Local Feature Analysis with Class Information

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Abstract. In this paper, we propose a new feature extraction method for face recognition. This method is based on Local Feature Analysis (LFA), a local method for face recognition since it constructs kernels detecting local structures of a face. However, LFA has shown some problems for recognition due to the nature of unsupervised learning. Here, we point out the problems of LFA and propose a new feature extraction method with class information to overcome the shortcomings of LFA. Our method consists of three steps. First, using LFA, a set of local structures are extracted. Second, we select some extracted structures that are efficient for recognition. At last, we combine the selected local structures to represent them in a more compact form. This results in new bases which have compromised aspects between kernels of LFA and eigenfaces for face images. Throughout the experiments, our method has shown improvements on the face recognition over the previously proposed methods, LFA, eigenface, and fisherface.

1 Introduction

In face recognition, feature extraction is one of the most important steps and it represents high dimensional image data into low dimensional feature vectors. In feature extraction, there are two approaches, a global and a local method. Among the global methods, eigenface [1] and fisherface [2] are the two most representative methods, which use Principal Component Analysis(PCA) and Fisher Linear Discriminant(FLD) respectively. Both methods construct bases and the bases are named as *eigenfaces* and *fisherfaces*, and they are considered as models for faces, where the features are extracted by linearly projecting a face image onto the bases. The eigenfaces and fisherfaces describe the whole shape of a face rather than local structures of a face such as nose, eye, jaw-line, and cheekbone. While eigenfaces are constructed from the covariance matrix

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of face images, fisherfaces are obtained from between-class scatter matrix and within-class scatter matrix. In other words, eigenface is an unsupervised method and fisherface is a supervised method. Previous experiments show that fisherface performs better than eigenface, and it is robuster to the variations of illumination and poses than eigenface [2]. However, fisherface is known to be prone to overfit to the classes whose data are used in basis construction [3]. Global methods are easy and fast but it is said that they are weak to such variations although fisherface somehow overcame the limitations.

On the contrary, it is known that local methods are robust to the variations. Local Feature Analysis(LFA) [4] is referred to as a local method since it constructs a set of kernels that detects local structures; e.g., nose, eye, jaw-line, and cheekbone, and the kernels are used as bases for feature extraction as in eigenface and fisherface. However, LFA requires feature selection step since the number of the constructed kernels is as the same as the dimension of input images, and it does not use any class information as in eigenface.

In this paper, we point out the problems of LFA and propose a new feature extraction method to overcome the shortcomings of LFA. We exploit class information to construct and select kernels that are useful for face recognition. The rest of the paper is organized as following: In Sec. 2, LFA will be briefly reviewed. In Sec. 3, we propose our method and experimental results are given to verify the efficiency of our method in Sec. 4.

2 Local Feature Analysis

Local Feature Analysis constructs kernels, which are basis vectors for feature extraction. Kernels are constructed using the eigenvectors of the covariance matrix of face images as in eigenface. However, unlike eigenface, kernels describe local structures of a face(see Fig. 3) rather than a whole face structure, and they are *topographic* since the kernels are indexed by spatial location [4] [3].

Let's suppose that there is a set of n d-dimensional sample images $\boldsymbol{x}_1, \ldots,$ $\boldsymbol{x}_n$. Hence, the covariance matrix, $\boldsymbol{C}$, of the images is computed as

$$\boldsymbol{C} = \frac{1}{n}\sum_{t=1}^{n}\left(\boldsymbol{x}_t - \boldsymbol{m}\right)\left(\boldsymbol{x}_t - \boldsymbol{m}\right)^T \tag{1}$$

where $\boldsymbol{m} = \frac{1}{n}\sum_{t=1}^{n}\boldsymbol{x}_t$. When there are N largest eigenvalues of $\boldsymbol{C}$, λ_r, and the corresponding eigenvectors, $\boldsymbol{\Psi}_r$, a set of kernels, $\boldsymbol{K}$, is derived by enforcing topology into the eigenvectors. In addition, the outputs of kernels, $\boldsymbol{O}$, and the covariance of the outputs, $\boldsymbol{P}$, are written in a matrix form,

$$\boldsymbol{K} = \boldsymbol{\Psi}\boldsymbol{\Lambda}\boldsymbol{\Psi}^T \tag{2}$$

$$\boldsymbol{O} = \boldsymbol{K}^T\boldsymbol{X} \tag{3}$$

$$\boldsymbol{P} = \boldsymbol{\Psi}\boldsymbol{\Psi}^T \tag{4}$$

where $\boldsymbol{\Psi} = [\boldsymbol{\Psi}_1 \ldots \boldsymbol{\Psi}_N]$, $\boldsymbol{\Lambda} = diag\left(\frac{1}{\sqrt{\lambda_r}}\right)$, and $\boldsymbol{X} = [\boldsymbol{x}_1 \cdots \boldsymbol{x}_n]$. Since $\boldsymbol{K}$ is symmetric, we only consider the columns of $\boldsymbol{K}$ as the bases. Note that the