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A local spectral feature based face recognition approach for the one-sample-per-person problem

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ABSTRACT

Face recognition for the one-sample-per-person problem has received increasing attention owing to its wide range of potential applications. However, since only one training image is available for each person, and the face images may have large appearance variations, how to achieve a high recognition accuracy is still a challenging work. In this paper, we propose a more accurate local spectral feature based face recognition approach for the one-sample-per-person problem. In the proposed algorithm, multi-resolution local spectral features are first extracted to represent the face images to enlarge the training set. A weaker classifier is then constructed based on the spectral features of each local region. Since a good diversity is observed for the outputs of the weaker classifiers, a strategy of classifier committee learning is adopted to combine the results obtained from different local spectral features. Moreover, inspired by the fact that the iterations are completely independent of each other, a scheme of multiple worker based parallel computing is designed to improve the loop speed by distributing iterations to the MATLAB workers simultaneously. Experimental results on the standard databases demonstrate the feasibility and effectiveness of the proposed method.

1. Introduction

In recent years, face recognition for the one-sample-per-person problem has received increasing attention owing to its wide range of potential applications, e.g., law enforcement, surveillance identification, forensic identification and access control, etc [1,2]. It is well known that, for the traditional statistical learning methods, the recognition performances generally heavily rely on the number of training sample. Thus, the lack of enough training samples often results in poor generalization ability, or even failure, for these methods. Since only one training image is available for each person, and the face images may have large appearance variations in terms of expression, illumination, disguises, pose, and so on, the one-sample-per-person problem has become an extremely challenging work of face recognition [3–6].

So far, many approaches have been developed to address the one-sample-per-person face recognition problem. Generally speaking, the common strategy to deal with the problem is to enlarge the training set by extracting the various discriminative features [7], generating the virtual samples [8], or constructing the discriminant model by means of the generic set [9]. A typical strategy of the discriminative feature extraction method is to employ the features from the local region [10]. A prominent advantage of using local representations is its fair robustness to variations in lighting, expression and occlusion. In order to capture the intra-class variations for each single sample, some researchers proposed to synthesize virtual samples by using the learned information [11], by means of the various transformation [12], or by rendering the recovered 3D face model [2], etc. Among these methods, the information in the frequency domain are frequently utilized to strengthen the recognition performance [13]. In [14], the frequency invariant features and the moment invariant features [14] are combined for face recognition with a single training sample. In [15], the one-sample-per-person problem is addressed via a fusion of the directionality of edges and the intensity facial features. Moreover, different recognition approaches, such as sparse representation [16], and linear regression [17,18], are proposed for the one-sample-per-person problem.

Recently, we presented a very effective recognition method for the one-sample-per-person problem, named MR_2DLDA [19]. In the proposed method, multi-resolution spectral feature images are constructed to represent the face images, which greatly enlarge the training set. 2DLDA (two-dimensional linear discriminant analysis) is then applied on the spectral representations. Experimental results on multiple databases demonstrated the superiority of the spectral feature representation.

Inspired by the robustness of the local feature, and the superiority of the spectral feature representation, in this paper, we

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propose a more accurate local spectral feature based face recognition approach for the one-sample-per-person problem. One issue with the one-sample-per-person problem is that the number of training samples available is too few. In the proposed method, multi-resolution spectral features are first extracted and used as the representations of training face images by means of a method similar to [20]. Further, the spectral feature images are divided into patches with the same sizes. Then, the patches of the same position are collected, and used as the training samples of one weak classifier. Thereby, the size of the training set is greatly enlarged via the local spectral representation.

As we do not know exactly which patches, orientations and scales are robust for all testing images, an alternative approach is to use all of local spectral features in the decision-making process. In our method, each patch with a certain orientation and scale will form one weak classifier. In order to determine the classes of the testing images, a strategy of classifier committee learning (CCL) is designed further to combine the results obtained from different local spectral feature images. With the strategy of CCL, on the one hand, most of the correct categorizations can be retained. On the other hand, it is not necessary for us to choose the optimal patches and filters, which is a very difficult task for the one-sample-per-person problem. Using the above strategies, the negative effects caused by those unfavorable factors, such as variations of illumination and facial expression, can be alleviated greatly in face recognition. It should be pointed out that, for the MR_2DLDA method [19], the diversity of weak classifiers is mainly due to the scale variation of spectral features. Nevertheless, for the proposed method, besides the scale variation, the local features of each scale can also increase the diversity of weak classifiers. As a result, the final recognition results obtained by the CCL are significantly improved.

Because local spectral features are used in the proposed method, the iteration computation number of the block distances becomes increasingly large. Inspired by the fact that the iterations are completely independent each other, a scheme of multiple worker based parallel computing is designed to improve the loop speed by distributing iterations to the MATLAB workers simultaneously.

The contributions of the proposed algorithm can be summarized as two aspects. A multi-resolution local spectral feature representation is proposed to enlarge the training set, and increase the diversity of the weaker classifiers at the CCL stage. Moreover, a scheme of multiple worker based parallel computing is designed to decrease the training times. Experimental results on some standard databases demonstrate the feasibility and effectiveness of the proposed method.

The remainder of the paper is organized as follows. In Section 2, we present our proposed algorithm. Experimental results and related discussions are given in Section 3, and concluding remarks are presented in Section 4.

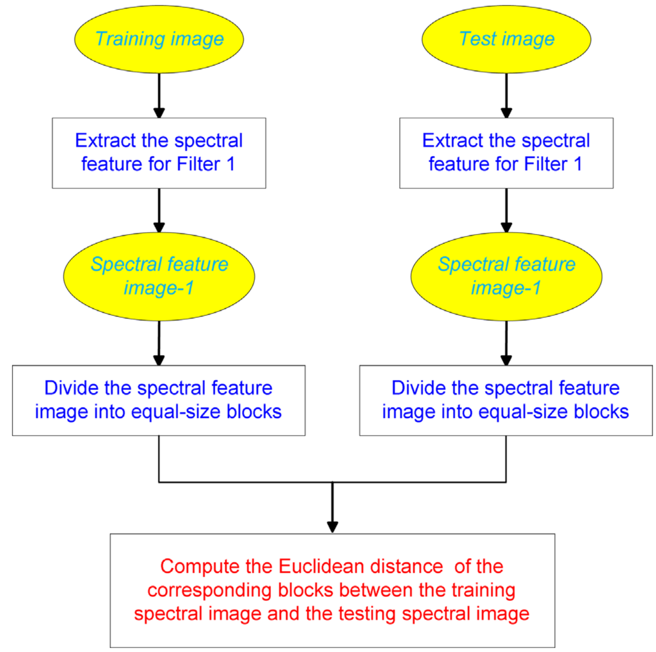

Fig. 1. The flowchart of the local spectral feature extraction process, and the distance computation of the corresponding blocks between the training spectral image and the testing spectral image.

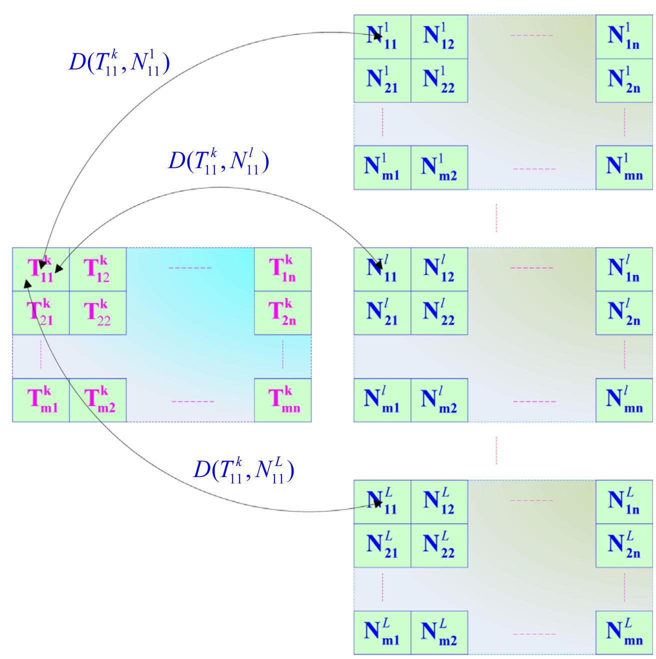

Fig. 2. The division of the spectral images, and the distance computation of the local spectral features between the testing image and the training images.

2. Methodology

2.1. Local spectral feature image representation

Assume that there are L training images $\mathbf{I}_i$ $(i = 1, \ldots, L)$, and that each belongs to one subject. The training image is first pre-filtered to reduce the effect of illumination. The Fourier transform of the prefiltered image is then filtered by a set of Gabor filters with n_s scales and n_o orientations [20]. Further, the corresponding amplitudes are computed as the spectral feature images. Thus, for the given N_f (i.e. $n_s \times n_o$) filters, N_f spectral feature images can be obtained for each training sample. In the same way, N_f spectral feature images can also be extracted for each test sample, as shown in Fig. 1.

Subsequently, the spectral images of the training images and the testing images are divided into blocks with the same sizes. Take the kth testing image for example, we then compute the Euclidean distances $D(T_{ij}^k, N_{ij}^l)$ $(i = 1, 2, \ldots, m, j = 1, 2, \ldots, n, l = 1, \ldots, L)$ of the pixel values between the blocks $T_{ij}{}^k$ and $N_{ij}{}^l$, as shown in Fig. 2.

2.2. Combining the weaker classifiers

After computing the distances $D(T_{ij}^k, N_{ij}^l)$, we arrange the distances $D(T_{ij}^k, N_{ij}^l), (l = 1, \ldots, L)$ of each block as one row of the matrix $\mathbf{D}^k$, as shown in Fig. 3(a). If we consider to construct a nearest-