

FACIAL RECOGNITION/VERIFICATION USING GABOR WAVELETS AND KERNEL METHODS

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ABSTRACT

A novel Gabor-Kernel face classification method is proposed in this paper. This involves convolving a face image with a series of Gabor kernels at different scales, locations, and orientations to obtain feature vectors. Kernel methods such as Kernel Principal Component Analysis (KPCA) and Kernel Discriminant Analysis (KDA) are then applied to the feature vectors for dimension reduction as well as class separability enhancement. The method has been applied to both face recognition and verification for performance evaluation. Two standard databases: FERET and BANCA database are used for testing. Both results show the robustness of the method: Gabor + KDA against the variance of expression, illumination and pose.

1 INTRODUCTION

Face recognition/verification has a wide range of potential applications in commercial and law-enforcement such as security surveillance, telecommunication, and human-computer interaction.

For a period linear transform based methods such as Eigenface [1], Fisherface [2], and Independent Component Analysis (ICA) [3] fascinated the face recognition verification community. Eigenfaces are a set of eigenvectors arising from applying Principle Component Analysis to a collection of images and any face image could then be described by its projection coefficients onto the eigenfaces. This significantly reduces the dimension of face vectors. Fisherfaces are based on Linear Discriminant Analysis (LDA), the objective of which is to maximize class separability, defined as the ratio of the between-class scatter matrix to the within-class scatter matrix. Whilst in PCA the emphasis is on de-correlation of variables, ICA aims at variable independence, a much stronger condition. However, Baek [4] presented a comparison of PCA and ICA and concluded that, when a proper distance metric was used, PCA outperformed ICA significantly on the FERET face database [5] of more than 1000 images.

Kernel based methods [6], exemplified by Kernel Principle Component

Analysis (KPCA) [7], Kernel Discriminant Analysis (KDA) [8][9][10] have significantly outperformed PCA, LDA, ICA and neural networks in recognition tasks. Support vector machine (SVM) [11] is another example of Kernel methods, which seeks a unique hyperplane yielding the maximum margin of separation between two classes through constrained optimisation. Phillips [12] trained a single SVM to distinguish between within-class and between-class images. Jonsson [13] trained a SVM for each class. Both used linear transform based methods for feature extraction.

The face recognition methods introduced in this paper combine Gabor wavelets and Kernel methods in a novel way. Gabor wavelets, especially for frequency and orientation representations, have similar characteristics to those of the human visual system. Gabor wavelets can be applied locally to extract local image features [14][15][16], or applied to the image as a whole through a convolution/filtering process, resulting in Gabor filtered images [17][18]. The effect of filtering an image is to break down image content to different scales, locations, and orientations that can be extracted effectively for recognition. Example applications of Gabor wavelets are face recognition [14]-[18], texture segmentation [19], handwritten numerals recognition [20] and fingerprint recognition [21]. Our methods, thereafter the Gabor-Kernel methods, first convolve a face image with a set of Gabor wavelets then apply KPCA and KDA to the resultant feature vectors to extract robust and discriminative features for recognition. The feature vectors contain all the information produced by different Gabor kernels and their discrimination power is further enhanced by nonlinear kernel analysis. Our method is applied to face recognition and verification and tested by using two databases: the FERET database and the BANCA database.

2 GABOR FEATURE EXTRACTION

A family of complex Gabor wavelets can be defined as:

$$\varphi_{u,v}(\vec{x}) = \frac{\|\vec{k}_{u,v}\|^2}{\sigma^2} \exp\left(\frac{-\|\vec{k}_{u,v}\|^2 \|\vec{x}\|^2}{2\sigma^2}\right) \left[\exp(i\vec{k}_{u,v} \cdot \vec{x}) - \exp\left(-\frac{\sigma^2}{2}\right) \right] \quad (1)$$

where u and v define the orientation and scale of the Gabor kernels and the wave vector $\vec{k}_{u,v}$ is defined as follows:

$$\vec{k}_{u,v} = k_v \exp(i\phi_u) \quad (2)$$

where $k_v = \frac{k_{\max}}{f^v}$ and $\phi_u = \frac{u\pi}{8}$, k_{\max} the maximum frequency and f the spacing factor between kernels in the frequency domain.

The Gabor wavelet representation of a face image is the convolution of the image with the family of Gabor kernels as defined in (1). The convolution of image $I(\vec{x})$ and a Gabor kernel $\varphi_{u,v}(\vec{x})$ can be defined as follows:

$$G_{u,v}(\vec{x}) = (I * \varphi_{u,v})(\vec{x}) \quad (3)$$

where $G_{u,v}(\vec{x})$ denotes the convolution result corresponding to the Gabor kernel at orientation u and scale v . As a result, the image $I(\vec{x})$ can be represented by Gabor wavelet $\{G_{u,v}(\vec{x}), v = 0, \dots, 4; u = 0, \dots, 7\}$. To encode information on different spatial frequencies, spatial localities and orientations, each $G_{u,v}(\vec{x})$ is firstly down-sampled by a factor r , normalized to zero mean and unit variance, and then turned to a vector $x_{u,v}^r$ by concatenating its rows [17]. Therefore, a discriminative feature vector x^r can be derived to represent the image I by concatenating those vectors $x_{u,v}^r$:

$$x^r = ((x_{0,0}^r)^t \ (x_{0,1}^r)^t \ \dots \ (x_{4,7}^r)^t)^t \quad (4)$$

The derived feature vector x^r thus encompasses all the elements of set $\{G_{u,v}(\vec{x}), v = 0, \dots, 4; u = 0, \dots, 7\}$.

3 KERNEL DISCRIMINANT ANALYSIS

Kernel Discriminant Analysis (KDA) is a generalized version of Linear Discriminant Analysis (LDA). Consider

a C classes problem and let N_c be the number of samples in class c . The set of training patterns in class c can be defined as $\{x_{ck}, c = 1, 2, \dots, C; k = 1, 2, \dots, N_c\}$. The total

number of input vectors can be denoted as: $M = \sum_{c=1}^C N_c$.

For a centred data set in feature space, the between-class scatter matrix S_b and within-class scatter matrix S_w can be defined as:

$$S_w = \frac{1}{C} \sum_{c=1}^C \frac{1}{N_c} \sum_{k=1}^{N_c} \phi(x_{ck}) \phi(x_{ck})^T \quad (5)$$

$$S_b = \frac{1}{C} \sum_{c=1}^C \mu_c \mu_c^T \quad (6)$$

where μ_c is the mean vector of class c :

$$\mu_c = \frac{1}{N_c} \sum_{k=1}^{N_c} \phi(x_{ck}) \quad (7)$$

Similar to LDA, the purpose of KDA is to maximize the quotient between the inter-class variance and the intra-class variance. This maximization process is equivalent to finding the eigen value $\lambda \geq 0$ and eigen vectors $v \in F \setminus \{0\}$ satisfying

$$\lambda S_w v = S_b v \quad (8)$$

Similar to (8),

$$v = \sum_{c=1}^C \sum_{k=1}^{N_c} \alpha_{ck} \phi(x_{ck}) \quad (9)$$

Let K be a $M \times M$ matrix defined on the class elements by $((K_{pq})_{p=1, \dots, C})$, where K_{pq} is a matrix composed of

dot products between vectors from class p and q in feature space:

$$K_{pq} = (k_{ij})_{\substack{i=1, \dots, N_p \\ j=1, \dots, N_q}} = (\phi(x_{pi}) \cdot \phi(x_{qj}))_{\substack{i=1, \dots, N_p \\ j=1, \dots, N_q}} \quad (10)$$

We also define a $M \times M$ block diagonal matrix:

$$U = (U_c)_{c=1, \dots, C} \quad (11)$$

where U_c is $N_c \times N_c$ a matrix with terms all equal to $\frac{1}{N_c}$. By substituting (6), (7), (8) and (10) into (9) and

taking inner-product with vector $\phi(x_{ij})$ on both sides, the solution of (19) can be achieved by solving:

$$\lambda \mathbf{K} \mathbf{K} \mathbf{a} = \mathbf{K} \mathbf{U} \mathbf{K} \mathbf{a} \quad (12)$$

where \mathbf{a} is denotes a column vector with entries $\alpha_{ck}, c = 1, \dots, C, k = 1, \dots, N_c$. Similar to Kernel PCA, we can also construct a lower dimensional space and project a new input vector x into the KDA sub space.

3. EXPERIMENTAL RESULTS

3.1 Face Recognition

Firstly, we test the performance of our Gabor-Kernel methods for face recognition using the FERET database, which is a standard test-bed for face recognition technologies [4]. 600 frontal face images corresponding to 200 subjects are extracted from the database for the experiments. The 600 face images were acquired under varying illumination conditions and facial expressions. Each face image is cropped to the size of 128×128 to extract facial region according to the location of eyes, with pixel values normalized to zero mean and unit variance. To compare our method with other subspace projection techniques, we also implement PCA, LDA and KPCA in our experiments. The comparative results on the FERET database are shown in Table 1. As shown in this table, Gabor + KDA achieves the best recognition rate: 92%, which is significantly better than other methods.

| | Gabor + PCA | Gabor + LDA | Gabor + KPCA | Gabor + KDA |
|----------------------|-------------|-------------|--------------|-------------|
| Recognition Rate (%) | 57 | 76.5 | 62 | 92 |

Table 1 Recognition Results on the FERET Database

3.2 Face Verification

In the following experiments, we test our algorithms in the application of face verification using the BANCA database [22]. The database consists of images from 52 subjects captured in 12 sessions. 10 face images are captured for each person in each session. The 12 sessions are composed of 3 different scenarios: 1) Controlled scenario (c) for sessions 1-4, 2) Degraded scenario (d) for sessions 5-8, 3) Adverse scenario (a) for sessions 9-12. A web cam was used in the Degraded scenario and a high quality camera was used in the Controlled and Adverse scenarios. Images are captured with normal pose in the Controlled and Adverse scenarios, whilst the head down pose is required in the Adverse scenario. Figure 2 shows

the sample images captured in different scenarios. Seven test protocols, which identify different training and testing images, are defined in [22] to evaluate verification algorithms. We selected *protocol P* in our experiments since it is the most challenging. The protocol specifies the partitioning of the database into two disjoint sets: a *development set* (26 subjects) and an *evaluation set* (26 subjects). For each set, 5 images from each person captured in the 1st session (Controlled scenario) are used as training images, while 2730 selected images captured in all three scenario are used for testing. Each set thus consists of 130 training images, and test images consisting of 1170 client accesses and 1560 impostor accesses [22].

All of the images used in our experiments are normalized semi-automatically. To achieve spatial normalization, face images are rotated, translated and scaled according to the position of the eyes. The images are cropped to standard size 48×48 and rotated so that the eyes are placed at fixed points. To reduce illumination variations, all of the images are first histogram equalized and then shifted and scaled such that the mean values of all pixels equals zero, while the standard deviation equals one.

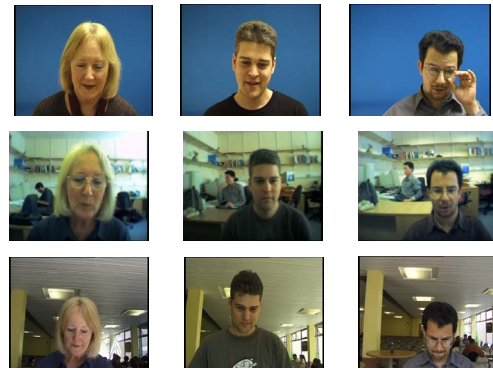


Figure 1 Sample Images in the BANCA Database

| Method | FAR | FRR | EER |
|--------------|-------|-------|-------|
| Gabor + PCA | 8.20 | 8.11 | 8.15 |
| Gabor + LDA | 16.47 | 16.23 | 16.35 |
| Gabor + KPCA | 10.38 | 10.34 | 10.36 |
| Gabor + KDA | 6.02 | 5.89 | 5.96 |

Table 2 Verification Results on the BANCA Database

Table 2 shows the False Accept Rate (FAR), False Reject Rate (FRR) and Equal Error Rate (EER) of the Gabor feature based verification algorithms using different subspace projection techniques. The optimal feature

dimension and distance measures for different algorithms are also shown in the table and the threshold has been adjusted to minimize EER. It can be observed that again, Gabor + KDA method achieves the lowest EER. As low as 5.96% EER has been achieved by the proposed method. Please note that PCA perform better than LDA and KPCA in this test, which might be caused by the small size of the training set. However, Gabor + KDA has shown its robustness against the variance of camera, pose and the non-representative training set.

4 CONCLUSION

This paper has considered a Gabor and Kernel based face recognition method. Gabor filters and Kernel methods are combined in order to achieve highly discriminative features for classification. By mapping the input features to a high dimensional non-linear feature space, the Kernel methods can not only greatly reduce the feature dimension, but also increase the discrimination power of the extracted features. The robustness and discrimination ability can be further improved by using the Gabor feature vectors which are extracted from the Gabor filtered images. Encompassing different scale, locality and orientation information, our method has been successfully applied to both face recognition and verification. The experimental results of our method on the FERET database and BANCA database are competitive to that obtained by other methods, which shows its robustness against the variance of expression, illumination and pose.

5 REFERENCE

- [1] M. Turk and A. Pentland. Eigenfaces for recognition, *J. Cognitive Neuroscience*, vol.3, No.1, pp.71-86, 1991.
- [2] P.N.Belhumeur, J.P. Hespanha and D.J.Krieman. Eigenfaces vs. Fisherfaces: Recognition using class specific linear projection. *IEEE Trans. Pattern Anal. Machine Intel.*, vol. 19, pp.711-720, 1997.
- [3] Comon P., Independent Component Analysis, a new concept? *Signal Processing*, 1994.
- [4] Baek Kyungim, et al, PCA vs. ICA: A Comparison on the FERET data set, *International Conference on Computer Vision, Pattern Recognition and Image Processing*, Durham, North Carolina, March 2002.
- [5] P. Phillips, H. Moon, S. Rizvi, and P. Rauss. The feret evaluation. *Face Recognition: From Theory to Applications*, pages 244-261, 1998.
- [6] Scholkopf, B.; Mika, S.; Burges, C.J.C etc. Input space versus feature space in kernel-based methods. *IEEE Transactions on Neural Networks*, 10(5), 1999.
- [7] B. Scholkopf, A. Smola, and K. R. Muller. Nonlinear component analysis as a kernel eigenvalue problem. *Neural Computation*, 10(5), pp.1299-1319, 1998.
- [8] MingHsuan Huang. Kernel Eigenfaces vs. Kernel Fisherfaces: Face recognition using Kernel methods. *Proceedings of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition*, pp.215-220, May 2002.
- [9] Qingshan Liu and Rui Huang, etc. Face recognition using Kernel-based Fisher Discriminant Analysis. *Proceedings of the Fifth IEEE International Conference on Automatic Face and Gesture Recognition*, pp.205-211, May 2002.
- [10] Kwang In Kim; Keechul Jung; Hang Joon Kim. Face recognition using kernel principal component analysis. *IEEE Signal Processing Letters*, 9 (2) , pp.40-42, 2002.
- [11] Nello Cristianini and John Shawe-Taylor, *An Introduction to Support Vector Machines*, Cambridge University Press, Cambridge, UK, 2000.
- [12] P. Phillips. Support Vector Machines applied to face recognition. *Advances in Neural Information Processing Systems*, volume 11, 1998, pp.803--809. MIT Press.
- [13] K. Jonsson, J. Kittler, Y.P. Li and J. Matas. Support vector machines for face authentication. *Image and Vision Computing* (20), 2002, pp. 369-375.
- [14] Martin Lades et al, Distortion Invariant Object Recognition in the Dynamic Link Architecture. *IEEE Transactions on Computers*, 42, pp.300-311, 1993.
- [15] Laurenz Wiskott et al. Face recognition by elastic bunch graph matching. *IEEE Trans. Pattern Analysis and Machine Intelligence*, 19(7), pp. 775-779, 1997.
- [16] Haiyuan Wu, Yukio Yoshida and Tadayoshi Shioyama. Optimal Gabor filters for high speed face identification. *Proc. of Int. Conf. on Pattern Recognition*. vol.1, pp.107-110, 2002.
- [17] Chengjun Liu and Harry Wechsler. Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE Trans. Image Processing*, vol. 11, No. 4, pp.467-476, 2002.
- [18] Lougbenga Ayinde and Yee-Hong Yang. Face recognition approach based on rank correlation of Gabor-filtered images. *Pattern Recognition*, Vol. 35, 2002.
- [19] A. K. Jain and F. Farrokhnia. Unsupervised Texture Segmentation Using Gabor Filters. *Pattern Recognition*, Vol.24, No.12, pp.1167-1186, 1991.
- [20] Y. Hamamoto, S. Uchimura, M. Watanabe, et al. A Gabor filter-based method for recognizing handwritten numerals. *Pattern Recognition*, Vol.31, No.4, 1998.
- [21] Lee, C.J., and Wang, S.D. Fingerprint Feature Extraction using Gabor Filters. *Electronic Letters*, 35, (4), pp.288-290, 1999.
- [22] E. Bailly-Baillere, S. Bengio etc. The BANCA database and evaluation protocol. *Proc. of the 4th International Conference on Audio- and Video-Based Biometric Person Authentication*, Guildford, 2003.