PRINCIPLE COMPONENT ANALYSIS AND ITS VARIANTS FOR BIOMETRICS

Tsuhan Chen, Yufeng Jessie Hsu, Xiaoming Liu, and Wende Zhang

Dept. of ECE, Carnegie Mellon University, Pittsburgh, PA 15213, USA
{tsuhan, yufengh, xiaoming, wendez}@andrew.cmu.edu

ABSTRACT

Principle component analysis (PCA) has been widely used for analyzing the statistics of data. While applied to biometrics as a classification scheme, PCA faces certain challenges. In this paper, we present a number of modifications to PCA in order to meet these challenges. Using face recognition as an example, we show how eigenflow, PCA applied to optimal flow, enables us to measure the difference between two images while allowing expression changes and registration error. We show how PCA can be updated to model time-varying statistics. We also show that PCA can be used to model the surface reflectance of human faces and reduce illumination variation that defeats most existing face recognition algorithms. Finally, we present distinguishing component analysis (DCA) and apply it to multimodal biometric authentication.

1. INTRODUCTION

Principle component analysis has been widely used in modeling the statistics of a set of data. In the vector space, PCA identifies the major directions, and the corresponding strengths, of variation in the data. PCA achieves this by computing the eigenvectors and eigenvalues of the covariance matrix of the data. Keeping only a few eigenvectors corresponding to the largest eigenvalues, PCA can be also used as a tool to reduce the dimensions of the data while retaining the major variation of the data. Both the variation modeling aspect and the dimension reduction aspect of PCA have been used in biometric person authentication and recognition. In face recognition, one of the most well-known results is the eigenface [1]. In practice, PCA-based face recognition is challenged by changes in facial expressions, poses, and illuminations. In addition, PCA is known to be sensitive to any offset in the images, i.e., registration error. Face recognition is also difficult in general when the subject has grown facial hair, is wearing a hat or glasses, or simply aging. In this paper, we present a number of new ways to use PCA to create robust biometric schemes.

In Section 2, we will present eigenflow that aims to make face recognition robust to expression changes and registration error. In Section 3, we will present PCA updating in order to enhance face recognition over time. In Section 4, we will use PCA to model surface reflectance and make face recognition robust to illumination changes. Finally in Section 5, we will present distinguishing component analysis (DCA).

2. EIGENFLOW

Traditional PCA applied to the pixel domain is very sensitive to expression changes and registration error. To deal with these issues, we present a new PCA-based method using optical flow. Optical flow [2] characterizes the motion of each pixel between two images. When two face images of the same subject with different expressions are fed into an optical flow estimation algorithm, the resulting optical flow will indicate the areas of facial feature changes, such as eyes and the mouth. On the other hand, when we try to estimate the optical flow between two images from different subjects, the resulting optical flow can be very *random*. This gives us a clue to tell whether the two images belong to the same subject or not, which is useful for both authentication and recognition.

To compare the identity of two images using optical flow, we use PCA to model the statistics of optical flow. First, we apply PCA to the optical flows resulting from training images of the same subject with different expressions. We refer to the resulting eigenvectors as *eigenflows*. Example eigenflows for one subject in our database are shown in Figure 1. In these eigenflows, note that large motion can be observed around facial features such as mouth corners and eyebrows. Assuming that all expression variations of this subject can be represented by the subspace spanned by these eigenflows, we can determine that two images do not belong to the same subject if the optical flow in-between cannot be reconstructed well by these eigenflows. In addition to the

0-7803-7622-6/02/$17.00 ©2002 IEEE

reconstruction error, we also found that the residue obtained while estimating the optical flow is also indicative of the identity of the two images. By combing the reconstruction error and the optical flow residue using linear discriminant analysis (LDA) [3], we can determine very reliably identify of the two images. We have shown that this approach outperforms traditional PCA in both face authentication and recognition, especially for face images with expression changes and registration error [4].

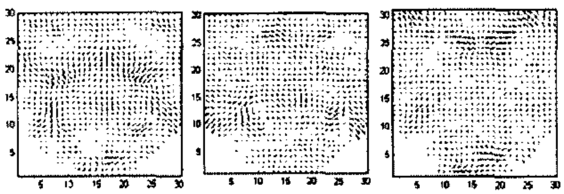

Figure 1. First three eigenflows trained from face images of one subject with difference expressions.

3. PCA UPDATING

To deal with variations in face images, a common approach is to include training images with all variations. As the classifier is trained with images covering more and more variations (with the hope that classification becomes more and more robust to such variations), its classification power actually degrades because a simple statistic model cannot handle all variations. In some application scenarios where face images of the subject are available as a video, one alternative for achieving robust face recognition is to learn the time-varying statistics of the subject while the recognition system is being used. Images that can be recognized with reasonably high confidence are used to update the statistic model for this subject. This way, instead of trying to use a static model to handle all variations, we use a dynamic model that handles some variations at each point in time.

We have developed a PCA updating technique that generates new eigenvectors based on old eigenvectors and every new input sample [5]. Summarizing, the mean $\mathbf{m}_n$ and covariance matrix $\mathbf{C}_n$ are estimated as follows

$$\mathbf{m}_n = \alpha_m \mathbf{m}_{n-1} + (1-\alpha_m)\mathbf{x}_n$$

$$\mathbf{C}_n = \alpha_v \mathbf{C}_{n-1} + (1-\alpha_v)(\mathbf{x}_n - \mathbf{m}_n)(\mathbf{x}_n - \mathbf{m}_n)^T$$

We have also theoretically and experimentally explored how to set the weights, α_m and α_v, between the old model and the new input. Figure 2 shows that for video containing pose variation, the PCA updating method outperforms the traditional static PCA method, by keeping the recognition error rate low. Figure 3 shows similar result for video involving expression variation.

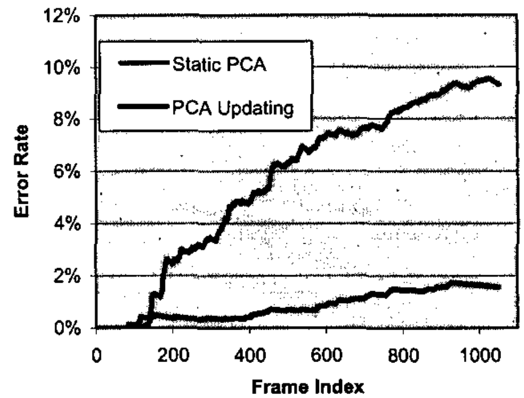

Figure 2. Experiment results with pose variation.

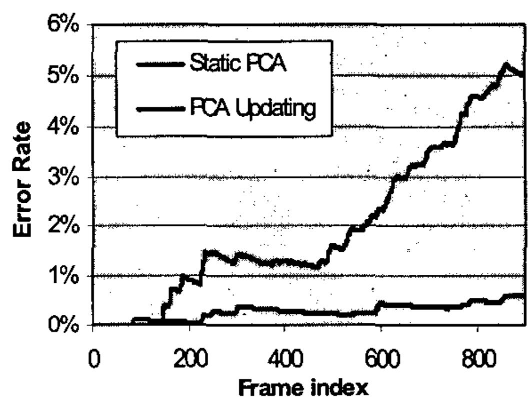

Figure 3. Experiment results with expression variation.

4. ILLUMINATION NORMALIZATION

Most existing face recognition algorithms work only under well-controlled illumination. To remove such limitation, it will very useful if we can preprocess any face image by *normalizing* its illumination before it is used for face recognition. Illumination normalization hence takes a face image under poor illumination and synthesizes the same face under good illumination. We now describe our illumination normalization technique based on PCA.

A 2D face image is the result of the light reflected from the 3D surface of a face. A commonly used model for the surface reflectance process is the Lambertian model [6]:

$$\mathbf{b} = \rho\mathbf{N}^T\mathbf{s}$$

where ρ is the albedo indicating how much energy is reflected, $\mathbf{N}$ is the 3D surface normal vector pointing outwards from the surface of the face, $\mathbf{s}$ is the illumination vector indicating the direction of the incoming light and its strength, and $\mathbf{B}$ is the observed pixel intensity, i.e., the resulting 2D face image.

Given a set of images of the same subject under different known illumination conditions, we can apply shape-from-shading [7] to obtain $\rho\mathbf{N}$ for the subject. Suppose there are p subjects, totally p of these $\rho\mathbf{N}$ can be obtained. These data can be modeled as a jointly Gaussian distribution (rather than pixel-wise independent Gaussian distributions, as done in [8]) and PCA can be performed to identify the mean $\mathbf{m}_{\mathrm{N}}$ and the eigenvectors of these data, and retain only the eigenvectors with the largest eigenvalues. These eigenvectors compose a matrix $\mathbf{H}$. Hence any $\rho\mathbf{N}$ of a new subject can be reconstructed by a set of coefficients, forming $\mathbf{c}$, as follows

$$\rho\mathbf{N} = \mathbf{m}_{\mathrm{N}} + \mathbf{Hc}$$

Once the PCA model is obtained, we are ready to perform illumination normalization. Given an input image $\mathbf{b}$ under unknown illumination, we first estimate the illumination $\mathbf{s}_{est}$ [9]. Then we can solve for the least squares (LS) solution of $\rho\mathbf{N}$ using the PCA model and $\mathbf{s}_{est}$, in terms of $\mathbf{c}$:

$$\mathbf{c}_{LS} = (\mathbf{H}^T\mathbf{S}_{est}\mathbf{S}_{est}{}^T\mathbf{H})^{-1}\mathbf{H}^T\mathbf{S}_{est}(\mathbf{b} - \mathbf{S}_{est}^T\mathbf{m}_{\mathrm{N}})$$

where the matrix $\mathbf{S}_{est}$ is composed of elements in $\mathbf{s}_{est}$. Then $\rho\mathbf{N}_{LS} = \boldsymbol{\mu}_{\mathrm{N}} + \mathbf{Hc}_{LS}$ can be obtained. Combining the estimated surface normal $\rho\mathbf{N}_{LS}$ with the new illumination $\mathbf{s}_{new}$, we can then synthesize the desired image:

$$\mathbf{b}_{new} = \rho\mathbf{N}_{LS}{}^T\mathbf{s}_{new}$$

We have applied this technique to the PIE database [10]. A subset of the database, including 24 people and 21 illuminations, with image size 32×32, is used. Out of these illuminations, six are used as training images for shape-from-shading and for training the PCA model. The results are shown in Figure 4. The quality of illumination-normalized images is shown in terms of correlation values with respect to a reference face that is under god frontal illumination. The higher the correlation value, the better the image quality. Some example images are also shown in Figure 4. Clearly all the illumination variation has been removed. Feeding these illumination-normalized images to face recognition, we have shown that can reduce the recognition error rate to 0.8%, compared to 21% if the original images were used.

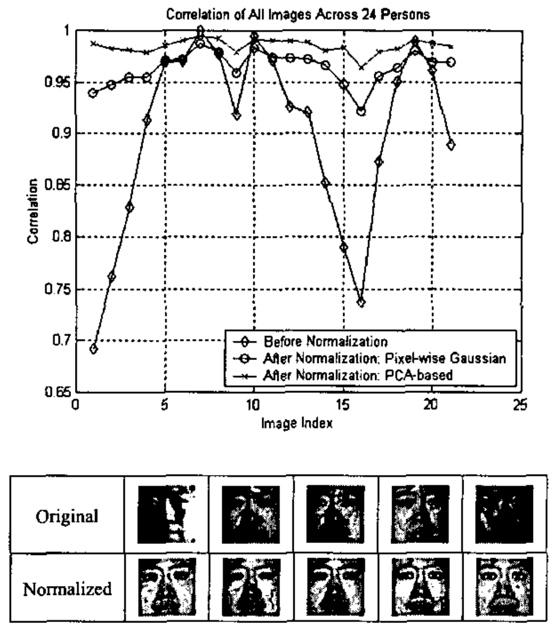

Figure 4. Results of illumination normalization.

5. DISTINGUISHING COMPONENT ANALYSIS

While PCA is useful for modeling the statistics of data from a certain subject, it is not very effective in distinguishing this subject from other subjects. This is due to the fact that when PCA tries to capture the variations of each subject, it does not consider any data from other subjects. Attempting to capture what distinguishes one subject from the others, we propose distinguishing component analysis (DCA).

DCA can be illustrated as in Figure 5. Given the training samples of a subject, labeled by p, and training sampling of other subjects, labeled by Q, the goal is to identify the distinguishing components that would span a subspace to which all p-points are as close as possible, and to which all Q-points are as far as possible. The subspace for each subject is characterized by its center $\mathbf{m}$ and a number of orthogonal unit vectors $\mathbf{e}_i$. Given a sample $\mathbf{q}$, its distance to the subspace is therefore its distance to its own projection onto the subspace

$$\left\| \mathbf{q} - \left(\sum_i \mathbf{e}_i{}^T(\mathbf{q} - \mathbf{m})\mathbf{e}_i + \mathbf{m} \right) \right\|^2$$

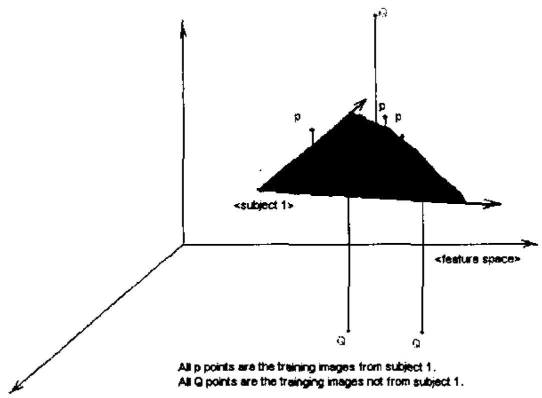

Figure 5. Illustration of DCA.

To demonstrate the effectiveness of DCA, we apply it to multimodal biometric person authentication using face images and fingerprints. Our datasets are composed of face images and fingerprint images. Using DCA, we identify the subspace for each subject and use it for authentication. The results are shown in the following table for four different datasets, where EER represents the equal error rate, and the FRR represents the false reject rate when the false accept rate (FAR) is 0.1%. DCA clearly outperforms traditional Bayesian classification.

	Dataset 1	Dataset 2	Dataset 3	Dataset 4
EER: Baysian	0.015%	0.056%	0.250%	0.006%
EER: DCA	0.000%	0.020%	0.050%	0.006%
FRR: Baysian	0.004%	0.046%	0.280%	0.006%
FRR: DCA	0.000%	0.020%	0.038%	0.000%

6. REFERENCES

[1] M. Turk, A. Pentland, Eigenfaces for Recognition. *Journal of Cognitive Neuroscience*, 3(1), pp. 71-86, 1991.

[2] C.L. Fennema, W.B. Thompson, Velocity determination in scenes containing several moving objects. Computer Graphics and Image Processing, no. 9, pp. 301-315, 1979.

[3] R.O. Duda, P.E. Hart, D.G. Stork, Pattern classification, 2nd edition. John Wiley & Sons. Inc., New York, 2001.

[4] X. Liu, T. Chen and B.V.K. Kumar, "Face Authentication for Multiple Subjects Using Eigenflow," to appear in *Pattern Recognition, Special Issue on Biometric*, 2002.

[5] X. Liu and T. Chen, "Shot Boundary Detection Using Temporal Statistics Modeling," ICASSP, Orlando, FL, May 2002.

[6] R. Jain, Kasturi R., and B. Schunck, *Machine Vision*, McGraw Hill, 1995.

[7] B.K.P. Horn and M.J. Brooks, *Shape from Shading*, MIT Press. Cambridge, MA, 1989.

[8] T. Sim, T. Kanade, "Combining Models and Exemplars for Face Recognition: An Illuminating Example," *Proceedings of the CVPR 2001*, Workshop on Models versus Exemplars in Computer Vision, Dec. 2001.

[9] Q. Zheng and R. Chellappa, "Estimation of Illuminant Direction, Albedo, and Shape from Shading," *IEEE Trans. on PAMI*, July 1991.

[10] T. Sim, S. Baker, and M. Bsat, "The CMU Pose, Illumination, and Expression (PIE) Database of Human Faces", Technical Report CMU-RI-TR-01-02, Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, Jan 2001.