, we present some details about our algorithm. Given any two training images, we generate the optical flow using the follow procedure. 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 authentication. Zero is filled into the two triangle regions in the lower part of the face square. Next, we determine the optical flow using the Lucas-Kanade algorithm [14]. 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.

The first data set has only expression variations. Thirty subjects are included in this set. Each subject 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 Receiver Operating Characteristic (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. Some of the images are shown in Figure 7. Here we implement three algorithms: the universal PCA approach, the individual PCA approach, and the proposed eigenflow approach. As shown in Figure 8, we can see that the eigenflow approach yields the best performance. The improvement is significant compared to the universal PCA approach.

The second data set contains registration errors. Given one well-registered face image, we synthesize 25 images by shifting the location of each eye into five positions: one pixel above, one pixel below, one pixel left, one pixel right, and its original position. These images are used for training the eigenflows of the subject. The same method is used to generate the 81 test images except there is larger offset while shifting, which means test images have larger registration errors than training images. Again, the eigenflow-based approach has shown much better performance than the PCA approaches, as shown in Figure 9.

The third data set has both expression variations and registration errors. First, for each one of the 30 subjects, 5 expression images are obtained to be the reference images. Then, for each reference image, 5 images are synthesized to include registration errors. Thus, 25 training images are available for each subject. We also generate 56 test images for each subject using the same approach. The experiment results in Figure 10 also show that the better performance has been obtained in the eigenflow approach compared to the other two methods.

5. Conclusions

In this paper, we presented a scheme for face authentication in the presence of variations. To deal with variations, such as facial expressions and registration errors, with which traditional appearance-based methods do not perform well, we proposed the eigenflow approach, which models the variations by applying PCA to the optical flows caused by the variations. Experimental results showed that the proposed scheme outperforms the traditional methods in the presence of facial variations.

The advantage of the eigenflow 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, the eigenflow method can also been extended to model other variations that appear in faces, such as illumination and pose changes.

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Figure 7. Sample images from our database.

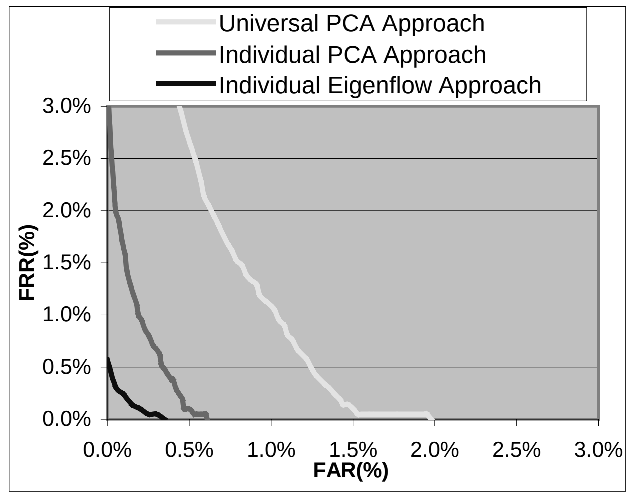

Figure 8. The experiment results on the expression database.

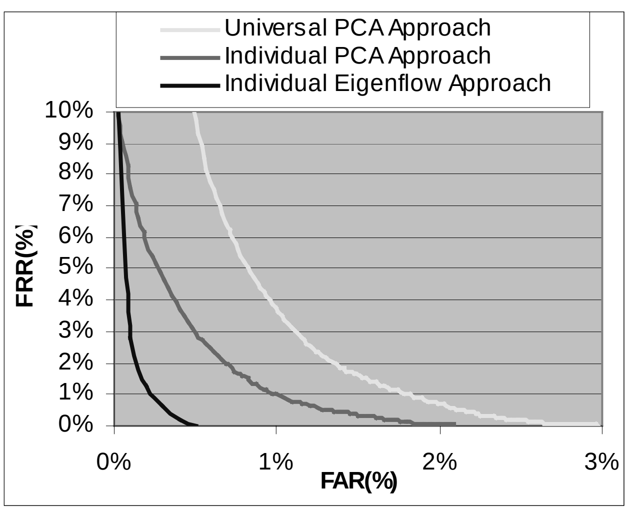

Figure 9. Experiment results on the data set with registration errors.

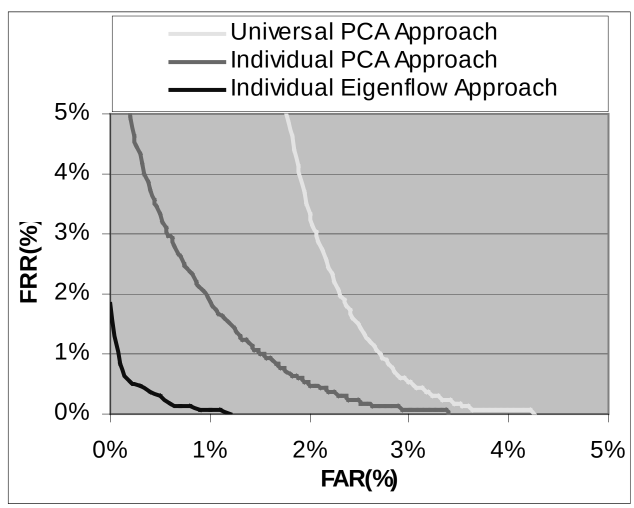

Figure 10. Experiment results on the data set with both expression variations and registration errors.