MODIFIED LOCAL BINARY PATTERN (MLBP) FOR ROBUST FACE RECOGNITION

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Keywords: Local binary patterns, Object recognition, Illumination invariance, Modified local binary pattern.

Abstract: This paper presents an improvement of Local Binary Pattern (LBP) for robust face representation under varying lighting conditions. Original LBP operator compares pixels in a local neighbourhood with the centre pixel and converts the resultant binary string to 8-bit integer value. So, it is less effective under difficult lighting conditions where variation between pixels is negligible. Our proposed MLBP uses two stage encoding procedure which is more robust in detecting this variation in a local patch. The performance of the proposed method is compared with the baseline LBP under different illumination conditions.

1 INTRODUCTION

Face recognition, although not a new area of research, still attracting a lot of researchers for its wide range of applications and the challenges that occur in real world environments. In practice, face images are obtained from different sources (ex. Facebook, Flickr etc) and at different times causing pose, appearance and illumination variations. So, a key challenge in face recognition problems is to find an efficient descriptor which is robust to these unconstrained conditions. Many face representation techniques have been proposed so far including Gabor feature (Liu and Wechsler, 2002); (Let et. al., 2011); (Yang and Zhang, 2010), principal component analysis (PCA) (Turk and Pentland, 1991), modified PCA (Gottumukkal and Asari, 2004), 2D PCA (Yang et. al., 2004), Fisher's linear discriminant analysis (FLDA) (Belhumeur et. al., 1997), independent component analysis (ICA) (Liu and Wechsler, 2003; Comon, 1994) etc. All these methods have been widely investigated and found to perform well under controlled settings.

Recently, local texture descriptor using LBP has been shown to be effective in face recognition (Tan and Triggs, 2010); (Ahonen et. al., 2006). It has been used in combination with other descriptors such as Gabor, histogram etc. (Zhang et. al., 2005); (Xie et. al., 2010) in order to improve recognition accuracy but a little attention is given to the improvement of original LBP operator. Zhao and Pietikäinen proposed volume local binary patterns (VLBP) for dynamic texture recognition which extracts textures in spatiotemporal domain by applying LBP in three orthogonal directions (Zhao and Pietikäinen, 2007). Another extension (Lei et. al., 2011) was conducted on Gabor face volume to explore the neighbouring relationship in spatial, frequency and orientation domains. Wolf et al. (Woolf et. al., 2010) proposed three-patch and four-patch LBP codes where the centre pixel in a 3×3 neighbourhood is encoded using 8 (for three-patch and 16 for four-patch) additional 3×3 patch and the distance between two patches is thresholded to estimate the corresponding bit value. Tan and Triggs (Tan and Triggs, 2010) quantized LBP to three levels namely local ternary patterns (LTP) in order to reduce noise effects in near uniform regions. All these methods perform well under small perturbation of lighting conditions.

The contribution of this paper can be summarised as follows: We propose a novel technique to improve conventional LBP coding which can better handle lighting variations. Any small change or uniform texture pattern (which is the case in difficult lighting conditions) can easily be detected using the proposed MLBP coding scheme and it is computationally efficient. Unlike other methods, we do not require any pre-processing to adjust illumination effects.

Moinul Islam M., K. Asari V., Nazrul Islam M. and A. Karim M..
MODIFIED LOCAL BINARY PATTERN (MLBP) FOR ROBUST FACE RECOGNITION.
DOI: 10.5220/0003678001470152
In *Proceedings of the International Conference on Neural Computation Theory and Applications* (NCTA-2011), pages 147-152
ISBN: 978-989-8425-84-3

2 LOCAL BINARY PATTERN

The LBP operator, introduced by Ojala et al. (Ojala et. al., 1996) is a powerful tool for texture description. It has been widely used in various recognition algorithms for its discriminative nature in texture classification. The LBP operator was originally defined for a 3×3 neighbourhood and 8-bit binary pattern which gives $2^8 = 256$ possible texture units. It takes a neighbourhood around each pixel and compares every pixel in the neighbourhood with its centre pixel. The result of the comparison is then thresholded to give a binary number which is given a particular weight based on its position in the neighbourhood. This gives an integer number of 8-bit LBP code around the centre pixel and is a local descriptor of that pixel.

The LBP coding of a 3×3 example patch with the centre pixel as threshold is shown in Figure 1.

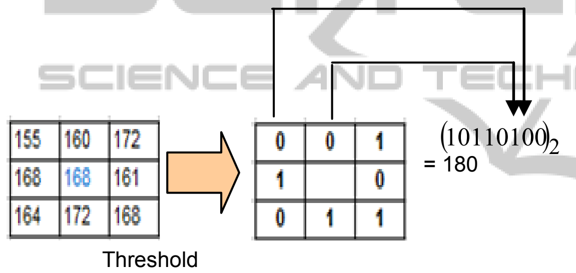


Figure 1: LBP encoding is shown for a 3×3 neighbourhood with the centre pixel as the threshold.

Mathematically, LBP operator can be described as (Ahonen et al., 2004).

$$L(p_k - p_c) = \begin{cases} 1, & p_k \geq p_c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

$$\text{LBP} = \sum_{k=0}^{7} 2^k L(p_k - p_c) \tag{2}$$

Where p_k where k = 0, 1, 2, ..., 7) represents neighborhood pixels and p_c is the center pixel of that neighborhood. The LBP pattern of the pixel is calculated by assigning a binomial factor 2^k for each $L(p_k - p_c)$. The LBP operator was later extended to different sizes of neighborhood in order to deal with textures at different scales (Ojala et. al., 2002). Another extension is the so-called uniform patterns (Zhao and Pietikäinen, 2007). A pattern is called uniform if it contains at most two bitwise transitions from '0' to '1' or vice versa in a circular fashion.

3 MODIFIED LOCAL BINARY PATTERN (MLBP)

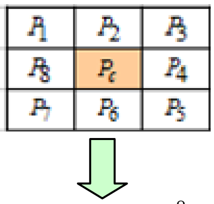
LBP operator has been successfully applied in many recognition applications for discriminative feature extraction. It has also proven its robustness in small change in lighting conditions. Since texture features are usually described by the relative change in pixel itensity with respct to its neighborhood and since LBP operator compares and thresholds the neighborhood pixels at exactly the center pixel, it can extract the texture feature when there are significant variations in image intensity. But in case of difficult lighting conditions (extreme dark or bright), there are small variations in a local neighborhood; i.e, the variance of a local patch is negligibly small and pixel intensity repeats itself. So, there is a tendency that a '0' is encoded as '1' or vice versa when compared with an image with neutral light settings. As a result, the bit error rate increases and decoded value differs significantly.

In order to overcome the problem of LBP operator, we propose a modified local binary pattern (MLBP). Our method uses two steps to encode the final pattern. First, we assign a status bit to each pixel based on its local neighbours. Then, these status bits are used to encode the LBP of the centre pixel. Figure 2 illustrates the proposed MLBP coding scheme. An input image is first converted to a binary status image. For each pixel we select a 3×3 (for MLBP3 and 5×5 for MLBP5) local neighbourhood and calculate absolute intensity differences of all the pixels within the patch with respect to the centre pixel. The sum of all deviations is denoted as total deviation (TD) for the centre pixel, P_c. Then we compare all the pixels in the patch with P_c and select those pixels which are equal or above the centre pixel. Now, deviation for these pixels are estimated and denoted as positive deviation (PD). The status bit of P_c is calculated as:

$$S_c = \begin{cases} 1, \text{ if } \text{PD} > \frac{1}{2}\text{TD} \\ 0, \text{ otherwise} \end{cases} \tag{3}$$

This gives us a binary status image where each bit is estimated based on its local neighbourhood. Now, this status image is taken as the input and a 3×3 neighbourhood is taken to calculate MLBP code. The MLBP code of the centre pixel is denoted using the status bits of all the neighbouring pixels as shown in Figure 2. Thus the value of the centre pixel is calculated by assigning a binomial factor as:

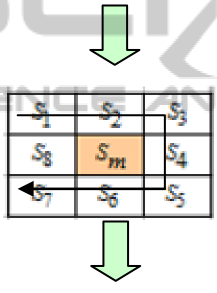
$$\text{MLBP} = \sum_{k=0}^{7} 2^k S_{k+1} \tag{4}$$



$$\text{Total deviation (TD)} = \sum_{i=1}^{8} \left| P_i - P_c \right|$$

$$\text{Positive deviation (PD)} = \sum_{\substack{k \in i \\ s.t\, P_k \geq P_c}} \left| P_k - P_c \right|$$

$$S_c = \begin{cases} 1, & \text{if PD} > \frac{1}{2}\text{TD} \\ 0, & \text{otherwise} \end{cases}$$



$$(S_8 S_7 S_6 S_5 S_4 S_3 S_2 S_1)_2$$

Figure 2: MLBP encoding; from left to right: a 3 x 3 neighbourhood for calculating the status bit of the centre pixel P_c, status bit calculation, MLBP code of centre pixel is calculated from the status bits of its neighbourhood.

In order to investigate robustness of the proposed method, we plot histograms of three segments extracted from three images of the same person with different lighting. We consider three white rectangle regions shown in Figures 3a, 3b and 3c to illustrate this and obtain their LBP and MLBP generated histograms and are shown in Figure 4. In Figure 3, image ‘a’ represents the most neutral lighting condition. Figure 4(a) shows original intensity plot of the images and they are at three different regions of the dynamic range of gray level. Figure 4(b) and Figure 4(c) plot histograms of their LBP and MLBP encoded images respectively. From the figures, we can see that LBP generated histograms are separated from each other significantly whereas their MLBP generated histograms resembles each other. We also measure this deviation quantitatively.

The L2-norm distances of image ‘b’ and image ‘c’ from image ‘a’ are calculated as 14.63 and 21.17 for LBP while it is more uniform in the case of MLBP, which are obtained as 12.65 and 12.73 respectively. Figures 3a to 3c show images of a person with three different lighting conditions and their LBP and MLBP images are depicted in Figure 3(d) and Figure 3(e) respectively.

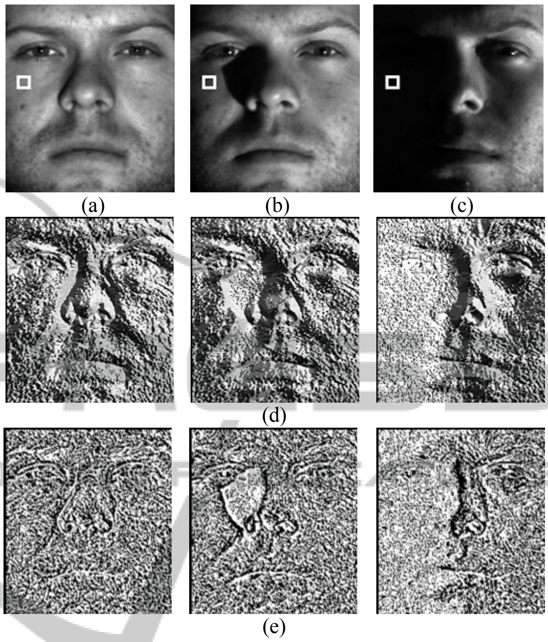


Figure 3: (a-c) An example image with three different illuminations and their corresponding (d) LBP image and (e) MLBP image.

4 EXPERIMENTAL ANALYSIS

In this section we illustrate the effectiveness of our proposed method on Extended Yale B database. The database contains 38 subjects under 64 illumination conditions. It has little variability in pose and expressions but its extreme lighting variations make it a difficult problem in face recognition. From the database we select 2413 images of 38 individuals. The images are cropped and resized to 36×30 pixels. We divide the database into two non-overlapping groups (group A and group B). Group A contains the subjects with odd numbered ID in total of 20 subjects and group B contains the remaining 18 subjects. For training purpose, we select two images from each subject which have the most neutral lighting conditions. We applied the proposed MLBP to each of the cropped face image and perform nearest neighbour (NN) classification in Euclidean space.

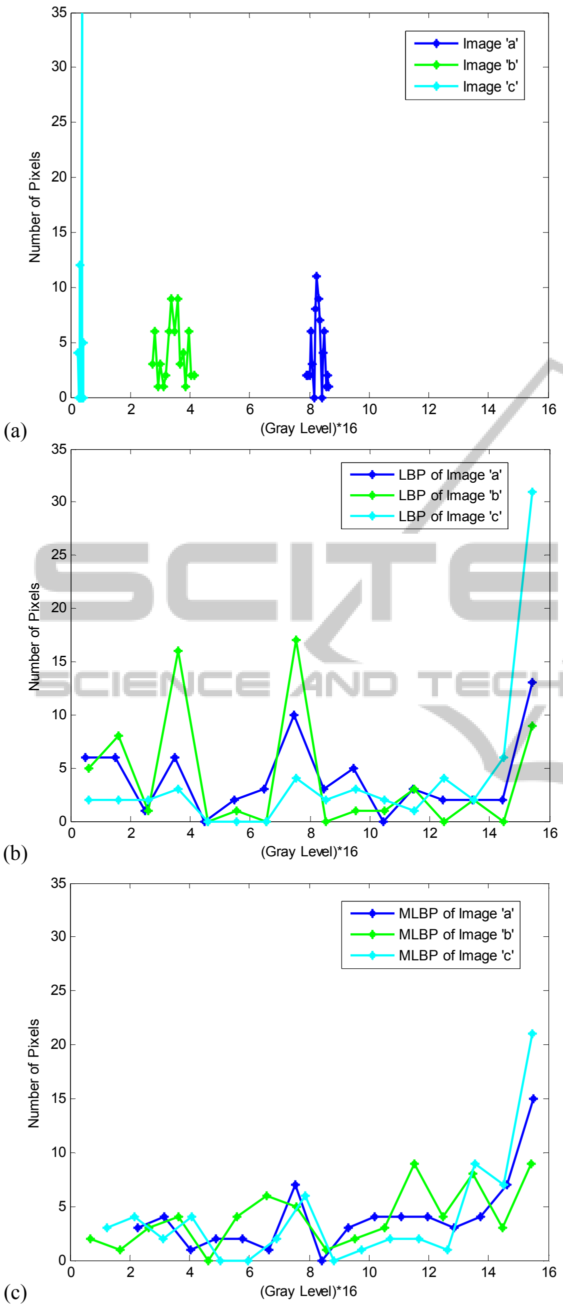


Figure 4: Histogram plot for three different illuminations (a) Original intensity histograms (b) histograms of LBP images and (c) histograms of MLBP images.

The experimental results are listed in Table 1. It shows that LBP has higher error rate than MLBP and increasing the neighbourhood size further improves recognition accuracy.

Table 1: Comparison of the Performance on Error Rate Using Yale B Database.

Method	**Error Rate**
LBP-NN	**0.14**
MLBP3-NN	**0.08**
MLBP5-NN	**0.05**

In this experiment we compare our MLBP approach with LBP operator for determining recognition accuracy at various illumination conditions. For this purpose, we divide the database into six subsets according to their azimuth angles (5°, 20°, 35°, 50°, 85° and 120°). The performance of LBP and MLBP algorithms are compared for each test image and the results are plotted in Figure 5. From the figure, we see that at small lighting variations both LBP and MLBP perform almost equally, but at strong lighting variations the performance of LBP degrades significantly.

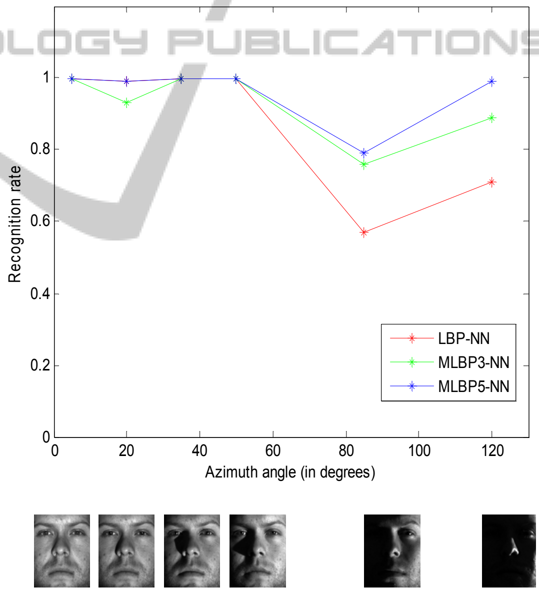


Figure 5: Performance comparison of LBP and MLBP with respect to variations of different illumination conditions.

At 85° and 120° our proposed method outperforms LBP by as much as 20%. In all these experiments MLBP5 shows better performance than both LBP and MLBP3. We also compare the performance of LBP and MLBP at various dimensionalities. Figure 6 is a plot of recognition accuracy with dimensionality (row × column). This indicates that the performance of MLBP is much better than LBP at reduced dimensions.

5 CONCLUSIONS

In this paper we present a new technique for image representation and feature extraction named modified local binary pattern (MLBP) which shows many advantages over original LBP approach. First, it is less sensitive to variations in lighting conditions. We conducted several experiments by changing lighting conditions and almost in all cases MLBP performed better than LBP in terms of recognition accuracy. Although in some experiments LBP showed better results but the difference is not significant and MLBP is more consistent in all cases. This is because LBP only compares with the centre pixel whereas MLBP uses two layer comparisons. It is noted that the recognition accuracy is improved in difficult lighting conditions based on the magnitude difference of each pixel from the centre pixel. MLBP considers this in every neighbourhood of a given pixel in a given patch. This was evident when we used MLBP5. It performed better than MLBP3. We only used two different neighbourhood size but it can also be used for different neighbourhood size although there will be maximum limit on recognition accuracy. In addition, MLBP has better recognition accuracy than LBP at reduced dimensions.

The objective of this paper is to improve the existing LBP method so that it is more robust in difficult lighting conditions. So, we use simple nearest neighbour classifier. The proposed MLBP method can also be combined with other feature extraction techniques to improve recognition accuracy.

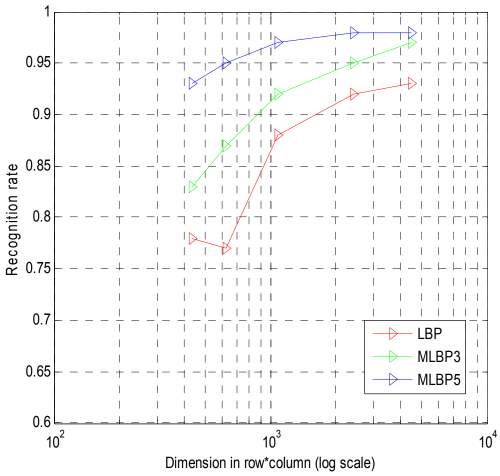


Figure 6: Performance comparison of LBP and MLBP with respect to dimensions in row*column vector.

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