A Comparative Study of Color Texture Features for Face Analysis

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Abstract. Although color texture features have proven to be highly effective for face analysis, the comparisons between the color texture features have not been presented in the literature. The aim of this paper is to find the best way for combining color and texture features for face analysis. For this purpose, four different approaches (proposed for face recognition or facial expression recognition) of extracting color texture features are reviewed and compared through extensive experiments. Experimental results show that the texture feature extracted using color vector can achieve the highest recognition performances for both face recognition and facial expression recognition, among the color texture features presented in this paper.

Keywords: Face analysis, face recognition, facial expression recognition, color, texture, face descriptor.

1 Introduction

Face analysis such as face recognition (FR) and facial expression recognition (FER) is a very active research topic in computer vision, human computer interaction (HCI), and biometrics [1]. For successful face analysis, we need to extract a face descriptor (or feature) that is robust against a variety of face appearance (e.g., illumination change) present in images.

Recently, texture features have gained reputation as powerful face features because they are known to be robust to variations of facial pose, illumination, etc. In particular, Gabor wavelet [2-3] and local binary pattern (LBP) [4-5] have proven to be highly discriminative for face analysis due to different levels of locality [8]. Most of the existing texture features have been designed for grayscale face images [2-6]. However, it has been known that use of color cue is able to significantly improve recognition performance, providing plenty of discriminative information [7-10]. Recently, there has been a limited but increasing amount of work on the combination of color and texture features for the purpose of face analysis [8-12], [15].

In [11-12], a simple sequential analysis of multiple color bands (e.g., R, G, and B color bands from RGB color space) was employed for FR purpose. In the method of [11], the LBP histogram vector was independently extracted from each of the different color band images. Subsequently, a low-dimensional feature extraction (such as Fisher's Linear Discriminant Analysis (FLDA) [23]) was applied to reduce the

dimensionality of each LBP histogram vector. After that, the resulting low-dimensional feature vectors were concatenated to form a face feature vector. Similarly, in [12], a set of Gabor filters was independently applied to each color band to extract the unichrome Gabor feature vector.

An alternative way to simply extend texture features to color images is to use multilinear image analysis [29]. In [9], a 2D tensor [29] of RGB color face image was generated via unfolding [29] and the Log-Gabor Filtering [26] was directly applied to this tensor for extracting the face feature for FER. To further improve the robustness to illumination change, the application of the above-mentioned 2D tensor Gabor method to other perceptually uniform color spaces (such as CIELuv) was studied [10].

The previous studies of [9-12] demonstrated that color texture features could achieve better recognition performance than grayscale texture features for face analysis. However, they did not consider the correlation between the color bands during the extraction of discriminative features.

Motivated by opponent process [13] of human eyes, the authors of [8] attempted to make use of discriminative information derived from the correlation between the color bands for FR purposes. Specifically, in addition to the unichrome (LBP or Gabor wavelet) feature independently computed from each color band, the opponent features [8] that capture the texture patterns of spatial interactions between different color bands were incorporated. Experimental result of [8] verified that opponent features could provide complementary information with unichrome features for FR.

More recently, vector processing [14] that treats each color image as a vector field has been employed for FR [15]. In [15], color vector [14] was defined at each pixel location of a color face image. The two kinds of discriminative texture patterns were extracted from color vector. Color norm pattern was extracted by comparing color vector norm values between neighboring color pixels. In addition, to utilize directional information of color vector, color angular pattern was extracted by computing the angles (or ratios) of pixel values between a pair of the color band images and comparing the angle values between neighboring color pixels. These color angular patterns could encode the texture patterns of the multiple inter-bands, which were based on the spatial interactions among the color band images.

Although a few of stand-alone face descriptors relying on color texture have been proposed as described, the comparative study of these descriptors has not been presented in the scientific literature. The comparisons between face descriptors for face analysis were given in some previous studies ([16-18]). However, face descriptors using color information were not considered in the comparisons.

In this paper, we aim to find the best way for combining color and texture features for face analysis. We review the existing methods of extracting color texture features, which have been developed for FR or FER. Through extensive experiments designed for FR and FER, we compare the effectiveness of these methods under different recognition conditions such as different color spaces or different recognition challenges etc. Experimental results obtained using three public face databases (DBs) reveal that for face analysis, texture feature based on color vector is more effective than the other color texture features compared. In addition, it is demonstrated that the color texture features that have been proposed for FR can also be effective for FER purposes, and vice versa.

The rest of this paper is organized as follows: Section 2 reviews the existing color texture features for face analysis. In Section 3, we present experiments of FR and FER to show the comparisons for the effectiveness of the color texture features. Conclusions are drawn in Section 4.

2 Review of Color Texture Features for Face Analysis

In this section, we review the existing methods for combining color and texture features for face analysis (i.e., FR or FER). As explained in Section 1, these can be divided into four different approaches: 1) Unichrome features, 2) Tensor based features, 3) Unichrome and opponent features, and 4) Color vector based features. A brief description of the aforementioned approaches is given in the following subsections.

2.1 Unichrome Features

Unichrome features are the straightforward way to deal with color images where a grayscale feature extraction is independently performed on each color band image. LBP is one of the most popular texture features for face analysis. The original LBP operator labels the pixels of an image by thresholding the 3x3 neighborhood of each pixel with the value of the center pixel and results in a binary number (refer to Fig. 1). In [11], to extend original LBP to color images, the uniform LBP operator [25] is separately applied to each of color band images (refer to Fig. 2). As in [25], a circular neighborhood of P and R is defined, where P is the number of pixels equally spaced on the circle and R is the radius size of the circle. The uniform LBP operator at a given pixel location (x, y) of a particular color band i is defined as [11]

$$LBP_{P,R}^{(i)}(x, y) = \begin{cases} \sum_{n=0}^{P-1} \delta(f_n^{(i)} - f^{(i)}) 2^n & \text{if } H^{(i)} \leq 2 \\ P(P-1) + 2 & \text{otherwise,} \end{cases} \quad (1)$$

where

$$H^{(i)} = |\delta(f_{P-1}^{(i)} - f^{(i)}) - \delta(f_0^{(i)} - f^{(i)})| + \sum_{n=1}^P |\delta(f_n^{(i)} - f^{(i)}) - \delta(f_{n-1}^{(i)} - f^{(i)})|, \quad (2)$$

and $\delta(x) = 1$ if $x \geq 0$, otherwise 0. In addition, $f^{(i)}$ and $f_n^{(i)}$ ($n = 0, \dots, P-1$) denote the color pixel values (of the i -th color band) at the center pixel location and its neighborhood pixel locations, respectively. After calculating the LBP values (using (1)) for entire pixels of each color band image, the color band image is spatially divided into a number of local regions. To reflect and encode the local properties of face, LBP histogram vector is extracted from each local region [11]. The unichrome LBP feature of a particular color band is obtained by concatenating the local LBP histogram vectors of the associated color band [11].

Fig. 1. Visualization of calculating a LBP pattern value for a given pixel location [25]

Fig. 2. Visualization of LBP operation performed on each color band image [11]. The text enclosed brackets (placed to the right-hand side of each face image) indicates the grayscale or color format of the corresponding face images.

To deal with multi-pose face recognition, the authors of [12] have presented a new color based Gabor wavelet features for FR. In this method, a set of Gabor filters is applied to each color band image to obtain the corresponding Gabor filtered image. Next, for given orientation and scale of Gabor filter, the mean and the standard deviation of the magnitude of the Gabor filtered image are computed. The mean and standard deviation values (for all of orientations and scales) computed from a given color band are then used as the unichrome Gabor feature of the color band.

For both feature extraction methods above, feature-level fusion [19] is used to combine multiple feature vectors obtained from different color bands. Specifically, the unichrome (LBP or Gabor) feature vectors are concatenated to form a face feature vector that is used for classification.

It is important to note that one of the limitations of the unichrome features is that only the interactions within color bands are exploited for classification, whereas the interactions between the color bands are not considered.

Fig. 3. Horizontal unfolding of color face image [9]. (a) Conceptual illustration for horizontal unfolding. (b) An example of RGB color face image represented by horizontal unfolding.

2.2 Tensor Based Features

For the purpose of utilizing color features for FER, a simple method that makes use of tensor [29] based representation of color face images has been proposed [9-10]. In this method, instead of applying grayscale texture operator to each color band individually, a 2D tensor of the color image is generated and the Log-Gabor filtering [26] is directly applied to this tensor [9-10].

A color image can be represented as a tensor $\mathbf{T} \in \mathbb{R}^{\Pi_1^{N_n}}$ of order 3, where N_1 is the height of the image, N_2 is the width of the image, and N_3 corresponds to the number of color bands. Tensor can be unfolded along any of its dimensions to obtain a mode- n matrix version of the tensor [9-10]. Thus, there are three different types available for tensor $\mathbf{T}^{(n\text{-mode})}$ as follows [10]:

$$\mathbf{T} \in \mathbb{R}^{\Pi_1^{N_n}} \rightarrow \mathbf{T}^{(1)} \in \mathbb{R}^{N_1 \times (N_2 \times N_3)} \quad (3)$$

$$\mathbf{T} \in \mathbb{R}^{\Pi_1^{N_n}} \rightarrow \mathbf{T}^{(2)} \in \mathbb{R}^{N_2 \times (N_1 \times N_3)} \quad (4)$$

$$\mathbf{T} \in \mathbb{R}^{\Pi_1^{N_n}} \rightarrow \mathbf{T}^{(3)} \in \mathbb{R}^{N_3 \times (N_1 \times N_2)}. \quad (5)$$

Although any types of (3)~(5) can be used, it has been experimentally proven in [9-10] that the best one is unfolding mode 1 (3), which is called horizontal unfolding. Fig. 3(b) shows an example of a RGB color face image represented by horizontal unfolding. RGB color space is used in [9], but note that any other color spaces can be applicable to this tensor based method. In [10], it has been demonstrated that for the tensor based Gabor method, the perceptual color spaces such as CIELab and CIELuv are better than the other color spaces such as RGB, by providing more effectiveness in the presence of illumination change in images.

The advantage of tensor based approach is that a separate post-process for combining information is not required. However, as unichrome features, the correlations between different color bands are not considered during the feature extraction.

2.3 Unichrome and Opponent Features

The opponent features are based on the opponent process theory of human color vision [13]. The opponent color Gabor filtering technique [13] and an opponent color version of the LBP operator [28] have been proposed for color texture analysis. In these methods, in addition to unichrome features derived from individual color bands, opponent features additionally exploit spatial interaction between color bands to mimic the opponent color processing of human eye. Motivated by the successful use in color texture analysis, opponent features of LBP and Gabor wavelet features have been presented in FR [8].

Given a pair of the i -th and the j -th color bands (for $i \neq j$), the opponent LBP operation at the pixel location (x, y) is defined as [8]

$$LBP_{P,R}^{(i,j)}(x, y) = \begin{cases} \sum_{n=0}^{P-1} \delta(f_n^{(j)} - f^{(i)}) 2^n & \text{if } H^{(i,j)} \leq 2 \\ P(P-1) + 2 & \text{otherwise,} \end{cases} \quad (6)$$

where

$$H^{(i,j)} = |\delta(f_{P-1}^{(j)} - f^{(i)}) - \delta(f_0^{(j)} - f^{(i)})| + \sum_{n=1}^P |\delta(f_n^{(j)} - f^{(i)}) - \delta(f_{n-1}^{(j)} - f^{(i)})|, \quad (7)$$

and $f^{(i)}$ denotes the pixel value of the i -th color band image at the center pixel (x, y) and $f_n^{(j)}$ ($n = 0, \dots, P-1$) denote the pixel values of the j -th color band image, which form a circular neighborhood of the center pixel of the i -th color band image. For the i -th color band, the unichrome LBP (histogram) feature vector, denoted by $\mathbf{x}_i^{U_LBP}$, can be obtained by using (1). In addition, the opponent LBP feature vector (denoted by $\mathbf{x}_{i,j}^{O_LBP}$) for the pair of the i -th and the j -th color bands can be calculated by using (6). Then, the proposed color (unichrome+opponent) LBP feature vector for the i -th color band can be defined as follows [8]:

$$\mathbf{x}_i^{C_LBP} = [(\mathbf{x}_i^{U_LBP})^T (\mathbf{x}_{i,j}^{O_LBP})^T \dots (\mathbf{x}_{i,K}^{O_LBP})^T]^T \quad \text{for } i \neq j, \quad (8)$$

where T is a transpose operator and K is the number of color bands. Note that in (8), $\mathbf{x}_i^{C_LBP}$ consists of one unichrome LBP feature vector $\mathbf{x}_i^{U_LBP}$ and $K-1$ opponent LBP feature vectors $\mathbf{x}_{i,j}^{O_LBP}$ [8].

To integrate the opponent theory into the extraction of Gabor features from a color face image, let $\mathbf{G}_{i,u,v}^{(m)}(x, y)$ and $\mathbf{G}_{j,u,v}^{(m)}(x, y)$ be the unichrome Gabor wavelet representations of the m -th local region ($m = 1, \dots, M$) of the i -th and the j -th color

band images, respectively, where u ($0 \leq u \leq U-1$) and v ($0 \leq v \leq V-1$) define the orientation and the scale of the Gabor filters [8]. Using $\mathbf{G}_{i,u,v}^{(m)}(x, y)$ and $\mathbf{G}_{j,u,v'}^{(m)}(x, y)$, the opponent Gabor representation between the i -th and the j -th color bands are then computed as follows [8]:

$$\mathbf{G}_{i,j,u,v,v'}^{(m)}(x, y) = \frac{\mathbf{G}_{i,u,v}^{(m)}(x, y)}{\mathcal{E}_{i,u,v}^{(m)}} - \frac{\mathbf{G}_{j,u,v'}^{(m)}(x, y)}{\mathcal{E}_{j,u,v'}^{(m)}} \quad \text{for } i \neq j \quad |v - v'| \leq 1, \quad (9)$$

where $\mathcal{E}_{i,u,v}^{(m)} = \sqrt{\sum_{(x,y)} \mathbf{G}_{i,u,v}^{(m)}(x, y)^2}$ ($\mathcal{E}_{j,u,v'}^{(m)}$ can be calculated in a similar way) and v and v' denote the different scales of Gabor filters used. In order to combine the multiple features, all Gabor wavelet representations $\mathbf{G}_{i,u,v}^{(m)}(x, y)$ and $\mathbf{G}_{i,j,u,v,v'}^{(m)}(x, y)$ of a particular color band i are concatenated, yielding an augmented feature vector called the Color Local Gabor Wavelet (CLGW) feature [8]. For the concatenation, a column vector $\mathbf{x}_{i,u,v}^{(m)}$ (or $\mathbf{x}_{i,j,u,v,v'}^{(m)}$) is obtained from $\mathbf{G}_{i,u,v}^{(m)}(x, y)$ (or $\mathbf{G}_{i,j,u,v,v'}^{(m)}(x, y)$) by stacking its rows or columns. The CLGW feature for the i -th color band is defined as [8]:

$$\mathbf{x}_i^{\text{CLGW}} = [(\mathbf{x}_i^{U-\text{GW}})^T (\mathbf{x}_i^{O-\text{GW}})^T \cdots (\mathbf{x}_i^{O-\text{GW}})^T]^T \quad \text{for } i \neq j, \quad (10)$$

where $\mathbf{x}_i^{U-\text{GW}} = [(\mathbf{x}_{i,u,v}^{(1)})^T \cdots (\mathbf{x}_{i,u,v}^{(m)})^T \cdots (\mathbf{x}_{i,u,v}^{(M)})^T]^T$ denotes the unichrome Gabor feature vector, and $\mathbf{x}_i^{O-\text{GW}} = [(\mathbf{x}_{i,j,u,v,v'}^{(1)})^T \cdots (\mathbf{x}_{i,j,u,v,v'}^{(m)})^T \cdots (\mathbf{x}_{i,j,u,v,v'}^{(M)})^T]^T$ ($|v - v'| \leq 1$) denotes the opponent Gabor feature vector [8].

2.4 Color Vector Based Features

It is believed that vector processing that treats each color image as a vector field is natural and desirable for color image processing (such as color image filtering [14]). This is mainly attributed to the fact that since color pixel is processed as a vector (called a color vector) one can prevent the loss of information contained in the correlation between the color bands [14].

Recently, there has been an attempt to exploit the effectiveness of using color vector for purpose of FR [15]. In the method of [15], by applying color space conversion to a given RGB color face image, we obtain a total of K color band images each of which is associated with a particular color component (e.g., Y from YIQ color space). Then a color pixel at a center pixel location (x, y) is represented as a color vector $\mathbf{c} = [v_1, \dots, v_K]^T$, where v_k represents the pixel value at (x, y) of the k -th color band image [15]. In addition, let $\mathbf{c}_n$ ($n=0, \dots, P-1$) denote the color vectors each defined at a particular point of the P equally spaced pixel locations on a circle of radius R , which form a circular neighborhood of the center pixel location (x, y) . Using the relationship between color vector $\mathbf{c}$ and its neighborhood color vectors

$\mathbf{c}_n (n=0, \dots, P-1)$, a color texture based face feature (so-called Local Color Vector Binary Pattern (LCVBP) [15]) is extracted, which consists of color norm pattern and color angular patterns (each of which is associated with a pair of different color bands) as below.

Fig. 4. Illustration of extracting color norm and color angular pattern from local region images obtained from three color bands (channels) in the YIQ color space [15]. (a) Extraction of color norm pattern. (b) Extraction of color angular pattern.

To extract the discriminative patterns from pixel intensity values within color band images, color norm pattern can be computed. As shown in Fig. 4(a), the computation of color norm pattern (denoted by $LBP_{cn}^{P,R}(x, y)$) at (x, y) can be achieved by comparing the norm value $r (= \|\mathbf{c}\| = \sqrt{v_1^2 + v_2^2 + \dots + v_k^2})$ of color vector $\mathbf{c}$ with the norm values $r_n (= \|\mathbf{c}_n\|)$ of the neighboring color vectors $\mathbf{c}_n$ as follows [15]:

$$LBP_{cn}^{P,R}(x, y) = \begin{cases} \sum_{n=0}^{P-1} \delta(r_n - r) 2^n & \text{if } H \leq 2 \\ P(P-1) + 2 & \text{otherwise,} \end{cases} \quad (11)$$

where

$$H = |\delta(r_{P-1} - r) - \delta(r_0 - r)| + \sum_{n=1}^{P-1} |\delta(r_n - r) - \delta(r_{n-1} - r)|. \quad (12)$$

For the purpose of extracting the discriminative patterns contained between different color bands, we calculate the ratio of pixels between a pair of the color band images. The ratio of pixel values between color bands is defined by [15]:

$$\pi^{(i,j)} = \frac{v_j}{v_i + \gamma}, \quad (13)$$

where v_i and v_j are the elements of color vector $\mathbf{c}$ associated with the i -th and j -th color bands, respectively. Using (13), the color angle between the i -th and j -th color bands is computed as follows [15]:

$$\theta^{(i,j)} = \tan^{-1}(\pi^{(i,j)}). \quad (14)$$

As shown in Fig. 4(b), $\theta^{(i,j)}$ represents the value of angle computed between the axis corresponding to the i -th color band and the reference line which is formed by projecting the $\mathbf{c}$ onto the plane associated with the i -th and j -th color bands [15]. Using (11) and (14), the LBP operator ($LBP_{ca_{i,j}}^{P,R}(x,y)$) for color angular pattern between the i -th and j -th ($i < j$, $i = 1, \dots, K-1$, and $j = 2, \dots, K$) color bands at pixel location (x,y) can be defined as follows [15]:

$$LBP_{ca_{i,j}}^{P,R}(x,y) = \begin{cases} \sum_{n=0}^{P-1} \delta(\theta_n^{(i,j)} - \theta^{(i,j)}) 2^n & \text{if } H \leq 2 \\ P(P-1) + 2 & \text{otherwise.} \end{cases} \quad (15)$$

where $\theta_n^{(i,j)}$ ($n = 0, \dots, P-1$) denote the angle values between i -th and j -th elements of $\mathbf{c}_n$. For each texture pattern (e.g., color norm pattern or color angular pattern derived from a pair of different color bands), the associated LBP histogram vectors are computed over the whole local regions and combined by concatenation to build a global LBP histogram vector [15].

3 Experiment

To evaluate different kinds of color texture features, three publicly available face DBs, i.e., AR DB [20], Color FERET DB [21], and CMU Multi-PIE DB [22], were used. All face images used in our experiments were manually cropped from original images based on the locations of the two eyes. Each cropped face image used in our experiments was rescaled to the size of 64x64 pixels (see Fig. 5).

For comparative evaluation, the following six kinds of color texture features were presented: (1) Unichrome LBP [8], [11]; (2) Unichrome Gabor [8]; (3) Unichrome and opponent LBP [8]; (4) Unichrome and opponent Gabor [8]; (5) Tensor Gabor [9-10]; (6) Color vector texture feature [15]. For the LBP based methods (including color vector texture feature), we selected the uniform LBP operator [25] of $P=8$ and $R=2$. In addition, for the LBP based methods, the local regions of 8x8 pixels were used. For the Gabor based methods, we used five scales and eight orientations to construct a set of Gabor filter banks [2]. Note that for fair comparison, for the tensor Gabor method

in [9-10], the original Gabor filters were employed instead of the Log-Gabor filters. In addition, although the method in [8] applied Gabor filters to local region images for obtaining the Gabor representations, in our experiments, we applied the Gabor filters to the entire face images as the conventional method of [2] to eliminate the effect of using local based feature extraction (i.e., the number of local regions denoted by M was set to 1 in our experiment).

In order to investigate the effectiveness of different color texture features in terms of recognition performance under different color representations, three widely used color spaces were used in our experiments: RGB, $YCbCr$, and CIE Luv.

Fig. 5. Examples of face images used in our experiments. (a) AR DB. (b) FERET DB. (c) CMU Multi-PIE DB.

Prior to the classifications, we applied a low-dimensional feature extraction to all the color texture features. As for the low-dimensional feature extraction, Fisher's Linear Discriminant Analysis (FLDA) [23] was used in this paper. For the unichrome feature or unichrome and opponent feature, following the method of [8], the low-dimensional feature extraction (i.e., FLDA) is independently applied to the feature vector (e.g., $\mathbf{x}_i^{C_LBP}$ in (8)) associated with a particular color band. Next, the resulting low-dimensional feature vectors of the multiple color bands are concatenated into a face feature vector. Similarly, for the color vector based texture feature [15], FLDA is individually applied to the histogram vector of each texture pattern (e.g., color norm pattern or color angular pattern derived from a pair of different color bands), and the low-dimensional feature vectors of the multiple texture patterns are concatenated to form a face feature vector as in [15]. The obtained face feature vectors are readily fed into their classifications.

In our experiments, rank-one identification rate [21] was used for measuring the recognition performances. Note that in general, the recognition performance relies on the number of low-dimensional feature vectors used [24]. Therefore, to realize a fair comparison, the best found correct recognition rate (BstCRR) [24] was selected as the identification rate. To determine the identity (for FR) or expression (for FER), a

nearest neighbor (NN) classifier was used. For FR, the identity of a given query face image was determined as the person whose gallery face image was closest to the query face image. For FER, the expression of a given query face image was determined by finding the closest training face images (from the query face image). All results reported in the experiments were averaged over 20 times.

3.1 Face Recognition

The objective of this section is to present experimental results to compare the effectiveness of different color texture features for FR. For this purpose, we have designed two separate experiments under the representative FR challenges.

Table 1. Comparisons of identification rate between different color texture features for face recognition with AR DB

Method	Identification rate (%)		
	RGB	YCbCr	CIE Luv
Unichrome LBP [8], [11]	95.43	98.54	95.48
Unichrome Gabor [8]	92.80	92.86	94.46
Unichrome and opponent LBP [8]	98.60	94.28	94.94
Unichrome and opponent Gabor [8]	94.57	95.41	95.26
Tensor Gabor [9-10]	92.93	91.82	97.18
Color vector [15]	99.06	99.34	95.12

Fig. 6. Comparisons of average identification rate obtained for the result in Table 5. The identification rates of Gray LBP and Gray Gabor are also indicated as baseline performances. For fair comparison, FLDA was applied to the both grayscale feature vectors.

Table 2. Comparisons of identification rate between different color texture features for face recognition with Color FERET DB

Method	Identification rate (%)		
	RGB	YCbCr	CIE Luv
Unichrome LBP [8], [11]	92.28	92.50	93.12
Unichrome Gabor [8]	87.72	88.64	90.61
Unichrome and opponent LBP [8]	87.60	90.93	93.28
Unichrome and opponent Gabor [8]	89.36	90.13	91.54
Tensor Gabor [9-10]	87.47	89.74	92.87
Color vector [15]	92.24	94.22	93.59

Fig. 7. Comparisons of average identification rate obtained for the result in Table 2

For designing an experiment under illumination and facial expression change, a total of 1,400 frontal face images of 100 identities were collected from the AR face DB. For each identity, we chose 14 images with different illumination conditions and facial expressions (see Fig. 5(a)). To construct the gallery set, we selected 100 face images (one for each identity) with neutral illumination and expression. In addition, by using random partition, 500 images (5 images $\times$ 100 identities) were used to construct the training set and the remaining 800 images (8 images $\times$ 100 identities) were used for the probe set.

For designing an experiment under facial pose change, a total of 1,057 face images of 70 identities were collected from the Color FERET face DB. The facial images used include five different pose angles ranging from -45° to $+45^\circ$ (see Fig. 5(b)). Also note that all the images have neutral expression and illumination. By using random partition, the training set consisted of 350 face images (5 images $\times$ 70 identities), while the probe set contained the 637 images of the same 70 identities. In addition, the 70 frontal-view face images with neutral illumination and expression were used to build the gallery set.

The comparison results are given in Table 1, Table 2, Fig. 6, and Fig. 7. Examining the results, the following observations can be made:

- The color texture features outperform the grayscale texture features for all color spaces used.
- Tensor Gabor and unichrome and opponent Gabor outperform unichrome Gabor.
- For both face DBs, unichrome LBP yields better recognition performance than the unichrome and opponent features. One possible reason for this observation is that unlike the unichrome features, the opponent features are not invariant to monotonic transformations of pixel values, as described in [27]. Thus, the opponent features could be sensitive to variations appearing in face images, such as illumination change or facial pose change.
- The effectiveness of the color spaces depends on the types of color texture features used. For example, the color vector texture feature relatively works well with YC_bC_r color space. In addition, it is observed that the perceptual color space (i.e., CIE Luv) is highly effective for tensor Gabor feature (especially under the illumination change), which is consistent with the result reported in [10].

- The effectiveness of a color space is also dependent with recognition condition. For example, we can see that the use of YC_bC_r or CIELuv color space is able to achieve higher recognition performance than RGB color space when AR DB (containing illumination change) is used. On the other hand, it is observed that RGB color space is much more effective than the other color spaces when Color FERET DB (containing pose change).
- Overall, as shown in Fig. 6 and Fig. 7, the color vector texture feature attains the highest recognition performance among all the color texture features compared.

Table 3. Comparisons of identification rate between different color texture features for face recognition with CMU Multi-PIE DB

Method	Identification rate (%)		
	RGB	YC_bC_r	CIELuv
Unichrome LBP [8], [11]	74.65	73.86	76.79
Unichrome Gabor [8]	75.51	71.77	75.40
Unichrome and opponent LBP [8]	75.90	75.74	76.94
Unichrome and opponent Gabor [8]	76.98	76.33	75.47
Tensor Gabor [9-10]	74.50	75.10	76.04
Color vector [15]	76.34	78.88	78.38

Fig. 8. Comparisons of average identification rate obtained for the result in Table 3

3.2 Facial Expression Recognition

Although most of the existing FER methods rely on only grayscale features, it has recently been demonstrated in [10] that color information has significant potential to improve FER performance. Through comparative evaluation, this section investigates the feasibilities of using different color texture features (most of which have been developed for FR) for FER.

A total of 822 frontal face images (137 face images per class) of 80 different persons were collected from the CMU Multi-PIE DB. Fig. 5(c) shows some examples of face images used in the experiment. In Fig. 5(c), we can see that the face images look quite challenging because they contain severe illumination change due to

different illumination settings (e.g., with or without flash, and different illumination directions etc). Note that the multiple face expression images from a single person contain almost same face appearance (except illumination) due to the quick data acquisition with varying illumination directions [22]. Thus, for designing more realistic condition, we decided to perform an experiment for person-independent recognition where the persons in training phases differ from the testing one. By using random partition, the 70 persons were used for training while the remaining 10 persons were used for constructing test set.

The comparison results are illustrated in Table 3, and Fig. 8. From the results, we can observe that most of the observations (except the third and fifth ones) obtained for the FR experiment holds true for the case of the FER experiment. The results indicate that the color texture features used for FR can also be applicable to FER. In particular, as in the FR experiment, it is shown in Fig. 8 that among the features compared, color vector texture feature is most appropriate for improving FER performance.

4 Conclusion

In this paper, we presented a performance comparison of distinct color texture features for face analysis. The two face analysis applications, i.e., face recognition (FR) and facial expression recognition (FER), were considered in experiments. Experimental results showed that for both FR and FER, color vector texture feature could be highly effective in terms of identification rate, compared with the other color texture features presented in the experiment. It was also shown that although most of the color texture features were developed for FR, they could be readily applied to FER for improving recognition performance.

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