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Gender and texture classification: A comparative analysis using 13 variants of local binary patterns

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A B S T R A C T

Among very popular local image descriptors which has shown interesting results in extracting soft facial biometric traits is the local binary patterns (LBP). LBP is a gray-scale invariant texture operator which labels the pixels of an image by thresholding the neighborhood of each pixel with the value of the center pixel and considers the result as a binary number. LBP labels can be regarded as local primitives such as curved edges, spots, flat areas etc. These labels or their statistics, most commonly the histogram, can then be used for further image analysis. Due to its discriminative power and computational simplicity, the LBP methodology has already attained an established position in computer vision. LBP is also very flexible: it can be easily adapted to different types of problems and used together with other image descriptors. Since its introduction, LBP has inspired plenty of new methods, thus revealing that texture based region descriptors can be very efficient in representing different images. Nowadays, many LBP variants can be found in the literature. This article reviews 13 variants and provides a comparative analysis on two different problems (gender and texture classification) using benchmark databases. The experiments show that basic LBP provides good results and generalizes well to different problems and hence can be a good starting point when trying to find an optimal variant for a given application. The best results are obtained with BSIF (binarized statistical image features) but at the cost of higher computational time compared to basic LBP. Furthermore, experiments on combining three best performing descriptors are conducted, pointing out useful insight into their complementarity.

Keywords:

Local binary patterns
Texture analysis
Gender classification
Face analysis

1. Introduction

Undeniably, a significant number of soft biometric traits can be extracted from face images and facial movements. This generally includes gender recognition (i.e. man vs. woman), age categorization (e.g. child, youth, adult, middle-age and elderly) and ethnicity classification (e.g. Asian, Caucasian and African). These are often referred to as demographic traits and are very useful for more affective human-computer interaction (HCI) and smart environments in which the systems should adapt to the users whose behaviors and preferences are not only different at different ages but also specific to a given ethnicity and/or gender. Automatic demographic classification is also useful in many other applications such as content-based image and video retrieval, restricting access to certain areas based on gender and/or

age, enhancing the performance of biometric identification systems, collecting demographic information in public places, counting the number of women entering a retail store and so on. Other soft biometric traits that can be extracted from face images include kinship information (i.e. verifying whether two persons are from the same family or not) and skin/eye color.

Among very popular local image descriptors which has shown interesting results in extracting soft facial biometric traits is the local binary patterns (LBP) [2,10,21,23]. LBP can be seen as statistics of labels computed in the local pixel neighborhoods. The LBP method describes each pixel's neighborhood by a binary code which is obtained by first convolving the image with a predefined set of linear filters and then binarizing the filter responses. The bits in the code string correspond to binarized responses of different filters. The LBP-like methods showed very good results in different computer vision tasks, including nontraditional texture problems such as face recognition, gender classification, age estimation and motion analysis [10,11,23].

The LBP method can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis.

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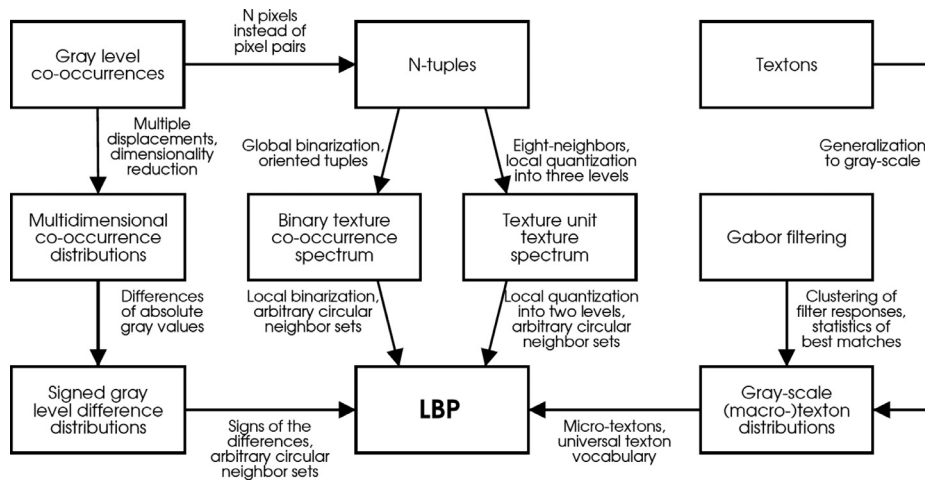


Fig. 1. Relation of LBP to some earlier texture methods [18].

Perhaps the most important property of the LBP operator in real-world applications is its invariance against monotonic gray level changes caused, for example, by illumination variations. Another equally important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings. Furthermore, LBP is also very flexible: it can be easily adapted to different types of problems and also used together with other image descriptors. The LBP is related to many well-known texture analysis operators as illustrated in Fig. 1 [18]. The arrows represent the relations between different methods, and the texts beside the arrows summarize the main differences between them. As shown in [3], local binary patterns can also be seen as a combination of local derivative filter operators whose outputs are quantized by thresholding.

Face analysis is perhaps the most fascinating application of LBP [10]. While texture features have been successfully used in various computer vision applications, only relatively few works have considered them in facial image analysis before the introduction of the LBP based face representations in 2004 [1]. Since then, the methodology has inspired plenty of new methods in face analysis. For instance, it has been successfully applied to face detection [8], face recognition [2], facial expression recognition [24], gender and age classification [28] and head pose estimation [17].

Nowadays, several variants of local binary patterns can be found in the literature. For a comprehensive bibliography of LBP-related research and links to many papers, see <http://www.cse.oulu.fi/MVG/LBPBibliography>. This article presents some recent and popular variants, and provides an experimental analysis comparing the performance of 13 different methods applied to two research problems namely face-based gender recognition and texture classification. Future directions are also discussed. The experimental results indicate that basic LBP still provides good results and generalizes well to different problems, hence suggesting that it can be a good starting point when trying to find an optimal variant for a given application. The best results are obtained with BSIF (binarized statistical image features) [13] but at the cost of higher computational time compared to basic LBP. Furthermore, experiments on combining three best performing descriptors are conducted, pointing out useful insight into their complementarity.

The preliminary results behind this work comparing the performance of three descriptors (LBP, BSIF and LPQ) were published as a short conference paper in [9]. We provide in this extended article a thorough investigation and new experiments comparing the performance of 13 descriptors. Obviously, it would be impossible to consider all the LBP variants in the literature as more than 100 variants of LBP have been proposed. So, we have chosen a number of

LBP variants mixing between popular and recent methods while selecting the variants with publicly available source code to ensure the reproducibility of the results and the variants using 2D still images (hence ignoring the methods based on 3D and video sequences). The obtained list is quite representative but not inclusive of all the LBP variants.

The rest of this paper is organized as follows. Section 2 first introduces and explains the basic form of the LBP operator. Then, some recent and popular variants of LBP are reviewed and thoroughly discussed in Section 3. Sections 4 and 5 describe the results of the experimental analysis comparing the performance of the 13 different variants of LBP on the gender and texture classification problems, respectively. Finally, directions for future work and concluding remarks are drawn in Section 7.

2. Basic local binary patterns operator

The LBP operator, introduced by Ojala et al. [21], is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. It is a powerful means of texture description and among its properties in real-world applications are its discriminative power, computational simplicity and tolerance against monotonic gray-scale changes. The original LBP operator forms labels for the image pixels by thresholding the 3×3 neighborhood of each pixel with the center value and considering the result as a binary number. Fig. 2 shows an example of an LBP calculation. The histogram of these $2^8 = 256$ different labels can then be used as a texture descriptor for further analysis (e.g. classification).

The LBP operator has been extended to use neighborhoods of different sizes. Using a circular neighborhood and bilinearly interpolating values at non-integer pixel coordinates allow any radius and number of pixels in the neighborhood. The notation (P, R) is generally used for pixel neighborhoods to refer to P sampling points on a circle of radius R . The calculation of the LBP codes can be easily done in a single scan through the image. The value of the LBP code of a pixel (x_c, y_c) is

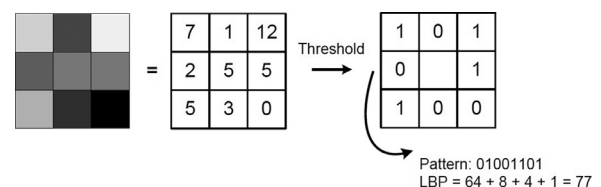


Fig. 2. The basic LBP operator.

given by:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p, \quad (1)$$

where g_c corresponds to the gray value of the center pixel (x_c, y_c) , g_p refers to gray values of P equally spaced pixels on a circle of radius R , and s defines a thresholding function as follows:

$$s(x) = \begin{cases} 1, & \text{if } x \geq 0; \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

Another extension to the original operator is the definition of so called *uniform patterns*. This extension was inspired by the fact that some binary patterns occur more commonly than others. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly. In the computation of the LBP labels, uniform patterns are used so that there is a separate label for each uniform pattern and all the non-uniform patterns are labeled with a single label. This yields to the following notation for the LBP operator: $LBP_{P,R}^{u2}$. The subscript represents using the operator in a (P, R) neighborhood. Superscript $u2$ stands for using only uniform patterns and labeling all remaining patterns with a single label. Each LBP label (or code) can be regarded as a micro-texton. Local primitives which are codified by these labels include different types of curved edges, spots, flat areas etc. The occurrences of the LBP codes in the image can be collected into a histogram. The classification can then be performed by computing histogram similarities. For an efficient representation, facial images are first divided into several local regions from which LBP histograms are extracted and then concatenated into an enhanced feature histogram for classification.

3. Variants of local binary patterns

The success of LBP methods in various computer vision problems and applications has inspired much new research on different variants. Due to its flexibility, the LBP method can be easily modified to make it suitable for the needs of different types of problems. The basic LBP operator has also some problems that need to be addressed. Therefore, several extensions and modifications of LBP have been proposed in the literature with an aim to increase its robustness and discriminative power. In this section, some recent and popular LBP variants are described.

A limitation of the original LBP operator is its small spatial support area. To cope with this problem (i.e. small spatial support area), [16] proposed the multiscale block LBP variant (MB-LBP) which has gained popularity especially in facial image analysis. The key idea behind MB-LBP is to compare average pixel values within small blocks instead of comparing pixel values. The operator always considers 8 neighbors, producing labels from 0 to 255. For instance, if the block size is 3×3 pixels, the corresponding MB-LBP operator compares the average gray value of the center block to the average values of the eight neighboring blocks of the same size, thus the effective area of the operator is 9×9 pixels. Instead of the fixed uniform pattern mapping, MB-LBP has been proposed to be used with a mapping that is dynamically learned from a training data. In this mapping, the N most often occurring MB-LBP patterns receive labels $0, \dots, N-1$, and all the remaining patterns share a single label. The number of labels, and consequently the length of the MB-LBP histogram is a free parameter that the user can set.

Wolf et al. [27] considered different ways of using bit strings to encode the similarities between patches of pixels, which could capture complementary information to pixel-based descriptors. The authors proposed a three-patch LBP (TPLBP) and four-patch-LBP (FPLBP) variants. For each pixel in TPLBP, a $w \times w$ patch centered at the pixel and S additional patches distributed uniformly in a ring of radius r around

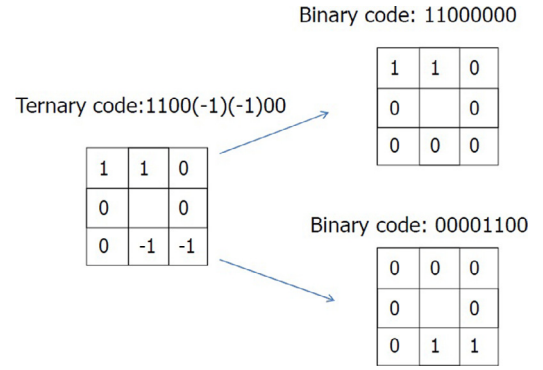


Fig. 3. Local ternary pattern operator.

it are considered. Then, the values for pairs of patches located on the circle at a specified distance apart are compared with those of the central patch. The value of a single bit is set according to which of the two patches is more similar to the central patch. The code produced will have S bits per pixel. In FPLBP, two rings centered on the pixel were used whereas only one ring is considered in TPLBP. TPLBP and FPLBP are designed to encode additional texture information compared to LBP.

Tan and Triggs [25] proposed a three-level operator called local ternary patterns (LTP), (using one threshold T) e.g. to deal with problems on near constant image areas. In ternary encoding the difference between the center pixel and a neighboring pixel is encoded by three values (1, 0 or -1) according to a threshold T . The ternary pattern is divided into two binary patterns taking into account its positive and negative components. The histograms from these components computed over a region are then concatenated. Fig. 3 depicts an example of splitting a ternary code into positive and negative codes. It is worth noting that LTP resembles the texture spectrum operator [26], which also used a three-valued output instead of two.

In [6], a completed modeling of the LBP operator was proposed and an associated completed LBP (CLBP) scheme was developed for texture classification and analysis. The image local differences are decomposed into two complementary components: the signs and the magnitudes and two operators, CLBP-Sign (CLBP_S which is equivalent to LBP) and CLBP-Magnitude (CLBP_M) were proposed to encode them. The center pixels representing the image gray level are also converted into a binary code (CLBP_C) by global thresholding. Compared to LBP, the CLBP_M and CLBP_C were combined with CLBP_S as complementary information to improve the texture classification.

In [7], LBP variance (LBPV) was proposed as a rotation invariant descriptor exploiting the contrast information by:

1. putting the local contrast information into one-dimensional LBP histogram. The variance $VAR_{P,R}$ was used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation. LBPV histogram is computed as:

$$LBPV_{P,R}(k) = \sum_{i=1}^N \sum_{j=1}^M w(LBP_{P,R}(i, j), k), \quad k \in [0, K] \quad (3)$$

$$w(LBP_{P,R}(i, j), k) = \begin{cases} VAR_{P,R}(i, j), & LBP_{P,R}(i, j) = k \\ 0, & \text{otherwise;} \end{cases}$$

2. learning the principal directions. The extracted LBPV features are used to estimate the principal orientations, and then the features are aligned to the principal orientations;
3. determining the non-dominant patterns and thus by reducing them, feature dimension reduction was achieved.

Liao et al. [15] introduced dominant local binary patterns (DLBP) which make use of the most frequently occurred patterns of LBP to

improve the recognition accuracy compared to the original uniform patterns. The method has also rotation invariant characteristics. Unlike basic LBP approach which only exploits the uniform patterns, DLBP computes the occurrence frequencies of all rotation invariant patterns defined in the LBP. These patterns are then sorted out in a descending order. The most frequently occurring patterns are expected to contain dominant information in the image and, therefore, are selected. It is empirically shown that the DLBP approach can be more reliable than LBP to represent the dominant information in textured images.

The extraction of LBP features is usually done in a circular or square neighborhood. A circular neighborhood is important especially for rotation-invariant operators. However, in some applications, such as face recognition, rotation invariance is not required, but anisotropic information may be important. To exploit this, [14] used an elliptical neighborhood definition, calling their LBP variant an elliptical local binary pattern (ELBP). ELBP combined with a local gradient (contrast) measure, provided improved results in face recognition experiments. In another related work, [19] investigated the use of different neighborhood topologies and encodings in their research on LBP variants for medical image analysis. In their experiments, an operator using quinary encoding in an elliptical neighborhood provided the best performance.

From the observation that basic LBP and many of its variants have some sparse sampling problems that need to be addressed, [29] proposed a novel LBP variant (called denseLBP) by introducing a dense sampling encoding strategy for extracting more stable and discriminative texture patterns in local regions. Compared to the conventional "sparse" sampling scheme commonly used in previous works, the proposed dense sampling aims to generate, through a form of up-sampling, more neighboring pixels so that more stable LBP codes, carrying out richer information, are computed. This yields in significantly enhanced image description which is less prone to noise and to sparse and unstable histograms. Another property of the dense sampling scheme is that it can be easily integrated with many existing LBP variants. Encouraging results were reported on face and texture analysis compared to basic LBP.

It has been shown by many studies that the dimensionality of the LBP distribution can be effectively decreased by reducing the number of neighboring pixels or by selecting a subset of available bins. In many cases, a properly chosen subset of LBP patterns can perform better than the whole set of patterns. In this direction, [5] proposed a learning framework (called disLBP) which can estimate the optimal pattern subset by simultaneously considering the robustness, discriminative power and representation capability of the features. This model was generalized and can be integrated with existing LBP variants such as basic LBP, rotation invariant patterns, local patterns with anisotropic structure, completed local binary pattern (CLBP) and local ternary pattern (LTP) to derive new image features.

LBP is shown to be relative sensitive to blur. To tackle this problem, a local phase quantization (LPQ) descriptor was proposed [22], based on quantizing the Fourier transform phase in local neighborhoods. The phase can be shown to be a blur invariant property under certain commonly fulfilled conditions. In texture analysis, histograms of LPQ labels computed within local regions are used as a texture descriptor similarly to the LBP methodology. The LPQ descriptor has received recently wide interest in blur-invariant face recognition. LPQ is insensitive to image blurring, and it has empirically proven to be a very efficient descriptor in face recognition and texture classification from blurred as well as sharp images.

Descriptors like LBP and LPQ can be seen as statistics of labels computed in the local pixel neighborhoods through filtering and quantization. These methods describe each pixel's neighborhood by a binary code which is obtained by first convolving the image with a manually predefined set of linear filters and then binarizing the filter responses. The bits in the code string correspond to binarized



Fig. 4. Samples from the Images of Groups (IoG) face database used in the gender classification experiments.

responses of different filters. Inspired by LBP and LPQ, [13] proposed a new local descriptor called BSIF (binarized statistical image features). The idea behind BSIF is to automatically learn a fixed set of filters from a small set of natural images, instead of using hand-crafted filters such as in LBP and LPQ. Interesting results were reported on the face recognition and texture classification.

4. A comparative analysis on the gender classification problem

In the previous section, we presented and discussed different LBP variants. To gain insight into the performance of these methods, we provide an experimental analysis on the problem of gender classification from still facial images. Automatic gender classification consists of determining whether the person whose face is in the given image is a man or a woman. This is a two-class pattern recognition task which is very useful in many applications. The main challenges in gender classification from facial images are due to geometrical non-uniformity, make-up and occlusions, pose and illumination variations, low-resolutions, and image degradations e.g. caused by blur and noise. These factors are unfortunately often present in real-world face images captured in unconstrained environments. A recent survey on gender classification can be found in [20].

Experimental data: We considered a large benchmark face database consisting of 28,231 facial images collected from Flickr and taken in uncontrolled conditions. This face database is referred to as Images of Groups (IoG¹) and is widely used for gender evaluation by the research community. Each face image is labeled with a gender and age category. We considered the face images of persons aged between 20–65 years. This resulted in 20,127 face samples. Some face samples from IoG are shown in Fig. 4.

Experimental setup: We applied different methods to extract the features from the face images. The features are then fed to a linear SVM for classification. The C parameter of the SVM was set to 1 in all the experiments. Each face image was normalized based on the eye coordinates, resulting in images of 64×64 pixels. These images are divided into 6×6 blocks with an overlap of 4 pixels. The extracted features from each block are concatenated into a feature vector which is fed to the SVM classifier. For a fair comparison, similar parameters were used in all the experiments. The dataset was divided into training and test sets such that 5449/4678 samples (females/males) are used for training and 5000/5000 for testing. The training set is used for tuning the parameters of the SVM classifier. The testing set was divided into 10 folds, each containing 500 male and 500 female faces. We used 10-fold cross validation where 9 folds are used for training and the remaining fold for testing. We report the average classification rates and the standard deviation errors (std).

Experimental results: Fig. 5 shows the average gender classification rates and the standard deviation errors for the 13 different LBP variants on the Images of Groups (IoG) face database. We can notice from these results that most of the methods perform quite well on this challenging database. The best results are obtained with the LPQ

¹ IoG: <http://chenlab.ece.cornell.edu/people/Andy/ImagesOfGroups.html>.

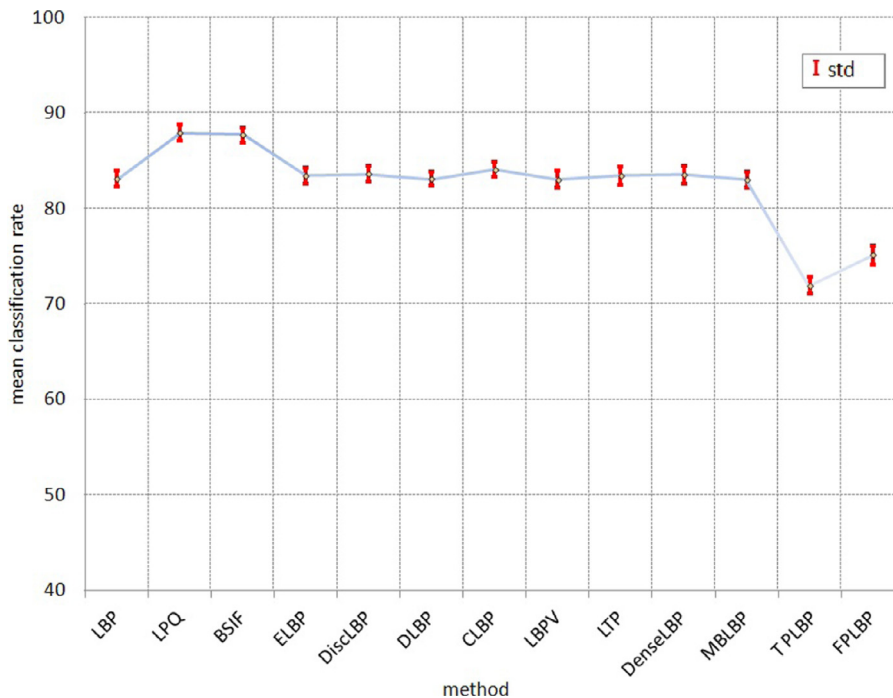


Fig. 5. The mean gender classification rates (in %) and the standard deviation errors (std) for the 13 different local binary patterns variants on the Images of Groups (IoG) face database.

descriptor which is a method robust to blur. This can be explained by the fact that many of the face images in the IoG face database are blurred and of low quality. BSIF method yields in the second best performance. The idea behind BSIF is to automatically learn a set of filters from natural images, instead of using predefined filters such as in basic LBP and LPQ. The good performance of BSIF highlights the importance of learning in LBP-like approaches. The basic LBP method yields in acceptable performance demonstrating that the method can still be a good starting point when trying to find the optimal variant for a given application. The worse results are given by TPLBP pointing out the difficulties of this variant to deal with gender classification on this benchmark IoG face database.

5. A comparative analysis on the texture classification problem

For comprehensive analysis, we also evaluated the different LBP variants on a second problem which is texture classification. The aim of texture classification is to assign an unseen texture sample into one of the predefined classes. The assignment is done based on rules which are typically derived from a training set consisting of texture samples with known classes. The basic LBP methodology was originally developed for texture analysis and has performed very well in many comparative studies on publicly available texture datasets. We provide in this section an experimental analysis on the performance of the 13 LBP variants on a benchmark texture database (CURET texture database).

Experimental data: For the experiments on texture classification, we considered the Columbia–Utrecht Reflectance and Texture Database (CURET) [4]. This database contains samples from 61 texture classes collected from real-world surfaces with varying properties. Fig. 6 depicts some samples from the database. Each texture class in the database contains 205 images captured under different viewing and illumination conditions. As such this database has been broadly used by the research community as a standard benchmark to examine the classification performance of various descriptors. In our experiments, we specifically considered the available cropped

dataset having a total of 5612 images with 92 samples for each class of texture.

Experimental setup: For texture classification evaluation, we randomly selected 46 images out of 92 per each texture class for training. The remaining 46 samples were used for testing. Throughout all the texture classification experiments, we used the nearest neighbor (NN) classifier with L1-distance metric for classification. For obtaining statistically significant results, we considered the average classification performance of 10 random permutations. For all the LBP variants, we selected the (8,1)-neighborhood. For BSIF and LPQ, 8 bits and 3×3 neighborhood were considered. For MBLBP, TPLBP, and FPLBP, we used the default parameters as suggested in the original papers. For discLBP and DLBP descriptors, we set the threshold value to 0.9.

Experimental results: Fig. 7 shows the texture classification performance of the 13 different LBP variants using 46 samples for training on the CURET texture database. As shown in the figure, the best results are obtained with BSIF. This highlights again the importance of learning in LBP-like approaches. As with the previous experiments on gender classification, the worst results are again obtained by TPLBP and FPLBP thus revealing the shortcomings of these methods to tackle the problem of texture classification and gender recognition. The other methods perform quite well and yield in more or less comparable performance. An interesting point is that the basic LBP approach



Fig. 6. Samples from the Columbia–Utrecht Reflectance and Texture Database (CURET) used in the experiments.

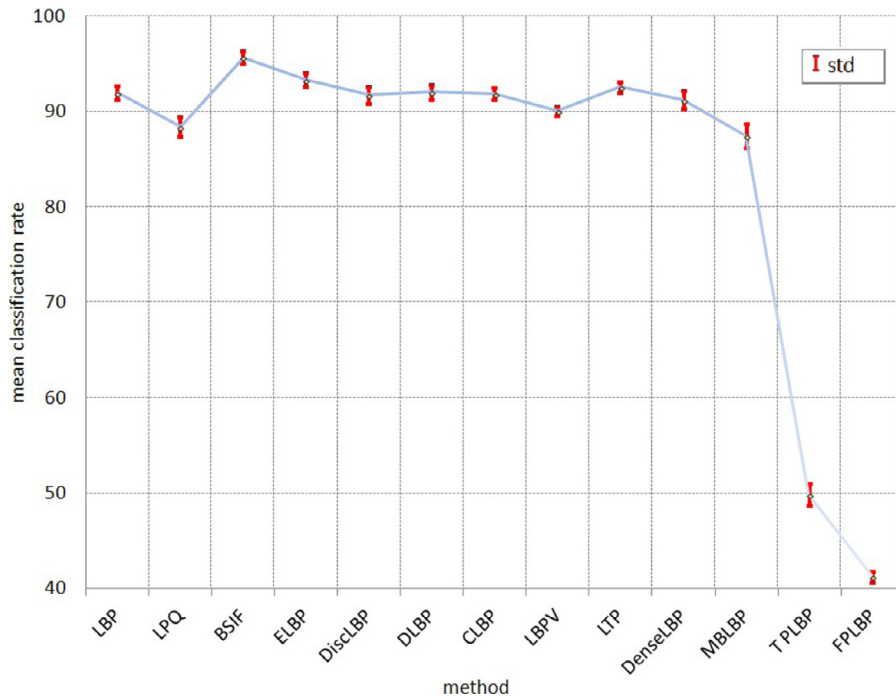


Fig. 7. The mean texture classification rates (and the standard deviation errors) for the 13 different LBP variants on the Columbia–Utrecht Reflectance and Texture Database (CURET).

outperforms some newer variants, meaning that the method still provides acceptable results and generalize well to different problems.

6. Experiments on descriptor fusion

So far, we reported the experimental results of the 13 different descriptors when applied separately. However, a new trend in the development of new effective local image descriptors is to combine the strengths of complementary descriptors. So, we selected three descriptors and analyzed the performance of their fusion. The previous experiments on Images of Groups (IoG) face database clearly showed that the top two performing descriptors are BSIF and LPQ. LBP also performed consistently well over the two databases. It is then of interest to gain insight into the complementary of LBP, LPQ, and BSIF. Hence, we conducted a set of additional experiments considering the different combinations of these three descriptors at feature level (i.e. by simply concatenating the histograms). We tested three different neighboring sizes (3×3 , 5×5 , and 7×7) with eight-bit binary coding. We used a circular topology with eight sampling points for LBP, the common four frequency-points coding of the phase information for LPQ and a bank of eight filters trained by using natural images for BSIF. The experiments results on the CURET texture database and on the Images of Groups (IoG) face database are shown in Tables 1 and 2,

Table 1

Experimental results on combining LBP, LPQ and BSIF at feature level for texture classification on the CURET texture database.

Method	Mean accuracy (in %)		
	3×3 pixels	5×5 pixels	7×7 pixels
LBP	86.77	94.38	93.66
LPQ	90.27	88.34	89.89
BSIF	94.83	95.67	95.68
LBP+LPQ	92.67	94.77	94.74
LBP+BSIF	94.13	96.50	96.69
LPQ+BSIF	94.62	94.43	94.55
LBP+LPQ+BSIF	94.59	95.80	95.85

Table 2

Experimental results on combining LBP, LPQ and BSIF at feature level for gender classification on the Images of Groups (IoG) face database.

Method	Mean accuracy (in %)		
	3×3 pixels	5×5 pixels	7×7 pixels
LBP	81.70	82.80	83.76
LPQ	85.79	86.43	87.90
BSIF	86.30	87.07	87.89
LBP+LPQ	85.80	87.17	87.45
LBP+BSIF	87.10	87.50	88.20
LPQ+BSIF	86.42	88.38	88.96
LBP+LPQ+BSIF	88.10	89.06	89.85

respectively. These results indicate that only minor performance gain is obtained by fusing the three descriptors. Preliminary additional experiments analyzing the fusing the rest of the 13 local descriptors pointed out similar conclusions. This can be explained by the fact that these 13 descriptors share many similar properties as they all codify the local texture features. One may expect better performance when combining these descriptors with e.g. Gabor filters [12], as the local texture descriptors would capture small and fine details, while Gabor filters would encode appearance information over a broader range of scales.

7. Discussion and conclusions

We discussed in this present work some recent and popular LBP variants and reported a comparative experimental analysis on gender and texture classification problems. It is worth noting that the reported results cannot be directly generalized to other problems or to other face/texture image datasets. Note also that there are currently several other LBP variants in the literature and the choice of a proper method for a given application depends on many factors, such as the discriminative power, computational efficiency, robustness to illumination and other variations, and the imaging system used. Therefore

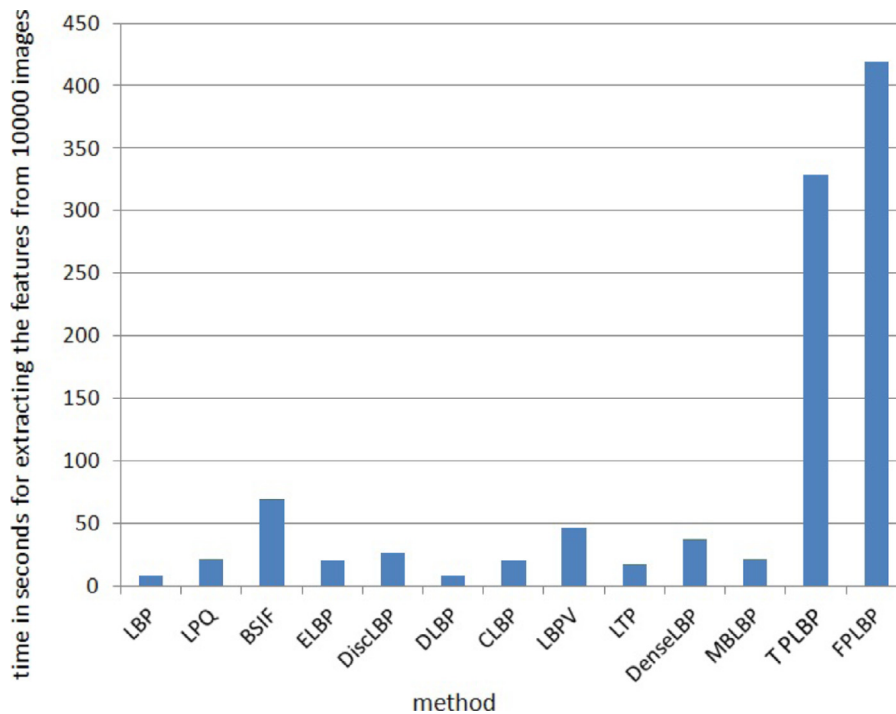


Fig. 8. The processing time (in seconds) taken by each of the 13 local binary pattern variants for extracting the features from a patch of 10,000 randomly chosen images of 100×100 pixels.

the basic LBP operator described in Section 2 usually provides a good starting point when trying to find the optimal variant for a given application.

Regarding the computational time, Fig. 8 shows the processing time taken by each LBP variants for extracting the features from a patch of 10,000 random images of 100×100 pixels. These simulations were run on MATLAB 2012b installed on a PC with 2 CPUs of i5-3570 3.4 GHz, 8 GB RAM and 64-bit Windows 7 operating system. These results, obtained using the default parameters of the methods and without code optimization, should only be taken as insights into the computational complexity of the different methods. As can be seen from Fig. 8, the basic LBP method is unsurprisingly the fastest approach while TPLBP and FPLBP are the most time consuming. BSIF which provides among the best results in terms of classification rates is also significantly more expensive than basic LBP in terms of computational time. The rest of the descriptors (including LPQ, ELBP, DiscLBP, CLBP, LBPV, LTP, DenseLBP and MBLBP) require relatively comparable computational time.

Our experiments on gender classification on the Images of Groups (IoG) face database showed that the best results are obtained with LPQ and BSIF while the other descriptors (except TPLBP and FPLBP) yielded in lower but comparable performance on this challenging database. The worse results are given by TPLBP and FPLBP. The experiments on texture classification on the CURET texture database showed that the best results are obtained with BSIF. The good performance of BSIF highlights the importance of learning in LBP-like approaches. As with the previous experiments on gender classification, the worst results are again obtained by TPLBP and FPLBP thus revealing the shortcomings of these methods to tackle the problem of texture classification and gender recognition. We expect TPLBP and FPLBP features to work better when combined with learning scheme for classification. The other methods perform quite well and yield in more or less comparable performance. An interesting point is that the basic LBP approach outperforms some newer variants, meaning that the method still provides acceptable results and generalize well to different problems.

A current trend in the development of new effective local image descriptors is to combine the strengths of complementary descriptors. We conducted experiments considering the different combinations of the top three descriptors (BSIF, LPQ and LBP). The results indicated that only minor performance gain was obtained by fusing the three descriptors. This can be explained by the fact that these descriptors share many similar properties as they all codify the local texture features. One may expect better performance when combining these descriptors with e.g. Gabor filters [12]. The methods based on LBP and Gabor filtering can indeed provide complementary information for face analysis: LBP captures small and fine details, while Gabor filters encode appearance information over a broader range of scales. It is however not simple to find the best descriptor combination and it is not always clear how different descriptors should be combined. These questions have lately received a lot of attention in the machine learning community. The new popular approaches, in addition to the direct feature concatenation, are provided by learning based feature selection methods like AdaBoost as well as feature combination using multiple kernel learning. As a future work, it is of interest to study the complementary of the 13 LBP variants considered in this work. This can be done by analyzing the performance of their fusion. It is also of great importance to derive a unified framework for describing how different local texture descriptors are related to each other and how they can be used in different classification tasks. This would allow a systematic comparison of the widely used descriptors. Such a framework will not only contribute to understanding and comparison of existing local texture descriptors, but it can also be utilized for a more systematic development of new and even better performing methods.

As a future work, it would be of interest to extend this study to include spatio-temporal descriptors and to analyze how the obtained results can be generalized to other problems and other datasets.

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