Descriptor Learning Based on Fisher Separation Criterion for Texture Classification

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Abstract. This paper proposes a novel method to deal with the representation issue in texture classification. A learning framework of image descriptor is designed based on the Fisher separation criteria (FSC) to learn most reliable and robust dominant pattern types considering intra-class similarity and inter-class distance. Image structures are thus be described by a new FSC-based learning (FBL) encoding method. Unlike previous handcraft-design encoding methods, such as the LBP and SIFT, supervised learning approach is used to learn an encoder from training samples. We find that such a learning technique can largely improve the discriminative ability and automatically achieve a good tradeoff between discriminative power and efficiency. The commonly used texture descriptor: local binary pattern (LBP) is taken as an example in the paper, so that we then proposed the FBL-LBP descriptor. We benchmark its performance by classifying textures present in the Outex_TC_0012 database for rotation invariant texture classification, KTH-TIPS2 database for material categorization and Columbia-Utrecht (CUReT) database for classification under different views and illuminations. The promising results verify its robustness to image rotation, illumination changes and noise. Furthermore, to validate the generalization to other problems, we extend the application also to face recognition and evaluate the proposed FBL descriptor on the FERET face database. The inspiring results show that this descriptor is highly discriminative.

1 Introduction and Previous Work

Texture is an inherent property of objects and scenes. Texture analysis aims to interpret and understand real-world visual patterns, which would be used in image filtering, classification, segmentation, indexing and synthesis. The general texture classification problem being addressed can be concluded as: given a texture image obtained under certain illumination and viewpoint condition, categorize it as belonging to one of the pre-learned texture classes. In this paper, we will focus on the classification of textures from their appearance taken under varying conditions. This is difficult as changing viewpoint and illumination could have dramatic impacts on the appearance of materials and may lead to large intra-class variation and small inter-class distance.

Automatic texture classification has been extensively studied in the past decades. Existing features and techniques vary from image patch exemplars to filter or wavelet based methods [1]. Some representative ones include scale-invariant feature transform (SIFT) and related methods [2, 3], local binary patterns (LBPs) and its extensions [4–9], texton-based representation methods [10, 11][1], grey level difference or co-occurrence statistics [12], methods based on multi-channel filtering or wavelet decomposition [13–15], Gaussian Markov random field (GMRF) and other random field methods [16, 17]. Impressively, descriptor based approaches performed surprisingly well in real world situations, such as LBP, SIFT and Histogram of Oriented Gradients (HOG) [18]. No matter they encode relative intensity magnitudes or quantized image gradients, an encoding method or descriptor would be better to get an ideal balance between discriminative ability (meanwhile the robustness against condition variance) and efficiency. However, as these handcrafted descriptors produce unevenly distributed histograms, they would inevitably encounter the problem brought by rarely occurring codes. The resulting histogram might be less informative and less compact, which could degrade the discriminative ability of the image descriptor.

For example, it has been pointed out that LBP, a widely used texture descriptor, using the full set of histogram may not be reliable to describe the input image and yield good classification result because some pattern types rarely happen [7]. Uniform patterns [5], an extension of the LBP, are supposed to represent fundamental images structures, such as edges, flat areas and spots, which are usually dominant patterns among all LBP types (i.e., have proportion above 85%). Using non-dominant LBP histogram bins as image features would lead to severe problems because the histogram might be sparse and many bins might have too few pattern occurrences. However, in some cases, uniform patterns are still not dominant patterns. When texture images have complicated shape and edge type, uniform patterns only occupy a small proportion among all LBP types [9]. As the radius and number of neighboring samples increase, uniform patterns will have a much smaller proportion among all LBP types [5]. Especially, when the number of neighboring samples increases, it is difficult for a particular LBP to match the criteria to become a uniform pattern. Because uniform patterns are defined to have at most two bit-wise transitions across binary digits of each neighboring pixel, the more neighboring samples the center pixel has the more possible transitions there will be. Meanwhile, the number of all possible pattern types will increase faster than that of the possible uniform patterns. In this way, it becomes difficult to cover a significant proportion among all LBPs.

Then the issue becomes whether effective dominant patterns could be learned so that those pattern types which are reliable, robust and highly discriminative can be used for image representation. One recent method is dominant local binary patterns (DLBPs) which extract dominant patterns from the original LBPs by statistics [8]. It was later combined with filter banks and reported a better result than LBP [9]. However, as it calculates the average pattern occurrence of all images in the training set regardless of intra-class similarity and inter-class differences, the discriminative ability can easily be weakened under varying conditions.

In this paper, we first propose the FSC-based learning framework, then apply it with LBP and present the FBL-LBP descriptor to extract dominant patterns as features for classification. The main contributions of the framework lie in: 1) learning the most reliable and robust dominant pattern types of each class instead of using fixed pattern types; 2) taking both the intra-class similarity and inter-class distance into account in the learning stage, which makes it obtain optimized pattern types according to its particular application; 3) considering dominant pattern type, which is the complementary discriminative information, and pattern type occurrence in image description; 4) being easily generalized by combining with other histogram descriptors for different purposes. The rotation invariance can be implemented by replacing the original histogram with, for example, rotation-invariant LBPs.

2 Texture Image Representation by FBL Descriptor

In this section, we describe the details of the FSC-based learning framework and the feature extraction by FBL-LBP descriptor. The learning framework includes three stages: (1) The learning stage. Determine most reliable dominant types for each class. Then, all the learnt dominant types of each class are merged and form the global dominant types for the whole database; (2) Extract global dominant types learnt in stage (1) of the training set; (3) Extract the global dominant types learnt in stage (1) of the testing set. Finally, features obtained in stages (2) and (3) are served as inputs to the classifier. Each stage will be explained in the following subsections, respectively.

2.1 The Learning Stage

The learning stage of the proposed framework is based on FSC [19, 20], which is often used to evaluate the discriminative ability of features. According to the Fisher criterion, the maximum ratio of between-class scatter to within-class scatter leads to the best separation among projected sets. Given a training set containing classes of objects, let the similarities of histograms from different samples of the same class compose the intra-class similarity space. Those samples from different classes compose the extra-class similarity space. The optimal discrimination among data can be obtained by maximizing the sample mean among different classes and, meanwhile, minimizing the intra-class scatter of data. In this way, to learn most reliable and robust dominant pattern types, we carry out FSC in the learning stage by first filtering reliable dominant types from the original histograms for each class to keep the intra-class similarity, and then form the global dominant types by merging dominant types among different classes. LBPs are adopted as the original histograms in this framework as its broad use in texture classification. We will explain how it could be combined with the FSC-based learning framework and obtain the FBL-LBP descriptor.

Supposing a training image set $x_1, x_2, .., x_m$, which belongs to C classes, we have n_c images belonging to class c. Let $\boldsymbol{f}_i$ denote the histogram of all possible LBP types of interest in image i for given radius R and neighboring samples N. If rotation invariant property is required, the framework should consider all possible rotation invariant LBP types in this step. Each LBP type is characterized by the general LBP type label, defined as Equation 1:

$$LBP_{N,R} = \sum_{l=0}^{N-1} u(t_l - t_c)2^l, \tag{1}$$

where $u(x)$ is the step function with $u(x) = 1$ if $x \geq 0$ and $u(x) = 0$ otherwise. t_l denotes the intensity of neighboring pixel l, and t_c denotes the intensity of the center pixel. When the rotation invariant property is required, LBP labels can be calculated by Equation 2:

$$LBP_{N,R} = \min_{0 \leq d < N} \left(\sum_{l=0}^{N-1} u(t_l - t_c)2^{[(l+d) mod\ N]} \right). \tag{2}$$

Let p denote the total possible number of LBP types of interest and $f_{i,j}$ denote the number of occurrences of pattern type j in image x_i. We define the set of dominant LBPs of each image as the following definition.

Definition 1: *Dominant LBP set of an image is the minimum set of LBP types which can cover n% of all LBPs of the image.*

Definition 1 is expressed using Equation 3 in order to find a set J_i for image x_i (i=1,...,m), which can be implemented by Algorithm 1:

$$J_i = \arg\min_{|J_i|} \left(\frac{\sum_{j \in J_i} f_{i,j}}{\sum_{k=1}^{p} f_{i,k}} \right) \geq n\%, \tag{3}$$

where p is the total number of all possible local binary pattern types and $|J_i|$ denotes the number of elements in set J_i ($J_i \subseteq [1, 2, ..., p]$).

Based on the FSC, the most discriminant features should have large inter-class mean distance and small intra-class variation. Thus, to learn reliable dominant LBP set of each class, we remove the outlier caused by noise or illumination variation for individual images in the same class, only considering the common features. This is reflected by Fig. 1. It is also shown that not only pattern types but also the number of dominant LBP set elements of each image belonging to the same class might be changed as illumination changes or due to other distortion factors. If we consider all possible pattern types that belong to dominant LBP set of each sample, the image description will be not robust and stable enough to characterize the whole class. Therefore, only the pattern types that consistently belong to dominant pattern type sets of each image in this class

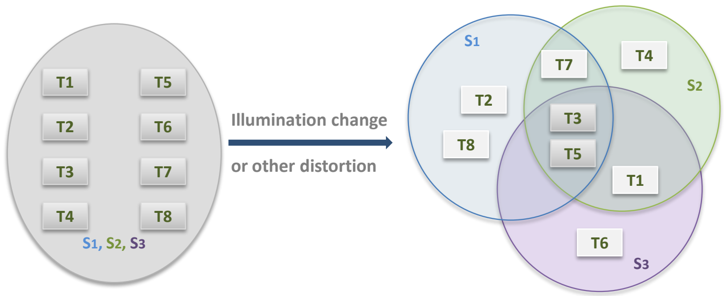

Fig. 1. The left circle denotes the ideal situation: three samples (i.e., S_1, S_2, S_3) belonging to the same class should have the same set of dominant LBPs (denoted by TN, where N is the pattern type label). The right circles denote the resulting dominant pattern types of each sample after distortion. Some dominant pattern types are changed because of imaging conditions. The number of the dominant LBP set elements of each sample might be different. In this example, only the pattern types T3 and T5 remain as dominant patterns for all samples after distortion, which would construct the most reliable dominant pattern set of this class

are adopted as the dominant pattern type set of this class. The procedure is described by Algorithm 2.

After the learning of most reliable dominant pattern set of each class c (c =1,...,C), we construct the global dominant pattern set of interest for the whole database using Algorithm 3. In this stage, pattern occurrences of pattern types are considered in J_{global} instead of using fixed pattern set as in conventional methods, e.g., the uniform LBP. This has at least two advantages. First, pattern types in J_{global} are more reliable to characterize the property of each class, as only the pattern types that consistently belong to the dominant pattern set of each sample are preserved for each class. Second, J_{global} is guaranteed to be able to cover all dominant patterns across different classes, as it is the union of the most reliable dominant patterns of each class. In following stages, each element of J_{global} represents a pattern type of interest whose frequency occurrence will be calculated.

2.2 The Training Stage

Given the global dominant pattern set of interest J_{global} obtained in the learning stage, we extract occurrence histogram of pattern types in J_{global} as features for each image. Then image x_i, belonging to training set S_{train}, can be represented by feature vector $\boldsymbol{y}_i$, which not only encodes the occurrence frequency of each dominant pattern type, but also considers pattern type information. Each dimension of $\boldsymbol{y}_i$ represents a particular fixed type of dominant pattern and these

Algorithm 1 Find the dominant LBP set of an input image x_i

Input: The original histogram $\boldsymbol{f}_i$ of x_i for all LBP types of interest.
Output: The dominant LBP set J_i of image x_i.

1. Initialize a reference pattern type record vector $\boldsymbol{V}$ where $V[i] = (i-1)$ (i=1,...,p).
2. Sort $\boldsymbol{f}_i$ in descending order, resulting in a new histogram $\hat{\boldsymbol{f}}_i$. Change the configuration of $\boldsymbol{V}$ according to the element switching order from $\boldsymbol{f}_i$ to $\hat{\boldsymbol{f}}_i$, resulting in a new vector $\hat{\boldsymbol{V}}$. Now the top h entries of $\hat{\boldsymbol{f}}_i$ denote the occurrence frequencies of the top h most dominant patterns and the top h entries of $\hat{\boldsymbol{V}}$ record the pattern labels of the top h most dominant patterns.
3. FOR k = 1 to p
   IF $\left(\left(\frac{\sum_{l=1}^{k} \hat{f}_{i,l}}{\sum_{l=1}^{p} \hat{f}_{i,l}}\right) \geq n\%\right)$
   BREAK;
   END IF
   END FOR
4. $J_i = \{\hat{V}[1], ..., \hat{V}[k]\}$
5. Return J_i

Algorithm 2 Find the dominant LBP set of class c

Input: n_c input training images belonging to class c.
Output: The dominant LBP set JC_c of class c.

1. Calculate the dominant LBP set J_1 of the first image belonging to class c, and initialize $JC_c = J_1$.
2. FOR each image $i = 2$ to n_c belonging to class c
   Calculate its dominant LBP set J_i by Algorithm 1.
   $JC_c = JC_c \cap J_i$.
   END FOR
3. Return JC_c.

dominant pattern types also contain discriminative information as the pattern occurrence, which makes the proposed feature more powerful in classification.

2.3 The Testing Stage

In the testing stage, the dominant LBP histogram is calculated for each testing image based on J_{global} similar to the procedure performed on the training set. The learning-based LBPs extracted from the training and testing set will be finally served as inputs to classifier for classification. The pipeline of the FSC-based learning framework is shown in Fig. 2.

3 Experimental Design and Results

We test the performance of the proposed method for texture classification on the Outex_TC_0012 database [21], KTH-TIPS2 database [22] and Columbia-Utrecht (CUReT) database [23] in three different scenarios: rotation invariant texture classification, material categorization, and texture classification under

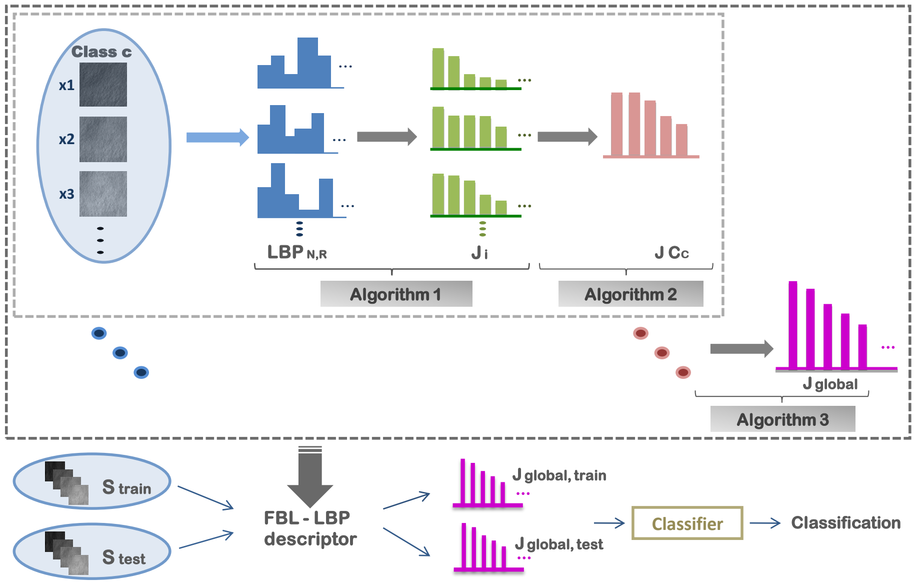

Fig. 2. The FSC-based learning framework

Algorithm 3 Construct the global dominant pattern set

Input: The dominant LBP set JC_c *(c = 1,...,C) of each class obtained by Algorithm 2.*
Output: The global dominant pattern set J_{global}.

1. Initialize $J_{global} = \emptyset$.
2. FOR $i = 1$ to C

   $J_{global} = J_{global} \cup JC_i$

   END FOR
3. Return J_{global}.

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variant imaging conditions. The proposed descriptor is compared against the non-invariant uniform local binary pattern LBP^{u2} (or the rotation invariant version LBP^{riu2}) and DLBP on all these databases. Some well-known methods are also compared with on some of these databases. The rotation invariant LBP is adopted as the original histogram of the framework for all texture classification tasks in this paper and the threshold is set to be 90%. The descriptor is further evaluated on the FERET face database [24] to prove its ability in Biometrics.

3.1 Rotation Invariant Texture Classification

We use the Outex_TC_0012 database to test rotation invariant texture classification methods. This database consists of 9120 images representing 24 different textures imaged under different rotations and lightings. The test set contains 20 training images for each texture class. The training images are under single orientation whereas different orientations are present in the total of 8640 testing images. The total classification rates over all test images are listed in Table 1, which are derived from the setup by using the nearest neighbor (NN) classifier.

It can be observed at all tested scales that rotation invariant features LBP^{riu2}, LBP-HF, DLBP and FBL-LBP provide higher classification rates than non-invariant feature LBP^{u2}. The performance of the new features is clearly better than that of the LBP^{riu2}. This improvement demonstrates its effectiveness in feature extraction. As the number of neighboring samples increases, the total number of possible LBPs will dramatically increase. In this case, many patterns will be produced with low occurrence frequencies and the pattern histogram becomes sparse, which makes the image representation unstable. The FBL framework solves this problem by considering only the most dominant patterns and eliminating unreliable patterns to reduce negative effects.

LBP-HF is cited as one representative method combining the LBP with pattern transform. FBL-LBP performs better than it at the scales (24,3) and (16,2)+(24,3). In addition, the proposed descriptor is compared with the recent DLBP, which is also a learning-based method. To be specific, in this paper, we adopt the nearest neighbor classifier for DLBP and do not use any preprocessing prior to feature extraction. The best result in Table 1 is achieved by our method at the scale (8,1)+(16,2)+(24,3). For fair comparison purpose, the dominant pattern threshold of DLBP is set to 90%, which is the same as FBL-LBP For further comparison, we refer to the MR8, a filter bank based texton method [11], which got 76.1% on this database [7], but not listed here.

Table 1. Texture classification rates on Outex_TC_0012 dataset

Parameters	LBP^{u2}[7]	LBP^{riu2}[7]	LBP-HF[7]	DLBP [9]	FBL-LBP
(8,1)	0.566	0.646	0.773	0.560	0.691
(16,2)	0.578	0.791	0.873	0.687	0.825
(24,3)	0.450	0.833	0.896	0.754	0.901
(8,1)+(16,2)	0.595	0.821	0.894	0.778	0.833
(8,1)+(24,3)	0.512	0.883	0.917	0.820	0.905
(16,2)+(24,3)	0.513	0.857	0.915	0.837	0.927
(8,1)+(16,2)+(24,3)	0.539	0.870	0.925	0.849	**0.928**

3.2 Material Categorization

Image descriptors are tested on the KTH-TIPS2 database [22] for material categorization. This database contains four samples of 11 different materials, each sample imaged at nine different scales and 12 lighting and pose setups, totaling 4572 images. The NN classifier is trained with one sample (i.e. 9×12 images) per material category. The remaining $3 \times 9 \times 12$ images are used for testing. This is repeated with 10000 random combinations as training and testing data and the mean categorization rate over the permutations is used to assess the performance.

Results of the LBP^{u2}, LBP^{riu2}, LBP-HF and DLBP are listed in Table 2. It can be observed that FBL-LBP has obvious superiority compared to other methods in all cases. This is most likely that abundant orientations are present in the training data for learning. Similarly, the performance of LBP^{riu2} is consistently lower probably because different orientations are contained in training samples so rotational invariance does not benefit much [7]. The multi-resolution (8,1)+(16,2)+(24,3) is able to give a good result but not the best as the scale (24,3) does not work well, which also happens to other methods at this scale. This might be brought by the scale variation properties of this database. However, FBL-LBP with the scale (8,1)+(16,2) achieves a slight improvement over it possibly as more discriminative information is contained within smaller radius.

3.3 Texture Classification under Variant Imaging Conditions

The CUReT database contains images of 61 materials and includes many surfaces commonly seen in our environment [23]. Each of the materials in the database has been imaged under 205 different viewing and illumination conditions. The effects of surface normal variations such as specularities, reflections and shadowing are evident. This database also includes some man-made textures, and is highlighted due to abundant imaging conditions. These make it far more challenging and become a benchmark widely used to assess classification performance.

The experiments are conducted on the CUReT database in the same way as in [1]. The cropped database has a total of 5612 images. Out of these, 46 images per class are randomly chosen for training and the remaining 46 per class are chosen for testing. The cropped CUReT database can be downloaded from [25]. Table 3 lists the best classification rates of different features. For comparison, results obtained by LBP^{riu2}, texton based representation method and DLBP are presented. LBP^{riu2} and FBL-LBP follow the same setting (8,1)+(8,3)+(8,5), and DLBP is set to (16,2) with its best results. It is observed that FBL-LBP can even achieve a slightly higher classification rate 97.61% than 97.47% obtained by texton method when training samples are chosen randomly for 61 class problems.

From experimental results conducted on the three main challenging texture databases, the proposed descriptor is shown to be stable and discriminative enough to represent texture images.

3.4 Face Recognition

The last experiment is performed to assess whether FBL-LBP could provide effective representation in face recognition. The experiment is conducted on the FERET face database following the standard FERET protocol in [24] which is more challenging than the one used in [6] as less training images are available.

For the FERET database, we use Fa as gallery, which contains 1196 frontal images of 1196 subjects. The probe sets consist of Fb, Fc, Dup I and Dup II. Fb contains 1195 images of expression variations, Fc contains 194 images taken under different illumination conditions, Dup I has 722 images taken later in time and Dup II (a subset of Dup I) has 234 images taken at least one year after the

Table 2. Comparison of classification results for material categorizations

Parameters	LBP^{u2}[7]	LBP^{riu2}[7]	LBP-HF[7]	DLBP [9]	FBL-LBP
(8,1)	0.528	0.482	0.525	0.458	0.619
(16,2)	0.511	0.494	0.533	0.460	0.624
(24,3)	0.502	0.481	0.513	0.459	0.609
(8,1)+(16,2)	0.536	0.502	0.542	0.456	**0.631**
(8,1)+(24,3)	0.542	0.507	0.542	0.468	0.613
(16,2)+(24,3)	0.514	0.508	0.539	0.458	0.623
(8,1)+(16,2)+(24,3)	0.536	0.514	0.546	0.461	0.626

Table 3. Comparison of classification results on CUReT database

LBP^{riu2}[5]	Texton method[1]	DLBP [9]	FBL-LBP
0.9624	0.9747	0.9593	**0.9761**

corresponding Gallery images. Using Fa as the gallery, we design the following experiments: (i) use Fb as probe set to test the efficiency of the method against facial expression; (ii) use Fc as probe set to test the efficiency of the method against illumination variation; (iii) use Dup I as probe set to test the efficiency of the method against short time; (iv) use Dup II as probe set to test the efficiency of the method against longer time. All images in the database are cropped and normalized to the resolution of 128×128 using eye coordinates provided. They are uniformly divided into 7×7 non-overlapping sub-regions.

The feature extraction using FBL-LBP for face recognition includes these procedures: (1) divide each image from the training set uniformly into 7×7 sub-regions. Global dominant pattern sets are constructed for each region and then connected to be the overall dominant types for the whole database. (2) calculate LBP histogram of dominant types for the training set and testing set, which will be served as inputs to classifier. The recognition rates of different methods are listed in Table 4. We use the same setting as [6]: eight neighboring samples, radius two and the same block weights. The result is lower than that in [6] as a more strict protocol is adopted. For FBL-LBP, we also use the (8,2) setting and normal patterns as the original histogram with threshold 70%, while DLBP follows (16,2) setting with its best result on this database. The threshold has a different value from the one used in texture classifications considering that the number of classes and intra-class variations are higher in face database. As the number of classes increases, more dominant pattern types are needed, so that more patterns are used to construct dominant pattern histograms. However, the dominant pattern proportions of all original patterns in this experiment is just 34.77%, which means the learning-based method does not degrade with this threshold.

From the comparison, FBL-LBP has a better performance on the Fb, Dup I and Dup II than that of the uniform LBP, especially on Dup I. Although the classification rate is not the best on Fc, it is still higher than most other face recognition methods in [26], which follow the same protocol. FBL-LBP does not perform significantly better probably because the condition variations needed are not present enough in the training data, which could influence the performance of learning-based method.

Table 4. The recognition rates on the FERET database probe set

Methods	Fb	Fc	Dup I	Dup II
PCA [27]	0.749	0.113	0.302	0.081
LBP^{u2} [6]	0.874	**0.572**	0.389	0.385
DLBP [9]	0.881	0.516	0.362	0.349
FBL-LBP	**0.899**	0.536	**0.449**	**0.389**

4 Discussion

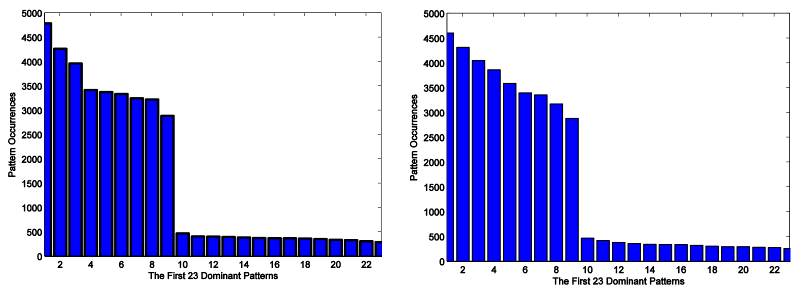
In this section, we will discuss how the FBL-LBP retains the discriminativeness of the original histogram and its relationships with DLBP, uniform LBP and texton-based approaches.

The concern is that previous methods mainly take pattern occurrence into account in image representation, which may not be able to provide enough discriminative patterns for texture classification. As illustrated in Fig. 3(a), there are two texture images G1 and G2 from the CUReT database belonging to two classes. We extract patterns using the DLBP (N = 8, R = 1, proportion = 90%). F1 and F2 are pattern occurrences of their first 23 dominant patterns in descending order, which are very similar to each other. Their histograms T1 and T2 are given for comparison in Fig. 3(b). The labels L1 and L2 listed in Fig. 3(c) are the dominant pattern types of F1 and F2 for each entry, respectively. Their corresponding dominant pattern types are obviously different from each other. In this case, it becomes difficult to classify them just using the pattern type occurrence. But it becomes possible when adding dominant pattern type information as we proposed in image representation, as shown in Fig. 4, the patterns that are obtained using the proposed framework (N = 8, R = 1, threshold = 90%). Moreover, considering intra-class similarity and inter-class distance of the database, FBL-LBP uses the intra-class intersection and inter-class unit as statistics to extract dominant patterns from the original histogram, instead of calculating the average pattern occurrence on the whole training set as in [9], from which its performance could further benefit in the texture classification.

In order to prove the ability in extracting discriminative patterns, we explore the relationship between the FBL-LBP and widely used uniform LBP by calculating the average uniform pattern proportions of FBL-LBPs, as listed in Table

5. The recognition rates of FBL-LBP remain higher even with less intersection with the uniform LBP, which shows it could capture effective patterns from the original histogram discarded by uniform LBP. Especially, when the number of neighboring samples increases, non-uniform patterns could be effective for image representation. We would suppose when the number of the neighboring samples and radius increase, FBL-LBPs performs even better comparing to the uniform patterns, since the former can take non-uniform patterns that are in dominant set but discarded, while the latter are not that dominant as with smaller number of neighboring samples and radius.

(a) Two texture images G1 and G2 belonging to two classes



(b) The histograms T1 and T2 of pattern occurrences of the first 23 dominant patterns

L1	1	34	35	8	27	4	0	16	2	32	5	21
L2	4	8	16	35	2	34	1	27	0	31	3	14
L1	7	24	26	3	6	25	31	18	14	13	10	
L2	24	18	13	10	25	7	6	15	12	21	26	

(c) Corresponding pattern type of each entry

Fig. 3. The dominant patterns produced by DLBP

Table 5. The average uniform pattern proportions of all FBL-LBPs (n=90)

Outex_TC_0012				KTH-TIPS			
(N,R)	Proportions	LBP^{riu2}	FBL-LBP	(N,R)	Proportions	LBP^{riu2}	FBL-LBP
(8,1)	88.13%	0.646	0.691	(8,1)	82.68%	0.482	0.691
(16,2)	67.71%	0.791	0.825	(16,2)	58.91%	0.494	0.624
(24,3)	42.97%	0.833	0.901	(24,3)	29.83%	0.481	0.609

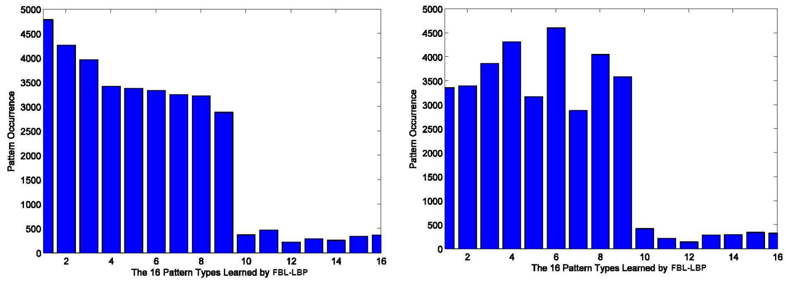


Fig. 4. The dominant patterns produced by FBL-LBP

5 Conclusions

In this paper, we propose a descriptor learning framework for texture classification. The framework is based on FSC to learn most reliable and robust dominant pattern types considering intra-class similarity and inter-class distance. LBP was taken as an input to this framework for texture classification and face recognition. Non-dominant LBP histogram would lead to severe problems caused by sparse histogram, however, it is shown that FBL-LBP, the descriptor obtained by combining the proposed framework with LBP, can retain dominant patterns and eliminate unreliable patterns to reduce negative effects. FBL-LBP differs from previous LBP approaches since FBL framework learns robust dominant types of each class instead of using fixed pattern types. To get reliable patterns adaptive to particular applications, the learning process takes intra-class similarity and inter-class distance into account. To strengthen the discriminativeness of image description, dominant pattern type is adopted as a complement to the pattern type occurrence. In addition, this framework is easy to generalize for other purposes by introducing different histogram descriptors.

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