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COLOUR FACE RECOGNITION:A NOVEL RECOGNITION METHOD

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Abstract— ***This paper presents an novel approaches to the detection and recognition of human face and describes an efficient real time colour face recognition system which tracks a subject's head and then recognizes the person by comparing local texture features of the face to those of know individual. This approach treats face recognition in different colour spaces other than RGB. We have implemented the face detection system using skin colour detection. To avoid the illumination problem and pose constraints in face recognition, two face descriptors are used,i.e., so called colour local Gabor wavelets (CLGWs) and local colour vector binary patterns(LCVBPs). These features are used along with eigen-faces for better recognition. The framework provides the ability to learn to recognize in a unsupervised manner.***

Keywords— ***Colour Face Recognition(FR), Skin Colour Detection, Eigen-faces, Gabor Wavelets,Local Vector Binary Pattern***

I. INTRODUCTION

In todays world face recognition is built to accomodate the changes in texture colour expression orientation etc as this technology is gaining relevence in wider applications. So there has been an ever increasing need to optimise these feature detection algorithm. Gray scale textures [3] stood as the basis of most feature extraction,but recently the effect of colour gradients and their significance in increasing the accuracy in both feature extraction and detection has gained importance. The method of extracting local texture features [4]&[8] like eye, mouth, nose orientation etc has gained reputation as powerful face descriptors since they are more robust to variation of facial pose, expressions etc. Here we use this approach in robust face detection and recognition.

Most of the current face recognition systems assume that faces are readily available for processing but in reality we do not get images with just faces. So we need a system which will detect or locate faces from an image. This located/detected face can be given as input to the face recognition system.We have implemented the face detection system in three phases. In the first phase of this method, the skin region of the human is detected from the still image or video clip. The second phase deals with grouping and connected component analysis. The final phase deals with finding the face region and creating the boundary across the face region.

Post detection, the next step is to extract the features.As mentioned in [4], the local features and regions based on centre of eye, nose etc is used as extracts for further image recognition.In particular, Gabor wavelets [5] and local vector binary pattern (LVBP) [6] texture features have proven to be highly discriminative for FR due to different levels of locality.These features are able to provide much better FR performance for face images taken under severe variation in illumination, as well as for small-resolution face images.

While there exists a huge body of work dealing with texture face features, most of them are based on grayscale texture patterns. However, a few research efforts have been recently dedicated to incorporate colour information into the extraction of texture features [9] for FR purposes. In [5], the authors attempted to extend the Gabor-based approach for FR to colour images by defining the concept of quaternion (i.e., four-component hypercomplex numbers). On a relatively limited set of experiments,the authors reported performance enhancement on the order of 3%–17% when using the proposed quaternion Gabor-based approach instead of the conventional monochromatic Gabor-based method. In [5], Liu and Liu proposed the FR method that fused multiple global and local features derived from the hybrid colour space RC_rQ. This colour FR method achieved considerably better FR performance. In addition, Choi *et al.* [7] suggested colour LBP (CLBP). In their solution, LBP-based texture feature is independently extracted from each of the different colour channels.

The previous works reviewed above successfully demonstrate that colour information can provide complementary information to FR using texture analysis, and consequently, it can be used to improve FR performance. However, it should be pointed out that most of the previous approaches are restricted to simply extending grayscale texture operations (such as the LBP and Gabor) to multiple spectral-band (colour channel) images in a separate manner. As such, most of them are limited to encoding the texture patterns of only colour pixel variations de-rived from each individual spectral-band image

II. OVERVIEW OF ALGORITHM

Colour images are input to the system for face detection. The first action is to normalise the image based on the colour components and then extract their Chrominance components that aid better face detection.The detected Skin Areas may be clustered so we need to group the pixels together. If any detected part has a similar detected area within the pixels in its visinity then they are grouped as one. Till now we used Pixel based approach, from here on its region based. Now we compare the region with the height and width golden ratio and teh respective matching region is takes as face region.

The algorithm for face detection is given as:

Algorithm: Face Detection
Input : Front facial RGB image.
Output: Face detected region
Step 1: Convert the RGB image into YCbCr image
Step 2: For each pixel get the corresponding Cb and Cr value
Step 3: If((Cr,Cb) > threshold) then skin(i,j) = 1 i.e. is a skin pixel else skin(i,j) = 0 i.e. is a non-skin pixel
Step 4: Find the different regions in the image by implementing connectivity analysis using 8-connected neighborhood and labeling that regions
Step 5: Find area of each region
Step 6: Finding the region having the largest area
Step 7: Declare that region as a face.
End of Algorithm

For feature extraction we separately extract CLGW and LCVBP.

1) This paper uses the first so-called colour local texture features. Specifically, we develop two effective colour local texture features, i.e., colour local Gabor wavelets (CLGWs) and colour 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 colour and texture information, the opponent colour texture features that capture the texture patterns of spatial interactions between spectral bands are incorporated into the generation of CLGW and LCVBP. This allows for acquiring more discriminative colour local texture features, as compared with conventional grayscale texture features, for improving FR performance.

2) In the LCVBP, colour vector is defined (using a colour pixel value) at each pixel location within each of the local face regions of multiple spectral-band images, with each corresponding to a particular colour band (or channel). In order to extract the discriminative features, the following two different texture patterns are extracted (from each local face region) via LBP texture operation: 1) the colour norm pattern of a colour vector; and 2) the colour angular patterns between pairs of element (i.e., pixel) values of a colour vector. In order to perform FR tasks, LCVBP feature is generated by integrating multiple discriminating features extracted from both colour norm patterns and colour angular patterns, leading to maximize a complementary effect.

3) The effective way of combining colour local texture features is the feature-level fusion approach in order to integrate multiple colour local texture features [each extracted from an associated colour component (or spectral) image] for the final classification.

Low dimensional feature extraction technique (principal component analysis) is used for feature extraction. The local texture features are used along with eigen faces for better recognition.

III. FACE DETECTION USING SKIN COLOUR

Face detection from human front image belongs to an image processing,computer vision and an essential in many multimedia systems and real time applications.Face detection system is implemented in three phases [16]. In the firstphase of this method, the skin region of the human is detected from the still image or video clip. The second phase deals with grouping and connected component analysis. The final phase deals with finding the face region and creating the boundary across the face region. Our approach treats this method as a two dimensional recognition problem taking an advantage of the fact that human faces are normally upright and thus may be described by a set of 2-D characteristic views.. The steps performed under this phase are shown in Fig.1.

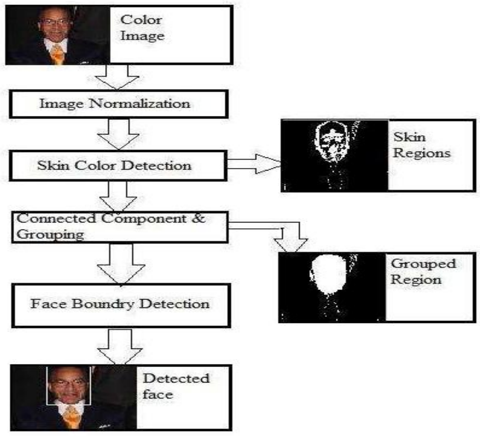

Fig.1. Steps in face detection

A. Skin Colour Detection

The first step in skin colour detection is pixel-based skin detection, where the skin detector tests every pixel of the input image and computes its normalized red value Cr and normalized blue value Cb. If Cb and Cr values of the pixels satisfy the threshold value then the pixel is considered skin pixel otherwise non-skin pixel. The output of the pixel- based skin detector is a binary mask that contains ones in the skin regions and zeros in non-skin regions.

B.Connected Component and Grouping

The detected skin regions may be discontinuous; this discontinuity may be due to lighting effects that leads to missed skin pixels or due to the presence of non-skin face features like the eyes and brows. In order to make the detected skin regions continuous, region-based skin detection is applied to the output of the pixel-based skin detection. In region-based skin detection, all detected skin regions are considered as face candidates. To do so we need to categorize the skin pixels into different groups so that they will represent something meaningful as a group, for example a face, a hand etc. Since we have to form meaningful groups of pixels, it makes sense to group pixels that are connected to each other geometrically. We group the skin pixels in the image based on an 8-connected neighborhood i.e. if a skin pixel has got another skin pixel in any of its 8 neighboring places, then both the pixels belong to the same region.

C. Face Boundary Detection

At this stage, we have different regions and we have to classify each of these regions as a human face or not. This is done by finding the centroid, height and width of the region as well as the percentage of Skin in the rectangular area defined by the above parameters. The centroid is found by the average of the coordinates of all the pixels in that region After finding height and width of each component we reject region one by one on basis of certain condition. First we check that whether region satisfy golden ratio or not. Golden ratio is term defined as ratio of height and width of particular region.If the region is having golden ratio above standard golden ratio for face then we can assume that it can be face. If it does not satisfy above condition, we reject that particular region. Then after we check whole image searching for largest region, we consider it as face.

IV. FRAMEWORK OF FR USING COLOUR LOCAL TEXTURE FEATURES

As shown in Fig.2, the implemented colour FR framework using colour local texture features consists of three major steps: colour space conversion and partition, feature extraction, and combination and classification. A face image represented in the *RGB* colour space is first translated, rotated, and rescaled to a fixed template [13], yielding the corresponding aligned face image.

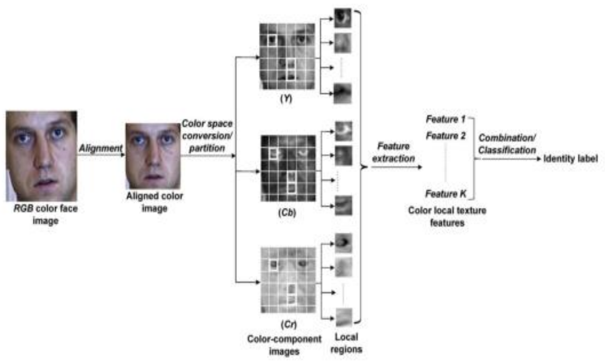

Fig.2. Implemented Framework of FR

Subsequently, the aligned *RGB* colour image is onverted into an image represented in *YCbCr* colour space. Each of the colour-component images of current colour model is then partitioned into local regions as suggested by [4].

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 *colour channels*, they are referred to as "colour local texture features."

V. EXTRACTION OF COLOUR LOCAL GABOR WAVELETS

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]:

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

where *u* and *v* define the orientation and the scale of the Gabor.

The Gabor wavelet representation can be obtained by convoluting the Gabor kernels with the image. The Fig. 3 shows, 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 Gaborwavelet representations. This indicates that they can provide different complementary information for the purpose of FR.Inorder to exploit the additional information contained between spectral bands,an opponent local Gabor representation is used. In order to make an effective use of different complementary information, we have to reserve *locality* information and to encompass *color texture* information.

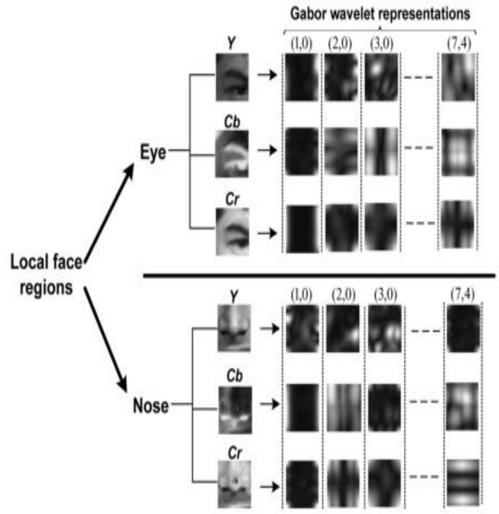

Fig.3. Illustration of Gabor wavelet representation with five scales and eight orientation

Finally all Gabor wavelet representations are concatenated,resulting in an augmented feature vector named the CLGW feature. For concatenation, we form a column vector, which is formed by stacking the rows or columns of the Gabor wavelet representation values (for detailed equations refer [1].

VI. LCVBP

In this section, we describe the way of extracting the LCVBP from a color face image. For this, we introduce notation commonly used throughout the following subsections.

Let $\mathbf{I}$ be a *RGB* color face image with size of $W \times H$ pixels. Let us assume that $K (K = 3)$ different kinds of spectral-band images are generated from $\mathbf{I}$ via color space conversions prespecified. Then, let $\mathbf{S} = \{\mathbf{S}_k\}_{k=1}^{K}$ be a set consisting of K different spectral-band images, where $\mathbf{S}_k$ denotes the kth spectral-band image (e.g., the spectral component *Cb* from *YCbCr* color space). The LCVBP consists of color norm patterns and color angular patterns. A detailed description of extracting these two different patterns is given in the following subsections.

A. Extraction of Color Norm Patterns

In this section, we describe the process of extracting the color norm patterns from the given set $\mathbf{S} = \{\mathbf{S}_k\}_{k=1}^{K}$. To compute the color norm pattern, a color vector is defined at the center pixel location $z = (x, y)$, given all $\mathbf{S}_k (k = 1, \ldots\ldots, K)$. Specifically, the pixel at z can be represented as a K-component vector denoted by $\mathbf{c} = [v_1 \ldots\ldots v_k]^T$, where the kth element v_k is the pixel value at z of the associated$\mathbf{S}_k$ and T denotes the transpose operator. In addition, let $\mathbf{c}_n (n = 0, \ldots\ldots, P - 1)$ denote the color vectors that 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 z.To extract the discriminative patterns from pixel intensity values within
spectral-band images contained in $\mathbf{S}$, we compute the color norm value of $\mathbf{c}$ as follows:

$$r = \|c\| = \sqrt{v_1^2 + v_2^2 + \cdots + v_k^2} \qquad (2)$$

Note that, in (2), combining K different color channels (via the usage of norm operation) allows effectively facilitating a complementary effect of the individual color channels for improving FR performance. Using (2), we compute an LBP histogram so as to represent the patterns of color norm values for $\mathbf{S} = \{\mathbf{S}_k\}_{k=1}^{K})$ [2]. Note that, in the computation of LBP histogram, a uniform LBP operator is adopted because typical face images contain only a small number of LBP values (called uniform pattern), as reported in [15]. The uniform LBP operator for computing color norm pattern at the center pixel location z of $\mathbf{S}$ can be defined as follows:

$$\mathrm{LBP}_{cn}^{P,R}(z) = \begin{cases} l\left(\sum_{n=0}^{P-1} \delta(r_0 - r) 2^n\right), & if\ H \leq 2 \\ P(P-1)+2, & otherwise \end{cases} \qquad (3)$$

where

$$H = |\delta(r_{P-1} - r) - \delta(r_0 - r)| + \sum_{n=1}^{P-1} |\delta(r_n - r) - \delta(r_{n-1} - r)| \qquad (4)$$

and$\delta(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}, r_n = \|\mathbf{c}_n\| \ (n = 0, \ldots\ldots, P - 1)$ and $l(.)$ is an indexing function that labels a particular index to each of the uniform patterns such that $l(.) \in [0. P(P-1) + 13]$.
To reflect and encode local properties of a face image associated histograms are computed [2] by dividing the each spectral band images into M nonoverlapping region , each denoted by $\mathbf{S}_k^{(m)} (m = 1, \ldots\ldots, M)$.Then,LBP histogram values of the color norm patterns for a set of the mth local regions $\mathbf{S}^{(m)} = \{\mathbf{S}_k^{(m)}\}_{k=1}^{K}$ are determined by

$$h_{cn}^{(m,l)} = \sum_{z in S^{(m)}} T\left(LBP_{cn}^{P,R}(z) = l\right), \text{for } 0 \leq l \leq P(P-1) + 2 \qquad (5)$$

where

$$T(A) = \begin{cases} 1, & if\ A\ is\ true \\ 0, & if\ A\ is\ false \end{cases} \qquad (6)$$

and l denotes the lth LBP label in the range of [0,P(P-1)+2], and $h_{cn}^{(m)}$ is the number of pixel locations with the LBP label l within the local region set $\mathbf{S}^{(m)}$. Using (2), the regional LBP descriptor for $\mathbf{S}^{(m)}$ can be written as follows:

$$\mathbf{h}_{cn}^{(m)} = \left[h_{cn}^{(m,0)}, h_{cn}^{(m,1)}, \ldots, h_{cn}^{(m,P(P-1)+2)}\right]^T \qquad (7)$$

In order to keep the information about the spatial relation of M facial local regions, all of the $h_{cn}^{(m)} (m = 1, \ldots\ldots, M)$ are concatenated into a single-column vector, resulting in the LBP histogram of color norm patterns derived from the $\mathbf{S}$

$$\mathbf{h}_{cn} = \left[\left(\mathbf{h}_{cn}^{(1)}\right)^T \left(\mathbf{h}_{cn}^{(2)}\right)^T \ldots \left(\mathbf{h}_{cn}^{(M)}\right)^T\right] \qquad (8)$$

B. Extraction of Color AngularPatterns

Inorder to effectively extract the directional information of a color vector we need to extract the discriminative patterns contained between different spectral bands, by calculating the ratio of pixels between a pair of the spectral-band images.This can be useful for extracting discriminative color angular patterns for FR. For instance, the ratio (or angle) value at a pixel location between a pair of spectral-band images does not change even in the illuminated image region, where the illumination changes are represented as scaling of pixel values (by a scalar) and proportional between bands, thus providing illumination invariance for FR.

The ratio of pixel values between spectral bands is defined by

$$\pi^{(i,j)} = \frac{v_j}{v_i + \gamma}, \text{for } i < j, i = 1, \ldots, K-1, \ and\ j = 2, \ldots, K \qquad (9)$$

where v_i and v_j are the elements of color vector $\mathbf{c}$ associated with the ith and jth spectral bands of the color image, respectively. Note that is a small-valued constant to avoid a zero-valued input in the denominator term. Using (9), the color angle between the ith and jth spectral bands is computed as follows:

$$\theta^{(i,j)} = \tan^{-1}\left(\pi^{(i,j)}\right) \qquad (10)$$

where the values of $\theta^{(i,j)}$ fall between 0^0 and 90^0. Note that $\theta^{(i,j)}$represents the value of angle computed between the axis (corresponding to the ith spectral band) and the reference line, which is formed by projecting $\mathbf{c}$ onto the plane associated with the ith and jth spectral bands. Using (3) and (10), the LBP operator ($\mathrm{LBP}_{ca_{i,j}}^{P,R}(z)$) for the color angular pattern (between ith and jth spectral bands) at location z of $\mathbf{S}$ can be defined [2] similarily as color norm pattern. Similarly LBP histogram values $h_{ca_{i,j}}^{(m,l)}$ and $\mathbf{h}_{ca_{i,j}}$ [2] can be determined as same as color norm patterns.

C. Computing LCVBP Feature

LCVBP features generated from colour norm and colour angular patterns are combined in this step. Inorder to maximize a complementary effect on recognition we adopt information fusion technique performed at the feature level, considering its effectiveness in terms of both computational cost and FR performance. Using feature-level information fusion technique, we combine the individual LBP histograms by concatenating them in column order. Low dimensional feature extraction technique like PCA is used. In order to generate the LCVBP features, the low-dimensional features of LBP histograms are combined at the feature level by concatenating the low-dimensional features in column order.The individual low dimensional features should be separately normalized to have zero mean and unit variance prior to their concatenation.

VII. COMBINING COLOR LOCAL TEXTURE FEATURES FOR FR

This section suggests the way to combine local texture features [1] for achieveing the best FR performance. In this we separately findout the local features for probe face (unknown RGB image tobe identified or verifed) and local features for gallery set (which contains RGB color face images to be recognized). These feature values are stored separately.

By using feature-level information fusion techniques,color local texture could be simply concatenated ito a longer glogal feature vector. However, it should be noted that directly applying a nearest-neighbor (NN) classifier to such a concatenated feature vector could suffer from the degradation in the FR performance caused by the high dimensionality and the redundant information.To overcome this limitation, low-dimensional feature extraction techniques are employed. Principal component analysis (PCA) is a common and easy extraction technique used nowadays. Here we are employing PCA for low dimensional feature extraction.

K complementary low dimensional features are extracted which are combined at the level of features by concatenating them in the column order. Each low- dimensional feature should be independently normalized in order to have zero mean and unit variance prior to their concatenation. By doing so, we may avoid the negative effect of the magnitude dominance of one low-dimensional feature over the others.

VIII. CONCLUSION

In this paper, we have presented an approach to the detection and recognition of the face. This approach uses skin colour for the detection of faces from the image and uses color local features for recognition. CLGW and LCVBP along with eigen faces are used as local features. This color local features allows better accuracy when recognizing face images taken under severe illumination, as well as for low- resolution face images,as compared with grayscale counterparts.Eigen faces provides an easier method for the reconstruction of the faces from eigen faces which will help in easy recognition. Combining these features gave a better recognition system which we can rely on.

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