QUANTIZED FUZZY LBP FOR FACE RECOGNITION

Jianfeng Ren

BeingThere Centre
Institute of Media Innovation
Nanyang Technological University
50 Nanyang Drive, Singapore 637553.

Xudong Jiang, Junsong Yuan

School of Electrical & Electronics Engineering
Nanyang Technological University
50 Nanyang Avenue, Singapore 639798

ABSTRACT

Face recognition under large illumination variations is challenging. Local binary pattern (LBP) is robust to illumination variation, but sensitive to noise. Fuzzy LBP (FLBP) partially solves the noise-sensitivity problem by incorporating fuzzy logic in the representation of local binary patterns. The fuzzy membership function is determined by both sign and magnitude of the pixel difference. However, the magnitude is easily altered by noise, hence could be unreliable. Thus, we propose to determine the fuzzy membership function by its sign only. We name the proposed approach as Quantized Fuzzy LBP (QFLBP). On two challenging face recognition datasets, it is shown more robust to noise, and demonstrates a superior performance to FLBP and many other LBP variants.

Index Terms— Fuzzy Local Binary Pattern, Quantized Fuzzy LBP, Face Recognition

1. INTRODUCTION

Face recognition has advanced significantly over last few years [1–3]. However, face recognition under large illumination variations is still challenging. LBP is popular in face recognition [3–6], as it is robust to monotonic illumination variations. LBP and its variants have also been widely used in other applications, e.g. texture classification [7, 8], dynamic texture recognition [9–11], human detection [12, 13] and others [14–19].

However, the performance of LBP is limited by its noise-sensitive problem [5, 6]. In [20], uniform LBP was proposed to reduce the noise in LBP histogram. In [8, 21, 22], information in non-uniform patterns was also used for classification. In dominant LBP, only the most frequently occurred patterns in a texture image were utilized [8]. Zhou et al. [21] and Fathi et al. [22] proposed to extract information from non-uniform patterns based on the number of ones in the LBP codes and a pattern-uniformity measure. Tan and Triggs proposed local ternary pattern (LTP) [5] to handle the image noise in a smooth image region. Subsequently, many LTP variants were proposed in the literature [15, 23, 24].

Instead of hard-coding the pixel difference, a probability measure is used in FLBP to represent the likelihood of a pixel difference to be encoded as “0” or “1”, e.g. a piecewisely linear fuzzy membership function in [7, 14] and a Gaussian-like membership function in [25]. After fuzzfication, a small image variation will only alter the FLBP histogram slightly compared with the LBP histogram. However, the membership is a function of the pixel difference, whose magnitude may be changed by noise easily. Thus, FLBP is still sensitive to noise.

Different from traditional FLBP that utilizes both sign and magnitude of the pixel difference, we determine the fuzzy membership function by the sign of the pixel difference only. Thus, even when a pixel difference is distorted by noise so that its magnitude changes significantly, as long as its sign does not change, its membership function remains the same. Thus, the proposed approach is more robust to noise than FLBP.

To validate the noise-robustness of the proposed approach, we first compare it with LBP, FLBP and many other LBP variants on the images of the CMU-PIE database [26] injected with uniform noise. We further conduct the comparison experiments on a challenging database: the extended Yale B dataset [27, 28]. On both datasets, the proposed approach consistently demonstrates a superior performance.

2. THE PROPOSED APPROACH

2.1. Problem Analysis of LBP and FLBP

LBP [20] encodes the pixel difference $z_p = i_p - i_c$ between a pixel i_c and its neighbor i_p. Each LBP bit is obtained as:

$$b_p = \begin{cases} 1 & \text{if } z_p \geq 0, \\ 0 & \text{if } z_p < 0. \end{cases} \tag{1}$$

LBP is sensitive to image noise. As shown in Fig. 1, a small noise causes the pixel difference encoded differ-

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ently. Ideally, such a smooth region should be encoded as "11111111". Due to noise, it is encoded as "01010111" instead.

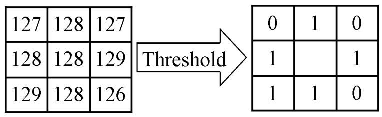


Fig. 1: Illustration of LBP encoding scheme for a smooth image region with a small image noise.

FLBP [7, 14, 25] partially solves this problem by introducing fuzzfication in the LBP encoding process. Instead of hard-coding the pixel difference as in Eqn. (1), a fuzzy membership function is used to represent the probability of z_p to be encoded as "0" or "1". Several membership functions were proposed in literature [7, 14, 25]. Among these, piecewisely linear fuzzy membership function [7] is most common:

$$f_{1,d}(z_p) = \begin{cases} 0 & \text{if } z_p < -d, \\ 0.5(1 + \frac{z_p}{d}) & \text{if } -d \le z_p \le d, \\ 1 & \text{if } z_p > d, \end{cases} \tag{2}$$

$$f_{0,d}(z_p) = 1 - f_{1,d}(z_p), \tag{3}$$

where $f_{1,d}(z_p)$ and $f_{0,d}(z_p)$ are the probabilities that pixel difference z_p should be encoded as "1" and "0", respectively. The parameter d controls the amount of fuzzfication.

The advantage of local binary pattern is its robustness to illumination variations, as it only encodes the sign of the pixel difference. However, it is sensitive to noise as a small noise may alter the code. FLBP solves the noise-sensitivity problem by fuzzifying the pixel difference so that a small image variation only alters the FLBP histogram slightly. However, the membership function defined in Eqn. (2) utilizes both magnitude and sign of the pixel difference. As the magnitude of a pixel difference is vulnerable to image noise, FLBP is still sensitive to image noise. In the next section, we introduce the proposed quantized FLBP, which is less sensitive to noise.

2.2. Proposed Quantized Fuzzy LBP

The small pixel difference is most vulnerable to image noise, whereas the large pixel difference is less affected by noise, i.e. a small image noise unlikely changes the sign of the large pixel difference. Thus, we treat them differently. Similarly as in FLBP, we encode the large positive pixel difference as "1" and large negative pixel difference as "0". We do not introduce fuzzfication to the large positive or negative pixel differences, e.g. the probability to encode a large positive pixel difference as "1" is 1.

The small pixel difference is tricky to handle. Traditional FLBPs [7,14,25] defined the membership function using both sign and magnitude of the pixel difference. As the magnitude can be easily altered by image noise, we propose to determine the membership function of a pixel difference using its sign only. Formally, we define the following membership function for the proposed quantized fuzzy LBP:

$$g_{1,d}(z_p) = \begin{cases} 1 & \text{if } z_p \ge d, \\ w & \text{if } z_p < d, z_p \ge 0, \\ 1-w & \text{if } z_p < 0, z_p > -d, \\ 0 & \text{if } z_p \le -d, \end{cases} \tag{4}$$

$$g_{0,d}(z_p) = 1 - g_{1,d}(z_p), \tag{5}$$

where $w \in [0.5, 1]$ is a pre-defined weight, which represents the likelihood that z_p to be encoded as 1 when the small pixel difference z_p is positive.

We plot the membership functions of FLBP [7,14] and the proposed QFLBP in Fig. 2. These two are clearly different. In traditional FLBP, $f_{1,d}(z_p)$ gradually increases with z_p for a small pixel difference. Any change in z_p will cause a change in $f_{1,d}(z_p)$. In contrast, a small image variation will not alter the membership function in the proposed QFLBP, as long as it does not change the sign of the pixel difference. Thus, the membership function of the proposed approach is invariant to the magnitude of the pixel difference, and purely determined by its sign. It is less sensitive to image noise than FLBP.

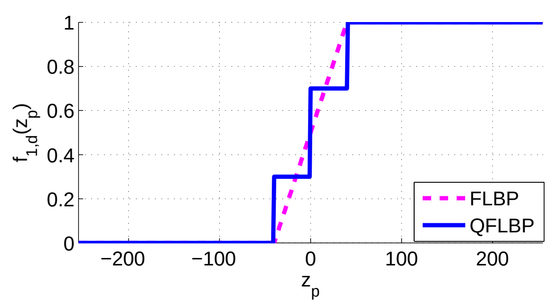


Fig. 2: Compare the membership functions of FLBP and proposed QFLBP.

Even an image variation does change the sign of the pixel difference, it will not alter the bit from "0" to "1" or vice versa, as LBP does. Instead, it only alters the probability $g_{1,d}(z_p)$ from w to $1 - w$ if the sign changes from positive to negative, or from $1 - w$ to w if the sign changes from negative to positive.

The proposed approach could flexibly handle different scenarios. If a small image variation may easily change the sign of pixel difference, e.g. in a smooth image region, we could assign w close to 0.5 so that it minimizes the cost of altering the sign. If an image variation is unlikely to change the sign, e.g. in a textured image region, we could assign a large weight w. If the noise level is low, we expect that the sign of pixel difference is reliable, and hence a small d is sufficient to handle the small image noise. On the other hand, we can handle large image noise by increasing d.

When constructing the QFLBP histogram, we calculate the probabilities of all 256 patterns as:

$$P_j = \prod_{i=0}^{7} c_i P_i^1(z) + (1-c_i)P_i^0(z), \quad (6)$$

where the LBP code $j = \sum_{i=0}^{7} c_i * 2^i$; c_i is *i-th* bit of the code; $P_i^1(z)$ and $P_i^0(z)$ are the probabilities that bit *i* should be encoded as *1* and *0*, respectively. The probabilities of all the pixels within one patch are summed up to form the QFLBP histogram of the patch.

3. EXPERIMENTAL RESULTS

The proposed QFLBP is compared with LBP [20], FLBP [7, 14], and other recent LBP variants, e.g. LTP [5], dominant LBP (DLBP) [8], novel extended LBP (NELBP) [21] and noise tolerant LBP (NTLBP) [22]. LBP and its variants utilize 8 neighbors at radius of 2 to the center pixel. We use the nearest-neighbor classifier with Chi-squared distance,

$$\chi^2(\mathbf{x}, \mathbf{y}) = \sum_{i,j} \frac{(x_{i,j} - y_{i,j})^2}{x_{i,j} + y_{i,j}}, \quad (7)$$

where $\mathbf{x}, \mathbf{y}$ are the concatenated LBP feature vectors of two image samples; $x_{i,j}$ and $y_{i,j}$ are j-th dimension of i-th patch, respectively.

We first conduct experiments on the CMU-PIE database [26] with injected uniform noise to validate the noise-resistant property of proposed approach. Then, we conduct experiments on the challenging extended Yale B database [27, 28]. The proposed approach demonstrates a superior performance compared with others. In order to reduce the illumination variations, all the images are pre-processed similarly as in [5]. We utilize the source codes provided by the authors of [5] to perform this photometric normalization.

3.1. Experimental Results on the CMU-PIE Database

The CMU-PIE database consists of over 40000 facial images of 68 subjects, with large variations in pose, illumination and facial expression. The illumination set is chosen for experiments, which contains 1407 images of 67 subjects.[1] Each subject has 21 images. We use only the image with frontal lighting (Image ID 08) as the gallery set and the rest with large illumination variations as the probe set. Beside the illumination variations, we inject additional uniform noise into the images. We normalize the image into $(0, 1)$, and add uniform noise $(-p/2, p/2)$ onto the image. We vary the noise level as $p = 0.1, 0.15, 0.2$. The sample images are shown in the first row of Fig. 3, and the photometrically normalized images are shown in the second row.

[1]The images of Subject 39 are not complete and hence excluded.

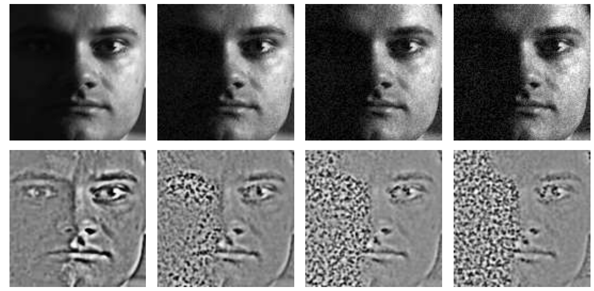


Fig. 3: The first row shows the sample images of CMU-PIE dataset with uniform noise $p = 0, 0.1, 0.15, 0.2$. The second row shows the photometrically normalized images.

The error rates of LBP, LTP, DLBP, FLBP and QFLBP are shown in Fig. 4. The proposed QFLBP consistently outperforms other approaches for all thresholds when $p = 0.1$ and $p = 0.2$, and for most thresholds when $p = 0.15$. We can also observe that the performance of QFLBP does not vary significantly with threshold, especially for $p = 0.1$ and $p = 0.2$.

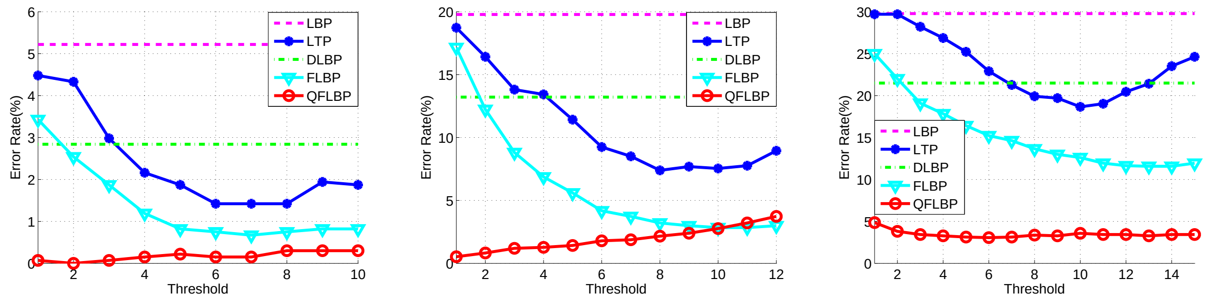
Method	$p = 0.1$	$p = 0.15$	$p = 0.2$
LBP [20]	5.22%	19.78%	29.78%
LTP [5]	1.42%	7.39%	18.66%
DLBP [8]	2.84%	13.21%	21.49%
NELBP [21]	27.76%	33.36%	47.84%
NTLBP [22]	24.70%	32.61%	47.76%
FLBP [7]	0.67%	2.84%	11.57%
Proposed QFLBP	**0.00%**	**0.52%**	**3.06%**

Table 1: The error rates under different noise settings for different approaches on the CMU-PIE database.

The performance of different approaches under optimal settings for different noise levels is summarized in Table 1. The proposed QFLBP achieves an error-free classification on this challenging dataset even with a low-level image noise. When the noise level increases, the performance of other approaches drops significantly, whereas the proposed QFLBP still preserves a very low error rate. For the most challenging setting $p = 0.2$, the proposed QFLBP reduces the error of FLBP from 11.57% to 3.06%. The proposed approach is shown more robust to noise than other approaches.

3.2. Experimental Results on the Extended Yale B Database

The extended Yale B database [27, 28] consists of images of 38 subjects under 9 poses and 64 illumination conditions. We use the same database partition as in [5]. The images with



(a) $p = 0.1$ (b) $p = 0.15$ (c) $p = 0.2$

Fig. 4: The error rate vs. threshold for different noise levels on the CMU-PIE database. The proposed QFLBP consistently outperforms others.

neutral light source ("A+000E+00") are used as the gallery set and all other frontal images are used as the probe set. In total, we have 2414 images of 38 subjects. The database contains large illumination variations. Some sample images are shown in Fig. 5. Even after photometric normalization, the images still contain a large amount of noise.

Fig. 5: Sample images and photometrically normalized images of the extended Yale B database.

Method	Error Rate
LBP [20]	3.40%
LTP [5]	2.60%
DLBP [8]	4.34%
NELBP [21]	20.38%
NTLBP [22]	20.97%
FLBP [7]	1.55%
Proposed QFLBP	**1.13%**

Table 2: The lowest error rate at optimal threshold for different approaches on the extended Yale B database.

The error rates for different approaches at different thresholds are shown in Fig. 6. The proposed QFLBP consistently outperforms others, and its performance does not vary significantly for different thresholds. The lowest error rate at the

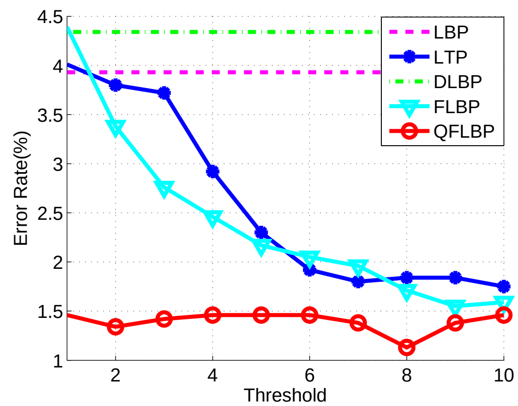


Fig. 6: Error rates for different approaches at different thresholds on the extended Yale B database.

optimal thresholds is summarized in Table 2. The lowest error rate is only 1.13% for the proposed QFLBP.

4. CONCLUSION

In this paper, we address the challenge of improving the robustness to image noise. LBP is popular in face recognition as it is robust to illumination variations. However, it is sensitive to noise. FLBP partially solves this problem by introducing fuzzfication to LBP encoding process. However, its membership function utilizes both sign and magnitude of a pixel difference. As the magnitude is easily altered by noise, we propose to determine the membership function using the sign only. The proposed approach is validated on two challenging face databases, and shown more robust to noise than LBP, FLBP and other recent LBP variants. The performance gain is more significant when the noise level is high. Furthermore, the performance of QFLBP is insensitive to the threshold.

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