A NOVEL LBP-BASED COLOR DESCRIPTOR FOR FACE RECOGNITION

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ABSTRACT

LBP-based color features have shown excellent performance for color face recognition tasks, such as Color LBP, CLBP and LCVBP. However, existing methods encode the inter-channel information on pairs of color channels by applying the same spatial structure as that used in the intra-channel encoding. This results in a very high dimensional feature vector yet ineffective in encoding inter-channel information. Moreover, the difference of pixel values across color channels may not be a proper measure if they are not quantitatively comparable. To tackle these problems of existing methods, we propose a novel LBP-based color feature, Ternary-Color LBP (TCLBP), to encode the inter-channel information more effectively and efficiently. Extensive experiments on 4 public face databases, Color FERET, Georgia Tech, FRGC and LFW, are conducted to verify the effectiveness of the proposed TCLBP color feature for face recognition. Results show that the proposed TCLBP leads to visibly better face recognition performance than Color LBP, CLBP and LCVBP consistently over the 4 databases.

Index Terms— Color face recognition, LBP.

1. INTRODUCTION

Color possesses discriminative information for face recognition [1] and considerable research efforts have been devoted to the efficient utilization of facial color information to enhance the face recognition performance [2–8]. Recently, local binary patterns (LBPs) [9–12] have gained reputation as powerful face descriptors as they are believed to be robust to variations in facial appearance (e.g., facial pose, illumination, misalignment, etc.).

For color face recognition, a few research efforts have been dedicated to incorporate color information into the extraction of LBP-based features. In [13], the authors proposed Color LBP based on color and LBP texture analysis. Color LBP was proven to be better than grayscale LBP and color features. Later, Choi proposed color local binary pattern (CLBP) in [14]. The authors incorporated the opponent LBP features that capture the texture patterns of spatial interactions between spectral channels into the generation of CLBP. After that, local color vector binary patterns (LCVBPs) was proposed in [6]. The LCVBP consists of two patterns: color norm patterns and color angular patterns. The color angular patterns were claimed to encode the discriminative texture patterns derived from spatial interactions among different spectral-band images.

Works reviewed above demonstrate that color information combined with LBP-based features can greatly improve the face recognition performance. However, it should be noted that existing color LBP features are restricted to extracting inter-channel features from each pair of color channels using the same spatial structure as that used for the intra-channel features. Both CLBP and LCVBP suffer from the curse of high dimensionality and the redundant information. What's more, pixel values from different channels in certain color spaces are not quantitatively comparable. It is still an open problem that how to effectively combine color and texture information using LBP for the purpose of face recognition.

In this paper, we propose a novel LBP-based color face descriptor, Ternay-Color LBP (TCLBP), for face recognition. It consists of Intra-channel LBP and Inter-channel LBP, which are combined using weighted concatenation to balance the contribution of spatial structure and spectral structure to the face recognition. The main contribution of this paper is to propose the Inter-channel LBP feature of extremely low dimensionality, which is generated by encoding the spectral structure of R,G,B color channels at the same location. Comparative experiments have been conducted to test the effectiveness of the proposed TCLBP color feature on 4 public face databases including Color FERET [15], Georgia Tech [16], FRGC [17] and LFW [18]. Experimental results show that TCLBP yields consistently better face recognition performance than other state-of-the-art color LBP descriptors.

2. THE PROPOSED COLOR DESCRIPTOR TCLBP

Here, we present how to extract the proposed TCLBP feature from color face images.

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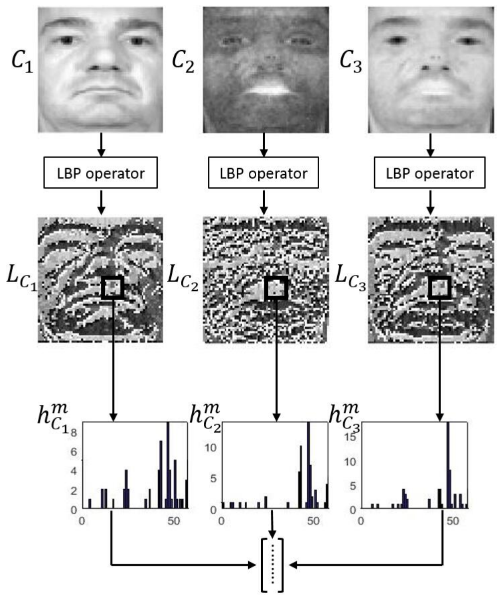

Fig. 1. Feature extraction process of Intra-channel LBP.

2.1. The LBP Operator

The traditional LBP operator [9] was extended in [19] to use neighborhoods of different sizes by using circular neighborhoods and bilinearly interpolating. Another extension in [19] is the definition of so-called uniform patterns. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. The uniform LBP operator is defined as below:

$$LBP_{P,R}^{u2}(i_c) = \begin{cases} \sum_{p=0}^{P-1} 2^p s(i_p - i_c) & \text{if } T \leqslant 2 \\ P(P-1)+2 & \text{otherwise} \end{cases}, \quad (1)$$

where $i_p(p = 0, 1, 2, ..., P-1)$ and i_c indicate the intensity values of neighboring points and the center pixel, respectively. $s(i_p - i_c)$ equals 1, if $i_p - i_c \geq 0$; and 0, otherwise. $T = |s(i_{P-1} - i_c) - s(i_0 - i_c)| + \sum_{p=1}^{P-1} |s(i_p - i_c) - s(i_{p-1} - i_c)|$ and $u2, P, R$ mean uniform LBP, P sampling points on a circle of radius of R respectively. For the uniform LBP operator used in our method $LBP_{8,1}^{u2}$, there are 59 local binary patterns in total.

2.2. Intra-channel LBP

Different from the traditional gray-level images, color faces have 3 color-component images such as RGB, RQCr, YIQ, etc. Let $C_i, i = 1, 2, 3$ represent the 3 color-component images as shown in Fig. 1. Authors in [13] proposed to apply the uniform LBP operator (1) to each C_i separately. Thus each pixel value in C_i is now replaced with the LBP code defined in (1). Let $L_{C_i}, i = 1, 2, 3$ represent the resulted LBP-code images. The local LBP histograms $h_{C_i}^m, m = 1, 2, ..., M$ are further extracted from L_{C_i}. Here m represents the m-th local region indicated by a rectangular box on L_{C_i} in Fig. 1 and M is the total number of local regions in a face image. All local LBP histograms $h_{C_i}^m, i = 1, 2, 3, m = 1, 2, ..., M$ are concatenated together to form the Color LBP feature, which is also referred to as Intra-channel LBP in our paper. Before concatenation, all LBP histograms have been normalized to unit norm.

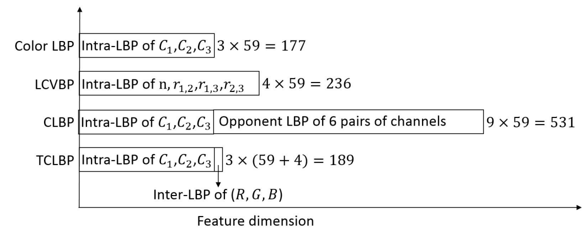

Fig. 2. Dimensionality of LBP-based color features.

2.3. Inter-channel LBP

Simply extending the LBP feature from a single gray-level image to three color-component images could suffer from the loss of correlation information of pixels from different color channels. Besides the Intra-channel LBP feature, which is used in Color LBP, LCVBP, CLBP and our proposed TCLBP as shown in Fig. 2, the inter-channel feature plays an important role in the color face recognition process. To capture the texture patterns of spatial interactions between each pair of color channels, authors in [5] proposed opponent LBP features, where the neighboring points i_p and center point i_c in (1) are taken from two different color channels. The opponent LBP extracted from each pair of C_i is then combined with Intra-channel LBP extracted from C_i to obtain CLBP. While in [6], the authors extracted Intra-channel LBP features from 4 new component images including one norm image n and three ratio images $r_{i,k}, (i < k, i = 1, 2, k = 2, 3)$ computed by (2) [6] to form the LCVBP feature.

$$\begin{cases} n = \sqrt{C_1^2 + C_2^2 + C_3^2} \\ r_{i,k} = C_k / C_i, i < k, i = 1, 2, k = 2, 3 \end{cases} \quad (2)$$

One obvious limitation of existing methods is that inter-channel features are extracted by comparing the pixel values from each pair of color channels rather than from all three color channels. Also, since the local spatial structure of pixel values has been encoded by Intra-channel LBP of each color channel, the comparison of pixel values at different locations is unnecessary for inter-channel features. To effectively explore the inter-channel correlation of pixel values of 3 color channels at the same location, we reconfigure the traditional LBP operator. Suppose a 3-dimensional vector $\mathbf{v} = [v_{C_1}, v_{C_2}, v_{C_3}]$ represents the 3 pixel values of 3 color

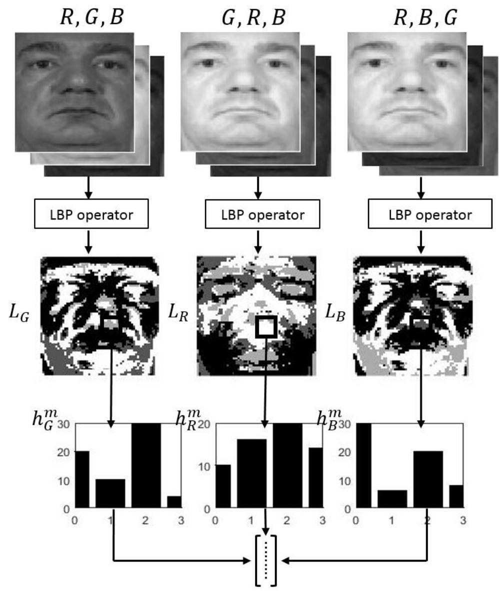

Fig. 3. Feature extraction process of Inter-channel LBP.

channels at a certain location. Then the reconfigured LBP code for $\mathbf{v}$ taking C_i as the center channel is defined as below:

$$LBP(v_{C_i}) = \sum_{j=0}^{1} 2^j s(v_{C_j} - v_{C_i}), \tag{3}$$

where $C_j, j \in \{0,1\}$ represents two neighboring channels of C_i. It is important to note that the number of bins in the reconfigured LBP is only 4, almost $1/15$ of the number of bins in the uniform LBP operator (59), which is used in Intra-channel LBP. This low dimension cost helps in avoiding the curse of dimensionality and makes TCLBP contain much less redundant information.

By taking different color channels as the center channel, we can have 3 different combinations (R,G,B),(G,R,B) and (R,B,G) as shown in Fig. 3. Note that the color space $C_1C_2C_3$ for extracting Intra-channel LBP can be any effective color space such as RQCr [14], but the color space for Inter-channel LBP has to be RGB. R,G,B describe the quantitized strength of the light at different wavelengths, so pixel values of R,G,B can be directly compared. Even though some other color spaces achieve better face recognition performance than RGB color space, their pixel values are not quantitatively comparable. Take RQCr as an example, R describes luminance information while Q,Cr describe chrominance information [3]. Thus R and Q, Cr have totally different physical meanings and direct comparisons between pixel values of R,Q,Cr may cause problems.

After going through the reconfigured LBP operator defined in (3), different combinations of R,G,B components are converted to LBP-code images $L_C, C \in \{R,G,B\}$. Similar to L_{C_i}, L_C is partitioned into M local patches $L_C^m, m = 1,2,...,M$ and a corresponding histogram h_C^m is extracted from each local patch L_C^m. All local LBP histograms $h_C^m, C \in \{R,G,B\}, m = 1,2,...,M$ are normalized to unit norm and concatenated together to form the Inter-channel LBP feature.

By concatenating the Intra-channel LBP that describes local spatial structure of pixel values and the Inter-channel LBP that describes spectral structure of three color channels at the same location, we can obtain the final feature vector TCLBP. As the norm of both Intra-channel LBP and Inter-channel LBP is set to be 1 before concatenation, the average magnitude of each bin in Inter-channel LBP is $\sqrt{1/4} = 1/2$, which is much larger than that in Intra-channel LBP, $\sqrt{1/59} \approx 1/8$. To balance the contribution of spatial structure and spectral structure to the face recognition performance, we multiply Intra-channel LBP and Inter-channel LBP with weights 1 and 0.5, respectively before concatenation.

2.4. Face Recognition

Dimension reduction methods are applied to the extracted color features and the nearest-neighbour classifier using Mahalanobis distance is subsequently performed between probe and gallery low-dimensional features to determine the identity of probe images.

3. EXPERIMENTS

The effectiveness of our proposed TCLBP feature for face recognition is verified by comparing it with 3 state-of-the-art color LBP features including Color LBP, CLBP and LCVBP. Extensive experiments are carried out on 4 publicly available datasets: Color FERET, Georgia Tech, FRGC and LFW.

3.1. Experimental Settings

A translated, rotated, cropped and resized color face image is firstly transformed from the RGB color space to the RQCr color space. Face images are resized to the resolution of 64×64 and the patch size is set to be 8×8. Also P, R in (1) are set to be 8 and 1, respectively. As for the dimension reduction methods, PCA is used on LFW and EFM [20] is used on Color FERET, Georgia Tech and FRGC. PCA is commonly used as a benchmark for the evaluation of the performance in FR algorithms [15] and it may significantly enhance the recognition accuracy [21, 22]. Plenty of color face recognition methods employ EFM method for low-dimensional feature extraction [3, 14]. The face recognition rate/accuracy and the face verification rate (FVR) at the false accept rate (FAR) are used for measuring the identification or verification performance. As the face recognition performance relies on the dimension of low-dimensional features, we present the best found recognition rates/accuracies or verification rates.

Table 1. Results on Color FERET

Color feature	face recognition rate (%)
Gray LBP	77.8820
Color LBP [13]	84.7185
CLBP [14]	86.1930
LCVBP [6]	76.6756
TCLBP	**86.7292**

Table 2. Results on Georgia Tech

Color feature	face recognition rate (%)
Gray LBP	82.5714
Color LBP [13]	90.8571
CLBP [14]	93.4286
LCVBP [6]	92.0000
TCLBP	**94.5714**

Table 3. Results on FRGC

Color feature	FVR (%) at FAR = 0.1%
Gray LBP	53.3635
Color LBP [13]	74.0783
CLBP [14]	73.9662
LCVBP [6]	66.6004
TCLBP	**75.3234**

Table 4. Results on LFW

Color feature	face verification accuracy (%)
Gray LBP	74.2666
Color LBP [13]	77.4667
CLBP [14]	76.3000
LCVBP [6]	75.8500
TCLBP	**78.5667**

3.2. Results on Color FERET

Among 994 subjects in the Color FERET database [15], we select 992 subjects that have both 'fa' and 'fb' frontal images. Two hundred subjects from the subject '00043' to the subject '00245', which are the first 200 subjects having true color images, are used for training, while the remaining 792 subjects are used for testing. So there are 400 images in the training set, 792 'fa' images in the gallery, and 792 'fb' images for probe. The face recognition rates using different color features are shown in Table 1.

3.3. Results on Georgia Tech

The Georgia Tech (GT) Face Database [16] consists of 750 color images of 50 subjects (15 images per subject). These images have large variations in both pose and expression and some illumination changes. The first eight images of all subjects are used for training and the remaining seven images of all subjects serve as testing images. The face recognition rates using different color features are shown in Table 2.

3.4. Results on FRGC

Face images in the FRGC database [17] are partitioned into three datasets, i.e., training, target and query datasets. There are 12,776 controlled or uncontrolled images in the training set, 16,028 controlled images in the target set, and 8,014 uncontrolled images in the query set. The controlled images have good quality, while the uncontrolled images display poor quality, such as large illumination variations, low resolution, and blurring. FRGC Experiment 4 has been reported to be the most challenging FRGC experiment [2], so it is chosen to assess the face recognition performance in our experiments. The face verification rates using different color features are shown in Table 3.

3.5. Results on LFW

The LFW database [18] has been widely used as a benchmark dataset to evaluate face recognition algorithm [23, 24]. It consists of 13,233 images of 5,749 subjects. All images are collected from the internet with large pose, illumination and facial-expression variations, as well as occlusions. We report the averaged face verification accuracies over 10 folds of View 2 on Table 4. More precisely, 3000 positive pairs and 3000 negative pairs are divided into 10 subsets. In each fold, 9 subsets are used as the training set and the hold-out subset is used for testing. We follow the LFWs restricted protocol. No outside dataset is used for training.

Experimental results show that the proposed TCLBP color feature outperforms the Color LBP, CLBP and LCVBP consistently over all 4 databases.

4. CONCLUSION

This work proposes a novel LBP-based color feature, TCLBP, which consists of intra-channel and inter-channel parts. As the image local spatial structure is encoded by the intra-channel features in 3 individual color channels, the proposed inter-channel feature encodes the spectral structure of the whole 3 channels at the same location. This leads to a more effective and efficient Inter-channel LBP feature than CLBP and LCVBP features. Moreover, the weighted concatenation of Intra-channel and Inter-channel LBP features balances the contribution of spatial structure and spectral structure to the face recognition. In addition, Intra-channel and Inter-channel LBP features are encoded in different color spaces because they compare the pixel values in different dimensions. Comparative experiments show that the proposed TCLBP yields visibly better face recognition performance than other state-of-the-art color LBP descriptors, Color LBP, CLBP and LCVBP, consistently on all 4 public face databases.

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