Color Local Texture Features Based Face Recognition

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Abstract- For the purpose of face recognition (FR), the new color local texture features, i.e., color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP), are being proposed. The proposed color local texture features are able to exploit the discriminative information derived from spatiochromatic texture patterns of different spectral channels within a certain local face region. This method encodes the discriminative features by combining both color and texture information as well as its fusion approach. To make full use of both color and texture information, the opponent color texture features are used. The opponent features capture the spatial correlation between spectral bands and taken into the generation of CLGW and CLBP. In addition, to perform the final classification, multiple color local texture features (each corresponding to the associated color band) are combined within a feature-level fusion framework. Particularly, compared with gray scale texture features, the proposed color local texture features are able to provide excellent recognition rates for face images taken under severe variation in illumination, as well as some variations in face images.

Keywords – Color face image recognition, color local texture features, color spaces, combination Gabor Transform, LBP.

I. INTRODUCTION

In pattern recognition and computer vision due to the wide range of applications includes video surveillance [1], biometric identification [2], and face indexing in multimedia contents [3]. As in any classification task, feature extraction is of great importance. Recently, local texture features [4]-[6] have gained reputation as powerful face descriptors because they are believed to be more robust to variations of facial pose, expression, occlusion, etc. In particular, Gabor wavelets [7] and local binary pattern (LBP) [8] texture features have proven to be highly discriminative for FR due to different levels of locality. There has been a limited but increasing amount of work on the color aspects of textured image analysis. Results in these works indicate that color information can play a complementary role in texture analysis and Classification/recognition, and consequently, it can be used to enhance Classification/recognition performance.

In the paper [9] , an empirical evaluation study is performed which compares color indexing, gray scale texture, and color texture methods for classification tasks on texture images data set taken under either constant (static) or varying illumination conditions. Experimental result shows that, for the case of static illumination condition, color texture descriptors generally perform better than their gray scale counterparts.

In the paper [10] , three gray scale texture techniques including local linear transform, Gabor filtering, and co-occurrence methods are extended to color images. The paper reports that the use of color information can improve classification performance obtained using only gray scale texture analysis techniques.

In the paper [11] , incorporating color into a texture analysis can be beneficial for classification /recognition schemes. In particular, the results showed that perceptually uniform color spaces and Hue, Saturation, and Value (HSV) perform better than Red, Green, and Blue (RGB) for color texture analysis.

Following the aforementioned studies, it is natural to expect better FR performance by combining color and texture information than by using only color or texture information. However, at the moment, how to effectively make use of both color and texture information for the purpose of FR still remains an open problem. The objective of this paper is to suggest a new color FR framework, which effectively combines color and texture information, aiming to improve FR performance. The main contributions of the paper are:

1) This paper proposes the first so-called color local texture features. Specifically, the development of two effective color local texture features, i.e., color local Gabor wavelets (CLGWs) and color LBP (CLBP), both of which are able to encode the discriminative features derived from spatiochromatic texture patterns of different spectral channels (or bands) within a certain local region. In addition, to make full use of both color and texture information, the opponent color texture features that capture the texture patterns of spatial interactions between spectral bands are incorporated into the generation of CLGW and CLBP. This allows for acquiring more discriminative color local texture features, as compared with conventional gray scale texture features, for improving FR performance.

2) The effective way of combining color local texture features has not been explored in the current FR works. This paper suggests the feature-level fusion approach in order to integrate multiple color local texture features [each extracted from an associated color component (or spectral) image] for the final classification.

The rest of this paper is organized as follows: In Section II, the proposed color FR framework using color local texture features is out-lined. Section III details the proposed color local texture feature extraction approach. We present our fusion approach to combining multiple color local texture features to perform FR. In Section IV, we present experimental results that demonstrate the effectiveness of color local texture features. Conclusions constitute Section V.

II. PROPOSED COLOR FR FRAMEWORK

The fig.1. shows proposed color face recognition framework for color local texture features as below. The proposed color FR system model using color local texture features consists of three major steps: color conversion and partition, feature extraction, and combination and classification. The proposed color face recognition framework for color local texture features is as shown in fig.1.

As shown in fig.1, face image represented in the color space is first translated, rotated, and rescaled to a fixed template, yielding the corresponding aligned face image. Subsequently the aligned color image is converted into an image represented in another color space. Not only conventional linear or nonlinear color spaces (e.g. YCbCr or L*a*b*) but also new color spaces devised for the purpose of FR can be used for color space conversion. Each of the color component images of current color model is then partitioned into local regions.

In the next step, texture feature extraction is independently and separately performed on each of these local regions. Since texture features are extracted from the local face regions obtained from different color channels, they are referred to as “color local texture features.” The key to FR using color information is to extract the so-called opponent texture features between each pair of two spectral images, as well as unichrome (or channel wise) texture features. This allows for obtaining much more complementary texture features for improving the FR performance, as compared with grey scale texture feature extraction, where only the luminance of an image is taken into account.

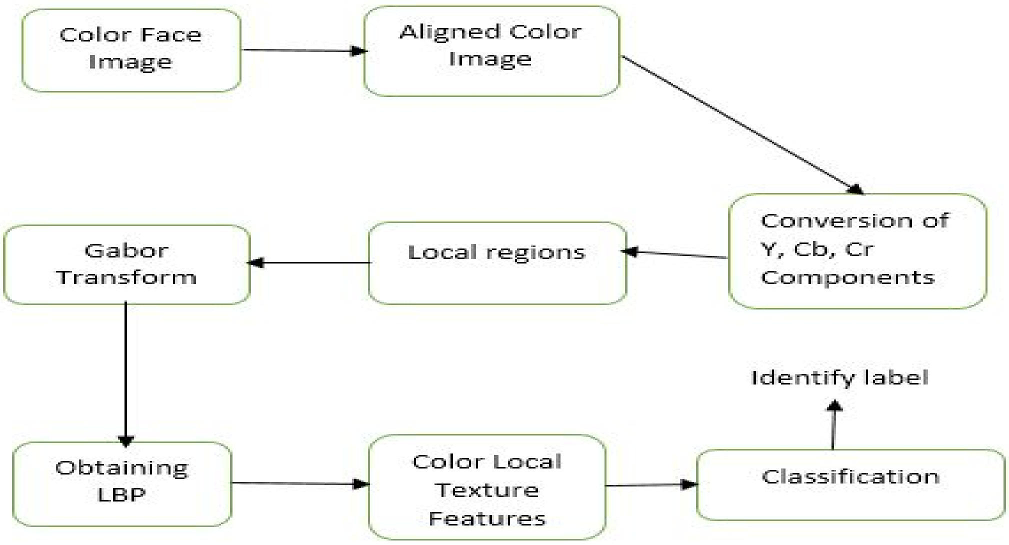

Fig.1. Proposed Color FR Framework for Color Local Texture Features.

Since color local texture features (each obtained from the associated local region and spectral channel) are available, we have to combine them to reach the final classification. To this end, multimodal fusion techniques are employed for integrating multiple color local texture features for improving the FR performance.

III. EXTRACTION OF COLOR LOCAL TEXTURE FEATURES

Here, we present the methods of extracting the proposed color local texture features from a color image. Two commonly used texture feature representations are considered, i.e., Gabor wavelet [7] and LBP [8]. Here, these grayscale texture features are extended to the multispectral texture features using color information. Specifically, given a color image, the texture operator is applied on each separate color channel. In addition, we can further extend the texture operator to make use of opponent colors.

A. Extraction of Color Local Gabor Wavelets

Gabor filters, which exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains, have been extensively and successfully used in face recognition. Gabor wavelets can be obtained based on Gabor filters [6] that detect amplitude-invariant spatial frequencies of pixel gray values. Gabor wavelet features have been widely adopted in FR due to the robustness against illumination changes. The 2-D Gabor filter can be defined as follows [7]:

$$\varphi_{u,v}(z) = \frac{||k_{u,v}||^2}{\sigma^2} e^{(-\left||k_{u,v}|\right|^2 ||z||^2/2\sigma^2)} [e^{ik_{u,v}z} - e^{-\sigma^2/2}] \quad (1)$$

Where u and v define the orientation and the scale of the Gabor filters, $z = (x, y)$, $\|.\|$ denotes the norm operator, $k_{u,v} = k_v e^{i\phi_u}$, $k_v = \frac{k_{max}}{f^v}$, $\phi_u = \pi u/8$, k_{max} is the maximum frequency, and f is the spacing factor between filters in the frequency domain[7].The Gabor filters in (1) can take a variety of different forms , along with different V scales and U orientations.

To reflect and encode the local properties of the i^{th} spectral image $S_i(z)$ when computing its associated Gabor wavelet, the following operation can be performed [7]:-

$$G_{i,u,v}^{(m)}(z) = S_i^{(m)}(z) * \varphi_{u,v}(z) \tag{2}$$

Where * denotes the convolution operator and $G_{i,u,v}^{(m)}(z)$ is a Gabor wavelet representation (with orientation and scale) of the m^{th} local region $S_i^{(m)}$ of the i^{th} spectral image. Hence, set $\left\{G_{i,u,v}^{(m)}(z) \middle| m = 1, \ldots, M, 0 \le u \le U-1, 0 \le v \le V-1\right\}$ forms a set of Gabor wavelet representations corresponding to M local regions of S_i.

The extraction of local facial features i.e. eyes, nose by using color local gabor wavelet is as shown in fig 2.

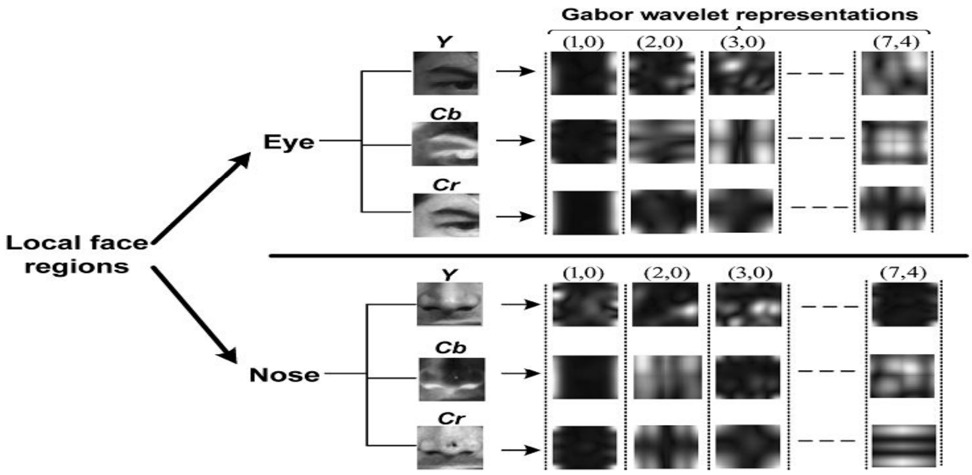

Fig 2.Gabor wavelet representations with five scales and eight orientations of local facial features.

Fig. 2 shows the Gabor wavelet representations (the magnitude) of sample local region images. In Fig. 2, three local region images (one for each color band) corresponding to the same facial component (e.g., eye or nose) differ in the pattern of Gabor wavelet representations. This indicates that they can provide different complementary information for the purpose of FR.

B. Extraction of Color Local Binary Pattern

The local binary pattern operator is defined as a grey-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in many empirical studies.

The LBP operator is one of the best performing texture descriptor and it has been widely used in various applications. LBP is introduced as a powerful local descriptor for micro features of images. The basic LBP operator assigns a label to every pixel of an image by thresholding the 3*3-neighborhood of each pixel with the center of each pixel value and considering result as a binary number (or called LBP codes).Then, the histogram of the labels can be used as a texture descriptor. Recently, the combination of Gabor and LBP has been demonstrated to be an effective way for face recognition.

Fig. 3. shows extraction of facial features globally by using color local binary pattern.

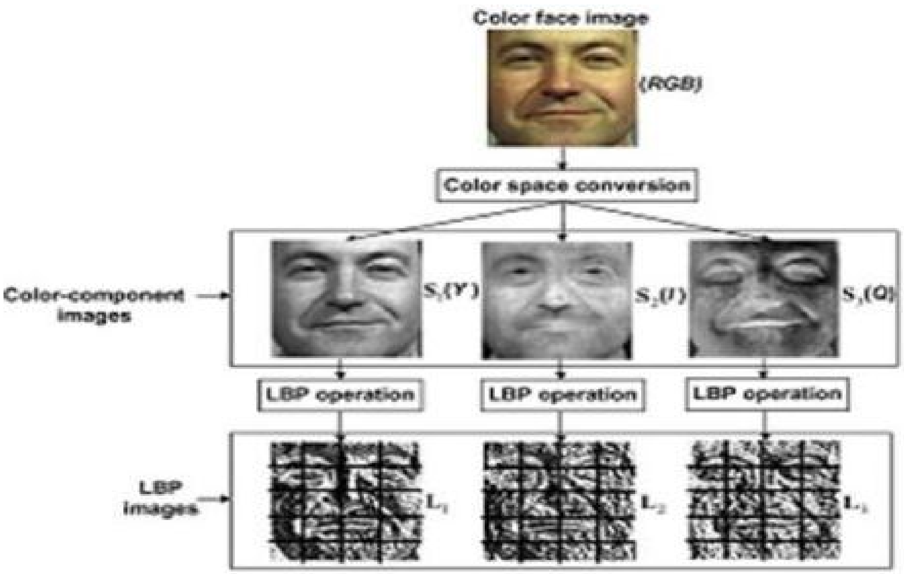

Fig. 3. LBP operation process.

Given K different color-component images, S_i (i=1, k) the unichrome (or channel wise) LBP feature is separately and independently computed from each S_i.In the computation of the unichrome LBP feature, the uniform LBP operator is adopted because a typical face image contains only a small number of LBP values (called the uniform pattern. Let us denote that is the center pixel position of S_i and z (0,…, P-1) are P equally spaced pixels (or sampling points) on a circle of radius R(R>0) that form a circular neighborhood of the center pixel z_c.

C. Combining Color Local Texture Features for FR

The way of combining color local texture features used for achieving the best FR performance. Our goal is to attain the best FR performance by combining them on the information fusion theory for pattern classification. Techniques for fusing multiple evidences (i.e., multiple classification results or multiple features) can be generally classified into two classes, i.e., fusion at the “feature level” and fusion at the “decision level.” In the proposed method, we make use of the feature-level fusion because “feature-level” The “feature-level” fusion methods achieve better FR performance than the competing “decision-level” fusion framework.

IV. RESULT AND DISCUSSION

A. Matlab code for Skin color detection

In this Matlab code, we have presented skin color detection algorithm for color image. The input image is converted into binary image. Then, binary image after dilation and erosion which represents skin region.

B. Matlab code for face local texture feature detection i.e. eye detection

In this Matlab code, we have presented an eye detection algorithm for color image. First input facial image is converted into YCbCr and Eye Map is obtained. The two highest peaks (brightest regions) in Eye Map are supposed to be eyes. We first build two separate eye maps from facial image, EyeMapC from the chrominance components and EyeMapL from the luminance component. These two maps are then combined into a single eye map, Eye Map. The resulting Eye Map is then dilated, masked, and normalized to brighten both the eyes and suppress other facial areas. The locations of the eye candidates are estimated and then refined using thresholding and binary morphological erosion on this Eye Map. Our method detects eyes in face image which is extracted over the entire image.

C. Matlab code for face detection

This is Matlab code for face detection. In this code input image is taken in RGB color space is converted into binary image. Then, binary image is processed and detect the face.

V. CONCLUSION

This work has investigated the contribution of color to existing texture features for improving the FR performance. Also how to effectively exploit the discriminating information by combining color and texture information, as well as its fusion approach has been examined. Color FR methods based on CLBP and CLGW significantly outperform the methods relying only on texture or color information. Color local texture features allows for a significant improvement in low-resolution face images, as compared with their gray scale counterparts. The final classification is performed using the DWT based Neural Network. The study in this work has been limited to evaluating the effectiveness of color local texture features that are extracted from fixed color-component configuration consisting of three components (such as RQCr).

A. Future Work

Hence, for the future work, the method of selecting an optimal subset of color components (from a number of different color spaces), aiming to obtain more discriminating color local texture features for FR can be developed.

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