Learning Discriminant Face Descriptor for Face Recognition

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Abstract. Face descriptor is a critical issue for face recognition. Many local face descriptors like Gabor, LBP have exhibited good discriminative ability for face recognition. However, most existing face descriptors are designed in a handcrafted way and the extracted features may not be optimal for face representation and recognition. In this paper, we propose a learning based mechanism to learn the discriminant face descriptor (DFD) optimal for face recognition in a data-driven way. In particular, the discriminant image filters and the optimal weight assignments of neighboring pixels are learned simultaneously to enhance the discriminative ability of the descriptor. In this way, more useful information is extracted and the face recognition performance is improved. Extensive experiments on FERET, CAS-PEAL-R1 and LFW face databases validate the effectiveness and good generalizations of the proposed method.

1 Introduction

Face recognition, due to its potential value for applications and its theoretical challenges, has attracted wide attention and been developed greatly during the last decades. Although face recognition in controlled environment has been well solved, its performance in real application is still far from satisfactory. The variations of expression, pose, occlusion and illumination are still critical issues that affect the face recognition performance. How to extract robust and discriminant features that make the face images more separable is an open question for face recognition.

Up to now, many face representation approaches have been introduced. These methods can be roughly categorized into holistic and local appearance features [1, 2]. The representative holistic methods include the well known principal component analysis (PCA) [3], linear discriminate analysis (LDA) [4], independent component analysis (ICA) [5] etc. PCA provides an optimal linear transformation from the original image space to an orthogonal eigenspace with reduced dimensionality in sense of the least mean square reconstruction error. LDA seeks a linear transformation by maximizing the ratio of between class variance to within class variance. ICA is a generalization of PCA, which is sensitive

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to high-order correlation among the image pixels. Since holistic features are extracted based on the whole image, some local changes in face images may result in completely different holistic face representation, which may not be robust to image variations.

Local appearance features, as opposed to holistic features like PCA and LDA, are more stable to local changes such as illumination, expression and inaccurate alignment. Gabor [6, 7] and local binary patterns (LBP) [8] are two representative features. Gabor wavelets capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation. It has been demonstrated to be discriminative and robust to illumination and expression changes. Local binary patterns (LBP) which describes the neighboring changes around the central point, is a simple yet effective way to represent faces. It is invariant to monotone transformation and is robust to illumination changes to some extent. Recently, researchers combine the advantages of Gabor and LBP representations and propose a series of novel face representation methods [9–11].

1.1 Related Work

Fig. 1. Three-step way to extract LBP like feature.

The proposed discriminant face descriptor (DFD) is an improvement of LBP like feature descriptor. In general, LBP like feature extraction can be decomposed into three steps (Fig. 1). First, a proper image filter is applied to the original image to remove the noise and enhance the useful information. Second, certain pixel patterns on the filtered image are sampled and compared. Third, the encoded image is derived based on the comparison results at the second step and the encoding rules. After that, the histogram based features are usually extracted from the encoded images as the face representation for face recognition. From this view, in ordinary LBP [8], the first image filtering step is skipped and the LBP feature is extracted from the original image by comparing the values of neighboring pixels with its central point. The LBP encoded image is derived according to the LBP binary string and the uniform pattern definition. In MBLBP [12], the mean filter is applied at the first step and the following procedure are the same to the ordinary LBP. In LGBP [9], a bank of Gabor filters are first applied to the face image and then LBP is extracted from the Gabor filtered images. These are all improvement of LBP at the first step.

Recently, there are also some efforts on the second and third steps of LBP extraction. In [13], a heuristic algorithm is used to find the optimal pixel comparison pairs for discriminative face representation. Cao et al. [14] proposed to define the dominant patterns by learning the random projection tree. Guo et al. [15]

proposed a supervised learning approach based on Fisher separation criterion to learn the encoder of LBP. In [16], authors propose to construct a decision tree for each region to encode the pixel comparison result. All these methods improve the face recognition performance by incorporating discriminant information learned from the face samples.

1.2 Our Contribution

As mentioned above, one can see that the existing learning based methods mainly focus on the second and third steps to improve the discriminative ability of LBP like features [14–16]. Recently, Lei et al. [17] propose a method to learn the discriminant image filter for LBP extraction. Different from the existing methods, in this paper, we propose a learning based discriminant face descriptor, which learns the discriminant filter (at the first step) and the pattern encoder (at the third step) simultaneously. For image filter learning, the elements of image filters are determined by enhancing the discriminative ability of the image. Moreover, we argue that the neighboring pixels are of different contributions for discriminant face representation. The equivalent treatment of neighboring pixels in ordinary LBP is not the best way for face representation. Therefore, in this work, we propose to learn weights for different neighboring pixels so that more discriminant information will be extracted. After the discriminant image filters and the optimal weights learning, the dominant patterns are determined in an unsupervised way. The contributions of this work are summarized as below.

(i) A learning based discriminant face descriptor is proposed. It improves the first step (image filtering) and third step (pattern encoder) of ordinary LBP extraction simultaneously.
(ii) Weight assignment of neighboring pixels is proposed to differentiate the importance of pixels so that more discriminant information useful for face recognition can be extracted.
(iii) A formulation and solution to learn discriminant image filters and optimal weights of neighboring pixels is provided. The process of discriminant descriptor based face representation is presented.

2 Discriminant Face Descriptor

The pipeline of the discriminant face descriptor learning is shown in Fig. 2. Given a face image, the pixel difference matrices (PDMs) are first extracted from each pixel. These PDMs are then used to learn the discriminant image filters and the optimal weights for neighboring pixels. After that, the projected PDMs are transformed into a vector and an unsupervised learning method (e.g., K-means) is adopted to obtain the final dominant patterns. In encoding phase, each pixel is labeled with the id of dominant pattern which is most similar to the extracted discriminant vector on it.

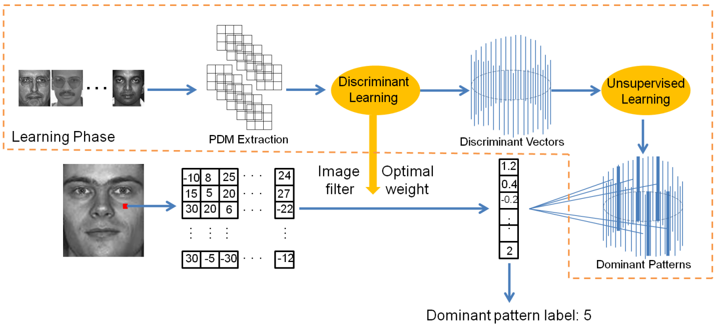

Fig. 2. The pipeline of discriminant face descriptor learning.

2.1 Discriminant Image Filter Learning

Given an face image I, its filtered image is denoted as $f(I)$. Considering the LBP pattern sampling strategy, the pixel difference vector (PDV) between the neighboring pixels and the central pixel can be extracted as $df(I)^p = [f(I)^{p_1} - f(I)^p, f(I)^{p_2} - f(I)^p, \cdots, f(I)^{p_d} - f(I)^p]$, where $f(I)^{p_i}$ is the pixel value of filtered image at position p_i, $\{p_1, p_2, \cdots, p_d\} \in Neighbor(p)$ and d is the number of sampling neighbors. The purpose of discriminant image filter learning is to find a filter f so that after the image filtering, the PDVs of images from the same person are similar and the differences of PDVs from different persons are enlarged. Following the Fisher criterion [18], this can be formulated to maximize the ratio of between class scatter S'_b to the within class scatter S'_w. Let $df(I)^p_{ij}$ be the p-th PDV of j-th sample from class i, the between class scatter S'_b and within class scatters S'_w can be defined as

$$
\begin{aligned}
S'_w &= \sum_{i=1}^{L}\sum_{j=1}^{C_i}\sum_{p=1}^{N}(df(I)^p_{ij} - df(m)^p_i)(df(I)^p_{ij} - df(m)^p_i)^T \\
S'_b &= \sum_{i=1}^{L}\sum_{p=1}^{N} C_i(df(m)^p_i - df(m)^p)(df(m)^p_i - df(m)^p)^T
\end{aligned}
\tag{1}
$$

where L is the number of face classes; C_i is the number of samples from the i-th class and N is the number of PDV on a single face image. $df(m)^p_i$ is the mean vector of p-th PDVs on filtered images from the i-th class and $df(m)^p$ is the total mean vector of p-th PDVs over the sample set.

Under linear assumption, suppose the image filter vector to be w, and the value of filtered image at position p can be represented as $f(I)^p = w^T I^p$, where I^p denotes the image patch vector centered at position p. Similarly, the PDV

$df(I)^p$ can be represented as $df(I)^p = w^T dI^p$[1]. Substituting it into Eq. 1, we get

$$
\begin{aligned}
S'_w &= \sum_{i=1}^{L} \sum_{j=1}^{C_i} \sum_{p=1}^{N} w^T (dI^p_{ij} - dm^p_i)(dI^p_{ij} - dm^p_i)^T w \\
S'_b &= \sum_{i=1}^{L} \sum_{p=1}^{N} C_i w^T (dm^p_i - dm^p)(dm^p_i - dm^p)^T w
\end{aligned} \tag{2}
$$

where dI^p_{ij} is pixel difference matrix (PDM) extracted from the j-th image of class i at position p, dm^p_i is the mean PDM for the i-th class and dm^p is total mean PDM at position p. Fig. 3 shows an example of how to extract PDM from each pixel.

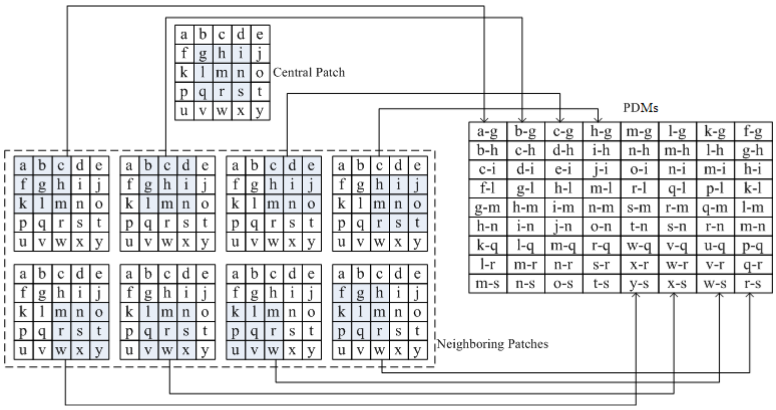

Fig. 3. Example of pixel difference matrix extraction for discriminant face descriptor learning. The image filter size is 3×3 and the neighboring radius is 1. For every central patch, 8 neighboring patches are compared respectively and then grouped to form the pixel difference matrix.

2.2 Optimal Weight Learning

In ordinary LBP, the neighboring pixels are compared with the central pixel sequentially and the results are grouped to form the LBP binary string. There is no priority among these neighboring pixels. In this work, we believe that there remains space to enhance the discriminant ability by taking into account the different contributions from these neighboring pixels. Actually, in many local filters like Gabor, different orientation filters are designed to capture the responses of different local image structures. Therefore, it is meaningful to differentiate the

[1] The expression dI^p is named pixel difference matrix (PDM) as it is a matrix rather than a vector.

importance of neighboring pixels in feature extraction. This paper proposes to find the optimal weights for different neighboring pixels in a discriminant learning way. Suppose the weight vector as $v = [v_1, v_2, \cdots, v_d]^T$, where d is number of neighboring pixels, after weight combination, the results of PDVs from the same person are supposed to be consistent and those results from different persons are different. By appropriate formulation, this problem can also be formulated as maximizing the ratio of between class scatter $S_b^{''}$ to within class scatter $S_w^{''}$, which are computed based on PDVs as follows,

$$\begin{aligned} S_w^{''} &= \sum_{i=1}^{L}\sum_{j=1}^{C_i}\sum_{p=1}^{N}(df(I)_{ij}^p - df(m)_i^p)vv^T(df(I)_{ij}^p - df(m)_i^p)^T \\ S_b^{''} &= \sum_{i=1}^{L}\sum_{p=1}^{N}C_i(df(m)_i^p - df(m)^p)vv^T(df(m)_i^p - df(m)^p)^T \end{aligned} \tag{3}$$

2.3 Optimization

By combining Eqs. 2 and 3, the between class scatter S_b and within class scatter S_w can be reformulated as

$$\begin{aligned} S_w &= \sum_{i=1}^{L}\sum_{j=1}^{C_i}\sum_{p=1}^{N}w^T(dI_{ij}^p - dm_i^p)vv^T(dI_{ij}^p - dm_i^p)^T w \\ S_b &= \sum_{i=1}^{L}\sum_{p=1}^{N}C_i w^T(dm_i^p - dm^p)vv^T(dm_i^p - dm^p)^T w \end{aligned} \tag{4}$$

Following Fisher criterion, the objective of discriminant descriptor learning is to find image filter vector w and neighboring weight vector v, so that the ratio of between class scatter to the within class scatter can be maximized. It is easy to find that this formulation is similar to the two-dimensional linear discriminant analysis (2D-LDA) [19], where the PDM is the basic matrix to compute the between and within class scatter and the left (discriminant image filter) and right projections (optimal weight vector) are required to be computed. Like 2D-LDA, we solve the above optimization problem in an iterative way. At each iteration, one of vectors w, v is fixed and the optimal solution for another one is derived by solving the generalized eigen-value problem. As indicated in [19], one loop iteration is enough to achieve good performance which reduces the computational cost of the algorithm.

With the learned image filter and weight vectors, the PDM can be projected onto a discriminant subspace. Suppose we finally preserve d_1' image filter vectors and d_2' neighboring weight vectors, after left and right projections, the PDM is projected onto a $d_1' \times d_2'$ matrix. This matrix is then transformed into a vector of $d_1' \times d_2'$ dimension. Unsupervised learning (i.e., K-means clustering) is then applied on these discriminant vectors to determine the most representative patterns (dominant patterns) of discriminant descriptor.

3 Face Recognition with Locally Discriminant Descriptor

As we know, different face parts have different structures. Therefore, the discriminant descriptors for different regions of the face should be different. Actually, previous work like [20, 11] have indicated that the optimal configures of Gabor filters for different regions are different. According to this methodology, we further partition the face image into several regions and learn discriminant descriptor locally for each region, respectively. In feature extraction phase, the face image is firstly partitioned into several parts and the pixels in each part are encoded with the corresponding locally discriminant face descriptor. In this way, the useful local structure of face image is described more precisely and the face recognition performance is hence believed to be improved.

After the image encoding, the histogram feature which describes the co-occurrence of dominant patterns is extracted. The weighted histogram intersection as adopted in [11] is finally used to measure the dissimilarity between different face images.

4 Experiments

We compare the proposed discriminant face descriptor with state-of-the-art methods, including LBP, MBLBP, LGBP, LLGP etc. Three popular face databases (FERET, CAS-PEAL-R1, LFW) are used to evaluate the performance of various methods in different scenarios.

The FERET [21] database is one of the largest publicly available databases. The training set contains 1002 images. In test phase, there are one gallery set containing 1196 images from 1196 subjects, and four probe sets (fb, fc, dup1 and dup2) including expression, illumination and aging variations. In our experiments, all the images are rotated, scaled and cropped to 150×130 size according to the provided eye coordinates.

The CAS-PEAL-R1 database [22] is a large-scale Chinese face database for face recognition algorithm training and evaluation. This database provides large-scale face images with different sources of variations, including pose, expression, accessory and lighting. In this experiment, we follow the standard testing protocols. The gallery set includes 1040 images from 1040 persons. For probe sets, we use the expression, lighting, accessory subsets, which contains 1570, 2243, 2285 images, respectively. All the images are cropped to 150×130 size according to the provided eye coordinates.

Labeled Faces in the Wild (LFW) [23] is a database collected from the web for studying the problem of unconstrained face recognition. There are $13,233$ images from $5,749$ different persons, with large pose, occlusion, expression variations. In testing phase, researchers are suggested reporting performance as 10-fold cross validation using splits which are randomly generated and provided by the organizers. In this experiment, we use the aligned images (LFW-a) [24] and crop the images with the size of 150×130 from the original images.

4.1 Parameter Clarification

There are several parameters in the proposed discriminant face descriptor. In discriminant image filter and optimal weight learning phase, the parameters include the size of image filter s (the dimension of image filter vector is $d_1 = s \times s$), the sampling number d_2 in the neighborhood and the reduced dimension d_1', d_2' for the image filter learning and the optimal weight learning, respectively. In representative pattern learning phase, the number of dominant patterns K is a parameter need to be determined.

In this work, most parameters' value is set empirically. For simplicity, the sampling number d_2 is fixed to 8 in all the experiments. The reduced dimension for image filters learning and optimal weight learning d_1', d_2' are set to 5 and 4, respectively. Therefore, the dimension of the dominant pattern is $5 \times 4 = 20$. For the size of image filter, we vary the size s from $\{3, 4, 5\}$, and the results with these different sizes are tested and fused. For the number of dominant patterns K, we test different values of K on FERET fb probe set. Table 1 lists the face recognition rates with respect to different values of K. From the result, one can see that it achieves the highest recognition rate when the number of dominant patterns equals 1024 and 2048. Considering the trade-off between the accuracy and computational cost, we finally set K to 1024 in the following experiments.

Table 1. Recognition rates on fb set with different numbers of dominant patterns in DFD.

No. of dominant patterns	16	32	64	128	256	512	1024	2048
Rec. rate	0.894	0.934	0.951	0.964	0.972	0.980	0.982	0.982

4.2 Results and Discussions

We compare proposed method with popular descriptors like LBP, LGBP, LVP, LLGP etc. We also compare the results of IFL-ELBP which is recently proposed by learning a discriminant image filter for LBP-like representation. The proposed discriminant face descriptor is learned from the FERET training set. In order to reduce the noise influence, the Tan & Triggs' preprocessing method [25] is firstly applied to the cropped images. The face recognition performance is reported following the four standard testing protocols (fb, fc, dup1, dup2) of FERET database.

Table 2 lists the rank-1 recognition rates of different methods on four probe sets of FERET. In all four probe sets, the proposed discriminant face descriptor achieves competitive recognition results with state-of-the-art descriptors. It achieves the best performance on fb, fc and dup2 subsets and is ranked as the third best method on dup1 subset. Specifically, it outperforms the recently proposed image filter learning based ELBP method on all four probe sets, indicating

Table 2. Recognition rates of different methods on FERET database.

Methods	fb	fc	dup I	dup II
LBP [8]	0.97	0.79	0.66	0.64
LGBP [9]	0.98	0.97	0.74	0.71
LVP [26]	**0.99**	0.80	0.70	0.60
LGT [7]	0.97	0.90	0.71	0.67
HGPP [10]	0.98	0.99	0.80	0.78
LLGP [27]	**0.99**	0.99	0.80	0.78
POEM-HS [28]	0.98	0.99	0.80	0.79
DT-LBP [16]	**0.99**	1.00	0.84	0.80
DLBP [13]	**0.99**	0.99	**0.86**	**0.85**
IFL-ELBP [17]	**0.99**	0.93	0.76	0.78
DFD$^{s=3}$	**0.99**	**1.00**	0.80	0.78
DFD$^{s=4}$	**0.99**	**1.00**	0.83	**0.85**
DFD$^{s=5}$	**0.99**	0.99	0.82	0.82
DFD$^{s=3+4+5}$	**0.99**	0.99	0.83	0.84

that the proposed discriminant face descriptor successfully extracts the discriminant information from the face image and is a good representation for face recognition.

In order to examine the generalization performance of the learned discriminant face descriptor, we further apply the DFD on CAS-PEAL-R1 face database, where the DFD is learned from the FERET training set. Three probe sets including expression, lighting, accessory variations are used to evaluate different methods. We compare the performance of proposed DFD with LGBP, LLGP, DT-LBP, DLBP etc. The recognition results for different methods are listed in Table 3. It shows that the proposed DFD method achieves the best results on expression and accessory probe sets. It indicates that the DFD learned from FERET training set has good generalization ability and it is practical in real application. In lighting probe set, the performance of DFD is worse than HGPP and LLGP methods. It is worth noting that the proposed DFD method is a data-driven based method. The lack of face samples with lighting variations on FERET training set may result in unsatisfactory face recognition performance on lighting probe set. Compared to the results of learning based methods (DT-LBP, D-LBP), the proposed DFD always achieves better recognition rate in all three probe sets, indicating that the proposed learning based DFD is able to extract more effective information useful for face recognition and is of better generalization performance. Comparing the results of DFD on FERET and CAS-PEAL-R1 databases, although the fusion of different scales of image filters does not help improve the best performance of single scale, its fusion result is more stable than single one and hence more practical in real application.

To better evaluate the effectiveness of the proposed method in real application, we compare the proposed discriminant learning based descriptor with LBP,

Table 3. Recognition rates of different methods on CAS-PEAL-R1 database.

Methods	Expression	Accessory	Lighting
LGBP [9]	0.95	0.87	0.51
LVP [26]	0.96	0.86	0.33
HGPP [10]	0.97	0.92	**0.63**
LLGP [27]	0.96	0.92	0.55
DT-LBP [16]	0.98	0.92	0.41
DLBP [13]	**0.99**	0.92	0.41
$\mathrm{DFD}^{s=3}$	**0.99**	**0.95**	0.54
$\mathrm{DFD}^{s=4}$	**0.99**	0.94	0.47
$\mathrm{DFD}^{s=5}$	**0.99**	0.93	0.45
$\mathrm{DFD}^{s=3+4+5}$	**0.99**	**0.95**	0.54

TPLBP, FPLBP, SIFT, POEM-HS and LARK face representation methods on LFW database. We test on the "View 2" set of LFW, which consists of 10 folds of 300 positive and 300 negative image pairs randomly selected from the original image set. In this experiment, all the methods are tested in an unsupervised way. Specifically, no training operation is involved in the 10-fold cross-validation. As in [29], the results of different methods are reported as the ROC curves at equal misclassification cost (ROC-EMC) over the 10-fold cross-validation.

Table 4. ROC-EMC classification results for different descriptors on LFW database.

Descriptor	Accuracy
LBP [29]	0.6833±0.006
TPLBP [29]	0.6690±0.004
FPLBP [29]	0.6737±0.004
SIFT [29]	0.6877±0.004
POEM-HS [28]	0.7400±0.006
LARK [30]	0.7223±0.005
$\mathrm{DFD}^{s=3}$	0.7348±0.007
$\mathrm{DFD}^{s=4}$	0.7455±0.004
$\mathrm{DFD}^{s=5}$	**0.7555**±0.005
$\mathrm{DFD}^{s=3+4+5}$	0.7532±0.004

From the results listed in Table 4, one can see that the proposed discriminant face descriptor achieves the best face verification performance compared to LBP, TPLBP, FLBP, SIFT, POEM-HS and LARK. It improves the recently proposed POEM-HS and LARK methods by about 1.5–3 percent, indicating the discriminant face descriptor is really a good face representation for face recognition. Different from other methods, the DFD is learned from face images rather than manually designed. Although an extra image set is utilized to learn the discriminant face descriptor, in our experiments, the DFD is learned from the FERET training set once and no further adjustment is applied to other scenarios. Note that the image appearances of FERET and LFW are very different. The good performance of DFD on CAS-PEAL-R1 and LFW show that the learning based discriminant face descriptor has good generalization ability and is practical in real application.

5 Conclusions

This paper proposes a learning based discriminant face descriptor (DFD) for face recognition. In training phase, by extracting the pixel difference matrices (PDMs), the discriminant image filter and the optimal neighboring weight vector are obtained through discriminant learning. After discriminant projection, the margin of samples from different persons is maximized and meanwhile the appearance difference of samples from the same person is minimized. The dominant pattern set is further determined by unsupervised learning. In labeling phase, for each pixel, the PDM is first extracted and projected with the learned discriminant image filters and neighboring weight vectors to obtain the discriminant pattern vector. The pixel is then assigned as the label of dominant pattern which is most similar to the discriminant pattern vector. The histogram based feature is finally extracted from the labeled face image as the face representation for face recognition. In the future, we will investigate the coupled discriminant face descriptor for heterogeneous (cross-modality) face recognition.

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