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Multi-resolution feature fusion for face recognition

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For face recognition, image features are first extracted and then matched to those features in a gallery set. The amount of information and the effectiveness of the features used will determine the recognition performance. In this paper, we propose a novel face recognition approach using information about face images at higher and lower resolutions so as to enhance the information content of the features that are extracted and combined at different resolutions. As the features from different resolutions should closely correlate with each other, we employ the cascaded generalized canonical correlation analysis (GCCA) to fuse the information to form a single feature vector for face recognition. To improve the performance and efficiency, we also employ "Gabor-feature hallucination", which predicts the high-resolution (HR) Gabor features from the Gabor features of a face image directly by local linear regression. We also extend the algorithm to low-resolution (LR) face recognition, in which the medium-resolution (MR) and HR Gabor features of a LR input image are estimated directly. The LR Gabor features and the predicted MR and HR Gabor features are then fused using GCCA for LR face recognition. Our algorithm can avoid having to perform the interpolation/super-resolution of face images and having to extract HR Gabor features. Experimental results show that the proposed methods have a superior recognition rate and are more efficient than traditional methods.

1. Introduction

In recent years, feature-fusion technology [1–13] has become one of the important technologies for face recognition. The key idea of feature fusion is to extract various features by different methods from same patterns, and fuse these multiple features via some optimization algorithms. We can obtain the effective discriminant information and reduce the redundant information between features. This can improve the efficiency and effectiveness of face recognition to some extent.

Basically, feature-fusion methods can be divided into two categories. One approach groups multiple feature vectors end to end to form a union-vector [2], and then extracts features in the higher-dimensional vector space. This approach dramatically increases the feature-vector dimension, which results in the small-sample-size (sss) problem [14], as the within-class dispersion matrix of the feature vectors easily becomes singular. The other approach combines two sets of feature vectors to form a combined vector [3,4], and then extracts features in the complex vector space. Both feature-fusion methods can improve the recognition rate. The feature-fusion approach based on union-vectors is referred as "serial feature fusion", while the other one, based on complex vectors, is called "parallel feature fusion" [4]. In general, these two approaches using simple, serial or parallel feature fusion find it difficult to effectively express inherent correlations, and to achieve effective feature fusion.

Some work considering multi-resolution information has been proposed for face recognition [15–19]. Ekenel and Sankur [15] proposed a multi-resolution face recognition method which uses discrete wavelet transform (DWT) to extract the features and represent the features using subspace analysis methods – independent component analysis (ICA) and principal component analysis (PCA). Different fusion schemes were also compared. Most of the methods [16–19] perform multi-resolution face recognition by extracting the Gabor features at different scales and orientations, which are fused to form multi-resolution features. However, our proposed approach is somewhat different from the conventional multi-resolution methods: our methods consider the Gabor features at different scales and orientations in face images at different resolutions. In addition, our methods employ a Gabor-feature hallucination method [28] to estimate the higher-resolution Gabor features from the LR Gabor features, which is more efficient and accurate than performing image super-resolution (SR) followed by feature extraction. Although Gabor features can be extracted using Gabor filters at different scales and orientations, the Gabor features extracted from images at different resolutions should be more complementary to each other than

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those extracted by Gabor filters with more scales. Theoretically, in the continuous domain, the same feature can be obtained by resizing the image or the Gabor filters. However, for a discrete image, the extracted features will be different, and the errors will become significant when the image resolution is very low.

Recently, fusion methods [1,20–22] based on canonical correlation analysis (CCA) have been used to extract two different feature vectors from the same samples, and a correlation criterion function has been established to compute the canonical correlation features from the two groups of feature vectors. These fusion methods form effective, discriminant feature vectors for pattern recognition. Other related and improved methods [23,24] have also been proposed. Kettenring [25] proposed the multi-set canonical correlation analysis (MCCA), which can be used to analyze linear relationships between more than two sets of variables. It is a generalized extension of CCA, in essence. Nielsen [26] described two- and multi-set canonical correlations analysis (CCA) for data fusion and for multi-source, multi-set, or multi-temporal exploratory data analysis. MCCA has been successfully applied to underwater target classification and signal processing [27]. Although MCCA can solve the multi-set variates problem, it is difficult to demonstrate the integral relation among the multi-set variables, and the constraints cannot guarantee that the transformed variables are statistically uncorrelated. This is because MCCA maximizes the correlation within two sets of data in each time. Recently, Yuan et al. [6] proposed a multi-set integrated canonical correlation analysis (MICCA) framework to solve the multi-set variables. MICCA solves this problem by iterations, which reduces the efficiency.

In face recognition, the features of images at different scales can be easily extracted. If we use a simple and effective feature-fusion method to combine these features, this can improve the efficiency and performance of face recognition. In this paper, we propose a novel feature-fusion method for face recognition. This method combines the multi-resolution Gabor features using cascaded generalized canonical correlation analyses (CGCCAs). Furthermore, to extend this method, we employ Gabor-feature hallucination [28] to estimate higher-resolution Gabor features from the LR Gabor features. This multi-resolution feature-fusion (MFF) method can significantly improve the efficiency and performance of face recognition, in particular if the face image is of low resolution.

The organization of this paper is as follows. In Section 2, we will discuss the use of generalized canonical correlation analysis (GCCA) to fuse features of different resolutions. In our proposed algorithm for face recognition, image features from an original resolution are fused with those features at both a lower and a higher resolutions in stages. In Section 3, we will first introduce the prediction of image features at a higher resolution from a low-resolution image using local linear regression. Then, we apply this facial-feature hallucination method for low-resolution face recognition. The performances of both our multi-resolution fusion algorithm for face recognition and our proposed low-resolution face-recognition algorithm are evaluated and compared to other existing methods in Section 4. Finally, we conclude our paper in Section 5.

2. Multi-resolution feature fusion for face recognition

In this section, we describe in detail our MFF method for face recognition. The Gabor wavelets will first be introduced, followed by the canonical correlation analysis (CCA), generalized canonical correlation analysis (GCCA), and generalized canonical projective vectors (GCPV). Finally, our MFF method for face recognition is presented.

2.1. Gabor wavelets

Gabor wavelets (GW) [29,30] have been commonly used for extracting local features for various applications, such as object detection, recognition, and tracking. Daugman et al. [31,32] discovered that the simple cells in the visual cortex of mammalian brains can be modeled using Gabor functions. These kernels are similar to the response of the two-dimensional receptive field profiles of the mammalian simple cortical cell and exhibit the desirable characteristics of capturing salient visual properties such as spatial localization, orientation selectivity, and spatial frequency selectivity [33]. In the spatial domain, a GW is a complex exponential modulated by a Gaussian function, which is defined as follows [34]:

$$\Psi_{\omega,\theta}(x,y)=\frac{1}{2\pi\sigma^2}e^{-(x\cos\theta+y\sin\theta)^2+(-x\sin\theta+y\cos\theta)^2/2\sigma^2}\cdot[e^{i(\omega x\cos\theta+\omega y\sin\theta)}-e^{-\omega\sigma^2/2}], \tag{1}$$

where (x, y) denote the pixel position in the spatial domain, ω is the radial center frequency of the complex exponential, θ is the orientation of the GW, and σ is the standard deviation of the Gaussian function. By selecting different center frequencies and orientations, we can obtain a family of Gabor kernels from (1), which can then be used to extract features from an image. GWs can effectively extract local and discriminating features. In [35–39], GWs are employed for face recognition, and achieve very high performance levels.

In Gabor feature representation, only the Gabor magnitudes are used because the Gabor phases change linearly with small displacements. Five scales and eight orientations of Gabor filters are usually adopted. The Gabor jet at a pixel position is formed by concatenating the outputs of the 40 (5×8) filters.

2.2. Basic idea of canonical correlation analysis

Canonical correlation analysis [40,41], developed by Hotelling et al. in 1936, is a way of measuring the linear relationship between two multidimensional variables. CCA finds two bases, one for each variable, that are optimal with respect to correlation and, at the same time, measures the corresponding correlations. In other words, it finds the two bases in which the correlation matrix between the projected variables is diagonal and the correlations are maximized. The dimensionality of these new bases is equal to or less than the smaller dimensionality of the two variables.

Suppose A and B are two feature sets defined on a pattern sample space Ω. For any pattern samples $\boldsymbol{\xi}\in\Omega$, the corresponding two feature vectors are $\boldsymbol{x}\in A$ and $\boldsymbol{y}\in B$. Considering the two zero-mean vectors $\boldsymbol{x}\in R^p$ and $\boldsymbol{y}\in R^q$, CCA finds pairs of directions $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ that maximize the correlation between the projections $\boldsymbol{x}^*=\boldsymbol{\alpha}^T\boldsymbol{x}$ and $\boldsymbol{y}^*=\boldsymbol{\beta}^T\boldsymbol{y}$. In general, the projective directions $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are obtained by maximizing the following criterion function:

$$J(\boldsymbol{\alpha},\boldsymbol{\beta})=\frac{\boldsymbol{\alpha}^T\boldsymbol{C}_{xy}\boldsymbol{\beta}}{\sqrt{\boldsymbol{\alpha}^T\boldsymbol{C}_{xx}\boldsymbol{\alpha}\cdot\boldsymbol{\beta}^T\boldsymbol{C}_{yy}\boldsymbol{\beta}}}, \tag{2}$$

where $\boldsymbol{C}_{xx}\in R^{p\times p}$ and $\boldsymbol{C}_{yy}\in R^{q\times q}$ are the covariance matrices of $\boldsymbol{x}$ and $\boldsymbol{y}$, respectively, while $\boldsymbol{C}_{xy}\in R^{p\times q}$ denotes the between-set covariance matrix of $\boldsymbol{x}$ and $\boldsymbol{y}$. Furthermore, $\boldsymbol{C}_{xy}^T=\boldsymbol{C}_{yx}$.

2.3. Generalized canonical correlation analysis

Generalized canonical correlation analysis [4,20–24] is an extension of CCA. Let $\boldsymbol{C}_{W_x}$ and $\boldsymbol{C}_{W_y}$ denote the within-class scatter matrix of the training samples in A and B, respectively, i.e.

$$\boldsymbol{C}_{W_x}=\sum_{i=1}^{c}P(\omega_i)\left[\sum_{j=1}^{n_i}(\boldsymbol{x}_{ij}-\boldsymbol{m}_i^x)(\boldsymbol{x}_{ij}-\boldsymbol{m}_i^x)^T\right], \tag{3}$$