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1D correlation filter based class-dependence feature analysis for face recognition

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ABSTRACT

In this paper, a novel one-dimensional correlation filter based class-dependence feature analysis (1D-CFA) method is presented for robust face recognition. Compared with original CFA that works in the two dimensional (2D) image space, 1D-CFA encodes the image data as vectors. In 1D-CFA, a new correlation filter called optimal extra-class origin output tradeoff filter (OEOTF), which is designed in the low-dimensional principal component analysis (PCA) subspace, is proposed for effective feature extraction. Experimental results on benchmark face databases, such as FERET, AR, and FRGC, show that OEOTF based 1D-CFA consistently outperforms other state-of-the-art face recognition methods. This demonstrates the effectiveness and robustness of the novel method.

1. Introduction

Over the past few decades, face recognition has become a popular area of research in pattern recognition and computer vision due to its wide range of commercial and law enforcement applications, such as biometric authentication, video surveillance, and information security [1].

Until now, a great number of face recognition methods have been developed and one of the most successful techniques is the appearance-based method. When using appearance-based methods, a face image is usually considered as a point in the high-dimensional space. Then, the statistical learning method is applied to derive an effective representation (a low-dimensional feature). Finally, a classifier is designed in the feature space. Linear subspace learning methods, such as Eigenface [2], Fisherface [3], LDA/FKT (linear discriminant analysis/Fukunaga–Koontz transform) [4], C-LDA (complete LDA) [5], MMSD (multiple maximum scatter difference) [6], and Laplacianface [7] are typical dimensionality reduction methods to find a low-dimensional feature space.

Turk and Pentland [2] proposed Eigenface algorithm for face recognition. The algorithm uses principal component analysis (PCA) which finds the principal components of the distribution of face images for dimensionality reduction. Note that PCA is optimal for representation, not necessarily for classification. Therefore, Fisherface algorithm [3] uses LDA to search a set of basis components which maximizes the ratio of between-class scatter to within-class scatter. Due to the 'small sample size' problem [8] in face recognition, the within-class scatter matrix is usually singular. Thus, the execution of LDA encounters computational difficulty. PCA is often used as a preprocessing step to reduce the dimensionality [3] and LDA is then performed in the low-dimensional PCA subspace where the within-class scatter matrix becomes nonsingular. However, this method may result in the loss of important discriminative information [4]. Many methods [4–6] have been developed to take full advantage of the discriminative information in the face space. LDA/FKT [4] obtains the discriminant subspace by applying FKT on the within-class scatter matrix and between-class scatter matrix while C-LDA [5] and MMSD [6] derive the discriminant features both in the range of the between-class scatter matrix and in the null space of the within-class scatter matrix. Unlike PCA and LDA which attempt to preserve the global Euclidean structure, Laplacianface algorithm [7] that is based on locality preserving projections (LPP) finds a face subspace to preserve the local structure of face manifold.

It can be seen that the projection matrices obtained by traditional linear subspace learning methods [2–7] are related to the statistical characteristics of all training samples. The projection axis tries to preserve (e.g. PCA) or discriminate (e.g. LDA) all classes.

Recently, Kumar et al. [9,10] proposed a novel linear subspace learning method called class-dependence feature analysis (CFA) for face recognition. Different from traditional linear subspace learning methods, the projection axis obtained by CFA tries to discriminate one specific class from all other classes. Different projection axes

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concern different classes. In particular, CFA is based on the design of advanced correlation filter technique which emphasizes the outputs of one face class and suppresses the outputs of other face classes. According to different criterions, different correlation filters [11] can be designed.

Original CFA [9,10] designs correlation filters in the two-dimensional (2D) image space. For simplicity, we call original CFA based on the 2D correlation filter 2D-CFA. As a result, 2D-CFA cannot be applied to vector data or M-th order ($M \geqslant 3$) tensor data directly. In our previous work [12], a tensor correlation filter based CFA (TCF-CFA) method which generalizes 2D-CFA by encoding the image data as tensors was presented. It has been proved that TCF-CFA can be derived in a similar way as 2D-CFA, which is a special case of TCF-CFA when the image data are encoded as second-order tensors (i.e. image matrices) [12]. Moreover, commonly used correlation filters in TCF-CFA, such as MACE (minimum average correlation energy) filter [13], MVSDF (minimum variance synthetic discriminant function) filter [14], and OTF (optimal tradeoff filter) [15], have the same form as those in 2D-CFA.

In this paper, we mainly concentrate on one-dimensional correlation filter based CFA (1D-CFA), since traditional algorithms [2–7] show great superiority by encoding the face image data as vectors. As far as we know, few investigations concern the design of correlation filters in the 1D form for the face recognition problem.

It is worthwhile to highlight several aspects of the proposed approach here:

1. Correlation filters are designed in the low-dimensional PCA subspace. Compared with original CFA which designs correlation filters in the 2D image space [9,10], the correlation filters in 1D-CFA are designed in the 1D feature space. Designing correlation filters in the low-dimensional PCA subspace makes them less sensitive to noise.

Table 1
Summary of the notations used

Notations	Description
N	Number of training samples for all classes
N_l	Number of training samples for class l
L	Number of classes
p	Dimensionality of low-dimensional feature
$\vec{h}$	1D correlation filter in the space domain
$\vec{\mathbf{H}}$	1D correlation filter in the frequency domain
$\mathbf{Y}_l^{\mathrm{I}} = [\vec{\mathbf{Y}}_1^{\mathrm{I}}, \ldots, \vec{\mathbf{Y}}_{N_l}^{\mathrm{I}}]$	Intra-class transformed feature matrix, where $\vec{\mathbf{Y}}_i^{\mathrm{I}}$ is the 1D Fourier transform of intra-class low-dimensional feature $\vec{y}_i^{\mathrm{I}}$ for class l
$\mathbf{Y}_l^{\mathrm{E}} = [\vec{\mathbf{Y}}_1^{\mathrm{E}}, \ldots, \vec{\mathbf{Y}}_{N-N_l}^{\mathrm{E}}]$	Extra-class transformed feature matrix, where $\vec{\mathbf{Y}}_i^{\mathrm{E}}$ is the 1D Fourier transform of extra-class low-dimensional feature $\vec{y}_i^{\mathrm{E}}$ for class l

2. A new correlation filter is proposed. A new correlation filter called optimal extra-class origin output tradeoff filter (OEOTF) which focuses on the origin correlation outputs is proposed. Two related correlation filters called minimum average extra-class origin correlation output energy (MAEOCE) filter and minimum extra-class origin variance synthetic discriminant function (MEOVSDF) filter are also presented. Extensive experimental results show that OEOTF is very effective for feature vector extraction.

The rest of the paper is organized as follows: Section 2 briefly reviews original CFA (2D-CFA) and widely used correlation filters. In Section 3, 1D correlation filter based CFA (1D-CFA) and OEOTF are discussed in detail. In Section 4, extensive experimental results on the FERET, AR, and FRGC (face recognition grand challenge) face databases are given. Comparisons between different linear subspace learning methods are also shown. Finally, conclusions are provided in Section 5.

For convenience, important notations used throughout the rest of the paper are listed in Table 1. Vectors are denoted by an arrow on top of the alphabet. Bold and upper case symbols refer to the frequency plane term while light and lower case symbols represent quantities in the space domain.

2. 2D correlation filter based class-dependence feature analysis

During the training stage, a set of 2D-CFA projection vectors (correlation filters) is generated and all of these correlation filters are used for feature vector extraction. More precisely, a specific correlation filter which discriminates one class from all other classes in the training set is designed for each face class. Overall a bank of class-dependence correlation filters is obtained [10]. And a new face image evaluated on all the correlation filters generates a feature vector in which each component represents the similarity between the new face image and a certain face class in the training set. See Fig. 1 for illustration.

The key of 2D-CFA is the design of correlation filters. Correlation filters work in the frequency domain (i.e. the 2D Fourier transforms of images). On the other hand, the phase spectrum is usually believed to contain more structural information in images that derive human perception than the magnitude spectrum [9]. Therefore, by going to the frequency domain, phase information is directly modeled by correlation filters.

The most simple correlation filter is known as the matched filter which is simply the complex conjugate of the 2D Fourier transform of the reference pattern. It has been shown that the matched filter is optimal for detecting a pattern which is the addition of the reference pattern and white noise [16]. However, in applications like face

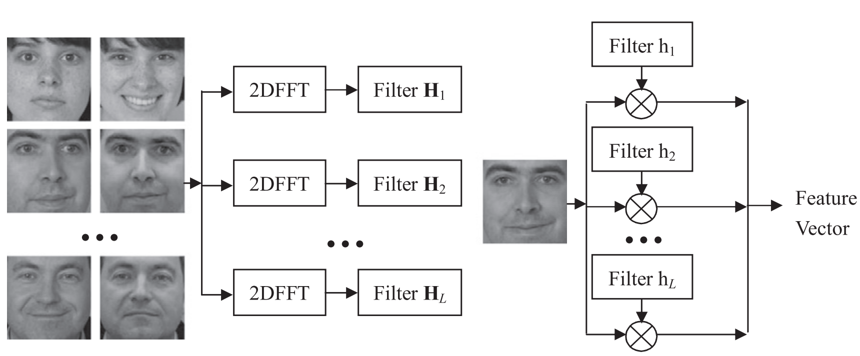

Fig. 1. Training of correlation filters (left) and feature vector extraction (right) in 2D-CFA. Note that 2D fast Fourier transform (2DFFT) is an efficient algorithm to compute 2D discrete Fourier transform (2DDFT).