

## Face Recognition using Multi Region Prominent LBP Representation

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### ABSTRACT

Various face recognition methods are derived using local features among them the Local Binary Pattern (LBP) approach is very famous. The histogram techniques based on LBP is a complex task. Later Uniform Local Binary Pattern (ULBP) is derived on LBP, based on the bitwise transitions and ULBP's are treated as the fundamental property of texture. The ULBP approach treated all Non-Uniform Local Binary Patterns' (NULBP) into one miscellaneous label. Recently we have derived Prominent LBP (PLBP), Maximum PLBP (MPLBP) and Smallest PLBP (SPLBP). The PLBP consists of the majority of the ULBP's and some of the NULBP's. The basic disadvantage of these various variants of LBP's is they are basically local approaches and completely failed in representing features derived from large regions or macrostructures, which are very much essential for faces. This paper derives PLBP's on the large region. The rectangular region of this paper is assumed with a size of multiples of three and PLBPs are evaluated on dividing each region into multiple regions. The proposed Multi Region-PLBP (MR-PLBP) approach is tested on three facial databases namely Yale, Indian and AT&T ORL. The experimental results show the proposed approach significantly outperforms the other LBP based face recognition methods.

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## 1. INTRODUCTION

Face recognition is one of the significant and prominent research topics for the last two decades, due to its potential applications and challenges. Face recognition deals with recognition of a test facial image from a feature library or data set of facial images. The researchers in image processing and facial image analytics of big data are showing tremendous interest because of its wide range of applications like human face interaction, surveillance in public and private military and other areas in various legal and property issues to identify the proper person. The face identification accuracy significantly decreases when obtained images do not have adequate quality either due to a variety of facial expressions, subject's alignment problem to the camera, gaze deviations or facial hair [1-5].

The human face can be identified based on the local and regional attributes. Today, the challenge in face recognition is, how to identify and capture this information. The Local Binary Pattern (LBP) is a powerful local descriptor for texture analysis and also extensively used in various applications [6]. The local information derived from LBP is used widely in facial analysis especially for the purpose of face recognition [7-13] age classification [14], [15-17] and facial expression recognition [18]. Few researchers

used pre-processing methods to improve classification performance [12], [19] on LBP because it is more prone to noise.

The fundamental LBP operator has small spatial support area and they completely fail in capturing large scale structure (macrostructure) that may be the dominant feature of faces. In the literature, the Uniform Local Binary Pattern (ULBP) are used for classification and recognition purpose because they contain fundamental properties of the texture and ignored the majority of Non Uniform Local Binary Pattern (NULBP) as miscellaneous. The ULBPs alone may not describe stochastic attributes and characteristics of texture efficiently. Recently we have proposed a new variant of LBP called Prominent LBP (PLBP) that captures a set of ULBPs and a set of NULBPs. To capture local and regional information of faces with a uniformity of region and sub-region size the present paper proposes MR-PLBP. In the proposed method, the average value of each sub-region is converted into the grey level value of neighboring pixels. That's why the proposed method is more robust. The proposed MR-PLBP with various variants of PLBP is different from the other multi-block approaches because they have used uniform and other variants of LBP features [20].

The present paper is organized as follows. Section 2 describes the related work. The section 3 and 4 presents the methodology and results and discussion. Section 5 presents the conclusions.

## 2. RELATED WORK

### 2.1. Local Binary Pattern (LBP)

In the original LBP, introduced by the Ojala [6] a thresholding process between the grey level values of the central pixel and each of the neighborhood pixels on a 3\*3 window converts the neighboring pixel values into a binary value. The binary weights are multiplied with the binary value and sum of these values results as LBP code or weight as shown in Figure 1.

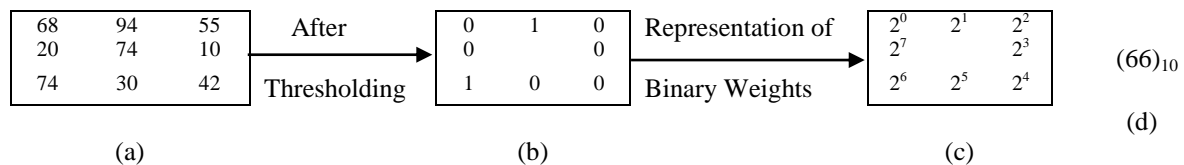


Figure 1. Representation of Basic LBP code (a) 3\*3 Neighborhood, (b) LBP Values after Thresholding, (c) Representation of LBP Weights, (d) LBP Code

The LBP Code can also be derived from the equation 1 [21]

$$LBP - Code = \sum_{i=0}^7 S(g_i - g_c) * 2^i \quad (1)$$

where  $g_i$  and  $g_c$  represent the grey level values of the neighboring and central pixel on a 3\*3 neighborhood,  $S$  represents the sign function, where

$$S(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

The Uniform Local Binary Pattern (ULBP) is derived on the LBP to improve the performance and to reduce overall features. The ULBP provides a majority of patterns: 90% for (8,2) type LBP; 70% for (16,2) type LBP [21], that's why they are treated as fundamental local texture properties of the image and researchers considered the NULBPs as miscellaneous. There will be 58 ULBPs and 198 NULBPs on a basic LBP i.e. (8, 1). This number of NULBPs increases drastically as we increase the size of the neighborhood or the number neighboring pixels.

### 2.2. Prominent Local Binary Pattern (PLBP)

Many researchers expressed their views on the capability of ULBP and NULBP in terms of texture image analysis, recognition etc., some researchers [21-25] explored extensively NULBP's and derived a few NULBP and ULBP in a feature vector and conducted experiments. H. Zhou et al. [23] suggested that ULBP alone do not describe the stochastic attributes of texture efficiently. As a result, texture primitive information

represented by these patterns is lost, especially when large neighborhoods are considered. This single pattern makes the uniform patterns sensitive to noise. An extended version of LBP operator (LBP extend) is also proposed in the literature [23], which tried to use more than one bin for describing non-uniform patterns and to reduce the effect of noise. Several other attempts were also made in the literature to use non-uniform patterns to overcome the limitation of the standard LBP [26-27], [9], [22], [13]. Some of the methods extracted rotation invariant non-uniform patterns [27], [9], [22].

The present research argues that some useful information can be obtained by using NULBPs. The major problem is what kind or type of NULBPs to be selected from the large set of NULBPs. So far there is no mechanism that derives the majority of the ULBPs and a few of NULBPs as one set. All the above researchers considered some NULBP in their own way. This has lead lot ambiguity. To overcome this ambiguity and to give a systematic way of selecting NULBPs the present paper utilized our previous derivation called Prominent Local Binary Pattern (PLBP) [8]. The interesting feature of PLBP is that it contains a set of ULBPs and NULBPs. The Prominent Local Binary Pattern (PLBP) considers the transition that occurs after two or more consecutive zeros immediately followed by two or more consecutive ones and vice versa, in a circular manner. For example, the LBP code 35 constitutes the PLBP and the LBP code 96 forms a Non Prominent Local Binary Pattern (NPLBP).

The PLBP contains a total of 92 patterns out of 256 of LBP on a  $(P,R)=(8,1)$ . The PLBP contains 40 ULBPs out of 58 and 52 NULBPs out of 198. This means the PLBP discards 18 ULBPs and 146 NULBPs into one label called "miscellaneous". For the efficient face recognition system, the present paper derived two variants of PLBP, namely Maximum Prominent Local Binary Pattern (MPLBP) formed from  $PLBP \cup ULBP$  and Small Prominent Local Binary Pattern (SPLBP) formed from  $PLBP \cap ULBP$  on facial images. The SPLBP and MPLBP contain a total of 40 and 110 patterns respectively on a  $3 \times 3$  neighborhood. The following Table 1 shows the relationship between various variants of LBP i.e. ULBP, NULBP, PLBP, NPLBP, MPLBP and SPLBP.

Table 1. Relationship between Various Variants of LBP

S. No.	BINARY PATTERN	DECIMAL VALUE	ULBP	NULBP	PLBP	NPLBP	MPLBP	SPLBP
1	00000000	0	√	X	X	√	√	X
2	00000110	6	√	X	√	X	√	√
3	00100011	35	X	√	√	X	√	X
4	00111110	60	√	X	√	X	√	√
5	01101111	111	X	√	X	√	X	X
6	10110001	177	X	√	√	X	√	X
7	11111011	251	√	X	X	√	√	X
8	11111111	255	√	X	X	√	√	X

The union of PLBP and ULBP ( $PLBP \cup ULBP$ ) contains a total of 110 patterns out of which 58 are ULBPs and 52 are NULBPs. This set is named as Maximum Prominent Local Binary Pattern (MPLBP) [8]. The MPLBP treats the remaining 146 NULBPs as a miscellaneous set. The intersection of PLBP and ULBP ( $PLBP \cap ULBP$ ) is named as the Smallest Prominent Local Binary Pattern (SPLBP) [8]. The SPLBP contains a total of 40 patterns out of which all 40 are ULBPs and it contains zero NULBPs. The SPLBP treats the remaining 216 LBPs (which contain 18 ULBPs and 198 NULBPs) as a miscellaneous set.

### 3. MULTI REGION PROMINENT LOCAL BINARY PATTERN (MR-PLBP)

The basic LBP operators with any  $(P, R)$  (where P corresponds to the number of neighboring pixels on a circle of radius of R) only capable of extracting features on small spatial neighborhood i.e. micro level features and thus they fail in capturing larger scale structures or macrostructures which are also dominant on faces. Further, the grey level comparison may prone to noise when differences of grey values of pixels are very small or equal [28-29]. To overcome this present paper proposes Multi Region- Prominent Local Binary Pattern (MR-PLBP). The main advantage of the MR-PLBP is the size of the block and sub-blocks are fixed (multiples of 3). The previous researchers derived only LBP or ULBP features are derived from multi blocks by treating all NULBPs of the region as miscellaneous. In the proposed MR-PLBP the size of the region is fixed as  $R \times S$  where R and S should be multiples of three. The region of size  $R \times S$  is subdivided into nine sub-regions of size  $N \times M$  where  $N=R/3$  and  $M=S/3$ . This gives the uniformity in the formation of MR-PLBP. The other advantage of the present method is it estimates the various variants of PLBP on multi regions.

The each multi region is represented by a single value and the value of each multi region is the average grey level value of the pixels of that sub-region. A binary code is derived from each sub-region by

comparing its value with the value of the middle sub- region. The circular bitwise transition of this sub- region neighborhood derives PLBPs on the multi region. The scalar values i.e. average pixel grey level values of each sub-region of size N\*M can be computed very efficiently from the integral image [30]. Therefore MR-PLBP features extraction process is very fast. However, it only incurs a little more cost when compared to basic LBP operator (8,1). Even as ‘P’ increases the basic LBP feature extraction becomes costlier. The basic parameters R and S of MR-PLBP influence the overall structure of the features. If R and S are small then MR-PLBP captures only the local features and when R and S are large (especially R and S>=9) the MR-PLBP captures both micro and macro structure features and especially the average grey level values of sub-regions N\*M overcomes the noise effect, makes MR-PLBP as robust, and provides large scale information in addition to micro level information. The MR-PLBP mechanism on a region size ‘S’ of 9\*9 is shown in Figure 2, the block sizes are 3\*3.

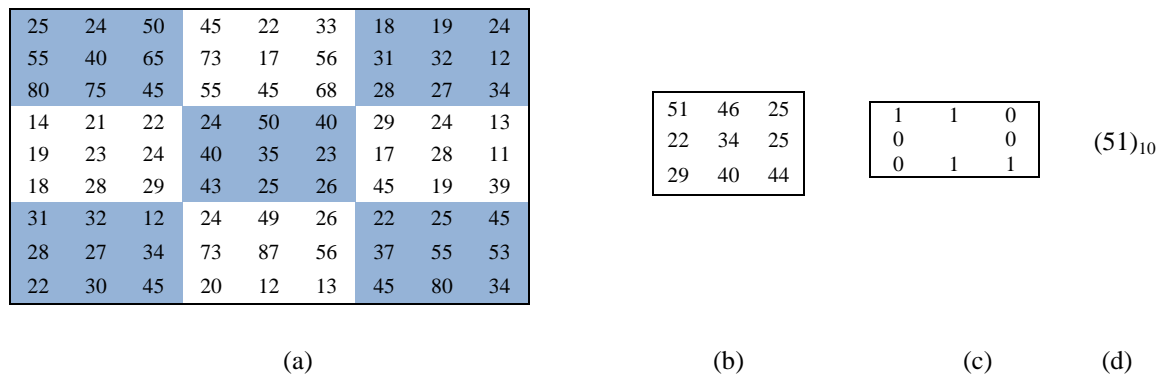


Figure 2. Multi Region Prominent Local Binary Pattern (MR-PLBP) Code Generation, (a) Division of Region of Size 9\*9 into ‘9’ Sub Regions of 3\*3 (b) Representation of Average Values of ‘9’ Sub-Region of 3\*3 (c) Representation r-Sub-Regions with Binary Values (d) MR-PLBP Code

The MR-PLBP code is evaluated in the same way as represented in Equation 1. The Figure 2 clearly shows the representation of large structures or macrostructures by MR-PLBP. The resulting binary patterns as features of MR-PLBP can detect diverse image structures such as lines, edges, spots, corners at different scale and location. There will be fewer numbers of MR-PLBP code features when compared to basic LBP. A basic LBP will generate (N-1)\*(M-1) LBP codes, whereas an MR-PLBP with a region size of R\*S generates a total number of (N\*M)/(R\*S) LBP codes in a non-overlapped manner.

#### 4. RESULTS AND DISCUSSION

The proposed MR-PLBP used three different databases i.e. Yale, Indian and AT&T ORL. The present paper considered 120 facial images out of 15 persons with 11 different facial expressions per person as training set from Yale database [31]. The present paper also considered 472 facial images as a training set from Indian database [32]. These 472 facial images correspond to 59 different individuals of both male and female, and on each individual 11 different expressions of Indian database. The present paper also considered 320 facial images as a training set from AT&T ORL database [33] for face recognition. The present paper performed experiments by considering two cases for test database.

Test Case 1: In case1 the remaining leftover facial images of the above three databases (which are not considered for the training set) are considered as test images. Test Case 2: In the second case the present paper considered the test images as a combination of leftover and training database images.

For efficient face recognition, the present paper evaluated histograms of LBP, ULBP, PLBP, MPLBP and SPLBP with different region sizes on each individual facial image and placed in the training database. In a similar way the above histograms are evaluated for test facial image and the face recognition is evaluated based on Chi-Square distance method as given in Equation 2.

$$R(d, t) = \min\left(\sum_{i=1}^n ((d_i - t_i)^2 / (d_i + t_i)) / 2\right) \tag{2}$$

where  $d, t$  are two image features (histogram vectors) and  $R(d,t)$  is the histogram distance for recognition.

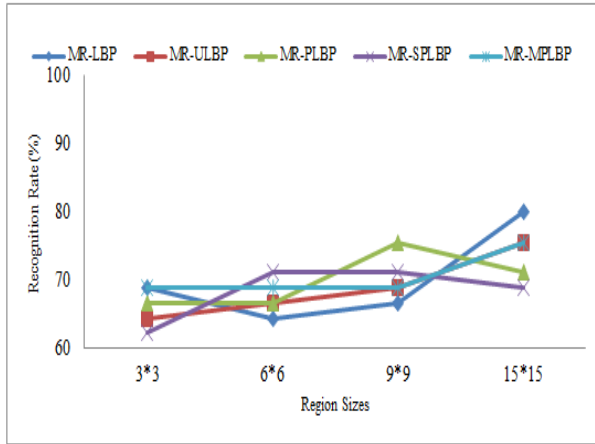


Figure 3. Face Recognition Rate for Yale Database for Test Case 1

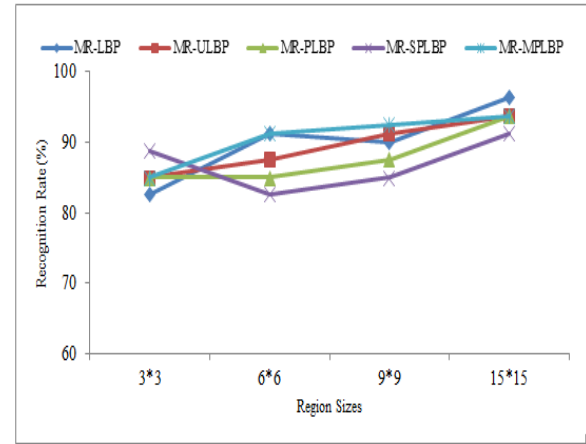


Figure 4. Face Recognition Rate for AT&T ORL Database for Test Case 1

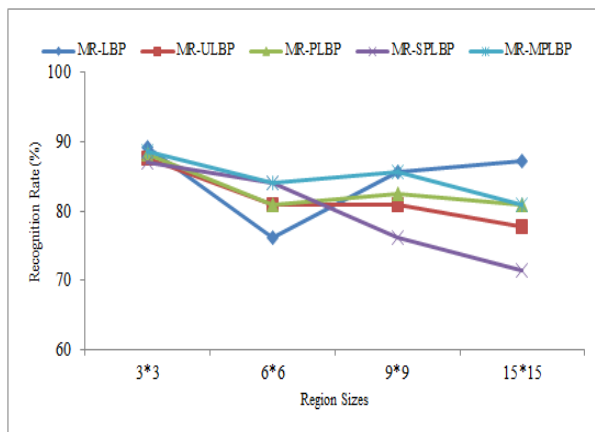


Figure 5. Face Recognition Rate for Indian Database for Test Case 1

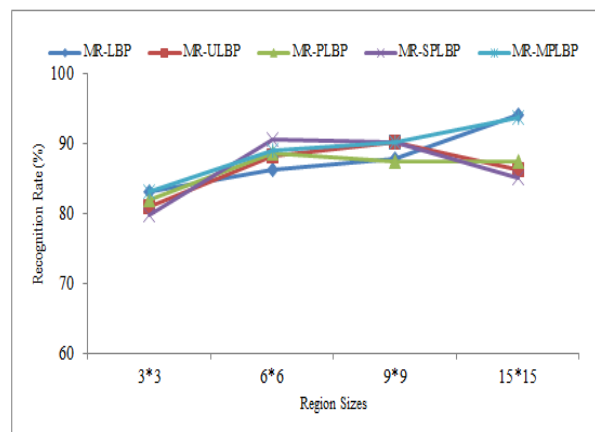


Figure 6. Face Recognition Rate for Yale Database for Test Case 2

The graphs of Figure 3, Figure 4, and Figure 5 shows the face recognition rate for Yale, AT&T ORL and Indian databases for Test Case 1 with different region sizes. The same is also represented in graphs of Figure 6, Figure 7 and Figure 8 for Test Case 2.

The following factors are noted down from the graphs of figures from Figure 3 to Figure 8. In the above graphs, the region size of 3\*3 represents the basic representation of LBP with (8, 1).

1. As the macro region increases the facial recognition rate increases slightly by the proposed MR PLBP and its variants i.e. MR-MPLBP and MR-SPLBP. This clearly reflects the fact that macro structure features are dominant in facial images and they are well captured by the proposed MR-PLBP, MR-SPLBP, and MR-MPLBP.

2. The face recognition rate for AT&T ORL and Indian databases are high when compared to Yale database for case 1 and case 2. This is because the Yale database is prone to noise and illumination effects.

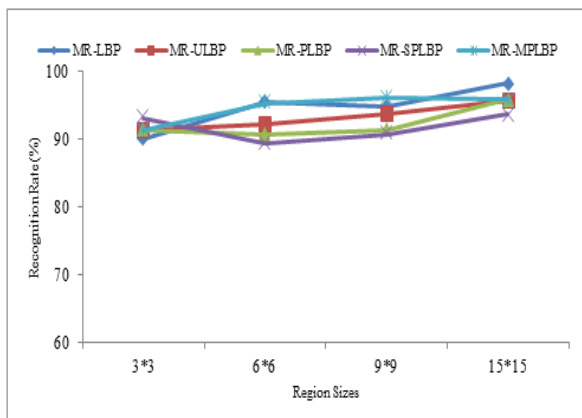


Figure 7. Face Recognition Rate for AT&T ORL Database for Test Case 2

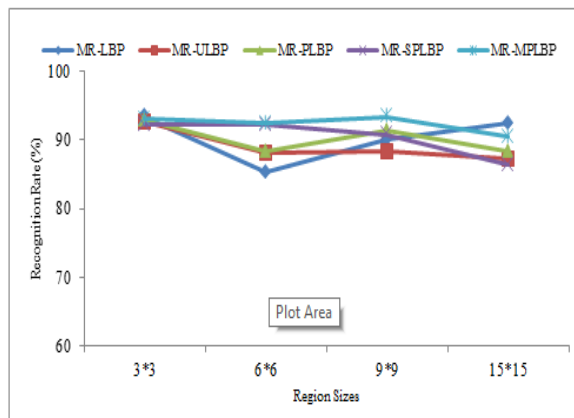


Figure 8. Face Recognition Rate for Indian Database for Test Case 2

## 5. CONCLUSIONS

In this paper, we proposed Multi Region Prominent Local Binary Pattern (MR-PLBP), MR-MPLBP and MR-SPLBP as a descriptor for face recognition to reflect the uniform appearance of the facial images. The Local Binary Pattern (LBP) is too local to be robust. Uniform patterns may not remain the same as those defined by Ojala et al [6] due to noise and they may not represent properly the stochastic information of textures. To describe fundamental and stochastic attributes efficiently, the present paper derived PLBP, MPLBP and SPLBP on the macro structures. Feature extraction for MR-PLBP is very fast using integral images. As the macro region increases the facial recognition rate increases slightly by the proposed MR-PLBP and its variants. This clearly reflects the fact macro structure features are dominant in facial images and they play a crucial role in face recognition than microstructure features. Moreover, our face recognition approach MR-SPLBP has shown very good performance on all databases with fewer uniform patterns and therefore it is more suitable for real time applications.

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