ILLUMINATION-ROBUST FACE RECOGNITION WITH BLOCK-BASED LOCAL CONTRAST PATTERNS

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ABSTRACT

This paper proposes a novel facial image representation Block-based Local Contrast Patterns (BLCP) for illumination-robust face recognition. This method is based on an effective texture descriptor local contrast patterns (LCP). We use the directed and undirected difference masks to calculate three types of local intensity contrasts: directed, undirected, and maximum difference responses. These response images are divided into several nonoverlapping blocks. In each block these responses are quantized and encoded into specific patterns. A joint histogram of these patterns is computed for each block and then we concatenate all the blocks' histograms into an enhanced feature vector to be used as a face descriptor. The experimental results on Extended Yale-B and FERET databases illustrate the effectiveness of our proposed method in illumination-robust face recognition.

Index Terms— Facial image representation, local contrast pattern, illumination-robust, face recognition

1. INTRODUCTION

Face recognition has recently received a lot of attention and has been applied in amounts of fields. Despite the tremendous advance, illumination-robust face recognition is still challenging in automatic face recognition. In recent years, there have been a lot of face recognition approaches for dealing with face image variations that are due to illumination changes. They can be classified into four categories roughly.

The first category attempts to handle illumination normalization problem with traditional image processing methods, such as Histogram Equalization (HE) [1], Gamma Intensity Correction (GIC) [2], etc. These methods are mostly based on intensity transformation and used as pre-processing methods. The second category learns the model of face images under varying illumination using the illumination samples. In [3] the author made the explanation that arbitrary illumination condition could be modeled by an image basis and showed that five eigenfaces suffice to represent face images under a wide range of lighting condition. The third category deals with illumination variations by removing the illumination component. Jobson *et al.* introduced the Retinex approach to obtain reflectance component by estimating the illumination component [4]. Some methods were proposed to remove the illumination component in transformation domain as well, such as Homomorphic filtering approach [5], discrete cosine transform in logarithm domain [6], etc. The fourth category attempts to find an representation which is insensitive to illumination variation. Weberface [7] and Generalized Weberface (GWF) [8] are representatives of this category.

Apart from the above methods dedicated to illumination normalization, some approaches originated from local pattern features are employed for illumination-robust face recognition as well. Local Binary Patterns (LBP) [9] is focused on the certain relationship of pixels in local neighborhood. Local ternary pattern (LTP) [10] and Local Quantized Patterns (LQP) [11] attempt to explore the encoding rules. They have proved to be effective face descriptors in face recognition due to their simplicity and micro-patterns.

In [12], Song *et al.* designed a filter bank consisting of directed and undirected masks to extract direction information and variation information from texture images. Their LCP descriptor performs excellently in texture recognition. But its global measurement and rotation invariable encoding method have become the major obstacle to directly introducing LCP into face recognition. In this paper we propose Block-based Local Contrast Patterns (BLCP). Our method is based on LCP which fully acquires texture information. Meanwhile, it solves the aforementioned problems so that we can apply it to face images.

2. ALGORITHMS

In this section, we will introduce the procedures of our approach. Especially, the differences between our BLCP and the origin LCP will be stated in detail. Fig 1 illustrates the proposed method.

2.1. Masks and Responses

The directed and undirected difference masks that we use are shown in Fig 2, where the white and black regions indicate positive and negative weights, respectively.

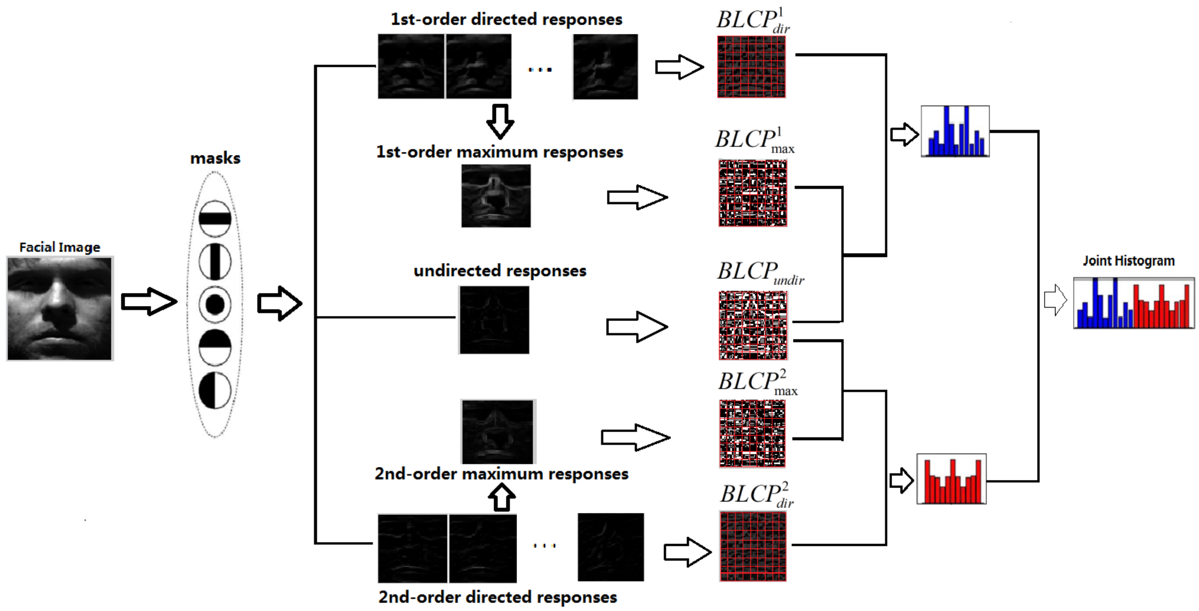

Fig. 1. Flowchart of proposed method.

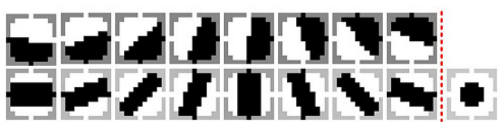

Fig. 2. Illustration of the directed and undirected difference masks. Top row: directed first-order difference masks. Bottom row: (left) directed second-order difference masks, (rightmost) undirected difference mask.

Now we will use these masks to calculate the three types of responses. Let $I(x, y)$ be a facial image, where (x, y) is the pixel index. The contrast response is calculated by

$$CR(x,y) = \frac{1}{|W^+|}\sum_{(u,v)\in W^+} I(u,v) - \frac{1}{|W^-|}\sum_{(u,v)\in W^-} I(u,v) \tag{1}$$

where W specifies a circular mask window centered at pixel (x, y) with radius r. W^+ and W^- are parts of W that have positive and negative weights, respectively, and $|\cdot|$ denotes the cardinality.

Then we can obtain the directed (first-order and second-order) and undirected difference responses for each pixel. Meanwhile, the maximum difference responses are derived from the maximum absolute values of first-order or second-order difference responses. To distinguish these responses, we denote the resulting directed, undirected and maximum difference responses as $CR^{l,d}_{dir}$, CR_{undir} and CR^l_{max}, respectively. Here, $l \in \{1, 2\}$ is the order, $d \in \{0, 1, \dots, D-1\}(D = 8)$ is the orientation index of directed difference masks and $CR^l_{max}(x, y) = \max_d \operatorname{abs}(CR^{l,d}_{dir}(x, y))$.

2.2. Block-based Local Contrast Patterns

We now attempt to quantize and encode these contrast responses into specific patterns.

(1) Directed contrast patterns

Firstly we review the operation which the LCP operator performed on texture images [12]. For pixel (x, y), it defines $dCR^{l,d}_{dir}(x, y) = CR^{l,d}_{dir}(x, y) - thr^{l,d}$, where $thr^{l,d}$ is a global threshold for the l-th order and the d-th specified orientation:

$$thr^{l,d} = \frac{1}{|CR^{l,d}_{dir}|}\sum_{(x,y)} CR^{l,d}_{dir}(x,y) \tag{2}$$

From formulation 2, we can see that the threshold is the mean value of a whole response image. For texture images like the example that Fig 3 shows, the global measurement performs well because a texture image generally includes only few simple types of texture. A face image as is shown in Fig 3 is much more complicated than a texture image. However, we can assume that in a local region of a face image, the texture varies slightly and is just as simple as a texture image.

Based on the assumption above, we want to divide each response image into N nonoverlapping blocks and let the

Fig. 3. Typical examples of texture (left) and face (right) images.

set of pixels in the i-th block be P_i. Then we calculate block-wise thresholds:

$$thr_i^{l,d} = \frac{1}{|P_i|}\sum_{(x,y)\in P_i} CR_{dir}^{l,d}(x,y), \quad (3)$$

and we redefine $dCR_{dir}^{l,d}(x,y) = CR_{dir}^{l,d}(x,y) - thr_i^{l,d}$, for pixel $(x,y) \in P_i$. The block-based thought is also applied in the other response images and will not be repeated in the following subsections. Then we let $bCR_{dir}^{l}(x,y) = [s(dCR_{dir}^{l,0}(x,y)), \cdots, s(dCR_{dir}^{l,7}(x,y))]$, where $s(x)$ is a sign function:

$$s(x) = \begin{cases} 1, x > 0 \\ 0, x \leq 0 \end{cases} \quad (4)$$

So $bCR_{dir}^{l}(x,y)$ is a 8-bit binary code corresponding to the pixel (x,y). To encode bCR_{dir}^{l}, the origin LCP operator uses the rotation invariant uniform 2 ($riu2$) measurement which is rotationally invariant. For instance, it encodes 10000000, 00100000 and 00000100 into the same pattern. Rotation invariance is necessary to adapt to texture with any angle of rotation, while it has a negative effect on face image recognition because texture's orientation is an important factor to distinguish different faces. To overcome the obstacle, we apply the uniform 2 ($u2$) used in [9] to encode these responses. This method is able to effectively distinguish texture's different orientations. We denote the encoding result as $BLCP_{dir}^{l}$. For an 8-bit binary code, the encoding result has 59 patterns.

(2) Maximum contrast patterns

For the maximum difference responses, the three-valued quantization via local thresholding is adopted, i.e., for pixel $(x,y) \in P_i$,

$$BLCP_{\max}^{l}(x,y) = \begin{cases} 2, & CR_{\max}^{l}(x,y) > \mu_i^l + k\sigma_i^l \\ 1, & CR_{\max}^{l}(x,y) < \mu_i^l - k\sigma_i^l \\ 0, & otherwise \end{cases} \quad (5)$$

where k is a scale factor, μ_i^l and σ_i^l are the mean and the standard deviation of the i-th block of the maximum difference responses, respectively.

(3) Undirected contrast patterns

Since the undirected difference responses contain the sign (polarity) information, we perform the signed three-valued quantization, i.e., for pixel $(x,y) \in P_i$,

$$BLCP_{undir}(x,y) = \begin{cases} 2, & CR_{undir}(x,y) > m_i^+ \\ 1, & CR_{undir}(x,y) < m_i^- \\ 0, & otherwise \end{cases} \quad (6)$$

where m_i^+ and m_i^- are local thresholds of the i-th block and defined by the means of positive and negative difference responses, respectively, i.e.,

$$\begin{aligned} m_i^+ &= \tfrac{1}{M_i^+}\sum_{(u,v)\in P_i, CR_{undir}(u,v)>0} CR_{undir}(u,v) \\ m_i^- &= \tfrac{1}{M_i^-}\sum_{(u,v)\in P_i, CR_{undir}(u,v)<0} CR_{undir}(u,v) \end{aligned} \quad (7)$$

Here, M_i^+ and M_i^- are the numbers of pixels which have positive and negative $CR_{undir}(x,y)$ in P_i, respectively.

2.3. Joint Histogram Representation

In this step, we will build joint histograms for each block and then concatenate these histograms into the BLCP facial descriptor. Now we have $BLCP_{dir}^{l}(0 \sim 58)$, $BLCP_{max}^{l}(0 \sim 2)$ and $BLCP_{undir}(0 \sim 2)$. We define $BLCP_{joint}^{l} = 3 * BLCP_{max}^{l} + BLCP_{undir}$. Obviously the value range of $BLCP_{joint}^{l}$ is $0 \sim 8$ and there is a one-to-one correspondence between an $BLCP_{joint}^{l}$ value and an $(BLCP_{max}^{l}, BLCP_{undir})$ point.

Now we have a point $(BLCP_{dir}^{l}(x,y), BLCP_{joint}^{l}(x,y))$ for each pixel (x,y) and the number of the two-dimension histogram bins will be 59×9. In each block, we respectively bulid two histograms for first and second order $BLCP$s ($l = 1, 2$), which are regarded as descriptors of the block. Finally, we concatenate each block's histograms to construct the facial descriptor for our following face recognition.

3. EXPERIMENTS

3.1. Experimental Setup

In our experiments, the radius r of these masks is set as 4 pixels, which means the size of a mask is 9×9. All the responses are divided into rectangular blocks with size 8×8. The coefficient k in maximum contrast patterns is 1. Our BLCP operator is tested on both Extended Yale-B [13] and fc subset of FERET database [14]. We use histogram intersection to measure the similarity between two histograms. The nearest neighborhood rule is used as the classifier.

(1) Extended Yale-B. In the extended Yale-B database, there includes 38 subjects under 9 poses and 64 illumination conditions. All images are divided into 5 subsets according to the angle between the light source direction and

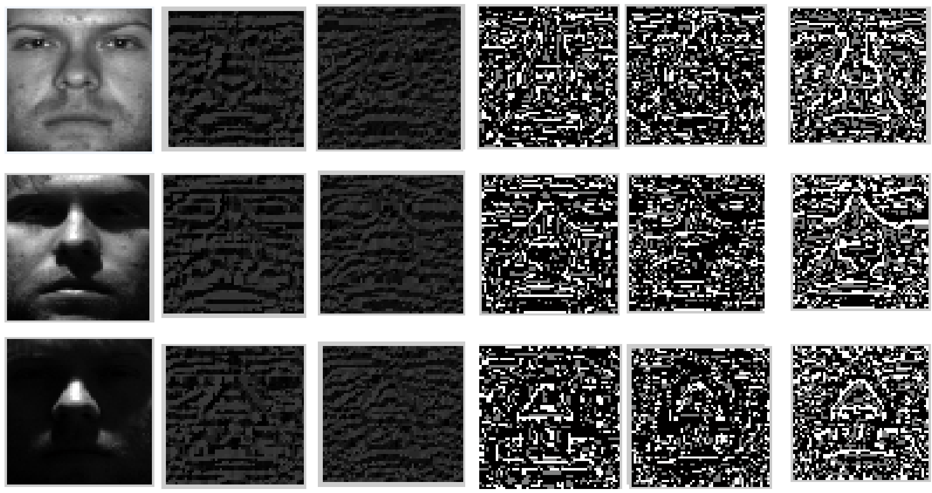

Fig. 4. Columns, from left to right, respectively, show: facial images under three illumination conditions; $BLCP^1_{dir}$; $BLCP^2_{dir}$; $BLCP^1_{max}$; $BLCP^2_{max}$; $BLCP_{undir}$.

the central camera axis. In our experiments, we used images with the most neutral light conditions ('$A+000E+00'$) as the gallery, and only frontal images in subsets as probes. All images are cropped and resized to 120×120.

(2) FERET-fc. In the standard FERET database, the basic gallery fa contains $1,196$ images of $1,196$ subjects. The fc set is designed for evaluating the illumination variation and includes 194 images of 194 subjects taken in the same time under significantly different lighting conditions. For our experiments, all images are aligned, cropped and resized to 128×128 based on the location of the eyes.

3.2. Results and Discussions

Table 1 and Table 2 respectively present the comparison results of recognition rates on Extended Yale-B and FERET-fc. LGBP (Gabor + LBP) achieves slightly better recognition results than BLCP on FERET-fc database, beacause a total of 40 Gabor filters are used to capture multi-scale and multi-orientation information of a face image, which leads to a descriptor with much higher dimension than our BLCP descriptor. Except that, it's obvious that our method performs excellently on both databases and outperforms most of the traditional local patterns methods.

Fig 4 presents the encoding results of three face images of the same person under different illumination conditions. We can see that although there are illumination changes, almost all the encoding results are able to keep the main information and hold high similarity. Different from the traditional methods aiming at the relationship between center pexel and its surrounding pixels, our descriptor shows each block's local texture feature. This determines that the BLCP descriptor tends to be more robust to the influence of illumination changes.

Table 1. Recognition rates $\%$ on Extended Yale B.

Methods	S1	S2	S3	S4	S5	AVG
LBP [9]	100	100	96.9	61.0	34.9	78.6
POEM [15]	100	100	96.5	75.7	80.5	90.5
LTP [10]	100	100	97.8	78.0	58.5	86.9
LSP [16]	100	100	99.3	79.7	48.9	85.6
BLCP	100	100	99.6	95.6	96.2	98.3

Table 2. Recognition rates $\%$ on FERET-fc.

Methods	Rate$\%$
LBP [9]	80.9
LTP [10]	70.6
LSP [16]	83.5
LQP [11]	69.6
LGBP [17]	97.0
POEM [15]	95.0
BLCP	96.4

4. CONCLUSION

In this paper, we have proposed a new facial descriptor based on local contrast patterns. Some approaches have been introduced to adapt LCP to facial image representation. The BLCP keeps the virtue of LCP so that it can obtain rich texture information of facial image. Experiments have proved that our proposed BLCP descriptor is an illumination insensitive representation.

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