Face Recognition using Orthogonal Combination of Local Binary Patterns with Color Information

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ABSTRACT

This paper presents a novel approach for face recognition based on orthogonal-combination of local binary patterns (OC-LBP). OC-LBP is the extended version of LBP. LBP is very efficient method to represent the features of an image and therefore is widely used for feature extraction. OC-LBP not only provides high classification rate of face recognition but also decreases dimensionality of original LBP operator. Also, OC-LBP is used for color images in RGB and YC_bC_r color spaces in this research work. To represent the effectiveness of proposed method, the method is applied on whole face image and also applied by dividing face image into regions and from each region OC-LBP features are extracted and concatenated into a feature vector which is used as a local face image region descriptor. Results of OC-LBP are compared with results produced by five methods LDA, PCA, BATCH-ILDA, SVM, ICA on ORL (grayscale face images) and Faces95 (color face images) face datasets using 50% of training dataset. These datasets consists of lot of variations in lighting conditions, facial expressions, time, emotions, orientations and configuration. Experiments show that OC-LBP achieves the high classification rate with small size of feature vector. Also, the results of OC-LBP are compared with original-LBP which proves the efficiency of OC-LBP over original LBP in terms of speed and small size of feature vector.

Keywords: Face recognition, Local binary patterns, Orthogonal combination of local binary patterns, Dimensionality, Classification rate, ORL, Faces95, Color OC-LBP, Feature vector.

1. INTRODUCTION

Face recognition system is a type of biometric software application that can identify a specific individual in a digital image or video by analyzing and comparing patterns. Currently a large number of face recognition systems is in use and research is still continuing in this field. The reason is that most of the systems give satisfactory results only in controlled environments but results are not much satisfactory when there is lot of variations in different factors such as lighting, expression, pose, age, time etc. of a face image. LBP [6] is good texture feature and used in large number of applications which include *face recognition, face expression analysis, face detection, face description etc. LBP operator has two main advantages –first one it is simple and fast to* *compute. Second LBP is robust to monotonic illumination changes.* These advantages make LBP a good texture descriptor. However *it has one disadvantage –the size of feature vector produced by LBP is large.* This disadvantage creates complexity to use LBP as a local region descriptor. So, there is need to reduce the dimensionality of feature vector in original LBP. Therefore, a new feature extractor named OC-LBP [1] is used for face recognition. Original LBP is divided into non-overlapped orthogonal groups by OC-LBP and then LBP codes are computed for each group and finally concatenate LBP codes for each group. *The main advantage of using OC- LBP is that it reduces dimensionality of feature vector and maintains high classification rate.* The remaining sections are organized as follows: The LBP and OC-LBP methodology are introduced in section II. Section III extends OC-LBP to color OC-LBP. Section IV explained brief introduction of ORL and Faces95 datasets used for experiments. Experimental results on ORL [9] and Faces95 [10] databases by different face recognition methods are presented in section V. Finally section VI concludes the paper.

2. ORIGINAL LBP AND OC-LBP OPERATOR

A. THE ORIGINAL LBP OPERATOR

The original LBP operator [2] works in 3 X 3 neighborhood of an image and use decimal numbers to label the pixels of an image. These decimal numbers are called LBPs or LBP codes. It works as shown in following fig.1.

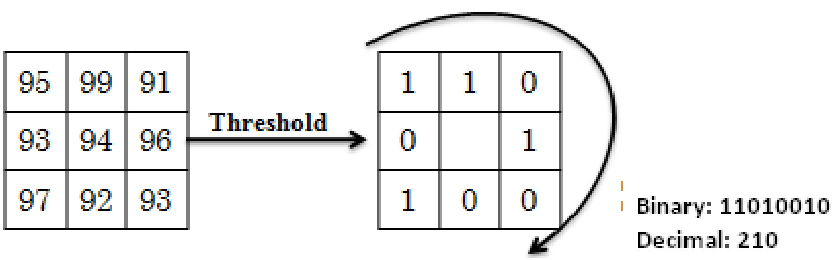

Fig.1. Original LBP operator

LBP code for each pixel in 3 X 3 neighborhood is obtained by subtracting each pixel value from value of the pixel whose LBP code is being computed. After performing subtraction the pixels with strictly negative values are changed with 0 otherwise pixels will be changed with 1. A binary number is obtained for each pixel by performing concatenation on all binary values obtained in clock-wise direction, starting from its top-left neighbor in 3 X 3 neighborhood. The obtained binary number is then converted into decimal number. This decimal number is used for labeling the pixel value. The LBP code for the pixel at (x_c, y_c) in original LBP operator is computed as:

$$LBP_P\left(x_c, y_c\right) = \sum_{p=0}^{P-1} s\left(i_p - i_c\right) 2^p$$

Where i_c and i_p are respectively, gray-level values of the central pixel and P neighboring pixels in 3 X 3 neighborhood of original LBP operator and value of P is 8 for original LBP operator. The function s(x) is defined as:

$$s(x) = \begin{cases} 1, & if \quad x \geq 0 \\ 0, & if \quad x < 0 \end{cases}$$

The main drawback of original LBP is high dimensionality of histograms produced by the LBP operator.

B. OC-LBP

OC-LBP [1] reduces the dimensionality of original LBP by considering fewer neighbors. For example, the original LBP operator considers 8 neighbors as discussed above and produces 256-dimensional histogram. We can reduce the size of histogram by considering only 4 neighbor pixels. However by reducing the number of neighboring pixels will also decreases the discriminative power of the LBP operator. So, we require an operator which reduces the LBP histogram dimensionality while keeping its high descriptive power. OC-LBP is a good tradeoff between the reductions of the LBP histogram dimensionality and maintains high descriptive power [1].

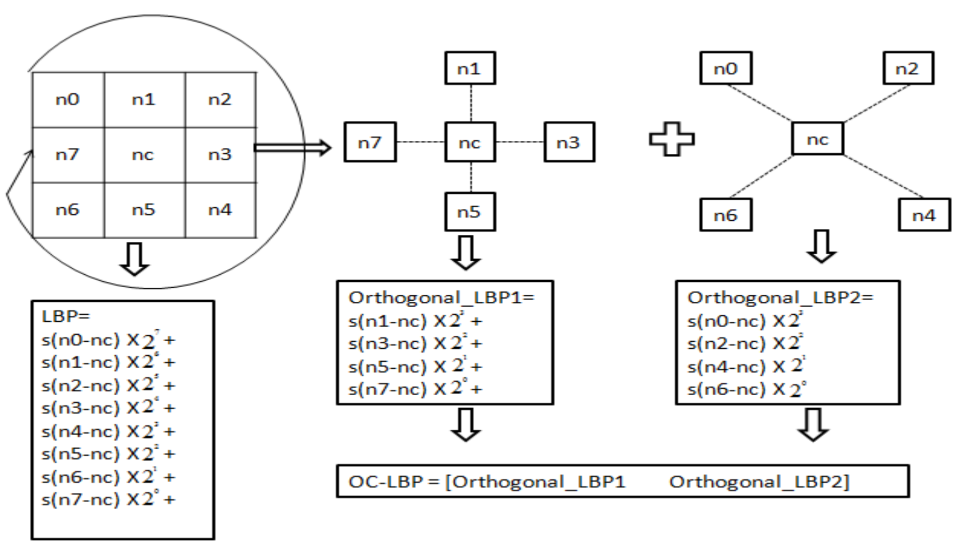

Fig.2. Description of LBP and OC-LBP operators in 3 X 3 neighborhood

In 3 X 3 neighborhood of original LBP operator we can compute the OC-LBP by dividing 3 X 3 neighborhood into non-overlapped orthogonal groups and compute OC-LBP histogram of each group, finally concatenated them and used as image descriptor. For 3 X 3 neighborhood we have [P/4] different orthogonal neighbors. Thus we get OC-LBP based histogram whose dimension is 2^4 X [P/4] or 4 X P, which is very small then original LBP histogram size which is 256 for 3 X 3 neighborhood. The process of implementing LBP and OC-LBP is shown in fig.2.

OC-LBP divides the original LBP into two regular 4-neighbor LBP operators.

- The first operator is obtained by considering only horizontal and vertical neighbors.
- The second operator is obtained by considering diagonal neighbors.
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Then we can obtain OC-LBP by concatenating these two OC-LBP histograms, the obtained OC-LBP histogram is of 32-dimensions which is eight times smaller than the original 8-neighbor LBP histogram with 256 dimensions.

3. COLOR OC-LBP

OC-LBP operator is extended into color OC-LBP [1], in which color information is used instead of gray information used by many classical LBP descriptors. Color information provides high discriminative power than grayscale information. *The main advantage of color OC-LBP is that it is photometric invariance and provides good results in illumination changes in color images [1].* The brief introduction about color spaces used for experiments in color-OC-LBP:

- In RGB color space, each color pixel is a triplet corresponding to the red, green and blue components which are primary colors and their additive mixing produce large number of colors. This is most widely used color space for imaging operations.
- YC_bC_r color space is used extensively in digital video. In this color space, luminance information is represented by a single component Y, and color information is stored as two color-difference components, C_b and C_r

The used color OC-LBP descriptors and their properties are explained below:

RGB-OC-LBP [1]: In this operator features are obtained by calculating OC-LBP descriptor over each channel of color space independently i.e. R, G, and B respectively and then concatenate them which are used as final image descriptor as shown in fig.3. *This descriptor provides invariance to monotonic illumination changes in face images.*

YC_bC_r-OC-LBP: In this operator features are obtained by calculating OC-LBP descriptor over each channel of color space independently i.e. Y, C_b, and C_r respectively and then concatenate them which are used as final image descriptor. *This color descriptor gives much better classification rate of face recognition than RGB-OC-LBP.*

Algorithm: Face recognition using OC-LBP for grayscale and color face images

Input: training set, testing set and the method OC-LBP

Output: classification rate

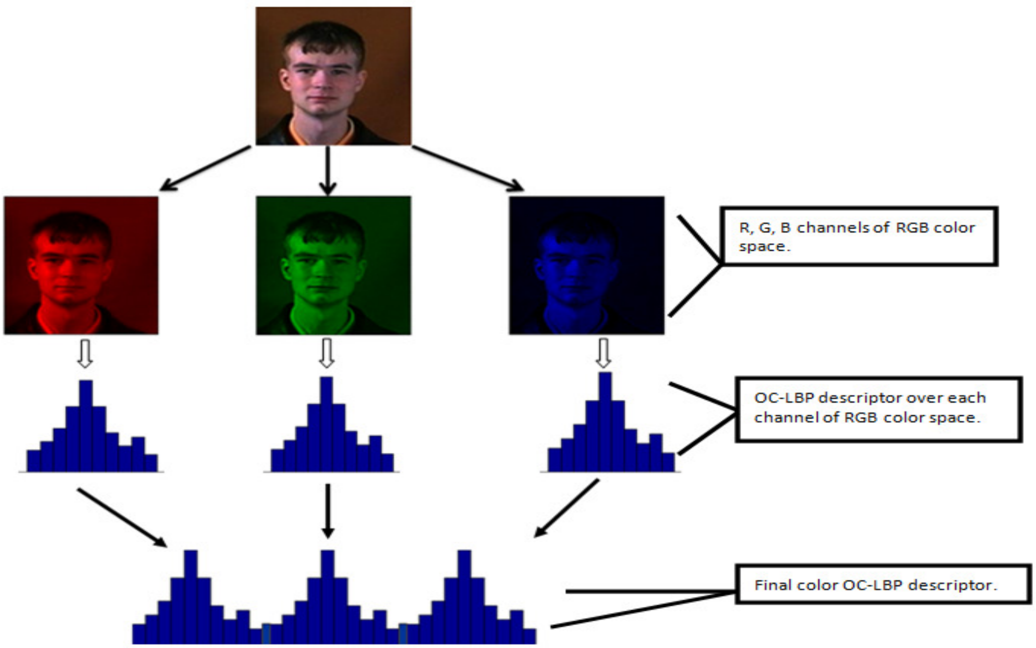

Fig.3. RGB-OC-LBP descriptor

- Read database.
- Compute OC-LBP. We can compute OC-LBP for whole image or we can divide whole image into regions and find OC- LBP for each region and then concatenate results from all regions.

Fig.4. A facial image divided into 7 X 7, 5 X 5, and 3 X 3 rectangular regions

- In case of image is divided into regions we will assign weights to regions depending on the recognition rate.
- Perform classification and identify similar images using chi-square dissimilarity measure [6]. For example, chi-square for weighted regions can be defined as:

$$\chi_w^2(x,\xi) = \sum_{j,i} w_j \frac{(x_{i,j} - \xi_{i,j})^2}{x_{i,j} + \xi_{i,j}}$$

In which x and ξ are histograms to be compared, indices i and j refer to the bin in histogram corresponding to jth local region and w_j is weight for region j. Assume w_j =1 for non-weighted LBP.

- Calculate classification rate.

The above algorithm is applicable for color face images also but in case of color faces we have to perform this procedure for each channel of color space.

4. DATABASES USED IN EXPERIMENTS

Experiments are carried out on two databases: ORL database of grayscale faces [9], Faces95 database of color faces [10]. Fig.4 and fig.5 show samples faces from two datasets. The brief description of datasets used in experiments is:

ORL database [9]: The ORL database of faces also called AT & T dataset. This dataset consists of 40

different subjects with ten different images per subject. ORL database consists of images with variations in lighting, facial expressions, taken at different times and facial details. The size of each image is 92X112 pixels.

Faces95 database [10]: This database consists of 72 different subjects with 20 different images. The size of each image is 180 X 200 pixels.

Fig.5. Sample faces from ORL database

Fig.6. Sample faces from Faces95 database

5. EXPERIMENTAL RESULTS

Results of five standard well known methods are compared with LBP and OC-LBP on ORL (grayscale face images) and Faces95 (color face images in RGB and YC_bC_r color space) datasets. In these experiments 50% of dataset is used for training and 50% is used for testing sets. Results of PCA [4], LDA [4], Batch-ILDA [4], SVM [4] and ICA [4] are used for comparison with results of implemented methods (original LBP and OC-LBP in grayscale and color variations) in this research work. Table1 shows the classification rate produced by all methods on ORL database. In table 1 when 50% of ORL dataset is used for training, then highest classification rate is 99% produced by weighted-LBP but at the same time weighted OC-LBP gives 98% classification rate which is higher than classification rates produced by all other methods. Moreover OC-LBP is also computationally efficient than LBP however original LBP gives 1% more classification rate but size of feature vector is very large for original LBP than OC-LBP. Table 2 shows the comparison of results produced by OC-LBP and LBP with five well known methods in RGB color space and table 3 shows the results of LBP and OC-LBP in YC_bC_r color space of Faces95 dataset with 50% training set. Results produced with OC-LBP are better than all other methods on Faces95 dataset in RGB color space with small size of feature vector. Moreover, recognition rate is much better for Faces95 dataset in YC_bC_r color space than RGB color space. Therefore we can say that YC_bC_r color space is better than RGB color space to represent color information. The feature vector produced by OC-LBP is eight times smaller than original LBP. For example, if we divided an image into 16 regions feature vector size for original LBP is 256 X 16 and for OC-LBP feature vector size will be 32 X 16, which is very small than LBP. So this is verified that OC-LBP is better in classification rate than other methods. OC-LBP is faster than original LBP.

6. CONCLUSION AND FUTURE WORK

After working with OC-LBP we conclude that this operator is powerful than other feature extraction methods and is much efficient to represent texture and shape of images. Moreover it is fast operator because of small size of feature vector and provides very good results of classification rate as compared to five well known methods. Classification rate of OC-LBP is high or comparable with original LBP in color face images. In future work, the main emphasis is on implementing OC-LBP in other color spaces and improves classification rate of color face images.

Table 1: Classification rates produced by different methods on ORL database.

Method	LDA [4]	PCA [4]	BATCH-ILDA [4]	SVM [4]	ICA [4]	Original-LBP non-weighted	Original-LBP weighted	OC-LBP non-weighted	OC-LBP weighted
Classification Rate	93.5	91.5	94.0	97.0	83	91.5	99	89.5	98

Table 2: Classification rates produced by different methods on Faces95 database in RGB color space.

Method	LDA [4]	PCA [4]	BATCH-ILDA [4]	SVM [4]	ICA [4]	RGB-LBP	RGB-OC-LBP
Classification Rate	61.2	58.8	61.2	61.6	48.4	79.03	79.30

Table 3: Classification rates produced by different methods on Faces95 database in YC_bC_r color space.

Method	YC_bC_r -LBP	YC_bC_r -OC-LBP
Classification Rate		
	85.42	85.56

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