Analysis of Face Recognition in Different Color Spaces using LBP and OC-LBP

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Abstract— **This paper presents a novel approach for face recognition based on OC-LBP (Orthogonal-Combination of Local Binary Patterns). OC-LBP is the new variation of LBP (Local Binary Pattern). LBP is simple method to extract the features of an image and therefore is used commonly in many applications for feature extraction. LBP is non-parametric descriptor that efficiently summarizes the local features of an image and provides high recognition rate but the feature vector produced by original LBP is generally very large. OC-LBP not only provides high recognition rate for face recognition but also decreases dimensionality of original LBP operator. Both LBP and OC-LBP are implemented for color face images of Faces95 database in five different color spaces such as RGB, HSV, XYZ, L*a*b* and YC_bC_r. Results produced by LBP and OC-LBP in different color spaces are compared and analyzed in this research work. To represent the effectiveness of proposed method, the method is applied on whole face image. LBP and OC-LBP extracts features from images and Chi-square dissimilarity measure is used to make classification. In these experiments 50% of Faces95 dataset is used for training and 50% of dataset is used for testing. Faces95 dataset consist of lot of variations in facial expressions, lighting conditions, time, emotions, orientation and configuration in face images. Experiments show that OC-LBP achieves the high recognition 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. Recognition rates produced by OC-LBP are high or comparable to recognition rates produced by original LBP. Also experiments are performed on individual color component of each color space and results are compared with brightness component of each color space. Experimental results show that brightness component of each color space gives less recognition rate than other components because brightness is grayscale and other components provide color information which has more discriminative power than grayscale information.**

Keywords— Face Recognition; LBP; OC-LBP; Histogram; Feature Vector; Dimensionality; Recognition Rate; Faces95; Color OC-LBP.

I. INTRODUCTION

Face Recognition is the process of matching a face to many faces in the dataset. It is a type of biometric software application. For example, face recognition system is used for visa processing. Automated face recognition systems is used in lot of areas other than security oriented applications such as biometrics, access management, entertainment, law enforcement, human-computer interaction etc. Though face recognition have been a grown up research area, however, there are still many problems that must be overcome to develop a robust face recognition system that works well under various variations such as illumination, pose, expressions and orientation etc. Faces can be easily detected by humans, in minimum time, but with the advent of new automatic tools, there is need for machine based automatic recognition systems for face recognition. Despite the success of many face recognition systems many issues remain to be addressed. Among these issues size of feature vector is important. The existing systems that used original LBP, are not a good choice for face recognition because they are time consuming systems because of large size of feature vector produced by original LBP, so new method named OC-LBP is used in this research work to reduce the size of feature vector. This method significantly reduces the size of feature vector. Also face recognition is extended in this research work from grayscale images to color images, in which color information is used instead of gray information used by many classical LBP descriptors system.

The focus of proposed research work **is** to analyze the recognition rates for color images in different color spaces using LBP and OC-LBP. OC-LBP aims at reducing the dimensionality of the original LBP operator while keeping its high recognition rate and computational efficiency. LBP and OC-LBP are used for feature extraction in this research work. LBP is used in large number of applications such as face recognition, face expression analysis, face detection, face description etc. LBP operator has several 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 is used for face recognition which reduces dimensionality of feature vector and at the same time this operator maintains the efficient discriminative ability of LBP. The 3 X 3 neighborhood of original LBP is divided into non-overlapped orthogonal groups by OC-LBP and then OC-LBP codes are computed for each group and finally concatenate LBP codes for each group. This method gives small size of feature vector while maintaining high recognition rate.

The remaining sections are organized as follows: The LBP and OC-LBP methodology are introduced in section II. Section III introduced the color spaces used for experiments. Section IV explained the color LBP and OC-LBP. Section V gives brief introduction of Faces95 dataset used for experiments. Experimental results on Faces 95 database are presented in section VI. Finally section VII concludes the paper.

II. ORIGINAL LBP AND OC-LBP

A. *The original LBP operator*

The original LBP operator works in 3X3 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.

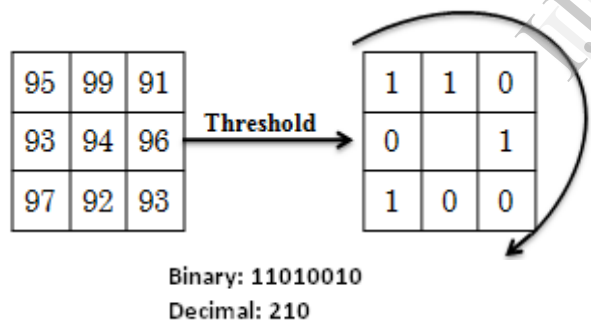Binary: 11010010
Decimal: 210
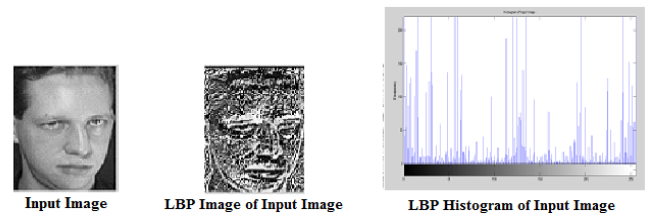
Fig. 1. Original LBP operator.

Fig. 2. Example of LBP image and Histogram.

LBP code for each pixel in 3X3 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 encoded with 0 otherwise pixels will be encoded 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 3X3 neighborhood. The obtained binary number is then converted into decimal number. This decimal number is used for labeling the pixel value. **LBP is fast to calculate and invariant to monotonic illumination changes therefore efficient for local image region description. The main drawback of original LBP is high dimensionality of histograms produced by the LBP operator.** For original LBP operator, LBP histogram consists of 256 bins. So we need to reduce dimensionality of original LBP. LBP image and its corresponding LBP histogram of an input image are shown in fig.2.

B. *OC-LBP*

OC-LBP 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 because we considered only horizontal and vertical neighbors and are not considering the diagonal neighbors. 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.
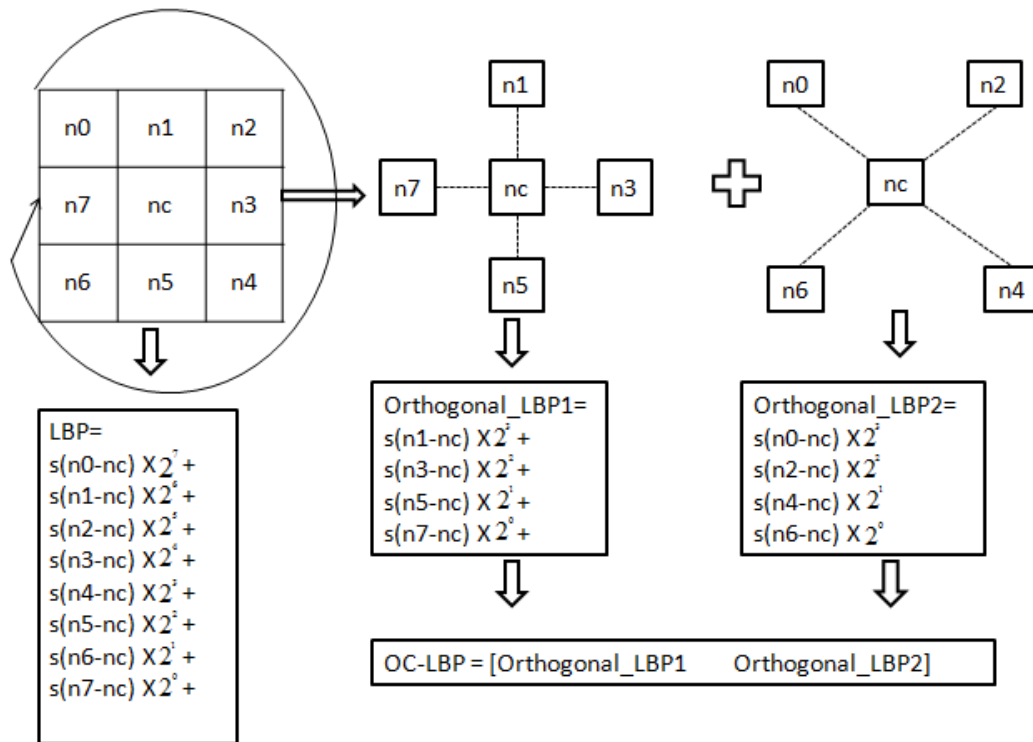
Fig. 3. Description of LBP and OC-LBP operators in 3 X 3 neighborhood.

In 3X3 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 neighborhoods 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 in 3 X3 neighborhood is shown in fig.3. 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.

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. So this new OC-LBP operator is not only fast but keeping high discriminative ability.

III. COLOR SPACES

A color space is a defined range of colors or a mathematical representation of a set of colors. In this research work, LBP and OC-LBP operators are extended for color images and experiments are performed on color images in different color spaces, 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 LBP and OC-LBP is that it is photometric invariant and provides good results in illumination changes in color images. In color version of any LBP operator features are obtained by calculating descriptor over each channel of color space independently e.g. in RGB color space, features are extracted from R, G, and B respectively using LBP or OC-LBP operator and then concatenate them which are used as final image descriptor as shown in fig.5.1. The brief introduction about color spaces used for experiments in this research work:

RGB color space: 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: This color space is used extensively in digital video. In this color space, brightness (luma) information is represented by a single component Y, and color information is stored as two color-difference components, C_b is blue minus luma and C_r is red minus luma.

HSV color space: HSV (hue, saturation, value) is one of the several color systems used by people to select colors (e.g. of paints or inks) from a color wheel or palette. This color system is considerably closer than the RGB color system to the way in which humans experience and describes color sensations.

XYZ color space: The XYZ color space is an international standard developed by the CIE (Commission Internationale de I' Eclairage). This model is based on three hypothetical primaries X, Y, Z and all visible colors can be represented by using only positive values of X, Y and Z. The Y primary is intentionally defined to match closely to luminance, while X and Z primaries give color information. The main advantage of the CIE XYZ space (and any color space based on it) is that this space is completely device- independent.

L*a*b* color space: This color space covers all potential colors mean every color that human eye are able to see. The L*a*b* color model was developed with the goal of linearizing the representation with respect to human color perception and at the same time creating a more intuitive color system. The dimension in this color space are luminosity L* and two color components a*, b* which specify the color hue and saturation along the green-red and blue-yellow axes respectively.

IV. COLOR LBP and OC-LBP

LBP and OC-LBP operator are extended for color images, in which color information is used instead of gray information used by many classical LBP descriptors. Color LBP /OC-LBP mainly focus on implementing original LBP/OC-LBP descriptor on each channel of a given color space independently and then concatenate them into a final color LBP/OC-LBP descriptor shown in fig.4. Color information provides high discriminative power than grayscale information. **The main advantage of color LBP/OC-LBP is that it is photometric invariant and provides good results in illumination changes in color images. For e.g. in RGB color space** features are obtained by calculating LBP/OC-LBP descriptor over each channel of color space independently.

Algorithm: Face Recognition using LBP/OC-LBP for color face images

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

Output: recognition rate

- Read database.

- Compute LBP/ OC-LBP for whole image

- Formulate the feature vector matrix.

- Division of feature vector matrix into trains and test sets.

- Perform classification and identify similar images using Chi-square dissimilarity measure. Images in databases are compared by measuring the similarities (distance) between their histograms. In these experiments, Chi-square distance statistics is used to measure distance between histograms of face images in database. This measure is used to perform classification of feature vector. Chi -square distance can be defined as:

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

Where x and ξ are the normalized enhanced histograms to be compared, indices i and j refer to the bin in histogram corresponding to the jth local region and w_j weight for region j. Assume w_j =1for non-weighted/non-region LBP. Chi-square distance between exactly same face images will be zero. Chi-square distance between images of same person however with different variations will be minimum.
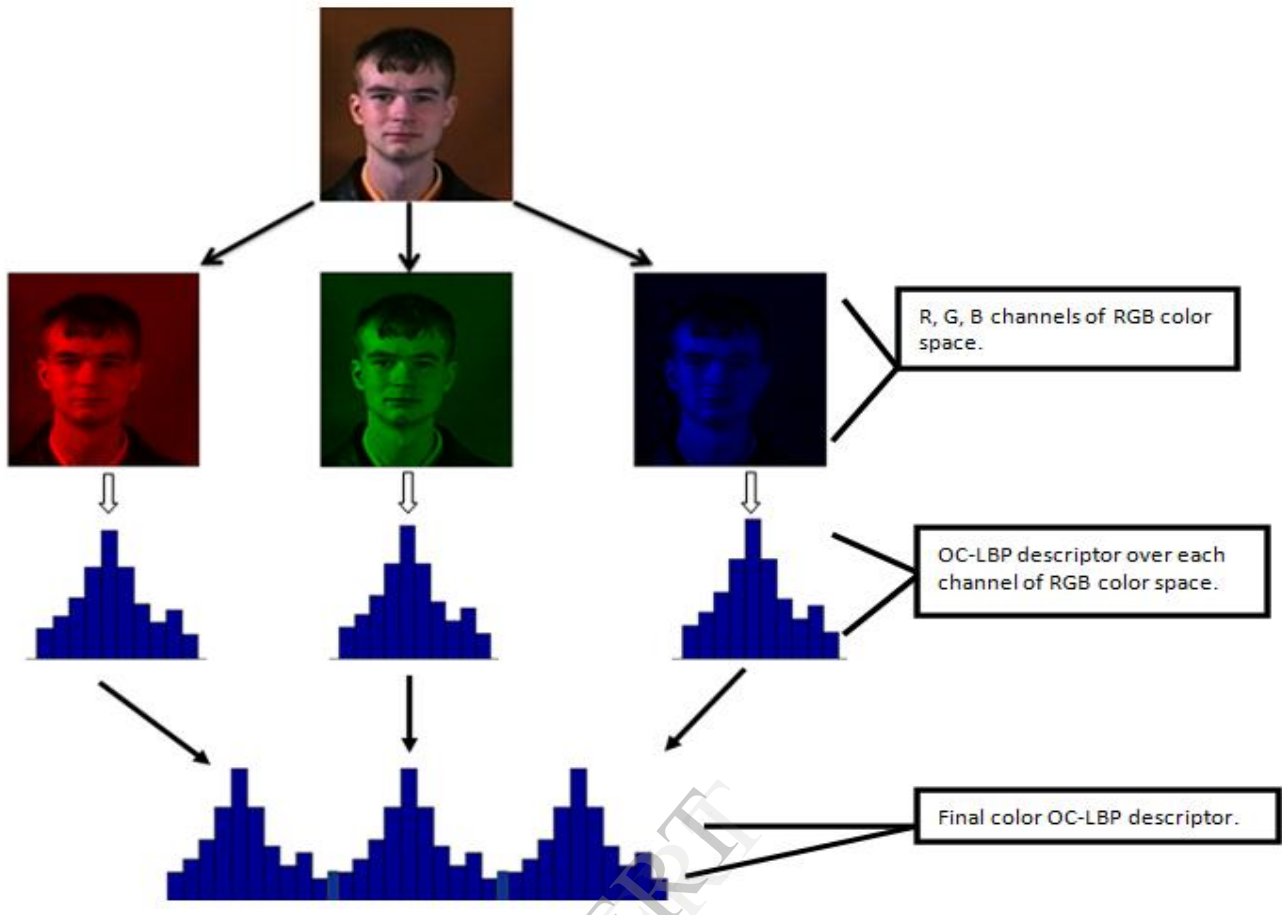
- Calculate recognition rate.

Fig. 4. RGB-OC-LBP descriptor.

V. DATABASE USED IN EXPERIMENTS

Experiments are carried out on Faces95 database of color faces [11]. Figure.5. show samples faces from Faces95 dataset. These datasets consists of different subjects and have several face images for each subject with different orientations, expressions, time variations, and emotions. The brief description of Faces95 dataset used in experiments is:

Faces 95 database [11]: This database consists of 72 different subjects with 20 different images per subject. Faces95 dataset consists of male and female images. The size of each image is 180X200 pixels. Artificial lighting arrangement is used for incorporating lighting variations in images.

VI. EXPERIMENTAL RESULTS

In this research work, LBP (Local Binary Pattern) and OC-LBP (Orthogonal Combination of Local Binary Patterns) operators are implemented in MATLAB (Matrix Laboratory). This implementation is used to test performance comparison between Original LBP (alias LBP in this research work) and OC-LBP on color face images for face recognition.

Experiments are carried out in 32-bit or 64-bit MATLAB version 7.10.0.499(R2010a), under windows7 ultimate on a PC with Intel 2.10GHz CPU and 2 GB RAM.

Fig. 5. Sample faces from Faces95 database with different variations.

Experiment: Experiments are performed to calculate recognition rate produced by LBP and OC-LBP in different color spaces on Faces95 database.

Experiments are performed to calculate recognition rate produced by LBP and OC-LBP in five different color spaces RGB, YC_bC_r, HSV, L*a*b*, XYZ on Faces95 database. Face images in Faces95 dataset are originally in RGB color space. Experiments are performed on Faces95 database by converting images into particular color space in which experiments are to be performed. In MATLAB conversion from one color space to other is easy and straightforward because predefined functions are available which can be used directly to convert image in one color space to other color space.

Table 1: Recognition rates produced by LBP and OC-LBP on Faces95 database in different color spaces.

Color Space	Recognition Rate using LBP (256 X 3 features)	Recognition Rate using OC-LBP (32 X 3 features)
RGB	79.03%	79.30%
YC_bC_r	85.42%	85.56%
HSV	83.47%	82.92%
XYZ	78.06%	78.19%
L*a*b*	85.28%	85.00%

In these experiments 50% of Faces95 dataset are used for testing and 50% of dataset is used for training. Table 1 shows comparison of the recognition rates produced by LBP and OC-LBP in five different color spaces RGB, YC_bC_r, HSV, L*a*b*, XYZ for Faces95 database.

Recognition rates produced by OC-LBP operator are better and comparable with recognition rates produced by original LBP operator with small size of feature vector in all color spaces shown in table 1. For original LBP operator number of features produced for each color space is 256 X 3 (i.e. 256 features for each color component) and for OC-LBP number of features produced for each color space is 32 X 3(i.e. 32 features for each color component), which are very less than features produced by LBP. Since each color space consists of different color components so, features need to be extracted from each color component individually and then concatenate features from all components of particular color space to get final feature vector. Therefore, performing operations on color images take more time than performing operations on grayscale images.

Moreover recognition rates are highest for Faces95 dataset in YC_bC_r color space than other color spaces i.e. 85.42% and 85.56% using LBP and OC-LBP respectively. Therefore we can say that YC_bC_r color space is better than other color spaces to represent color information as shown in table 1. These experiments in different color spaces for Faces95 database also proves efficiency of OC-LBP which provides high recognition rates in different color spaces with less number of features.

Experiment: Experiments are performed on individual color component of each color space used in this research work.

Experiments are performed on individual color component of each color space and compare recognition rates produced by LBP and OC-LBP on Faces95 database by extracting features from individual component of each color space. A color space consists of different color components. Every component of

color space has its own representation. Each color space consists of brightness component which is easiest to understand as it is grayscale. So, experiments are carried out to check recognition rate provided by each component individually. Recognition rate produced by brightness component of each color space is compared with other components in each color space. Performing experiments on individual color component will reduces the number of features. If we perform operations on all three components of a color space features produced will be 256 X 3 by LBP and 32 X 3 by OC-LBP but if we perform operation on a single color component features produced will be 256 by LBP and 32 by OC-LBP.

Experiment: Experiments are performed on individual color component of YC_bC_r color space.

In YC_bC_r color space Y is brightness (luminance) component, where C_b or C_r are chrominance components contains color information. C_b is blue minus luma and C_r is red minus luma. Table 2 shows the recognition rates produced by individual color component in **YC_bC_r** color space using LBP and OC-LBP on Faces95 database.

Table 2: Recognition rates produced by individual component of YC_bC_r color space on Faces95 database.

YC_bC_r Color Space	Recognition Rate using LBP (256 features)	Recognition Rate using OC-LBP (32 features)
Y	77.22%	73.3%
C_b	87.36%	82.91%
C_r	90.56%	87.50%

LBP and OC-LBP operators produced recognition rate of 85.42% and 85.56% respectively on Faces95 database in YC_bC_r color space by applying operations on all three component together shown in table 1. On the other hand only C_r component of YC_bC_r color space gives recognition rate of 90.56% and 87.5% using LBP and OC-LBP operators respectively shown in table 2 which is more than applying operations on three components together of YC_bC_r color space. Y component which is corresponds to brightness in YC_bC_r color space produces recognition rate of 77.22% and 73.3% using LBP and OC-LBP respectively. C_r produces recognition rate of 87.36% and 82.91% using LBP and OC-LBP respectively. From the results given in table 2 we can say that C_b and C_r components of YC_bC_r color space provides more recognition rate than brightness component Y, because these two components contain color information. Thus we can say that color information has more discriminative power than grayscale information because brightness is grayscale. However recognition rates produced by LBP operator is high than OC-LBP but LBP operator used 256 features and OC-LBP used 32 features for providing this recognition rate. This shows that OC-LBP maintains high recognition rate with less number of features.

Experiment: Experiments are performed on individual color component of RGB color space.

In RGB color space R, G, B are corresponds to red, green, blue which are primary colors and brightness component in RGB color space is computed as:

$$I = (R+G+B)/3$$

The recognition rates for individual color component in RGB color space using LBP and OC-LBP on Faces95 database is shown in table 3. LBP and OC-LBP operators produced recognition rate of 79.03% and 79.30% respectively on Faces95 database in RGB color space by applying operations all three components together shown in table 1. On the other hand only R component of RGB color space gives recognition rate of 79.31% and 77.78% using LBP and OC-LBP operators respectively which is high (for LBP) or comparable (for OC-LBP) to applying operations on three components of RGB color space together.

Table 3: Recognition rates produced by individual component of RGB color space on Faces95 database.

RGB Color Space	Recognition Rate using LBP (256 features)	Recognition Rate using OC-LBP (32 features)
R	79.31%	77.78%
G	76.94%	73.3%
B	76.94%	74.03%
I	77.36%	733%

Brightness component I give recognition rate of 77.36% and 73.3% using LBP and OC-LBP respectively which is comparable to applying operation on all three components of color space. G component produces recognition rate of 76.94% and 74.03% using LBP and OC-LBP respectively. B component produces recognition rate of 76.94% and 74.03% using LBP and OC-LBP respectively. From these results we can say that R component of RGB color space provides more recognition rate than other two components of RGB color space shown in table 3. However recognition rates provided by LBP operator is high than OC-LBP but LBP operator used 256 features and OC-LBP used 32 features for providing this recognition rate.

Experiment: Experiments are performed on individual color component of HSV color space.

In HSV color space H, S corresponds to hue, saturation respectively. V represents brightness component. Table 4 shows the recognition rates for individual color component in HSV color space using LBP and OC-LBP on Faces95 database. LBP and OC-LBP operators produced recognition rate of 83.47% and 82.92% respectively on Faces95 database in HSV color space by applying operations all three components together shown in table 1.

On the other hand only H component of HSV color space gives recognition rate of 83.61% and 78% using LBP and OC-LBP operators respectively which is more than applying operations on all components together of HSV color space. Brightness component V give recognition rate of 80.00% and 75.19% using LBP and OC-LBP respectively which is comparable to applying operation on all three components of color space. S component produces recognition rate of 75% and 71.39% using LBP and OC-LBP respectively. From these results we can say that H component of HSV color space produces more recognition rate than other two components shown in table 4. However recognition rates produced by LBP operator is high than OC-LBP but LBP operator used 256 features and OC-LBP used 32 features for providing this recognition rate. Thus we can say that OC-LBP maintains high recognition rate with less number of features.

Table 4: Recognition rates produced by individual component of HSV color space on Faces95 database.

HSV Color Space	Recognition Rate using LBP (256 features)	Recognition Rate using OC-LBP (32 features)
H	83.61%	78%
S	75.00%	71.39%
V	80.00%	75.19%

Experiment: Experiments are performed on individual color component of XYZ color space.

In XYZ color space X and Z primaries give color information. Y primary corresponds to brightness. Table 5 shows the recognition rates for individual color component of XYZ color space using LBP and OC-LBP.

Table 5: Recognition rates produced by individual component of XYZ color space on Faces95 database.

XYZ Color Space	Recognition Rate using LBP (256 features)	Recognition Rate using OC-LBP (32 features)
X	78.33%	77.50%
Y	77.22%	75.83%
Z	76.11%	74.17%

LBP and OC-LBP operators produced recognition rate of 78.06% and 78.19% respectively on Faces95 database in XYZ color space as shown in table 1 by applying operations on all components of color space. On the other hand only X component of XYZ color space gives recognition rate of 78.33% and 77.5% using LBP and OC-LBP operators respectively as shown in table 5 and brightness component Y

give recognition rate of 77.22% and 75.83% using LBP and OC-LBP respectively which is comparable to applying operation on all three components of XYZ color space. Z component produces recognition rate of 76.11% and 74.17% using LBP and OC-LBP respectively. From these results we can say that X component of XYZ color space provides more recognition rates than two other components shown in table 5. From the results given in table 5 we can say that X and Z components of XYZ color space provides more recognition rates than brightness component Y, because these two components contain color information. Thus we can say that color information has more discriminative power than grayscale information because brightness is grayscale. However recognition rates provided by LBP operator is high than OC-LBP but LBP operator used 256 features and OC-LBP used 32 features for providing this recognition rate. So we can say OC-LBP is more efficient than LBP.

Experiment: Experiments are performed on individual color component of L*a*b* color space.

In L*a*b* color space L* represents brightness component and a* and b* corresponds to color components. Table 6.8 shows the recognition rates for individual color component of L*a*b* color space using LBP and OC-LBP on Faces95 database.

LBP and OC-LBP operators produced recognition rate of 85.28% and 85% respectively on Faces95 database in L*a*b* color space after applying operations on all three components of color space shown in table 1 On the other hand only b* component of L*a*b* color space gives recognition rate of 81.66% and 79.17% using LBP and OC-LBP operators respectively. Brightness component L* give recognition rate of 78.61% and 74.6% using LBP and OC-LBP respectively. a* component produces recognition rate of 80.83% and 74.17% using LBP and OC-LBP respectively.

Table 6: Recognition rates produced by individual component of L*a*b* color space on Faces95 database.

L*a*b* Color Space	Recognition Rate using LBP (256 features)	Recognition Rate using OC-LBP (32 features)
L*	78.61%	74.6%
a*	80.83%	78.88%
b*	81.66%	79.17%

From these results we can say that b* component of L*a*b* color space provides more recognition rate than two other components shown in table 6. From the results given in table 6 we can say that a* and b* components of L*a*b* color space provides more recognition rates than brightness component L*, because these two components contain color information. Thus we can say that color information has more discriminative

power than grayscale information because brightness is grayscale. However recognition rates provided by LBP operator is high than OC-LBP but LBP operator used 256 features and OC-LBP used 32 features for providing this recognition rate.

Therefore it's more efficient to apply operator on single component of color space than applying operators on all the three components together because operation on single color component provides comparable recognition rates with less number of features than applying operations on all components together of a color space. Also, components containing color information provides more recognition rates than brightness component in each color space.

A good local descriptor should be both discriminative and computationally efficient. The discriminative power of the proposed OC-LBP descriptor has been demonstrated by the previous experiments that OC-LBP provides comparable or better (in some cases) recognition rate with less number of features. From above experiments we can say that OC-LBP is eight times more compact than original LBP. So this is verified that OC-LBP is both discriminative and computationally efficient as LBP with less number of features.

VII. CONCLUSION AND FUTURE WORK

At the end we concluded from this research work that OC-LBP is simple to implement. It is eight times compact than original LBP and also OC-LBP is robust to databases with large sizes. OC-LBP can handle many variations in face images such as face images taken at different times, face images with different light variations, face images with different expressions, lightening changes and many other variations present in databases used for experiments and it maintains high recognition rate and computational efficiency as original LBP with less number of features.

In future work, we are willing to extend OC-LBP operator for facial expression recognition, object recognition and for many other applications because of its efficiency. We also want to implement it on large size databases with many different other variations that are not covered in databases used for experiments in this research work so as to check its efficiency and recognition rate on large databases. We also want to integrate OC-LBP with some other well- known feature extraction method to increase recognition rate.

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