Weber Binary Pattern and Weber Ternary Pattern for Illumination-Robust Face Recognition

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***Abstract*—Local ternary pattern (LTP) is a noise-robust version of local binary pattern (LBP). They are both encoding for the differences between the intensity of the center pixel and its neighborhoods. In this paper, based on Webers law we propose two new local descriptors, named Weber binary pattern (WBP) and Weber ternary pattern (WTP), which utilize binary and ternary encoding separately for the evaluation of the relative local gray-scale difference. While sharing the merits of computational simplicity and noise tolerance embedded in LBP and LTP, WBP and WTP are more illumination-robust and can be regarded as adaptive versions of LBP and LTP. Experimental results in Extended Yale-B face database demonstrate the effectiveness of the proposed WBP and WTP in illumination-robust face recognition.**

I. Introduction

As one of the most successful biometric technologies, face recognition has recently attracted a lot of researchers and has a range of applications in the field of entertainment, information security, smart cards, law enforcement and surveillance [1]. Though tremendous advance has been achieved during the last decades, illumination-robust face recognition is still challenging in automatic face recognition [2] [3].

In recent years, a number of face recognition approaches with illumination invariant have been proposed. They could be divided into four main categories. The first category handles the illumination normalization problem using conventional image processing methods such as Histogram Equalization (HE) [4], Gamma Intensity Correction (GIC) [5], Logarithm Transform (LT) [6], etc. The second category attempts to learn a face model under different illumination variations from the illumination samples. Batur and Hayes [7] proposed a segmented linear subspace model for illumination robust face recognition and Georghiades et al. [8] made use of Illumination Cone. This category requires a lot of training images and is not practical for applications. The third category attempts to remove the illumination component such as such as Homomorphic filtering approach [9], discrete cosine transform in logarithm domain [10], wavelet transform in the frequency domain [11], etc. The forth category tries to find an representation which is insensitive to illumination variation. Gradientface (GF)[12], single scale retinex approach (SSR) [13] and self-quotient image (SQI) [14] are representatives of this category.

Except for the above methods dedicated to handling illumination variation, some texture classification approaches are applied to illumination-robust face recognition as well. Relying on its tolerance regarding monotonic illumination variations and computational simplicity, Local Binary Pattern (LBP) [15] has been applied in face recognition widely. However, LBP is sensitive to noise, particularly in near-uniform image region. To improve the robustness to noise, Tan et al. introduced local ternary pattern (LTP) in [16], which utilized ternary encoding instead of binary encoding in LBP. On the one hand, both LBP and LTP encode the differences between the intensity of the center pixel and its neighborhoods, while the perceptual increment varies with the background intensity, i.e. the Webers law, which has been employed by Weber local descriptor (WLD) [17] and Weber-face [18]. On the other hand, the choice of the threshold in LBP, which is 0 and that of LTP, which is a pre-set fixed value, is very important and the best one should vary depending on the region of the face image.

Based on the above two considerations and our previous work [18][19], Weber binary pattern(WBP) and Weber ternary pattern (WTP) are proposed and they have the following satisfactory characteristics: 1) The WBP and WTP employ the relative intensity difference of the center pixel and its neighborhood, which conforms to the human visual system better; 2) The WBP and WTP are insensitive to illumination variations and noises, and share computational simplicity with LBP and LTP; 3) The WBP and WTP can be regarded as adaptive versions of LBP and LTP.

II. Weber binary pattern and Weber ternary pattern

A. Weber Binary Pattern (WBP)

Weber's law hypothesizes that the ratio between the intensity increment (ΔI) and the background intensity (I) is a constant as:

$$\frac{\Delta I}{I} = const. \tag{1}$$

The WBP operator encodes a local neighborhood around each pixel. It thresholds the relative difference between the intensity of the neighborhood and the center pixel with binary encoding, in which the relative differences above τ are quantized to 1, ones below τ to 0. We define $s_b(I_i, I_c, \tau)$ as

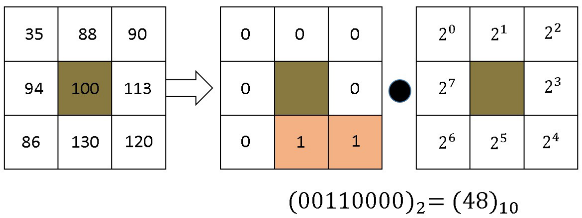

Fig. 1. An example of the WBP computation schema on a 3×3 neighborhood with τ = 0.2.

a 2-value relative difference indicator in (2).

$$s_b(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{I_i - I_c}{I_c} \geq \tau \\ 0, & \text{if} \quad \frac{I_i - I_c}{I_c} < \tau \end{cases} \tag{2}$$

where I_i and I_c are the intensities of the ith neighborhood pixel and the center pixel with the coordinates (x_c, y_c), and τ is the threshold. Fig. 1 presents an simple example of the WBP computation schema on a 3×3 neighborhood with $\tau = 0.2$.

B. Weber Ternary Pattern (WTP)

Different from WBP, WTP utilizes ternary encoding for the evaluation of the relative local gray-scale difference and we define $s_t(I_i, I_c, \tau)$ as a 3-value relative difference indicator in (3).

$$s_t(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{I_i - I_c}{I_c} \geq \tau \\ 0, & \text{if} \quad |\frac{I_i - I_c}{I_c}| < \tau \\ -1, & \text{if} \quad \frac{I_i - I_c}{I_c} \leq -\tau \end{cases} \tag{3}$$

Next, the WTP code for the center pixel in (x_c, y_c) can be formulated as

$$\mathrm{WTP}(x_c, y_c) = \sum_{i=1}^{P} 3^i [s_t(I_i, I_c, \tau) + 1], \tag{4}$$

where P denotes the number of neighborhood pixels.

Similar to LTP, the WTP will generate a histogram of size 3^P which will grow drastically as P becomes larger. To reduce the dimension of the histogram, we split the WTP histogram into two binary patterns (upper pattern and lower pattern) according to the following equations:

$$s_t^U(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{I_i - I_c}{I_c} \geq \tau \\ 0, & \text{if} \quad \frac{I_i - I_c}{I_c} < \tau \end{cases} \tag{5}$$

$$s_t^L(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{I_i - I_c}{I_c} \leq -\tau \\ 0, & \text{if} \quad \frac{I_i - I_c}{I_c} > -\tau \end{cases} \tag{6}$$

The corresponding upper WTP and lower WTP are as follows.

$$\mathrm{UWTP}(x_c, y_c) = \sum_{i=1}^{P} 2^i s_t^U(I_i, I_c, \tau), \tag{7}$$

$$\mathrm{LWTP}(x_c, y_c) = \sum_{i=1}^{P} 2^i s_t^L(I_i, I_c, \tau), \tag{8}$$

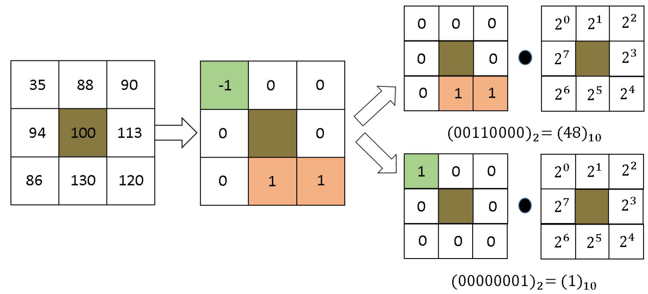

Fig. 2. An example of the WTP computation schema on a 3×3 neighborhood with τ = 0.2.

By the above method, the dimension of the WTP histogram is reduced from 3^P to 2^{P+1}. Fig. 2 presents an simple example of the WTP computation schema on a 3×3 neighborhood with $\tau = 0.2$.

C. Illumination Robustness

Based on the Lambertian reflectance model, we can prove that WBP and WTP are illumination-insensitive representations of the original face images and we have

$$I_i = r_i \cdot i_i, \tag{9}$$

and

$$I_c = r_c \cdot i_c. \tag{10}$$

in which r_i and r_c are the reflectance components for the neighborhood pixel and the center pixel and the illumination component i_i and i_c vary slowly in local areas except for the shadow boundaries, i.e,

$$i_i \approx i, \quad i_c \approx i. \tag{11}$$

Therefore, (2) and (3) can be reformulated as follows:

$$s_b(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{r_i - r_c}{r_c} \geq \tau \\ 0, & \text{if} \quad \frac{r_i - r_c}{r_c} < \tau \end{cases} \tag{12}$$

$$s_t(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad \frac{r_i - r_c}{r_c} \geq \tau \\ 0, & \text{if} \quad |\frac{r_i - r_c}{r_c}| < \tau \\ -1, & \text{if} \quad \frac{r_i - r_c}{r_c} \leq -\tau \end{cases} \tag{13}$$

From the above equations, we can observe that WBP and WTP are illumination insensitive representations because they depend only on the reflectance component and have nothing to do with the illumination component.

WBP and WTP can be viewed as adaptive versions of LBP and LTP since (2) can be reformulated as

$$s_b(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad I_i - I_c \geq \tau I_c \\ 0, & \text{if} \quad I_i - I_c < \tau I_c \end{cases} \tag{14}$$

and (3) can be reformulated as

$$s_t(I_i, I_c, \tau) = \begin{cases} 1, & \text{if} \quad I_i - I_c \geq \tau I_c \\ 0, & \text{if} \quad |I_i - I_c| < \tau I_c \\ -1, & \text{if} \quad I_i - I_c \leq -\tau I_c \end{cases} \tag{15}$$

The threshold is computed based on the intensity of the center pixel of the region so that a larger threshold is assigned

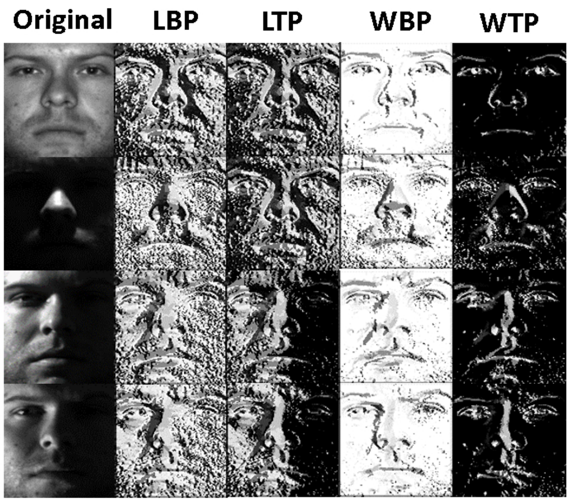

Fig. 3. Illustration of the comparison of the LBP, LTP, WBP and WTP image.

in a lighter region and vice versa. The resulting WBP and WTP features thus can enhance the robustness to the noise and illumination variations. Fig. 3 illustrates the LBP, LTP, WBP and WTP image of four images under different illumination conditions.

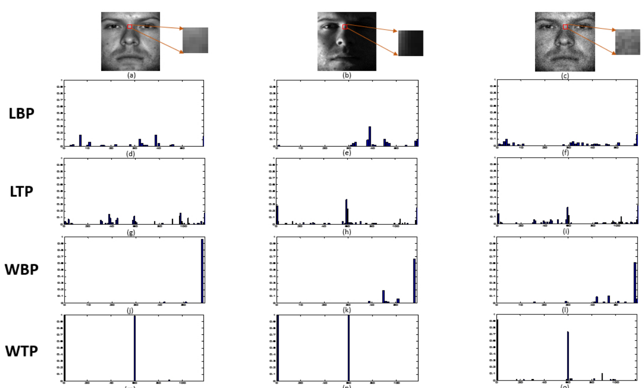

Fig. 4. Histograms of face blocks with method LBP, LTP, WBP and WTP. (a) A face block with well illumination; (b) A face block with bad illumination; (c) A face block with zero-mean Gaussian noise; (d)∼(f) The LBP histograms of face blocks; (g)∼(i) The LTP histograms of face blocks; (j)∼(l) The WBP histograms of face blocks; (m)∼(o) The WTP histograms of face blocks .

III. EXPERIMENTS

In this section, we use the WBP and WTP for illumination-robust face recognition and our experiments are conducted on Extended Yale Face Database B with large illumination variations. All face images from Extended Yale Face Database B are properly aligned, cropped and resized to 120 × 120. To obtain a robust feature, each face image is divided into 8×8 blocks. Then histograms in each block are calculated and concatenated as features. The thresholds of WBP and WTP are set -0.2 and 0.3 separately. We use the normalized histogram intersection $\mathrm{IS}(H_1, H_2)$ and χ^2 distance $\chi^2(H_1, H_2)$ as similarity measurements of two histograms respectively.

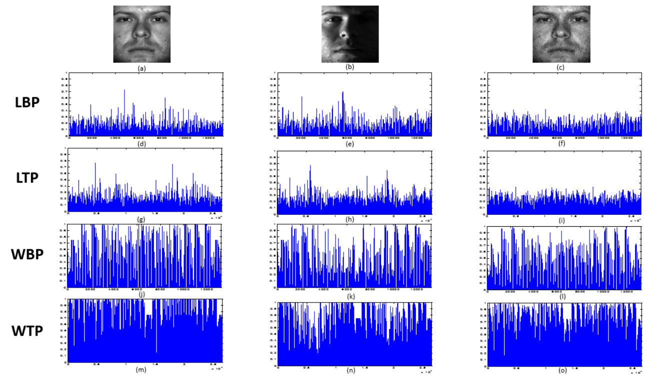

Fig. 5. Histograms of face images with method LBP, LTP, WBP and WTP. (a) A face image with well illumination; (b) A face image with bad illumination; (c) A face image with zero-mean Gaussian noise; (d)∼(f) The LBP histograms of face images; (g)∼(i) The LTP histograms of face images; (j)∼(l) The WBP histograms of face images; (m)∼(o) The WTP histograms of face images .

$$\mathrm{IS}(H_1, H_2) = \sum_{i=1}^{L} \min(H_1^i, H_2^i), \tag{16}$$

$$\chi^2(H_1, H_2) = \sum_{i=1}^{L} \frac{(H_1^i - H_2^i)^2}{H_1^i + H_2^i}. \tag{17}$$

TABLE I
RECOGNITION RATES (%) ON EXTENDED YALE FACE DATABASE B

Method	S1	S2	S3	S4	S5	Average
LBP(IS)	100	100	96.92	61.03	34.87	78.56
LBP(χ^2)	100	100	96.70	62.73	37.39	79.40
LTP(IS)	100	100	97.80	76.62	58.40	86.56
LTP(χ^2)	100	100	97.36	76.05	59.24	86.53
WBP(IS)	100	100	98.46	92.59	86.97	95.60
WBP(χ^2)	100	100	99.12	95.25	92.58	**97.39**
WTP(IS)	100	100	97.36	93.34	87.11	95.56
WTP(χ^2)	100	100	98.02	94.49	92.16	96.93

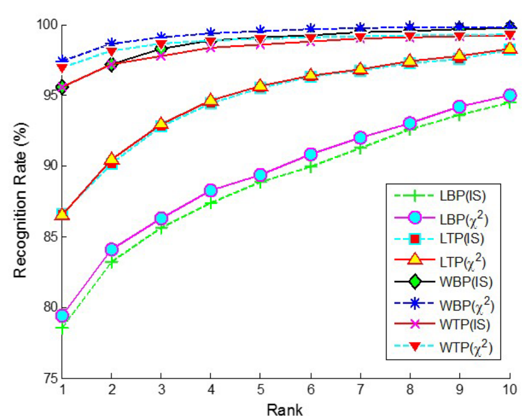

Fig. 6. The rank 10 recognition rate on Extended Yale Database B with different methods

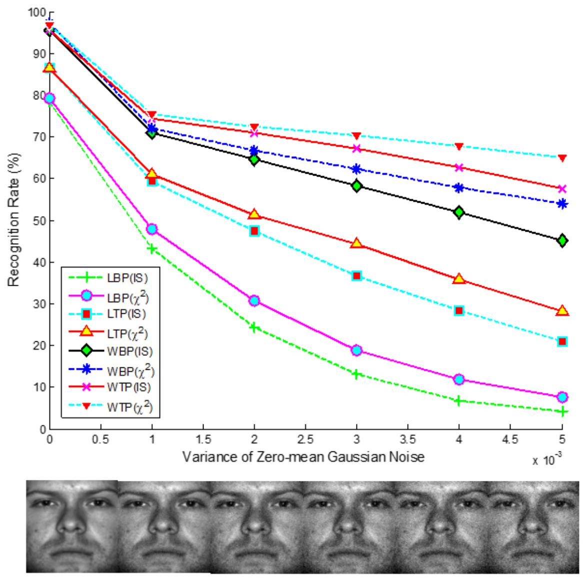

Fig. 7. The robustness to Gaussian noise.

Fig. 4 and Fig. 5 illustrate the LBP, LTP, WBP and WTP histograms of 3 face blocks and 3 face images separately. We can find that the histograms of WBP and WTP are much sparser than those of LBP and LTP. As we know, the illumination component varies slowly in local areas and the relative differences between the intensity of the center pixel and its neighborhoods are usually smaller than the absolute value of threshold. Since we set thresholds of WBP and WTP -0.2 and 0.3 separately, we are more likely to encode the relative difference into $(11111111)_2$ and $(00000000)_2$, which are the 58th bin and the first bin.

Table I shows the WBP and WTP recognition performance on the five subsets of the Extended Yale Face Database B. The WBP with χ^2 distance achieves the highest average recognition rate 97.39% and that is 17.99% and 10.86% higher than LBP and LTP with χ^2 distance respectively. WTP has similar results as the WBP. Both the WBP and the WTP have better performance than LBP and LTP in each subset, and in the last two subsets WBP and WTP perform significantly better than LBP and LTP, which demonstrates their robustness to the severe illumination degradation. Fig. 6 illustrates the rank 10 average recognition rate. Our methods achieve a more stable and satisfactory result than the other two.

Fig. 7 demonstrates the robustness to noise of the different local descriptors. The white Gaussian noise with different variances (0.001, 0.002, 0.003, 0.004, 0.005) were added to the probe images. The recognition rates of WBP and WTP drop much slower compared to LBP and LTP while WTP is more robust to noise than WBP due to ternary encoding.

IV. Conclusion

The proposed WBP and WTP are adaptive versions of LBP and LTP based on Weber's law. They are illumination insensitive representations and more robust to the noises. Experimental results on extended Yale-B database have demonstrated that our proposed WBP and WTP show better performance than the conventional approaches. This provides new insights into the role of robust feature extraction under uncontrolled illumination conditions for face recognition.

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