A Local Min-Max Binary Pattern Based Face Recognition Using Single Sample per Class

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Abstract

In this paper, we propose a new representation, called Local Min-Max Binary Pattern (LMin-MaxBP), and apply it to face recognition with single sample per class. The local appearance based methods have been successfully applied to face recognition and achieved state-of-the-art performance. The Local Binary Pattern (LBP) has been proved to be effective for image representation. The motivation for the LMin-MaxBP is to find texture information to cope with the variation due to facial expression and perspective changes as well as reducing the length of the feature vectors in LBP's histogram to speed up the matching process. Experiments on Yale, ORL and Indian face datasets shows that the proposed approach improves the performance in the scenario of one training sample per person with significant facial expression and perspective variations with large rotation angle up to 180^{θ}.

***Keywords**: Face recognition; Local Binary Pattern; Pose and Expression Invariant Face recognition; Facial Feature Vector; Single Sample Problem.*

1. Introduction

In recent years face recognition received more attention in the field of biometric authentication. This is due to increased concerns in security. However, the general problem of face recognition remains to be solved, since most of the systems to date can only successfully recognize faces when images are obtained under prescribed conditions. Their performance will degrade abruptly when face images are captured under varying pose, lighting, with accessories and expression. Another one of the most challenging problems for face recognition is the so-called Single Sample Problem (SSP) problem, i.e., a single face for a subject is used for training. Large training samples can not be guaranteed in practice such as identity card verification, passport verification, etc.

Face recognition methods can be generally divided into two categories: holistic matching methods and local matching methods. In the holistic methods [3], [4], [12] whole face region is taken as the input to face recognition system. The face images are then projected and compared in a low-dimensional subspace in order to avoid the curse of dimensionality. Compared with holistic methods, local methods may be more suitable for handling the one sample problem [15] due to its low dimensional local feature vectors, recognize a face based on its parts and different facial features can increase the diversity of the classifiers. The local matching approaches have shown some promising results in face recognition [1], [2], [7], [8],

[13]. These methods first extract several facial features and then compare on the basis of local statistics for recognition. The comparison of local approaches with global approaches shows the local system outperformed the global system with 60% [5]. There exist several local appearance based methods for extracting the most useful features from face images to perform face recognition.

The Local Binary Pattern (LBP) methodology [9] was originally proposed as an image texture descriptor [10], but it also applied on face recognition application [1]. 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. The idea of using LBP for face description [2] is motivated by the fact that faces can be seen as a composition of micro patterns which are well described by such operator. LBP-based approaches are arousing researchers' high attention due to the advantages of simple computation, robustness to illumination variation and discriminative ability.

2. Background Study

In this section, we will briefly introduce those techniques that are used in our approach.

2.1. Local Binary Pattern

Ojala [9] introduced the Local Binary Pattern operator in 1996 as a means of summarizing local gray-level structure. The operator takes a local neighbourhood around each pixel, the pixels of the neighbourhood at the value of the central pixel and uses the resulting binary-valued image patch as a local image descriptor. It was originally defined for 3x3 neighborhoods, giving 8 bit codes based on the 8 pixels around the central one. Formally, the LBP operator takes the form

$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n S(i_n - i_c) \tag{1}$$

where in this case n runs over the 8 neighbours of the central pixel c, i_c and in are the gray-level values at c and n, and s(u) is 1 if u >= 0 and 0 otherwise. The LBP encoding process is illustrated in fig.1

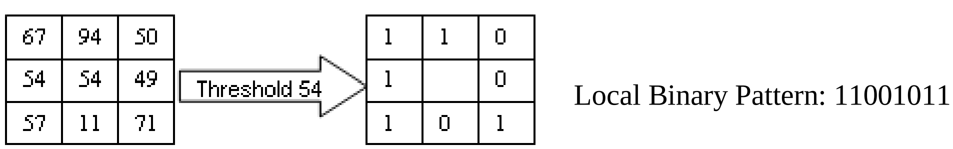


Figure 1. Illustration of the LBP Operator.

Later the LBP operator was extended to use neighborhoods of different sizes. In this case a circle is made with radius R from the center pixel. LBP is resistant to lighting effects in the sense, that it is invariant to monotonic gray-level transformations. We can use $LBP_{P,R}$ to denote LBP operators with different sizes, in which (P,R) means P sampling points on a circle of radius R. It allows for any value of P and R, for the gray values of neighbours which do not fall exactly in the center of pixels are estimated by bilinear interpolation. The total 2^P different patterns are concatenated into a histogram by their number of occurrences. Allowing for that experimental results show certain local binary patterns are fundamental properties of texture images, Ojala proposed an improved LBP operator called uniform patterns, which contain at most two 0/1 or1/0 transitions when the binary string is considered circular. We denote it by $LBP_{P,R}^{u2}$, in which u2 reflects the use of rotation invariant uniform patterns with bit transitions at most two. For example, the $LBP_{8,1}^{u2}$ operator quantifies the total 256 LBP values into 59 bins according to uniform strategy (58 uniform patterns and the other patterns are assorted to the 59^{th} pattern).

2.2 Face Recognition Using Local Binary Patterns

With LBP, face image is divided into small blocks and LBP features are extracted for individual blocks to represent the texture of a face locally and globally. A histogram of the labelled image $f_l(x, y)$ can be defined as

$$H_i = \sum_{x,y} I\{ f_l(x,y) = i\}, i = 0,\ldots,n-1, \tag{2}$$

in which n is the number of different labels produced by the LBP operator and

$$I\{A\} = \begin{cases} 1, & A \text{ is } true \\ 0, & A \text{ is } false \end{cases} \tag{3}$$

We spatially divide the image into m small regions R_0, R_1, R_2, ... R_{m-1}. The histogram of each region R_j is defined as

$$H_{i,j} = \sum_{x,y} I\{ f_l(x,y) = i\} I\{(x,y) \in R_j\} \quad i=0,\ldots, n-1, j=0,\ldots,m-1 \tag{4}$$

in which n is the number of different labels produced by LBP operator, m is the number of rectangular blocks of the image and I(A) is 1 or 0 depending on whether A is true or false. In this histogram, we effectively have a description of the face on three different levels of locality: the 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. By this way we can collect local pattern information with spatial information of the whole image together. From the pattern classification point of view, a usual problem in face recognition is having a plethora of classes and only a few, possibly only one, training sample(s) per class. For this reason, more sophisticated classifiers are not needed but a nearest-neighbor classifier is used. Chi square statistic similarity measure is usually used for calculate the similarity of two histograms. It is defined as

$$X^2(p,q) = \sum_i \frac{(p_i - q_i)^2}{p_i + q_i} \tag{5}$$

Here p, q is two image descriptors (histogram vectors).

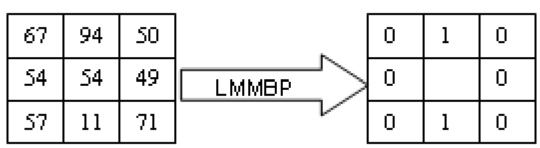
3. Proposed Local Min-Max Binary Pattern Based Face Descriptions

The number of bins required for LBP model is 256. In general N-ary case will receive N^8 bins. Normally the higher dimensional feature maintains more local texture features. But, as dimension of feature increases, the computational complexity increases. The uniform local binary pattern (ULBP) has given solution to reduce the dimension of LBP from 256 bins to 59 bins. The proposed new operator LMin-MaxBP further reduces the dimension of ULBP from 59 to 36. The local image texture information can be extracted from a neighbourhood of 3*3 local regions. Let g_c, g_1, $g_2 \ldots, g_8$ be the pixel values of a local region where g_c is the value of the central pixel and g_1, g_2, …, g_8 are the pixel values of its 8 neighbourhood. The calculation of LMin-MaxBP is described as; Find Min_j and Max_j from the eight neighbour positions. Where Min_j is the first index of least minimum or equal gray value of the neighbours g_i compared to g_c. Max_j is the first index of highest maximum or equal gray value of the neighbour's g_i compared to g_c. The Local Min-Max Binary Pattern is described as

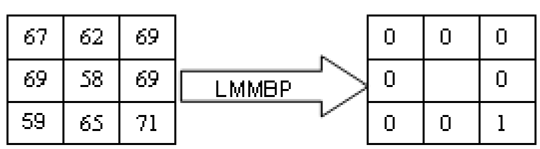
$$LBP(x_c, y_c) = \sum_{n=0}^{7} 2^n MinMax(i_c, i_n) \tag{6}$$

Where in this case n runs over the 8 neighbors of the central pixel c, i_c and i_n are the gray-level values at c and n.

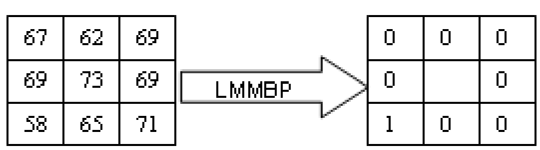
$$\text{Min-Max}(u,v) = 1 \text{ if } \begin{cases} \text{v is the first occurred least minimum or equal to u} \\ \text{among the gray values} <= \text{u;} \\ \text{or} \\ \text{v is the first occurred highest maximum or equal to u} \\ \text{among the gray values} >= \text{u;} \end{cases} \tag{7}$$



(a) LMin-MaxBP: 01000100; Weight: 34



(b) LMin-MaxBP: 00001000; Weight: 16



(c) LMin-MaxBP: 00000010; Weight: 64

Figure 2. Illustration of the LMin-MaxBP operator (a) Min and Max Index Pattern, (b),(c) Min or Max index Pattern

In the proposed new LMin-MaxBP operator according to the two index positions in the range of (0-7) for the least minimum (or=) and highest maximum (or=) gray value, there are twenty eight possible combinations. In some time there may be lack of either min or max index position, in that case there are only eight (0-7) possible combinations are available. Totally we are having 36 bin sizes, which is reduced from 59 in that case of ULBP and 256 in the case of LBP. The possible 36 weights for the LMin-MaxBP is (1, 2, 3, 4, 5, 6, 8, 9, 10, 12, 16, 17, 18, 20, 24, 32,33, 34, 36, 40, 48, 64, 65, 66, 68,72, 80, 96, 128, 129, 130, 132, 136, 144, 160, 192)

4. Experimental Results

This section evaluates the performance of LMin-MaxBP on Single Sample Problem. Three standard databases are used for evaluation of these results. The Yale [14], ORL [11] and Indian Databases [6] are used for analysis. The Indian database is published by IIT Kanpur which is widely used for research purpose. In this database images of 60 persons with 6 samples with different orientations (upto 180^{0}) and views, 5 samples with various expression and a normal face. In this database there are 22 female subjects and 28 male subjects are available. The resolutions of Indian faces are changed to 128 x 128 for computational purpose and one normal face of each subject is used for training. We use 240 expressions variant, 357 pos variant faces up to 180^{0} are used for testing. Different orientation in view of a one person is shown in the figure 3.

Figure 3. Various Views of Face Images with Different Face Orientations in Indian Face Database

In the case of ORL database there are 40 subjects. One normal face of each subject is used for training. We use 63 expressions variant, 189 normal face samples with slight changes on frontal view and scaling (42 faces) and 147 perspective variant faces for testing. One person of ORL database is shown in the figure 4. In the case of Yale database there are 15 subjects. One normal face of each subject is used for training. For testing we use 5 faces with expression, a normal face and centre light applied images of a single person. Person with various expressions in Yale database is shown in the figure 5. In both ORL and Yale datasets the images are cropped to the size of 64 X 64 from the middle of eye location.

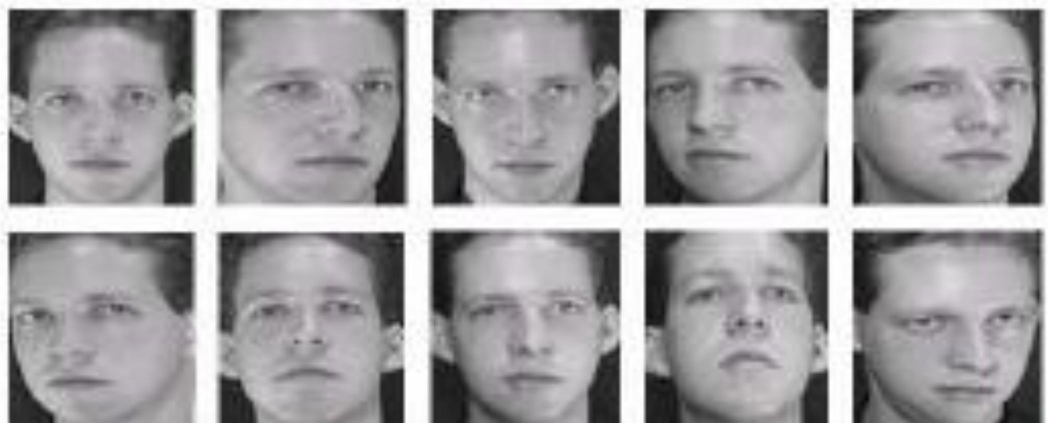


Figure 4. One Person in the ORL Database

Figure 5. One Person in the Yale Database

For an efficient representation of the face, first the image is divided into k^2 regions. In this experiment a face image is divided into $8^2 = 64$ regions. For every region a histogram with all possible labels is constructed. This means that every bin in a histogram represents a pattern and contains the number of its appearance in the region. The feature vector is then constructed by concatenating the regional histograms to one big histogram.

In the case of LBP for every region all non-uniform patterns (more than two transitions) are labeled with one single label. This means that every regional histogram consists of $P(P-1)+3$ bins, where P=8. $P(P-1)$ bins for the patterns with two transitions, two bins for the patterns with zero transitions and one bin for all non-uniform patterns. The total feature vector for an image contains $k^2 (P(P-1)+3)$ bins. So, for an image divided into 64 regions and eight sampling points on the circles, the feature vector has a size of 3776 bins. But in the case our new approach for each region the bin size is 36. The total feature vector for an image is 2304. This LMin-MaxBP reduces the feature vector dimension up to 61% for a single image.

The face recognition program was performed with an Intel Pentium(R) D 2.40GHz CPU and 512MB RAM with Matlab7.5. The overall feature vector reduction on the experimental data sets training samples is shown in the table1.

Table 1. Overall Feature Vector Length Reduction on LBP Operation

Datasets	LBP	LMin-MaxBP	Rate of feature detection
Yale(15 Subjects)	56640	34560	61.016949%
ORL (40 Subjects)	151040	92160	
Indian Faces (60 Subjects)	226560	138240	

The respective performances of the above described LMin-MaxBP method based on the expression variant faces with single training image are shown in table 2.

Table 2. Results of LMin-MaxBP for Face Recognition on the Expression Variant Faces with Single Sample per Class

Datasets	LBP	LMin-MaxBP
Yale	92%	92%
ORL	82.5396%	84.1269%
Indian Faces	85.41666%	87.75510%

Although remarkably robust, face recognition is not perfectly invariant to pose and viewpoint changes. The pose variation is one of the key challenges in the case of face recognition especially in single sample per class. The Indian Face Dataset consist samples of poses up to 180^{θ} rotation angle. The performance of the LMin-MaxBP method on perspective variant faces is shown in the table 3.

Table 3. Results on perspective and pose rotation up to 180θ invariant face recognition with single sample per class

Datasets	LBP	LMin-MaxBP
ORL	69.0212%	74.324%
Indian Faces	78.71148%	80.9524%

From the above result, we can see that the our new approach of LMin-MaxBP reduce the feature vector length of traditional LBP from 256 bin to 36 bin size which also speed up the matching process for the large face dataset.

Apart from vector length reduction it also improves the rate of matching. It outperforms LBP method in pose invariant recognition. It outperforms LBP with 5.3028% for ORL faces and with 2.24092% for Indian Faces. In the analysis of the expression invariant face recognition the LMin-MaxBP perform similar to LBP for Yale (Expression) data set and improves the recognition with 1.5873% for ORL, 2.338441% for Indian Face dataset compared to LBP.

5. Conclusions

In this paper, we have proposed a novel approach of Local Min-Max Binary Pattern based facial feature description for human face recognition. Yale, ORL and Indian Face datasets are used, which contains the face images with different orientations and expressions. The Local Min-Max Binary Patterns are generated for each pixel on the basis of first index position of the minimum (or equal) and maximum (or equal) intensity values among its neighbours. This approach divides the face into a regular grid of cells and finds histograms for the LMin-MaxBP's within each cell. Finally, the cell-level histograms are concatenated to produce a global descriptor vector.

Compared with the conventional LBP method this new approach makes reduction on feature vector dimension and time consumption. This approach not only considers the length of feature vector reduction, but also improves the rate of matching in face recognition with single sample per class. Especially it performs well for pose variation with view up to 180^{θ} changes. This paper has also evaluated the performances of the LBP and the LMin-MaxBP methods in terms of normal and changes in view point and facial expressions faces of ORL, Yale and Indian face datasets. Furthermore, only one image per person is used for training which makes it useful for practical face recognition applications.

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