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Person Authentication Using Color Face Recognition

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Abstract
Face is a complex multidimensional structure and needs good computing techniques for recognition. Our approach consists of two feature extraction algorithms that are Gabor wavelet and local binary pattern for the purpose of color face recognition. These methods provide excellent recognition rates for face images taken under severe variation in pose, illumination as well as for small resolution face images. Face recognition is done by Principal Component Analysis. This work shows the performance of color face recognition with YCbCr color space using GW and LBP. The experiments are performed on FEI color database. Result includes recognition rate (in percent) for different method such as YCbCr and Gray using GW and LBP for different pixels resolution such as 54x36, 81x54, and 108x72.
Keywords — Gabor wavelet, local binary pattern, Principal Component Analysis, FEI color database, YCbCr color space.

I. INTRODUCTION

The face is our primary focus of attention in social life playing an important role in conveying identity and emotions. We can recognize a number of faces learned throughout our lifespan and identify faces at a glance even after years of separation [1]. Face detection and recognition is attracting a lot of interest in areas such as network security, content indexing and retrieval, and video compression, because people are the object of attention in a lot of video or images. To perform such real-time detection and recognition, novel algorithms are needed which better current efficiencies and speeds.

After four decades of research and with today's wide range of applications and new possibilities, researchers are still trying to find the algorithm that best works in different illuminations, environments, over time and with minimum error [2]. This work pretends to explore the potential of a Gabor wavelet [4] and Local Binary Patterns (LBP) [5] and the main motivations to study it in this work are: It can be applied for both detection and recognition and robustness to pose, low resolution and illumination changes [3]. Features extracted from a face are processed and compared with similarly processed faces present in the database. If a face is recognized it is known or the system may show a similar face existing in database else it is unknown. In surveillance system if an unknown face appears more than one time then it is stored in database for further recognition. These steps are very useful in criminal identification.

The rest of this paper is organized as follows: section II, we describe generic face recognition system. In section III, we describe framework of color face recognition. In section IV, we describe feature extraction approach. In section V, we present face recognition using PCA. Experimentation and results generated in Section VI. Conclusions and future scope constitute Section VII.

II. FACE RECOGNITION SYSTEM

Figure 1 A generic face recognition system [3]

From figure 1, the input of a face recognition system is always an image or video stream. The output is an identification or verification of the subject or subjects that appear in the image or video. Face detection is defined as the process of extracting faces from scenes. So, the system positively identifies a certain image region as a face. The next step feature extraction involves obtaining relevant facial features from the data. These features could be certain face regions, variations, angles or measures, which can be human relevant or not. Finally, system does recognize the face. In an identification task, the system would report an identity from a database. This phase involves a comparison method, a classification algorithm and an accuracy measure [10].

III. FRAMEWORK OF COLOR FR

As shown in Figure 2, the color FR framework using GW and LBP consists of three major steps: color space conversion and partition, feature extraction, and combination and classification. A face image represented in the *RGB* color space is first translated, rotated, and rescaled to a fixed template, yielding the corresponding aligned face image.

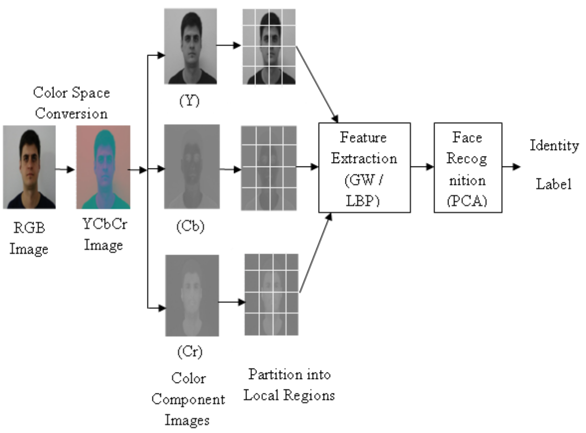

Figure 2 Framework of FR using GW and LB [3]

The aligned *RGB* color image is converted into an image represented in another color space (YCbCr). Each of the color-component images (Y, Cb, and Cr) of current color model is then partitioned into local regions. In the next step, feature extraction is independently and separately performed on each of these local regions using GW or LBP.

Since features are extracted from the local face regions obtained from different color channels, they are referred to as “color local features”. We have to combine them to reach the final classification. Multimodal fusion techniques are employed for integrating multiple color local features for improving the FR performance. PCA method is used for face recognition [3].

IV. FEATURE EXTRACTION

In our approach, two feature extraction methods such as Gabor Wavelet and Local Binary Pattern are used. Details of these methods are explained below.

1. Extraction of Gabor Wavelets

1.1 Introduction

Gabor wavelets were introduced to image analysis because of their similarity to the receptive field profiles in cortical simple cells. They characterise the image as localised orientation selective and frequency selective features. Low level features such as peaks, valleys and ridges are enhanced by 2-D Gabor filters. Thus, the eyes, nose and mouth, with other face details like wrinkles, dimples and scars are enhanced as key features to represent the face in higher dimensional space. Also, the Gabor wavelet representation of face image is robust to misalignment to some degree because it captures the local texture characterised by spatial frequency, spatial position and orientation. Due to the robustness of Gabor features, they have been successfully applied for FR [4].

1.2 Mathematical Expression

The Gabor functions proposed by Daugman are local spatial band pass filters that achieve the theoretical limit for conjoint resolution of information in the 2D spatial and 2D Fourier domains. Daugman generalized the Gabor function to the following 2D form:

$$\varphi_i(\vec{x}) = \frac{\|\vec{k_i}\|^2}{\sigma^2} e^{\frac{\|\vec{k_i}\|^2\|\vec{x}\|^2}{2\sigma^2}}\left[e^{j\vec{k_i}\vec{x}} - e^{-\frac{\sigma^2}{2}}\right] \quad (1)$$

Each φ_i is a plane wave characterized by the vector k_i enveloped by a Gaussian function, where σ is the standard deviation of this Gaussian. The center frequency of $i-th$ filter is given by the characteristic wave vector,

$$\vec{k_i} = \begin{pmatrix} k_{ix} \\ k_{iy} \end{pmatrix} = \begin{pmatrix} k_v \cos\theta_\alpha \\ k_v \sin\theta_\alpha \end{pmatrix};\ k_v = \pi 2^{-\frac{v+2}{2}};\ \theta_\alpha = \alpha\frac{\pi}{8} \quad (2)$$

Where the scale and orientation is given by (k_v, θ_α), being υ the spatial frequency number and α the orientation [3].

1.3 Gabor wavelet representation of image

The Gabor wavelet representation of an image is the convolution of the image with a family of Gabor wavelets [4]. An image is represented by the Gabor wavelet transform in four dimensions, two are the spatial dimensions and the other two represent spatial frequency structure and spatial relations or orientation. So, processing the face image with Gabor filters with 5 spatial frequency (υ = 0... 4) and 8 orientation (α= 0... 7) captures the whole frequency spectrum. So, we have 40 wavelets. The amplitude of Gabor filters are used for recognition. Once the transformation has been performed, different techniques can be applied to extract the relevant features. Gabor wavelets can be obtained based on Gabor filters 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 [9].

2. Extraction of Local Binary Patterns

2.1 Introduction

Local Binary Patterns (LBP) is a texture descriptor that can be also used to represent faces, since a face image can be seen as a composition of micro-texture-patterns. The LBP operator assigns a label to every pixel of an image by thresholding the 3*3 neighborhood of each pixel with the center pixel value and considering the result as a binary number. For example, as shown in Fig., “11001011” is the designed pattern of the central pixel. By applying LBP operator to one facial image, one pattern map can be computed. Then, the pattern map is divided into many blocks and the histogram computed in each block is concatenated together to form the description of the input facial image [6].

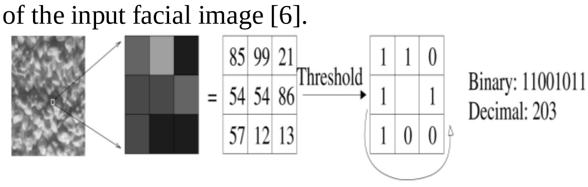

Figure 3 LBP defined in 3*3 neighborhoods [6]

In order to treat textures at different scales, the LBP operator was extended to make use of neighbourhoods at different sizes. Using circular neighbourhoods and bilinear interpolation of the pixel values, any radius and number of samples in the neighbourhood can be handled. Therefore, the following notation is defined: (P, R) which means P sampling points on a circle of R radius. The following figure shows some examples of different sampling points and radius:

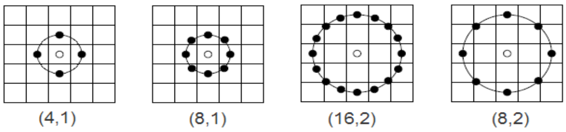

Figure 4 LBP different sampling point and radius [6]

In $LBP_{(4,1)}$ case, the reason why the four points selected correspond to vertical and horizontal Ones, is that faces contain more horizontal and vertical edges than diagonal ones.

2.2 Mathematical Expression

Given K different color-component images $S_i(i = 1, \ldots, K)$, the unichrome (or channel wise) LBP feature is separately and independently computed from each S_i . Note that, in the computation of the unichrome LBP feature, the uniform LBP operator [6] is adopted because a typical face image contains only a small number of LBP values (called the uniform pattern), as reported in [6]. Let us denote that z_c is the center pixel position of S_i and z_n $(n = 0, .. p-1)$ are P equally spaced pixels (or sampling points) on a circle of radius *R(R>0)* that form a circular neighbourhood of the center pixel z_c. The unichrome LBP operation for the center pixel position z_c of S_i is then defined as follows [8]:

$$LBP_{P,R}^{(i)}(z_c) = \begin{cases} \sum_{n=0}^{P-1} \delta\left(r_n^{(i)} - r_c^{(i)}\right)2^n, & if\ H \leq 2 \\ P(P-1)+2, & otherwise \end{cases}$$

(3)

Where

$$H = \left|\delta\left(r_{P-1}^{(i)} - r_c^{i}\right) - \delta\left(r_o^{(i)} - r_c^{i}\right)\right| + \sum_{n=1}^{P-1}\left|\delta\left(r_n^{(i)} - r_c^{i}\right) - \delta\left(r_{n-1}^{(i)} - r_c^{i}\right)\right|$$

(4)

And

$$\delta(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases}, r_n^{(i)}(n = 0, \ldots, P-1)$$

(5)

Denotes the pixel values of S_i at z_n , and r_c^i denotes the pixel value at z_c of a circular neighbourhood [1].

V. FACE RECOGNITION

Our work is based on Principal Component Analysis face recognition method. Principal component analysis (PCA) is a mathematical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. Goal of PCA is to reduce the dimensionality of the data by retaining as much as variation possible in our original data set. On the other hand dimensionality reduction implies information loss. The best low-dimensional space can be determined by best principal components. The major advantage of PCA is using it in eigenfaces approach which helps in reducing the size of the database for recognition of a test images. The images are stored as their feature vectors in the database which are found out projecting each and every trained image to the set of Eigen faces obtained. PCA is applied on Eigen face approach to reduce the dimensionality of a large data set [12]. Algorithm of Principal Component Analysis (PCA) using Eigenfaces Approach is as follow,

Step 1: Prepare the data-

The faces constituting the training set should be prepared for processing.

Step 2: Subtract the mean-

The average matrix has to be calculated, then subtracted from the original faces and the result stored in the variable.

Step 3: Calculate the covariance matrix.

Step 4: Calculate the eigenvectors and eigenvalues of the covariance matrix.

Step 5: Recognizing the faces-

The new image is transformed into its eigenface components. The Euclidean distance between two weight vectors $d\ (i, j)$ provides a measure of similarity between the corresponding images i and j.

VI. EXPERIMENTATION AND RESULTS

1. Algorithms

Detail of algorithms of Gabor Wavelets and Local Binary Patterns methods are explained below.

1.1 Gabor Wavelet

After introducing Gabor wavelets here method of characteristic extraction from human face photo is discussed. First input image of 27x18 pixels resolution is taken. Input image is processed using Adaptive histogram equalization. AHE is a computer image processing technique used to improve contrast in images. Then FFT (Fast Fourier transform) of AHE image is taken. On the other side, Gabor filters in time domain with 8 orientations and 5 scales that is total 40 filters are converted into frequency domain by FFT. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation.

Multiplication of FFT of input image and Gabor filters in frequency domain is taken. IFFT (Inverse Fast Fourier transform) of Multiplication gives output image of 135x144 pixels resolution. It's clear that this number of process characteristics in each classificatory is large and causes slow down in detection process. Here algorithms of space reduction.

So by considering process time, here reduction in dimensions of characteristics matrix is done by averaging blocks instead of 3*3 blocks. By doing so, characteristics matrix is reduced to 45x48. After extracting characteristic from windows referred to classifier, data will be transformed into the form of a vector with 2160 elements.

1.2 Local Binary Pattern

The facial image is divided into local regions and LBP texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face. In our algorithm, first input image of 27x18 pixels resolution is taken. If input image is color then it is converted to gray image otherwise take as it is. The original LBP operator forms labels for the image pixels by thresholding the 3 x 3 neighborhood of each pixel with the center value and considering the result as a binary number.

The LBP operator was extended to use neighborhoods of different sizes. The gray scale variance of the local neighborhood can be used as the complementary contrast measure. The notation (P, R) will be used for pixel neighborhoods which mean P sampling points on a circle of radius of R. Here, we uses P=8 and R=2 that is 8 sampling points on a circle of radius of 2. After processing LBP operator on entire image, we get a LBP image of 23x14 pixels resolution. Then data will be transformed into the form of a vector with 322 elements.

2. Face Database

When benchmarking an algorithm it is recommendable to use a standard test data set for researchers to be able to directly compare the results. Our project uses a FEI face database.

The FEI face database is a Brazilian face database that contains a set of face images taken between June 2005 and March 2006 at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil. There are 14 images for each of 200 individuals, a total of 2800 images. All images are colorful and taken against a white homogenous background in an upright frontal position with profile rotation of up to about 180 degrees. Scale might vary about 10% and the original size of each image is 640x480 pixels. All faces are mainly represented by students and staff at FEI, between 19 and 40 years old with distinct appearance, hairstyle, and adorns. The numbers of male and female subjects are exactly the same and equal to 100 [17].

2.1 Testing Set

Database for different set of conditions is maintained. Ten different rotations for left and right direction of up to about 180 degrees and last four images having different illumination conditions and expression. Size variations in an input face image can also change the output therefore input images by varying their size are also taken for recognition.

2.2 Training Set

Training set consists 80 images of 4 images from 20 folders for recognition purpose.

3. Results

In following section, Result includes recognition rate (in percent) for different method such as YCbCr, Gray using GW and LBP for different pixels resolution such as 54x36, 81x54 and 108x72.

Table 1 Recognition rates (in percent) for different method using GW and LBP

	% Face Recognition rate			
Algorithm-	GW		LBP	
Method-	YCbCr	Gray	YCbCr	Gray
54x36	88.57	80.36	84.64	75.71
81x54	90	81.79	89.29	77.14
108x72	93.93	90.71	90.57	81.07

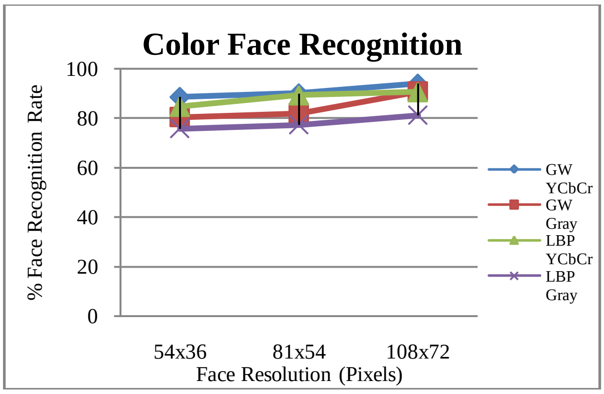

Figure 5 Recognition rates (in percent) for YCbCr color and Gray method using GW and LBP for different pixels resolution

Figure 5 shows recognition rates (in percent) for YCbCr color and Gray method using GW and LBP for different pixels resolution. With the decrease in the face resolution, the FR performances of grayscale method using GW or LBP drop much more quickly than those of YCbCr color method using GW or LBP respectively. Recognition rates (in percent) for YCbCr color method are higher than Gray method using GW and LBP for different pixels resolution.

VII. CONCLUSION AND FUTURE SCOPE

The recent trend is moving towards multimodal analysis combining multiple approaches to converge to more accurate and satisfactory results. Gabor wavelets and local binary pattern for the purpose of face recognition provide excellent recognition rates for face images taken under severe variation in illumination, pose as well as for small resolution face images. This work investigates the performance of color face recognition with YCbCr color space using GW and LBP. The experiments are performed on FEI color database. Recognition rates (in percent) using GW are higher than LBP for both YCbCr color method and Gray method.

The experimental study in this has been limited to evaluating the effectiveness of color local features using GW and LBP that are extracted from fixed color-component configuration consisting of three components (such as YCbCr). For the future work, we will develop the method of selecting an optimal subset of color components from a number of different color spaces. Also in this PCA is used for face recognition. For the future work, we will use different FR method such as Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), Fisher's linear discriminant analysis (FLDA) etc. For the future work, we also use different classifier to classify the face images.

REFERENCES

[1] A. K. Jain, A. Ross, and S. Prabhaker, "An introduction to biometric recognition," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 14, no. 1, pp. 4–20, Jan. 2004.

[2] K. W. Bowyer, "Face recognition technology: Security versus privacy," *IEEE Technol. Soc. Mag.*, vol. 23, no. 1, pp. 9–19, Spring 2004.

[3] J. Y. Choi, Y. M. Ro, and K. N. Plataniotis, "Color Local Texture Features for Color Face Recognition," *IEEE Trans. Image Process.*, vol. 21, no. 3, pp. 1366–1380, March 2012.

[4] Linlin Shen, Li Bai, "A review on Gabor wavelets for face recognition", Pattern Anal Applic Springer-Verlag London Limited, pp. 273–292, August 2006.

[5] S. Xie, S. Shan, X. Chen, and J. Chen, "Fusing local patterns of Gabor magnitude and phase for face recognition," *IEEE Trans. Image Process.*, vol. 19, no. 5, pp. 1349–1361, May 2010.

[6] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary pattern: Application to face recognition," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.

[7] J. Zou, Q. Ji, and G. Nagy, "A comparative study of local matching approach for face recognition," *IEEE Trans. Image Process.*, vol. 16, no. 10, pp. 2617–2628, Oct. 2007.

[8] Y. Su, S. Shan, X. Chen, and W. Gao, "Hierarchical ensemble of global and local classifiers for face recognition," *IEEE Trans. Image Process.*, vol. 18, no. 8, pp. 1885–1896, Aug. 2009.

[9] Z. Liu and C. Liu, "A hybrid color and frequency features method for face recognition," *IEEE Trans. Image Process.*, vol. 17, no. 10, pp. 1975–1980, Oct. 2008.

[10] Avinash Kaushal, J P S Raina, "Face Detection using Neural Network & Gabor Wavelet Transform" International Journal of Computer Science and Technology Vol. 1, Issue 1, pp. 58-63, September 2010.

[11] Di Huang, Caifeng Shan, Mohsen Ardebilian, Liming Chen, "Facial Image Analysis Based on Local Binary Patterns: A Survey", *IEEE Trans. Image Process,* September 2012.

[12] Sheifali Gupta, O.P.Sahoo, Ajay Goel, Rupesh Gupta, "A New Optimized Approach to Face Recognition Using Eigenfaces", Global Journal of Computer Science and Technology, Vol. 10, Issue 1 (Ver. 1.0), pp. 15-17, April 2010.

[13] Deepak Kumar Sahu, M.P.Parsai, "Different Image Fusion Techniques –A Critical Review International Journal of Modern Engineering Research (IJMER), Vol. 2, Issue. 5, pp-4298-4301, Sep.-Oct. 2012.

[14] Tom Fawcett, "ROC Graphs: Notes and Practical Considerations for Researchers" Kluwer Academic Publishers, March 2004.

[15] Mohammod Abul Kashem, Md. Nasim Akhter, Shamim Ahmed, and Md. Mahbub Alam, "Face Recognition System Based on Principal Component Analysis (PCA) with Back Propagation Neural Networks (BPNN)", Canadian Journal on Image Processing and Computer Vision, vol. 2, No. 4, pp. 36-45, April 2011.

[16] Proyecto Fin de Carrera, "Face Recognition Algorithms", doctoral diss., June 2010.

[17] FEI face database is publicly available on www.fei.edu.br/~cet/facedatabase.html.