Face Description with Local Binary Patterns: Application to Face Recognition

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Abstract—This paper presents a novel and efficient facial image representation based on local binary pattern (LBP) texture features. The face image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as a face descriptor. The performance of the proposed method is assessed in the face recognition problem under different challenges. Other applications and several extensions are also discussed.

Index Terms—Facial image representation, local binary pattern, component-based face recognition, texture features, face misalignment.

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1 INTRODUCTION

AUTOMATIC face analysis which includes, e.g., face detection, face recognition, and facial expression recognition has become a very active topic in computer vision research [1]. A key issue in face analysis is finding efficient descriptors for face appearance. Different holistic methods such as Principal Component Analysis (PCA) [2], Linear Discriminant Analysis (LDA) [3], and the more recent 2D PCA [4] have been studied widely but lately also local descriptors have gained attention due to their robustness to challenges such as pose and illumination changes. This paper presents a novel descriptor based on local binary pattern texture features extracted from local facial regions.

One of the first face descriptors based on information extracted from local regions is the eigenfeatures method proposed by Pentland et al. [5]. This is a hybrid approach in which the features are obtained by performing PCA to local face regions independently. In Local Feature Analysis [6], kernels of local spatial support are used to extract information about local facial components. Elastic Bunch Graph Matching (EBGM) [7] describes faces using Gabor filter responses in certain facial landmarks and a graph describing the spatial relations of these landmarks. The validity of the component-based approach is also attested by the study conducted by Heisele et al. in which a component-based face recognition system clearly outperformed global approaches on a test database containing faces rotated in depth [8].

Using local photometric features [9] for object recognition in the more general context has become a widely accepted approach. In that setting, the typical approach is to detect interest points or interest regions in images, perform normalization with respect to affine transformations, and describe the normalized interest regions using local descriptors. This bag-of-keypoints approach is not suited for face description as such since it does not retain information on the spatial setting of the detected local regions but it does bear certain similarities to local feature-based face description.

Finding good descriptors for the appearance of local facial regions is an open issue. Ideally, these descriptors should be easy to compute and have high extra-class variance (i.e., between different persons in the case of face recognition) and low intraclass variance,

which means that the descriptor should be robust with respect to aging of the subjects, alternating illumination and other factors.

The texture analysis community has developed a variety of different descriptors for the appearance of image patches. However, face recognition problem has not been associated to that progress in texture analysis field as it has not been investigated from such point of view. Recently, we investigated the representation of face images by means of local binary pattern features, yielding in outstanding results that were published in the ECCV 2004 conference [10]. After this, several research groups have adopted our approach. In this paper, we provide a more detailed analysis of the proposed representation, present additional results and discuss further extensions.

2 LBP-BASED FACE DESCRIPTION

The LBP operator [11] is one of the best performing texture descriptors and it has been widely used in various applications. It has proven to be highly discriminative and its key advantages, namely, its invariance to monotonic gray-level changes and computational efficiency, make it suitable for demanding image analysis tasks. For a bibliography of LBP-related research, see http://www.ee.oulu.fi/research/imag/texture/.

The idea of using LBP for face description is motivated by the fact that faces can be seen as a composition of micropatterns which are well described by such operator.

2.1 Local Binary Patterns

The LBP operator was originally designed for texture description. The operator assigns a label to every pixel of an image by thresholding the 3×3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. Then, the histogram of the labels can be used as a texture descriptor. See Fig. 1 for an illustration of the basic LBP operator.

To be able to deal with textures at different scales, the LBP operator was later extended to use neighborhoods of different sizes [12]. Defining the local neighborhood as a set of sampling points evenly spaced on a circle centered at the pixel to be labeled allows any radius and number of sampling points. Bilinear interpolation is used when a sampling point does not fall in the center of a pixel. In the following, the notation (P, R) will be used for pixel neighborhoods which means P sampling points on a circle of radius of R. See Fig. 2 for an example of circular neighborhoods.

Another extension to the original operator is the definition of so-called *uniform patterns* [12]. 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 considered circular. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not. In the computation of the LBP histogram, uniform patterns are used so that the histogram has a separate bin for every uniform pattern and all nonuniform patterns are assigned to a single bin. Ojala et al. noticed that in their experiments with texture images, uniform patterns account for a bit less than 90 percent of all patterns when using the (8,1) neighborhood and for around 70 percent in the (16,2) neighborhood. We have found that 90.6 percent of the patterns in the (8,1) neighborhood and 85.2 percent of the patterns in the (8,2) neighborhood are uniform in case of preprocessed FERET facial images.

We use the following notation for the LBP operator: $\text{LBP}_{P,R}^{u2}$. The subscript represents using the operator in a (P, R) neighborhood. Superscript $u2$ stands for using only uniform patterns.

2.2 Face Description with LBP

In this work, the LBP method presented in the previous section is used for face description. The procedure consists of using the texture descriptor to build several local descriptions of the face and combining them into a global description. Instead of striving for a

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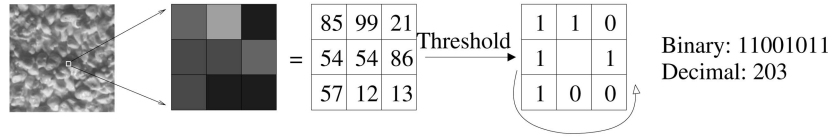
Fig. 1. The basic LBP operator.

holistic description, this approach was motivated by two reasons: the local feature-based or hybrid approaches to face recognition have been gaining interest lately [6], [8], [13], which is understandable given the limitations of the holistic representations. These local feature-based and hybrid methods seem to be more robust against variations in pose or illumination than holistic methods.

Another reason for selecting the local feature-based approach is that trying to build a holistic description of a face using texture methods is not reasonable since texture descriptors tend to average over the image area. This is a desirable property for ordinary textures, because texture description should usually be invariant to translation or even rotation of the texture and, especially, for small repetitive textures, the small-scale relationships determine the appearance of the texture and, thus, the large-scale relations do not contain useful information. For faces, however, the situation is different: retaining the information about spatial relations is important.

This reasoning leads to the basic methodology of this work. The facial image is divided into local regions and texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face. See Fig. 3 for an example of a facial image divided into rectangular regions.

The basic histogram can be extended into a *spatially enhanced histogram* which encodes both the appearance and the spatial relations of facial regions. As the m facial regions $R_0, R_1, \ldots R_{m-1}$ have been determined, a histogram is computed independently within each of the m regions. The resulting m histograms are combined yielding the spatially enhanced histogram. The spatially enhanced histogram has size $m \times n$, where n is the length of a single LBP histogram. In the spatially enhanced histogram, we effectively have a description of the face on three different levels of locality: The LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level, and the regional histograms are concatenated to build a global description of the face.

It should be noted that when using the histogram-based methods, despite the examples in Fig. 3, the regions $R_0, R_1, \ldots R_{m-1}$ do not need to be rectangular. Neither do they need to be of the same size or shape and they do not necessarily have to cover the whole image. For example, they could be circular regions located at the fiducial points like in the EBGM method. It is also possible to have partially overlapping regions. If recognition of faces rotated in depth is considered, it may be useful to follow the procedure of Heisele et al. [8] and automatically detect each region in the image instead of first detecting the face and then using a fixed division into regions.

The idea of a spatially enhanced histogram can be exploited further when defining the distance measure. An indigenous property of the proposed face description method is that each element in the enhanced histogram corresponds to a certain small area of the face. Based on the psychophysical findings, which indicate that some facial features (such as eyes) play more important roles in human face recognition than other features [14], it can be expected that, in this method, some of the facial

regions contribute more than others in terms of extrapersonal variance. Utilizing this assumption, the regions can be weighted based on the importance of the information they contain. For example, the weighted Chi square distance can be defined as

$$\chi^2_w(\mathbf{x}, \boldsymbol{\xi}) = \sum_{j,i} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}, \qquad (1)$$

in which $\mathbf{x}$ and $\boldsymbol{\xi}$ are the normalized enhanced histograms to be compared, indices i and j refer to ith bin in histogram corresponding to the jth local region and w_j is the weight for region j.

3   EXPERIMENTAL ANALYSIS

Our approach is assessed on the face recognition problem using the Colorado State University Face Identification Evaluation System [15] with images from the FERET [16] database. PCA [2], Bayesian Intra/Extrapersonal Classifier (BIC) [17], and EBGM were used as control algorithms.

3.1   Experimental Setup

To ensure the reproducibility of the tests, the publicly available CSU face identification evaluation system [15] was utilized to test the performance of the proposed algorithm. The system uses the FERET face images and follows the procedure of the FERET test for semiautomatic face recognition algorithms [18] with slight modifications.

The FERET database consists of a total of 14,051 gray-scale images representing 1,199 individuals. The images contain variations in lighting, facial expressions, pose angle, etc. In this work, only frontal faces are considered. These facial images can be divided into five sets as follows:

- *fa* set, used as a gallery set, contains frontal images of 1,196 people.
- *fb* set (1,195 images). The subjects were asked for an alternative facial expression than in the *fa* photograph.
- *fc* set (194 images). The photos were taken under different lighting conditions.
- *dup I* set (722 images). The photos were taken later in time.
- *dup II* set (234 images). This is a subset of the *dup I* set containing those images that were taken at least a year after the corresponding gallery image.

Along with recognition rates at rank 1, two statistical measures are used to compare the performance of the algorithms: the mean recognition rate with a 95 percent confidence interval and the probability of one algorithm outperforming another. The probability of one algorithm outperforming another is denoted by $P(R(\text{alg1}) > R(\text{alg2}))$. These statistics are computed by permuting
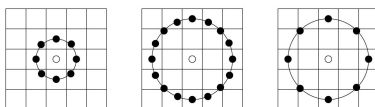

Fig. 2. The circular (8,1), (16,2), and (8,2) neighborhoods. The pixel values are bilinearly interpolated whenever the sampling point is not in the center of a pixel.

Fig. 3. A facial image divided into 7×7, 5×5, and 3×3 rectangular regions.
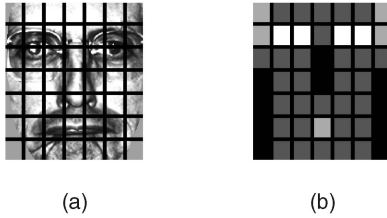
Fig. 4. (a) A facial image divided into 7×7 windows. (b) The weights set for the weighted χ^2 dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0, and white 4.0.

the gallery and probe sets, see [15] for details. The CSU system comes with implementations of the PCA, LDA, BIC, and EBGM face recognition algorithms. The results obtained with PCA, BIC, and EBGM are included here for comparison.

3.2 Parameters of the LBP Method

There are some parameters that can be chosen to optimize the performance of the LBP-based algorithm. These include choosing the type of the LBP operator, division of the images into regions $R_0, \ldots, R_{m-1}$, selecting the distance measure for the nearest neighbor classifier, and finding the weights w_j for the weighted χ^2 statistic (1). The extensive experiments to find the parameters for the proposed method are detailed in [10].

When looking for the optimal window size and LBP operator it was noticed that the LBP representation is quite robust with respect to the selection of parameters. Changes in the parameters may cause big differences in the length of the feature vector, but the overall performance is not necessarily affected significantly [10]. Here, the $\text{LBP}_{8,2}^{u2}$ operator in 18×21 pixel windows was selected since it is a good trade-off between recognition performance and feature vector length. When comparing different distance measures, the χ^2 measure was found to perform better than histogram intersection or log-likelihood distance. Therefore, the χ^2 measure was chosen to be used.

To find the weights w_j for the weighted χ^2 statistic (1), a simple procedure was adopted in which a training set was classified using only one of the 18×21 windows at a time and the windows were assigned a weight based on the recognition rate.

The obtained weights are illustrated in Fig. 4b. The weights were selected without utilizing an actual optimization procedure and thus they are probably not optimal. Despite that, in comparison with the nonweighted method, an improvement both in the processing time and recognition rate ($\text{P}(R(\text{weighted}) > R(\text{nonweighted})) = 0.976$) was obtained.

3.3 Comparing Local Binary Patterns to Other Local Descriptors

To gain better understanding on whether the obtained recognition results are due to general idea of computing texture features from local facial regions or due to the discriminatory power of the local binary pattern operator, we compared LBP to three other texture descriptors, namely, the gray-level difference histogram, homogeneous texture descriptor [19], and an improved version of the texton histogram [20]. The details of these experiments can be found in [21].

The recognition rates obtained with different descriptors are shown in Table 1. It should be noted that no weighting for local regions was used in this experiment. The results show that the tested methods work well with the easiest *fb* probe set, which means that they are robust with respect to variations of facial expressions, whereas the results with the *fc* probe set show that other methods than LBP do not survive changes in illumination. The LBP and texton give the best results in the *dup I* and *dup II* test sets.

We believe that the main explanation for the better performance of the local binary pattern operator over other texture descriptors is

its tolerance to monotonic gray-scale changes. Additional advantages are the computational efficiency of the LBP operator and that no gray-scale normalization is needed prior to applying the LBP operator to the face image.

3.4 Results for the FERET Database

The final recognition results for the proposed method are shown in Table 2 and the rank curves are plotted in Fig. 5. LBP yields clearly higher recognition rates than the control algorithms in all the FERET test sets and in the statistical test. The results on the *fc* and *dup II* sets show that especially with weighting, the LBP-based description is robust to challenges caused by lighting changes or aging of the subjects but further research is still needed to achieve even better performance.

It should be noted that the CSU implementations of the algorithms whose results are included here do not achieve the same figures as in the original FERET test due to some modifications in the experimental setup as mentioned in [15]. The results of the original FERET test can be found in [18].

3.5 Robustness of the Method to Face Localization Error

Real-world face recognition systems need to perform face detection prior to face recognition. Automatic face localization may not be completely accurate so it is desirable that face recognition works under small localization errors.

The proposed face recognition method calculates histograms over the local regions so a small change in the position of the face relative to the grid causes changes in the labels only on the borders of the local regions. Therefore, it can be expected that the proposed method is not sensitive to small changes in the face localization and that using larger local regions increases the robustness to errors.

The effect of localization errors to recognition rate of the proposed method compared to PCA MahCosine was systematically tested as follows: The training images for PCA and gallery (*fa*) images were normalized to size 128×128 using provided eye coordinates. The *fb* set was used as probes. The probes were also normalized to size 128×128 but a random vector $(\Delta X, \Delta Y)$ was added to the face location, where ΔX and ΔY are uncorrelated and normally distributed with mean 0 and standard deviation σ. Ten experiments were conducted with each probe totaling 11,950 queries for each tested σ value.

The recognition rates of the LBP-based method using window sizes 21×21 and 32×32 and PCA MachCosine as a function of the standard deviation of the simulated localization offset are plotted in Fig. 6. It can be seen that when no error or only a small error is present, LBP with small local regions works well but as the localization error increases, using larger local regions produces better recognition rate. Most interestingly, the recognition rate of the local region-based methods drops significantly slower than that of PCA.

4 FURTHER WORK USING LOCAL BINARY PATTERN-BASED FACE DESCRIPTION

Since the publication of our preliminary results on the LBP-based face description [10], our methodology has already attained an established position in face analysis research. This is attested by the increasing number of works which adopted a similar approach[1] [22], [23], [24], [25], [26], [27], [28].

For instance, local binary patterns computed in local regions for face detection was used in [22]. In that work, LBP features from local regions combined with a histogram representing the whole face area yielded an excellent face detection rate when used as features for a support vector machine classifier. Using LBP features for facial expression recognition has been studied by Feng et al. [23] and Shan et al. [24]. Using the JAFFE and Cohn-Kanade facial expression image data sets (see [1]), these papers show that LBP based descriptors compare favorably to other state-of-the-art methods in facial expression recognition.

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1. http://www.ee.oulu.fi/research/imag/texture/lbp/bibliography/#faceanalysis.

TABLE 1
The Recognition Rates Obtained Using Different Texture Descriptors for Local Facial Regions

Method	fb	fc	dup I	dup II	lower	mean	upper
Difference histogram	0.87	0.12	0.39	0.25	0.58	0.63	0.68
Homogeneous texture	0.86	0.04	0.37	0.21	0.58	0.62	0.68
Texton Histogram	0.97	0.28	0.59	0.42	0.71	0.76	0.80
LBP (nonweighted)	0.93	0.51	0.61	0.50	0.71	0.76	0.81

The first four columns show the recognition rates for the FERET test sets and the last three columns contain the mean recognition rate of the permutation test with a 95 percent confidence interval.

TABLE 2
The Recognition Rates of the LBP and Comparison Algorithms

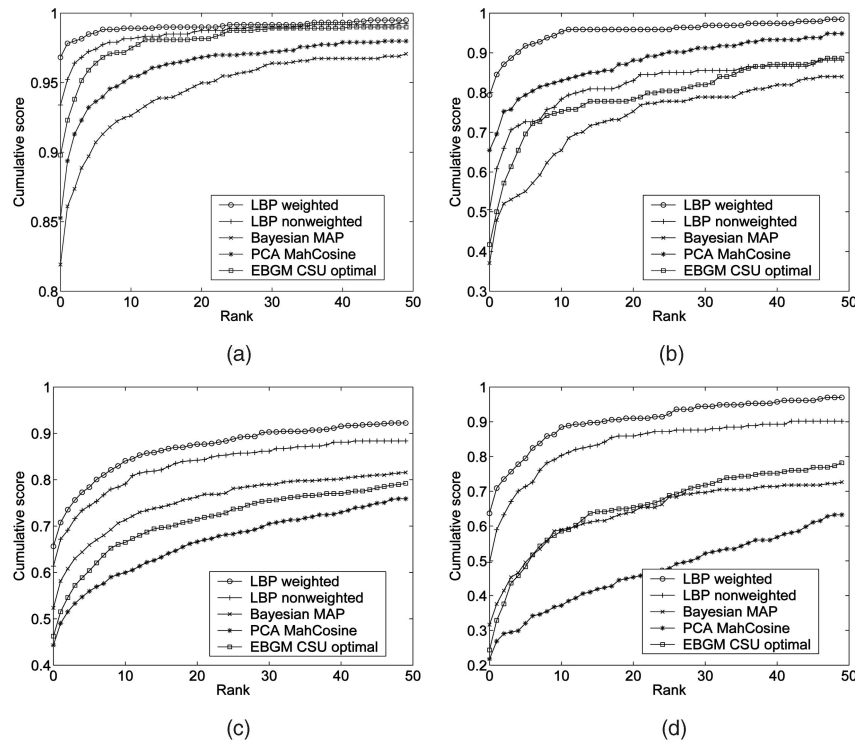| Method	fb	fc	dup I	dup II	lower	mean	upper
LBP, weighted	0.97	0.79	0.66	0.64	0.76	0.81	0.85
LBP, nonweighted	0.93	0.51	0.61	0.50	0.71	0.76	0.81
PCA, MahCosine	0.85	0.65	0.44	0.22	0.66	0.72	0.78
Bayesian, MAP	0.82	0.37	0.52	0.32	0.67	0.72	0.78
EBGM_Optimal	0.90	0.42	0.46	0.24	0.61	0.66	0.71

Fig. 5. The cumulative scores of the LBP and control algorithms on the (a) *fb*, (b) *fc*, (c) *dup I*, and (d) *dup II* probe sets.

In [25], Zhang et al. used AdaBoost learning algorithm for selecting a set of local regions and their weights. Then, the LBP methodology was applied to the obtained regions yielding in smaller feature vector length. Recently, Li et al. built a highly accurate, illumination-invariant face recognition system by combining near-infrared imaging with an LBP-based face description and AdaBoost learning [26].

Computing LBP features from images obtained by filtering a facial image with 40 Gabor filters of different scale and orientation are shown to yield excellent recognition rate on all the FERET sets in [27]. A downside of the method proposed in that paper is the high dimensionality of the feature vectors.

In [28], Rodriguez and Marcel proposed an approach based on adapted, client-specific LBP histograms for the face verification task. The reported experimental results show that the proposed method yields excellent performance on two face verification test databases.

5 DISCUSSION AND CONCLUSIONS

In this paper, a novel and efficient facial representation is proposed. It is based on dividing a facial image into small regions and
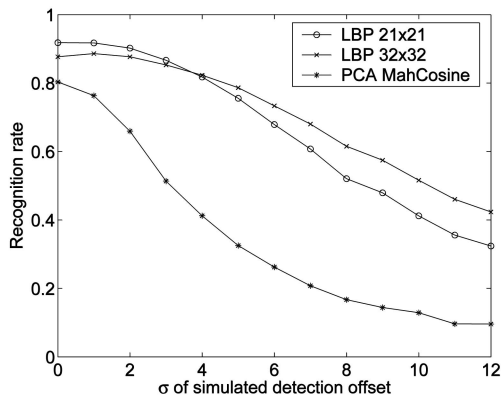
Fig. 6. The recognition rate for the *fb* set of two LBP-based methods and PCA MahCosine as a function the standard deviation of a simulated localization error.

computing a description of each region using local binary patterns. These descriptors are then combined into a spatially enhanced histogram or feature vector. The texture description of a single region describes the appearance of the region and the combination of all region descriptions encodes the global geometry of the face.

The LBP operator has been widely used in different applications such as texture classification, image retrieval, etc. Before our study, it was not obvious to imagine that such texture operator might be useful in representing also facial images. Our results clearly show that facial images can be seen as a composition of micropatterns such as flat areas, spots, lines, and edges which can be well described by LBP.

In this paper, the proposed methodology is assessed with the face recognition task. However, a similar method has yielded in outstanding performance in face detection [22] and facial expression recognition [23], [24]. We also believe that the developed approach is not limited to these few examples as it can be easily generalized to other types of object detection and recognition tasks.

Future work includes studying more advanced methods for dividing the facial image into local regions and finding the weights for these regions. The AdaBoost method presented in [25] serves as a good basis for this research. Another important topic is looking for image preprocessing methods and descriptors that are more robust against image transformations that change the appearance of the surface texture such as image blurring caused by imaging device being slightly out-of-focus.

ACKNOWLEDGMENTS

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