LBP Encoding Schemes Jointly Utilizing the Information of Current Bit and Other LBP Bits

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***Abstract*—Local binary pattern (LBP) is sensitive to image noise. Noise-resistant LBP (NRLBP) improves the robustness to noise by incorporating the prior knowledge of images and information of other LBP bits into encoding process. However, it encodes the small pixel difference in such a way that its sign and magnitude are ignored. Although the small pixel difference may be easily distorted by noise, some of its information is still useful for LBP encoding. In this letter, we propose two enhanced NRLBPs that jointly utilize the sign and the magnitude of the current pixel difference, and also the information of other LBP bits. The proposed approaches are validated on two benchmark databases and demonstrate a superior performance compared with NRLBP and other LBP variants. The performance gain is significant when the noise level is high.**

***Index Terms*—Noise-Resistant Local Binary Pattern, NRLBP+, NRLBP++, Face Recognition**

I. Introduction

LOCAL binary pattern (LBP) encodes the sign of the pixel differences between a pixel and its P neighbors. The histogram of LBP codes is often used as the feature descriptor. Fig. 1 illustrates the LBP feature extraction process. LBP is popular because of its simplicity and robustness to illumination variations and alignment error. LBP and its variants have been widely used in face recognition [1]–[4], texture classification [5]–[7], dynamic texture recognition [8]–[10], human detection [11], [12] and many others [13]–[18].

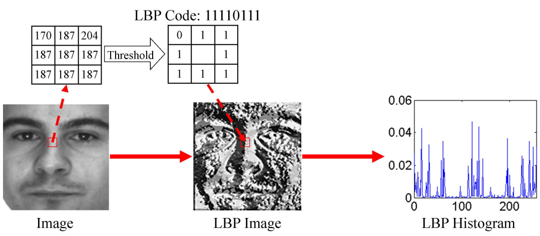

Fig. 1. Illustration of the feature extraction process for LBP.

However, LBP is sensitive to image noise [2], [3]. A small image variation may alter the LBP code. To tackle this problem, many approaches were proposed in literature. In [5], uniform patterns were proposed to capture image structures and noisy non-uniform patterns were grouped into one bin to suppress the noise. In dominant LBP (DLBP) [7], the most frequently occurred patterns were utilized instead of uniform patterns. Tan and Triggs proposed local ternary pattern (LTP) [2] to handle the image noise in a smooth image region. Subsequently, many LTP variants were proposed [19]–[21]. Instead of hard-coding the pixel difference, a probability measure is used in fuzzy LBP (FLBP) to represent the likelihood of a pixel difference to be encoded as "0" or "1", e.g. a piecewisely linear membership function in [6], [22] and a Gaussian-like membership function in [23]. After fuzzfication, an image variation will only slightly alter the FLBP histogram.

One limitation of the aforementioned approaches is that when encoding an LBP bit, only the sign and the magnitude of the current pixel difference are considered, and the information of other LBP bits is ignored. To address this issue, noise-resistant LBP (NRLBP) [3] utilizes the information of other bits when encoding the small pixel difference, towards the objective of forming image micro-structures, i.e. uniform patterns. When there are more than one possible uniform code, each code is assigned an equal weight to the histogram regardless the sign and the magnitude of the small pixel difference. As the small pixel difference is vulnerable to image noise, its sign and magnitude are unreliable, and hence discarded during the encoding of the current small pixel difference.

NRLBP incorporates the information of other bits and the prior knowledge of images into encoding process, and hence demonstrates a superior performance [3]. However, it ignores the sign and the magnitude of the current small pixel difference during encoding. This information can be also useful. Especially when a large threshold is used for high-level noise [3], the magnitude of the pixel difference below the threshold may not be that small, and hence its sign and magnitude play an important role in LBP encoding. In view of this, we propose two improved versions of NRLBP: NRLBP+ that utilizes the sign of the small pixel difference and NRLBP++ that utilizes both the sign and the magnitude of the small pixel difference. Besides, both approaches utilizes the information of other bits to form image micro-structures, in the same way as in NRLBP. As more information is utilized, the proposed approaches achieve a better performance than NRLBP [3].

LBP features have been extensively used in face recognition. To validate the proposed approaches, we compare them with other LBP variants on the AR database [24] injected with noise, and the challenging O2FN database [25]. On both databases, the proposed approaches consistently demonstrate a superior performance using three different distance measures.

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II. The Proposed Approach

A. Problem Analysis of Noise-Resistant Local Binary Pattern

Local binary pattern is sensitive to noise. A small image variation may alter the LBP bit from "0" to "1" or vice versa. Local ternary pattern partially resolves this problem by encoding the small pixel differences into a separate state. However, both LBP and LTP lack a mechanism to recover the distorted patterns. In [3], a noise-resistant local binary pattern with an embedded error-correction mechanism was proposed. As the small pixel difference is vulnerable to noise, it is encoded as the uncertain bit. Mathematically, the pixel difference z between a neighbor and its center is encoded as:

$$b = \begin{cases} 1 & \text{if } z \geq t, \\ X & \text{if } |z| < t, \\ 0 & \text{if } z \leq -t. \end{cases} \tag{1}$$

where state X represents the uncertain state, and t is a threshold. The uncertain bit is constrained to either "0" or "1", represented by a variable $x_i \in \{0,1\}, i = 1, 2, \ldots, n$, where n is the number of uncertain bits of an LBP code. For the certain code that does not have an uncertain bit, $n = 0$. The uncertain code is represented by a function $C(\mathbf{X})$, where $\mathbf{X} = (x_1, x_2, \ldots, x_n)$. Then, the uncertain bits are determined using other certain bits to form image micro-structures. In [5], it is shown that uniform codes represent image micro-structures while non-uniform codes represent noisy patterns. Thus, the uncertain bits are determined so as to form only uniform codes. Mathematically, let Φ_u denote the collection of all uniform codes. Based on the function $C(\mathbf{X})$, a set of NRLBP codes are generated as:

$$\mathbb{S} = \{C(\mathbf{X}) | \mathbf{X} \in \{0,1\}^n, C(\mathbf{X}) \in \Phi_u\}. \tag{2}$$

If the number of elements m in $\mathbb{S}$ is more than 1, each element is treated equally and each corresponding histogram bin is added by an equal weight of $1/m$. The small pixel difference is easily distorted by noise. Both its sign and magnitude are unreliable, and hence discarded during encoding. The small pixel difference is encoded solely based on other certain bits. As shown in [3], such an encoding scheme is robust to image noise and able to recover the distorted image micro-structures.

B. Proposed NRLBP+ and NRLBP++

In NRLBP, the small pixel difference $z \in (-t, t)$ is encoded as an uncertain bit regardless its sign and magnitude, as it is easily distorted by noise. However, the small pixel difference still carries certain useful information. This information becomes more important when the noise level is higher and a higher threshold t is applied. As shown in [3], a large threshold t is often needed to handle high-level image noise. In such a case, the pixel difference $z \in (-t, t)$ could differ largely from each other. To take account of the information of the uncertain bit, we propose two LBP-encoding schemes that jointly utilize the information of both certain bits and uncertain bits.

In the proposed NRLBP+ and NRLBP++, the pixel difference is encoded in the same way as in Eq. (1), and a set of NRLBP codes are generated using Eq. (2). Similarly as in NRLBP, the proposed approaches only form possible uniform codes by utilizing the information of other certain codes. Different from NRLBP in which an equal weight is assigned to each possible uniform code when constructing the histogram, in the proposed approaches the weights are assigned according to the information of the small pixel difference.

In the proposed NRLBP+, we assign the weight of each possible uniform code according to the sign of small pixel difference. Intuitively, when forming possible uniform codes, the uncertain bits corresponding to positive pixel difference should have a larger probability to be encoded as "1", and the uncertain bits corresponding to negative pixel difference should have a larger probability to be encoded as "0". Mathematically, we define the probability of the small pixel difference z_i to be encoded as "1" as:

$$f(z_i) = 0.5(1 + q \operatorname{sgn}(z_i)) \text{ for } |z_i| < t, \tag{3}$$

where $\operatorname{sgn}(z_i)$ is a sign function, i.e. $\operatorname{sgn}(z_i) = 1$ if $z_i > 0$, $\operatorname{sgn}(z_i) = 0$ if $z_i = 0$ and $\operatorname{sgn}(z_i) = -1$ if $z_i < 0$. $q \in [0, 0.5]$ is a small positive constant, which weighs the importance of the sign information. If $q = 0$, NRLBP+ is degraded to NRLBP. A larger q indicates a higher importance of the sign information. The optimal q is task-dependent. In this letter, q is set to 0.2 based on initial experimental results.

Now let us construct the histogram of NRLBP+ for a local image patch. If $m = 0$, no uniform codes can be formed, and hence the non-uniform bin is added by 1. If $m > 0$, the relative contributions of different codes $C(\mathbf{X}) \in \mathbb{S}$ to the histogram are determined as follows:

$$W(\mathbf{X}) = \prod_{i=1}^{n} \left(x_i f(z_i) + (1 - x_i)(1 - f(z_i)) \right), \tag{4}$$

where x_i is the *i*-th uncertain bit of the uncertain code $C(\mathbf{X})$. The summation $\sum_{C(\mathbf{X}) \in \mathbb{S}} W(\mathbf{X})$ is in general not equal to 1. Thus, we normalize the weight as:

$$W^N(\mathbf{X}) = \frac{W(\mathbf{X})}{\sum_{C(\mathbf{X}) \in \mathbb{S}} W(\mathbf{X})}. \tag{5}$$

This process is repeated for every pixel in the patch to generate the histogram of NRLBP+.

Now we introduce the proposed NRLBP++ that utilizes both the sign and the magnitude of the uncertain bits. Intuitively, the uncertain bit corresponding to a larger positive pixel difference should have a larger probability to be encoded as "1". Mathematically, we define the probability of small pixel difference z_i to be encoded as "1" as:

$$f'(z_i) = 0.5(1 + \frac{z_i}{t}) \text{ for } |z_i| < t. \tag{6}$$

Note that this probability depends on both the sign and the magnitude of z_i. When constructing the histogram of NRLBP++, the contribution of each NRLBP code to the histogram is derived using Eqs. (4) and (5), where f' from Eq. (6) is used in Eq. (4) instead of f from Eq. (3).

Algorithm 1 summarizes the procedures to construct the histogram of NRLBP+ and NRLBP++. As shown in Algorithm 1, these two approaches differ only in the weights of possible uniform codes to the histogram.

Algorithm 1 Histogram construction for the proposed NRLBP+ and NRLBP++

for Every pixel in a patch **do**
  Derive the NRLBP bits according to Eq. (1).
  if $n = 0$ **then**
    Accumulate the bin of the certain code by 1.
  else
    Search uncertain codes $C(\mathbf{X})$ in the space $\{0,1\}^n$ to generate a set of m NRLBP codes $\mathbb{S}$ as in Eq. (2).
    if $m = 0$ **then**
      Accumulate the non-uniform bin by 1.
    else
      Derive the weight of each code in $\mathbb{S}$ to the histogram using Eqs. (3), (4), (5) for NRLBP+, or using Eqs. (6), (4), (5) for NRLBP++, respectively.
    end if
  end if
end for

It is clear that the proposed NRLBP+ and NRLBP++ are different from NRLBP. In NRLBP, when determining the value of an uncertain code, only other certain bits are considered and the information of the uncertain bits is discarded. In the proposed NRLBP+ and NRLBP++, the information of the uncertain bits is also utilized for LBP encoding. Especially when the noise level is high and a large threshold is applied, the sign and the magnitude of the pixel difference below the large threshold are significantly beneficial to LBP encoding, despite the fact that they may be distorted by noise.

We briefly discuss the time complexity here. LBP [5], LTP [2] and DLBP [7] have a time complexity of $O(n_I P)$, and NRLBP [3] has a time complexity of $O(n_I(P + m))$, where n_I is the number of pixels in an image. Due to the histogram calculation in Eq. (4), the proposed NRLBP+ and NRLBP++ have a higher time complexity of $O(n_I nm)$, but it is lower than that of FLBP, i.e. $O(n_I P \times 2^P)$. Note that $n \leq P$ and $m < 2^P$.

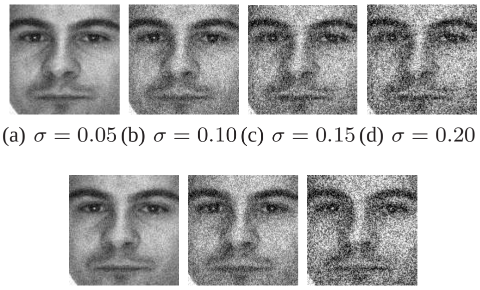
III. Experimental Results

We compare the proposed approaches with LBP [5], LTP [2], DLBP [7], FLBP [6] and NRLBP [3] on the AR database [24] injected with Gaussian noise and uniform noise, and the O2FN database [25]. All images are normalized to 128×128 pixels, and divided into patches of 10×10 pixels. We use the nearest-neighbor classifier with three distance measures: Chi-square distance, histogram intersection and modified G-statistic, same as in [3]. One image per subject is used as the gallery set and others are used as the probe set.

A. Face Recognition on the AR Database

The AR database is of high image quality, almost without image noise. In total, 75 subjects are chosen from the AR database, each with 14 images. The experiments are repeated 6 times. For each trial, we use image 1, 5, 6, 8, 12, 13 of each subject as the gallery set, respectively. The rest is used as the probe set. It is a challenging task as face images of large variations need to be identified using a single image.

1) Resistant to Additive Gaussian Noise: Gaussian noise is one of the most common types of noise. The images are normalized in the range of $[0, 1]$, and injected with additive Gaussian noise of zero mean and standard derivation $\sigma = 0.05, 0.10, 0.15, 0.20$. The sample images are shown in Fig. 2.



(a) $\sigma = 0.05$ (b) $\sigma = 0.10$ (c) $\sigma = 0.15$ (d) $\sigma = 0.20$

(e) $p = 0.2$ (f) $p = 0.4$ (g) $p = 0.7$

Fig. 2. Sample images of the AR database with Gaussian noise $\sigma = 0.05, 0.10, 0.15, 0.20$ and uniform noise $p = 0.2, 0.4, 0.7$, respectively.

LTP, NRLBP, NRLBP+ and NRLBP+ have one free parameter: threshold t, and FLBP also has one free parameter: fuzzification d. To study the effect of t (or d), we plot the recognition rates vs. t (or d) using Chi-square distance, as shown in Fig. 3. LBP and DLBP are plotted in dashed lines. At the low noise level, the proposed approaches slightly outperform NRLBP and DLBP, and significantly outperform LBP and FLBP. The proposed NRLBP+ achieves a slightly better performance than NRLBP++ when $t \leq 6$. When the noise level increases, LBP, LTP and DLBP fail to work, whereas FLBP, NRLBP, NRLBP+ and NRLBP++ can still achieve fairly good recognition rates if proper thresholds are applied. The optimal threshold for FLBP, NRLBP, NRLBP+ and NRLBP++ increases as the noise level increases. The proposed approaches consistently outperform FLBP for different noise levels at different thresholds, and outperform NRLBP for most thresholds. The performance gain is more significant when the noise level is high.

Table I summarizes performance comparison with others at the optimal threshold. The proposed approaches consistently outperform others under different noise levels using three distance measures. The performance gain over NRLBP is more than 10% at the high noise level. At the low noise level, NRLBP+ achieves a better performance than NRLBP++ as the magnitude of the small pixel difference is easily distorted by noise. On the other hand, when the noise level increases, the proposed NRLBP++ outperforms NRLBP+. This is because a larger threshold is needed at the higher noise level, and hence the magnitude of the pixel difference below the threshold becomes more significant in LBP encoding.

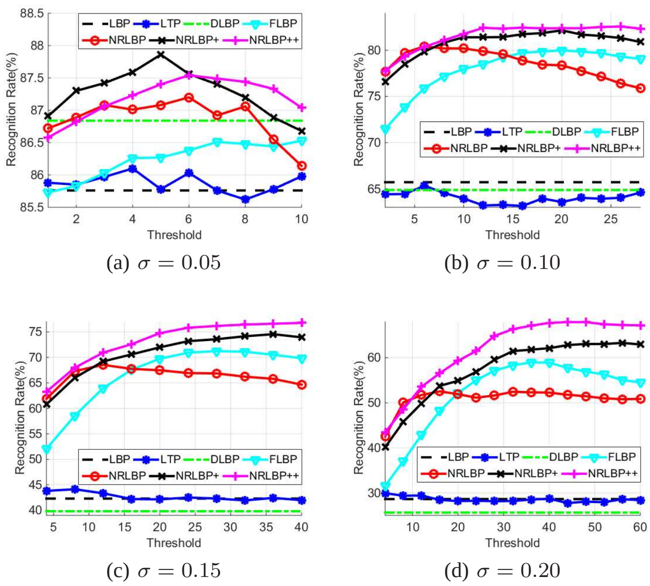
2) Resistant to Additive Uniform Noise: We also conduct experiments on the AR database injected with additive uniform noise in the range of $(-p/2, p/2)$, e.g. $p = 0.2, 0.4, 0.7$. The sample images are shown in the second row of Fig. 2. The performance comparison is shown in Table II. At the low noise level, the proposed NRLBP+ consistently achieves the best performance. At the middle and high noise levels, the proposed NRLBP++ consistently achieves the best performance.

TABLE I
COMPARISON OF RECOGNITION RATES AT THE OPTIMAL THRESHOLD ON THE AR DATABASE INJECTED WITH GAUSSIAN NOISE.

Algorithm	Chi-square Distance, $\sigma =$				Histogram Intersection, $\sigma =$				Modified G-Statistics, $\sigma =$			
	0.05	0.10	0.15	0.20	0.05	0.10	0.15	0.20	0.05	0.10	0.15	0.20
LBP [5]	85.76%	65.71%	42.29%	28.62%	83.61%	55.52%	34.77%	26.41%	81.35%	57.74%	36.00%	23.42%
LTP [2]	86.10%	65.33%	44.56%	29.98%	83.47%	54.74%	37.40%	27.98%	82.77%	63.21%	40.26%	25.97%
DLBP [7]	86.84%	64.87%	39.81%	25.62%	87.18%	61.52%	37.95%	26.22%	84.92%	61.26%	32.50%	15.83%
FLBP [6]	86.53%	79.98%	71.42%	59.06%	86.14%	74.21%	58.19%	43.91%	84.38%	76.85%	68.75%	57.62%
NRLBP [3]	87.20%	80.41%	68.53%	52.53%	88.14%	78.68%	64.97%	52.91%	86.63%	79.52%	67.59%	52.36%
Proposed NRLBP+	**87.86%**	**82.15%**	**74.55%**	**64.24%**	**88.60%**	**81.93%**	**73.79%**	**62.72%**	**86.85%**	**81.76%**	**74.05%**	**63.73%**
Proposed NRLBP++	**87.54%**	**82.56%**	**76.82%**	**67.91%**	**88.27%**	**83.15%**	**74.51%**	**65.33%**	**86.65%**	**81.93%**	**75.91%**	**67.03%**

TABLE II
COMPARISON OF RECOGNITION RATES AT THE OPTIMAL THRESHOLD ON THE AR DATABASE INJECTED WITH UNIFORM NOISE.

Algorithm	Chi-square Distance, $p =$			Histogram Intersection, $p =$			Modified G-Statistics, $p =$		
	0.2	0.4	0.7	0.2	0.4	0.7	0.2	0.4	0.7
LBP [5]	84.00%	55.81%	25.50%	79.26%	46.67%	24.12%	79.79%	48.80%	20.89%
LTP [2]	84.79%	63.44%	30.02%	80.31%	49.38%	24.74%	80.96%	55.86%	24.91%
DLBP [7]	84.84%	56.00%	24.79%	83.38%	50.22%	24.39%	81.21%	45.56%	8.92%
FLBP [6]	82.87%	77.37%	56.14%	82.65%	70.39%	41.59%	80.55%	74.10%	54.56%
NRLBP [3]	86.44%	77.73%	49.88%	**87.38%**	74.12%	47.52%	**85.64%**	75.64%	49.16%
Proposed NRLBP+	**86.75%**	**79.86%**	**59.97%**	**87.49%**	**78.65%**	**56.34%**	**85.83%**	**79.20%**	**59.32%**
Proposed NRLBP++	**86.46%**	**80.97%**	**66.82%**	87.35%	**80.72%**	**60.09%**	85.30%	**80.12%**	**65.81%**



(a) $\sigma = 0.05$ (b) $\sigma = 0.10$

(c) $\sigma = 0.15$ (d) $\sigma = 0.20$

Fig. 3. The recognition rates using Chi-square distance vs. threshold on the AR database injected with Gaussian noise $\sigma = 0.05, 0.10, 0.15, 0.20$.

Particularly, the proposed approaches significantly outperform NRLBP and other LBP variants at the high noise level.

B. Face Recognition on the O2FN Mobile Database

The O2FN mobile face database [25] was designed to evaluate face-recognition algorithms on images of low resolution and low image quality. It contains 2000 images of 50 subjects. The images are severely distorted by noise. To reduce the noise, the images are photometrically normalized as in [2]. We conduct the comparison experiment and repeat it for 5 times. For each trial, we randomly choose one image of each subject as the gallery images and the rest as the probe images. The recognition rates at the optimal threshold and the time consumption for feature extraction per image are reported in Table III. All approaches are implemented using Matlab R2015a on Intel®Core$^{\text{TM}}$2 i7-3770 CPU @ 3.4GHz with 8Gb memory. The proposed NRLBP+ and NRLBP++ achieve a slightly better performance than NRLBP and FLBP, and a much better performance than LBP, LTP and DLBP using three distance measures.

TABLE III
COMPARISON OF RECOGNITION RATES AND TIME CONSUMPTION ON THE O2FN DATABASE.

Algorithm	Chi-square Distance	Histogram Intersection	Modified G-Statistics	Time (ms)
LBP [5]	74.55%	71.75%	73.65%	**10.59**
LTP [2]	77.32%	74.44%	76.82%	16.90
DLBP [7]	76.11%	77.51%	75.64%	18.86
FLBP [6]	79.29%	77.39%	79.14%	100.42
NRLBP [3]	78.78%	78.46%	79.03%	11.71
Proposed NRLBP+	**79.52%**	**79.30%**	**79.86%**	54.50
Proposed NRLBP++	**80.34%**	**79.87%**	**80.27%**	54.03

IV. CONCLUSION

In this letter, we address the challenge of improving the robustness of LBP features to image noise. LBP is popular in face recognition, but it is sensitive to noise. NRLBP improves the robustness by incorporating the information of other bits into the encoding of small pixel difference. However, the small pixel difference is encoded without considering the information of itself. We show that this information is also useful and develop NRLBP+ and NRLBP++, which jointly utilize the information of certain bits and uncertain bits of an LBP code. The proposed approaches are validated by image matching using three distance measures on two benchmark face image datasets, and demonstrate a superior performance compared with NRLBP and other LBP variants. The performance gain is significant at the high noise level.

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