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Gabor wavelets and General Discriminant Analysis for face identification and verification

LinLin Shen [a,*], Li Bai [a], Michael Fairhurst [b]

[a] School of Computer Science & IT, University of Nottingham, UK
[b] Electronics Department, University of Kent, UK

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Abstract

A novel and uniform framework for both face identification and verification is presented in this paper. The framework is based on a combination of Gabor wavelets and General Discriminant Analysis, and can be considered appearance based in that features are extracted from the whole face image. The feature vectors are then subjected to subspace projection. The design of Gabor filters for facial feature extraction is also discussed, which is seldom reported in the literature. The method has been tested extensively for both identification and verification applications. The FERET and BANCA face databases were used to generate the results. Experiments show that Gabor wavelets can significantly improve system performance whilst General Discriminant Analysis outperforms other subspace projection methods such as Principal Component Analysis, Linear Discriminant Analysis, and Kernel Principal Component Analysis. Our method has achieved 97.5% recognition rate on the FERET database, and 5.96% verification error rate on the BANCA database. This is a significantly better performance than that attainable with other popular approaches reported in the literature. In particular, our verification system performed better than most of the systems in the 2004 International Face Verification Competition, using the BANCA face database and specially designed test protocols.

Keywords: Face identification; Face verification; Gabor wavelets; General Discriminant Analysis

1. Introduction

Automatic face recognition has rapidly developed over the years and is now a highly active field of research, with important applications in security surveillance, access control, human–machine interaction, and a host of other domains.

Early face recognition work was represented by Von der Malsburg's Dynamic Link Architecture [1], an elastic matching process in which a test face, represented as a graph with Gabor wavelet responses as the nodes, is associated with one of a number of stored face graphs. The matching process maximises the similarities between the test and the corresponding model face graph. A variant of this is the Face Bunch Graph [2], which was proposed to cope with the specific variability of face images. Gabor wavelets are applied at manually selected fiducial points (eyes, mouth, nose, etc.) of several images of a face and the results, referred to as "jets", are packed in a graph called the face bunch graph. Disadvantages of this approach include rigid alignment of facial features and limited ability in handling pose variations. Instead of graphs, Hidden Markov Models (HMMs) represent a face image as a sequence of 'states'. The goal of training a HMM is to optimise its parameters to 'best' describe the observation vectors representing a class, and recognition is carried out by matching a test image against each of the trained HHMs. An interesting variant of HMM is the Embedded HMM [3], in which super-states of an embedded HMM represent primary facial regions (forehead, eyes, nose,

* Corresponding author. Tel.: +44 115 8466567; fax: +44 115 951 4254.
E-mail addresses: lls@cs.nott.ac.uk (L. Shen), bai@cs.nott.ac.uk (L. Bai), m.c.fairhurst@kent.ac.uk (M. Fairhurst).

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mouth, and chin) whilst embedded states within each super-state describe in more detail each of the facial regions. This approach is computationally expensive, as it requires the computation of a probabilistic distance to each stored HHM when classifying a new image.

Linear transform based methods such as Eigenface [4], Fisherface [5], and Independent Component Analysis (ICA) [6] have had a significant influence within the face recognition community for a considerable time. Eigenfaces are a set of eigenvectors arising from applying Principal Component Analysis (PCA) to a collection of images, and any face image could then be described by its projection coefficients onto the eigenfaces thus generated. This significantly reduces the dimension of the relevant face vectors, giving greater tractability in practical application. 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 [7] 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 [8] of more than 1000 images. Kernel based methods [9], exemplified by Kernel Principal Component Analysis (KPCA) [10,11], Kernel Fisher Discriminant Analysis (KFDA) [12,13] and General Discriminant Analysis (GDA) [14] have significantly outperformed PCA, LDA, ICA and neural networks in similar recognition tasks. The support vector machine (SVM) approach [15] is another example of a Kernel method, which seeks a unique hyperplane yielding the maximum margin of separation between two classes through constrained optimisation. Phillips [16] trained a single SVM to distinguish between within-class and between-class images. Jonsson [17] trained a SVM for each class. Both used linear transform based methods for feature extraction.

Although significant progress has been made in appearance-based face recognition, to our knowledge, the application of KPCA or GDA in face verification has seldom been reported in the literature. Despite the wide application of Gabor filters for feature extraction [1,2,18], the design of Gabor filters is rarely discussed. In this paper, we describe an approach that combines Gabor feature extraction and Kernel subspace projection techniques to produce a robust and uniform system framework for both face identification and verification. This involves extracting discriminant features from images using a sequence of Gabor wavelets at different scale and orientations and projecting feature vectors to a subspace before identification, or verification, can take place. The design of Gabor filters is also discussed based on experiments. Our method is hereafter referred to in this paper as the Gabor + GDA.

Extensive experiments have been conducted to evaluate the performance of Gabor + GDA against existing methods in the literature. Gabor features have also shown robustness against variations of head pose and camera orientation The generalization ability of the novel Gabor + GDA method has also been observed. Since the FERET [8] and BANCA database [19,20], specially designed to test face identification and verification algorithms, are used for the evaluation of our algorithms, our results are directly comparable with other methods, and comparisons with a number of popular approaches will be made to illustrate the advantages of the proposed new method.

The contribution of this paper is therefore threefold. First, we discuss how to design Gabor filters empirically for facial feature extraction and demonstrate that the proposed novel Gabor + GDA framework is robust and uniform for both identification and verification. Second, we show that GDA outperforms other subspace projection techniques such as PCA, LDA, and KPCA, and that different distance measures can have significant effects on subspace based methods. Finally, we show evidence to support the findings reported by some other researchers that PCA outperforms LDA when the training set is nonrepresentative.

The paper is organized as follows. In Section 2, Gabor wavelets are defined and the methodology to extract discriminative Gabor features from face images are outlined. Section 3 introduces Generalized Discriminant Analysis, while the strategy to combine the Gabor and GDA concepts is given in Section 4. Experimental results for identification and verification using the FERET and BANCA database are given in Section 5, and some important conclusions are drawn in Section 6.

2. Gabor feature extraction

2.1. Gabor wavelets

The characteristics of the Gabor wavelets (filters), especially for frequency and orientation representations, are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. The Gabor filters-based features, directly extracted from gray-level images, have been successfully and widely applied to texture segmentation [21,22], handwritten numerals recognition [23] and fingerprint recognition [24]. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave:

$$\begin{aligned}
\varphi_{\Pi(f,\theta,\gamma,\eta)}(x,y) &= \frac{f^2}{\pi\gamma\eta}\exp(-(\alpha^2x'^2+\beta^2y'^2))\exp(j2\pi fx') \\
x' &= x\cos\theta + y\sin\theta \\
y' &= -x\sin\theta + y\cos\theta
\end{aligned} \quad (1)$$

where f is the central frequency of the sinusoidal plane wave, θ is the anti-clockwise rotation of the Gaussian and the plane wave, α is the sharpness of the Gaussian along the major axis parallel to the wave, and β is the