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Unsupervised Segmentation for Better FR within Human-Machine Interfaces

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Abstract*:* Automatic recognition of people is a challenging problem which has received much attention during the recent years due to its many applications in different fields. Face recognition is one of those challenging problems and up to date, there is no technique that provides a robust solution to all situations and different applications that face recognition may encounter.

This work elaborates the design of an new color local texture features, i.e., color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP), for the purpose of face recognition (FR). The proposed color local texture features are able to exploit the discriminative information derived from spatio chromatic texture patterns of different spectral channels within a certain local face region. In addition, to perform the final classification, multiple color local texture features are combined within a feature-level fusion framework. Experimental results show that FR approaches using color local texture features impressively yield better recognition rates than FR approaches using only color or texture information for recognition purpose, simulated in MATLAB.

Keywords: Color Local Gabor Wavelet (CLGW), Color Local Binary Pattern (CLBP), Face Recognition (FR), Gabor filter, Principal Component Analysis (PCA).

I. Introduction

Face recognition (FR) has received a significant interest in pattern recognition and computer vision due to the wide range of applications including video surveillance, biometric identification, and face indexing in multimedia contents. As in any classification task, feature extraction is of great importance

In the FR process. Recently, local texture features 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 and local binary pattern (LBP) texture features have proven to be highly discriminative for FR due to different levels of locality.

In Three grayscale texture techniques including local linear transform, Gabor filtering, and co-occurrence methods are extended to color images. This paper reports that the use of color information can improve classification performance obtained using only grayscale texture analysis techniques.

In incorporating color into a texture analysis can be beneficial for classification recognition schemes. In particular, the authors showed that perceptually uniform color spaces and YCbCr 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 aim of this paper is to suggest a new color FR framework.

II. System Analysis

Existing System:

As in any pattern classification task, feature extraction plays a key role in face recognition process. In feature extraction stage, a proper face representation is chosen to make the subsequent face processing not only computationally feasible but also robust to possible intrinsic and extrinsic facial variations. Existing face representations fall into two categories global-based and local-based. In the global-based face representation, each dimension of the feature vector contains the information embodied in every part (even each pixel) of the face image, thus corresponds to some holistic characteristic of the face. In contrast, for the local-based face representation, each dimension of the feature vector corresponds to merely certain local region in the face, thus only encodes the detailed traits within this specific area. In the literature of face recognition, there are various face representation methods based on global features, including a great number of subspace-based methods and some spatial-frequency techniques. Subspace-based methods such as principal component analysis.

Proposed System:

In our proposed system, new color local texture features that means color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP), for the purpose of face recognition (FR). In this method able to provide excellent recognition rates for face images taken under severe variation in illumination, as well as for small- (low) resolution face images. In addition, the feasibility of our color local texture features has been successfully demonstrated by making comparisons with other state-of-the-art color FR methods.

The color local texture features consists of three major steps: color space conversion and partition, feature extraction, and combination and classification.

So to allows for a significant improvement in the FR accuracy when recognizing face images taken under a severe change in illumination (at least, in the data sets used in our experimentation), as well as for low-resolution face images, as compared with their grayscale counterparts. In addition, comparative experimental results show that color FR methods using color local texture features yield better or comparable FR performance compared with those obtained using other recent advanced color FR methods.

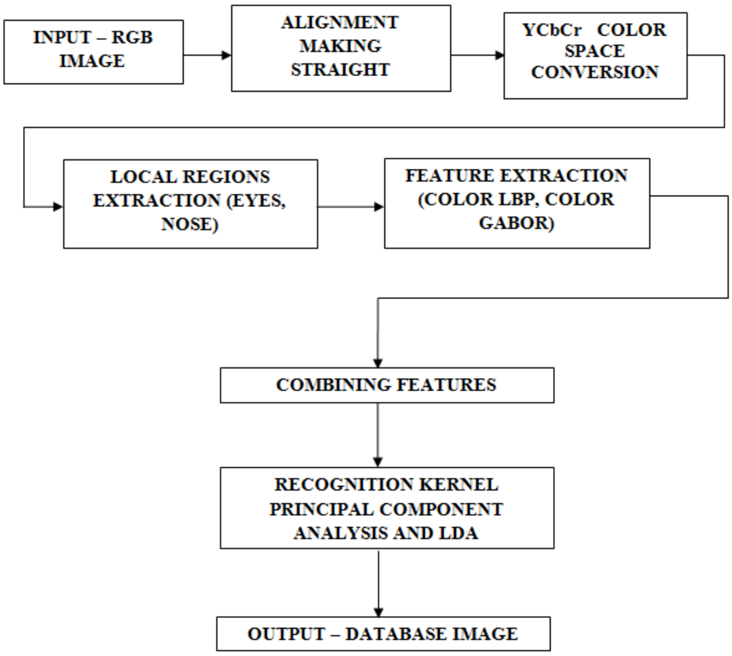


Figure 1: Block Diagram

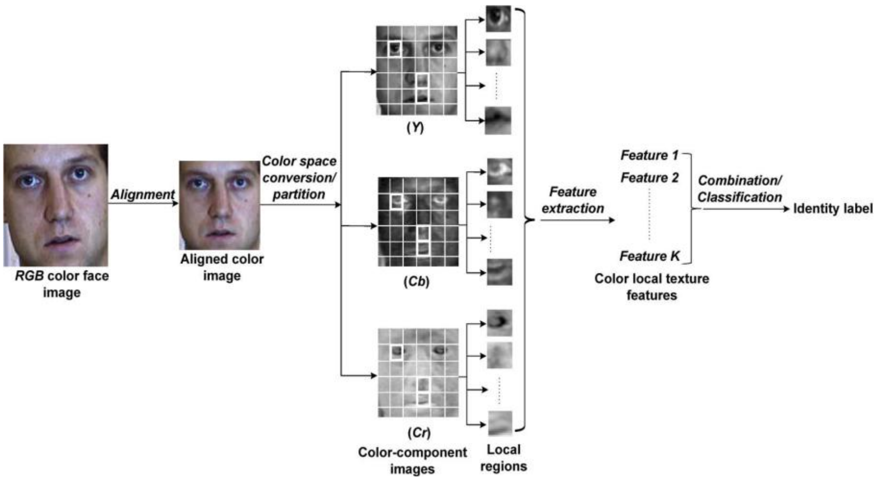


Figure 2: Brief Review of Color Face Recognition

III. Block Diagram Description:

Input – RGB Image:

RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue.

The main purpose of the RGB color model is for the sensing, representation, and display of images in electronic systems, such as televisions and computers, though it has also been used in conventional photography. Before the electronic age, the RGB color model already had a solid theory behind it, based in human perception of colors.

Alignment Making Straight:

Subsequent identication can condition on spatial position for a detailed analysis of the structure of the object in question. Thus, many recognition algorithms assume the prior rough alignment of objects to a canonical pose In general, the better this alignment is, the better identication results will be. In fact, alignment itself has emerged as an important sub-problem in the face recognition literature , and a number of systems exist for the detailed alignment of specic categories of objects, such as faces.

We point out that it is frequently muchasier to obtain images that are roughly aligned than those that are precisely aligned, indicating an important role for automatic alignment procedures. For example, images of people can be taken easily with a motion detector in an indoor environment, but will result in images that are not precisely aligned.

YCbCr Color Space Conversion:

YCbCr map = rgb2YCbCr(map) converts the RGB values in map to the YCbCr color space. Map must be an M-by-3 array YCbCr map is an M-by-3 matrix that contains the YCbCr luminance (*Y*) and chrominance (*Cb* and *Cr*) color values as columns. Each row in YCbCr map represents the equivalent color to the corresponding row in the RGB colormap, map.

YCbCr = rgb2 YCbCr (RGB) converts the truecolor image RGB to the equivalent image in the YCbCr color space. RGB must be a M-by-N-by-3 array.If the input is uint8, YCBCR is uint8, where Y is in the range [16 235], and Cb and Cr are in the range [16 240]. If the input is a double, Y is in the range [16/255 235/255] and Cb and Cr are in the range [16/255 240/255]. If the input is uint16, Y is in the range [4112 60395] and Cb and Cr are in the range [4112 61680].

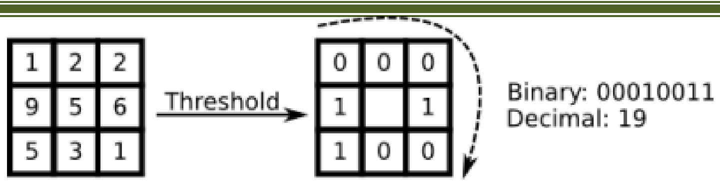
IV. Gabor Filter

Gabor filter is a linear filter used for edge detection. Frequency and orientation representations of Gabor filters are similar to those of the human visual system, and they have been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar: all filters can be generated from one mother wavelet by dilation and rotation.

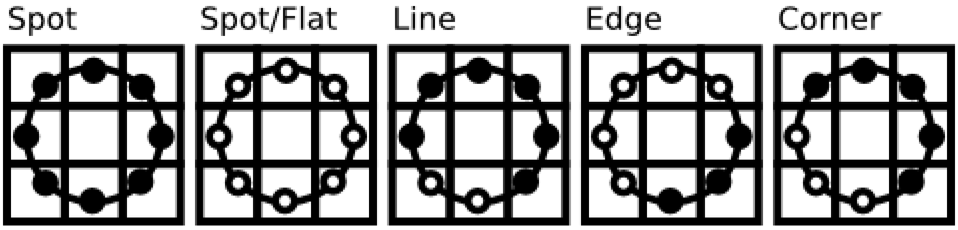
Local Binary Patterns:

Some research concentrated on extracting local features from images. The idea is to not look at the whole image as a high-dimensional vector, but describe only local features of an object. The features you extract this way will have a low-dimensionality implicitly. A fine idea! But you'll soon observe the image representation we are given doesn't only suffer from illumination variations. Think of things like scale, translation or rotation in images - your local description has to be at least a bit robust against those things.

The algorithm extracts local key points in your image that doesn't mind the scale, one of the reasons why it's called **S**cale-**i**nvariant **f**eature **t**ransform. Just like SIFT, the Local Binary Patterns methodology has its roots in 2D texture analysis. The basic idea is to summarize the local structure in an image by comparing each pixel with its neighborhood. Take a pixel as center and threshold its neighbors against. If the intensity of the center pixel is greater-equal its neighbor, then denote it with 1 and 0 if not. You'll end up with a binary number for each pixel, just like 11001111. With 8 surrounding pixels you'll end up with 2^8 possible combinations, which are called Local Binary Patterns or sometimes LBP codes. The first LBP operator actually used a fixed 3 x 3 neighborhood just like this:



This description enables you to capture very fine grained details in images. In fact the authors were able to compete with state of the art results for texture classification. Soon after the operator was published it was noted, that a fixed neighborhood fails to encode details differing in scale. So the operator was extended to use a variable neighborhood. The idea is to align an arbitrary number of neighbors on a circle with a variable radius, which enables to capture the following neighborhoods:



The operator is an extension to the original LBP codes, so it gets called the **E**xtended **LBP** (sometimes also referred to as **C**ircular **LBP**). If a point's coordinate on the circle doesn't correspond to image coordinates, the point get's interpolated.

Now using an arbitrary radius and sample points has two effects. With an educated guess I would say… The more sampling points you take, the more patterns you can encode, the more discriminative power you have, but the higher the computational effort. Instead the larger the radius, the smoother the image, the larger details can be captured, the less discriminative power the description has (if you don't increase the sampling points at the same time).

Local Binary Patterns (LBP):

The LBP operator assigns a label to every pixel of an image by thresholding the 3 x 3 neighborhood of each pixel with the center pixel value and considering the result as a binary number. For example, as shown in Fig. 3, "11010011" 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.

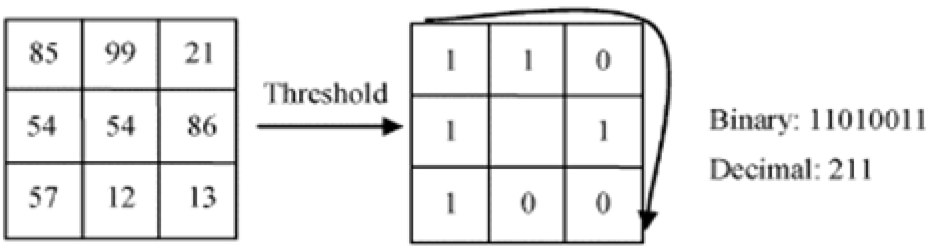


Figure 3: LBP operator defined in 3 x 3 neighborhood

Using Local Binary Patterns for Face Recognition:

In this chapter will be explained how the LBP-method can be applied on images (of faces) to extract features which can be used to get a measure for the similarity between these images. The main idea is that for every pixel of an image the LBP-code is calculated. The occurrence of each possible pattern in the image is kept up. The histogram of these patterns, also called labels, forms a feature vector, and is thus a representation for the texture of the image. These histograms can then be used to measure the similarity between the images, by calculating the distance between the histograms. Figure 2.1: Face image split in an image with only pixels with uniform patterns and in an image with only non-uniform patterns, by using LBPu2.

An image which is split in an image with only pixels with uniform patterns and in an image with only non-uniform patterns. These images are created by using the LBPu2 16,2-operator. It occurs that the image with only pixels with uniform patterns still contains a considerable amount of pixels, namely 79 % of the original image. So, 79 % of the pixels of the image have uniform patterns (with LBPu2 8,2 this is even 86 %). Another striking thing is the fact that, by taking only the pixels with uniform patterns, the background is also preserved. This is because the background pixels all have the same color (same gray value) and thus their patterns contain zero transitions. It also seems that much of the pixels around the mouth, the noise and the eyes (especially the eyebrows) have uniform patterns.

V. Color Local Texture Features

An **image texture** is a set of metrics calculated in image processing designed to quantify the perceived texture of an image. Image Texture gives us information about the spatial arrangement of color or intensities in an image or selected region of an image.

Image textures can be artificially created or found in natural scenes captured in an image. Image textures are one way that can be used to help in Segmentation (image processing) or classification of images. To analyze an image texture in computer graphics, there are two ways to approach the issue: Structured Approach and Statistical Approach.

Recognition:

The ability to recognize people by their facial characteristics. The most advanced technology is based on the Eigen face algorithm, which maps the characteristics of a person's face into a multi dimensional face space. Computers can conduct facial database searches and/or perform live, one-to-one or one-to-many verifications with unprecedented accuracy and split-second processing. Users can be granted secure access to their computer, mobile devices, or for online e-commerce, simply by looking into their Web camera.

The computer can distinguish the same person with different appearances; for example, with or without glasses, change of hair style and seasonal skin color changes. Neural networks were used for earlier face recognition systems, but with Eigen face, the computer cannot be easily fooled by photographs or by someone else with a similar appearance. One of the leading vendors in this area is L-1 Identity Solutions, Stamford, CT. See information security and biometrics.

Local Matching Approach for Face Recognition:

In contrast to holistic methods, local matching methods extract facial features from different levels of Locality and quantify them precisely. To determine how they can be best used for face recognition, we conducted a Comprehensive comparative study at each step of the local matching process. The conclusions from our experiments Include:

(1) Additional evidence that gabor features are effective local feature representations and are robust to Illumination changes.

(2) Discrimination based only on a small portion of the face area is surprisingly good.

(3) the Configuration of facial components does contain rich discriminating information and comparing corresponding local Regions utilizes shape features more effectively than comparing corresponding facial components.

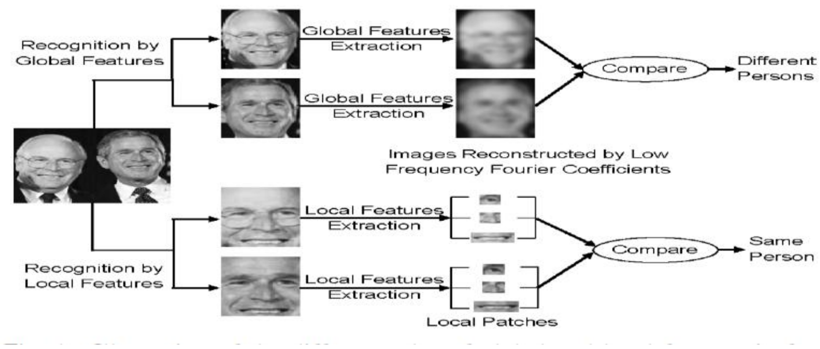
(4) Spatial multi-resolution Analysis leads to better classification performance.

(5) Combining local regions with board count classifier Combination method alleviates the curse of dimensionality.

We implemented a complete face recognition system by Integrating the best option of each step. Without training, illumination compensation and without any parameter tuning, It achieves superior performance on every category of the ferret test: near perfect classification accuracy (99.5%) on Pictures taken on the same day regardless of indoor illumination variations; and significantly better than any other Reported performance on pictures taken several days to more than a year apart. The most significant experiments were Repeated on the ar database, with similar results.

Global and Local Features For face Representation:

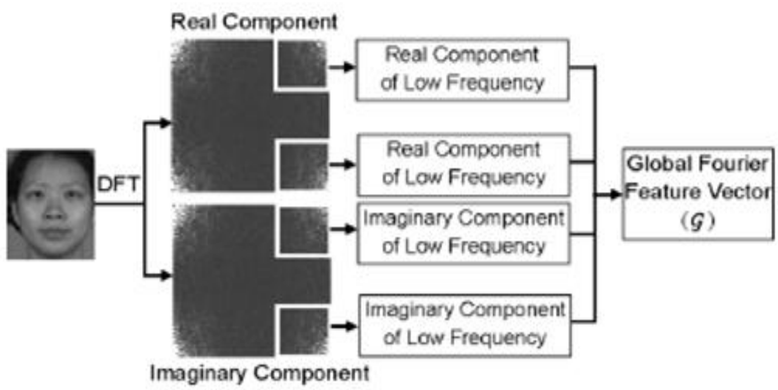
As mentioned previously, global and local facial features play different roles in face perception. Therefore, it is necessary to combine them together smartly. Intuitively, local information is embedded in the detailed local variations of facial appearance, while global information means the holistically structural configuration of facial organs, as well as facial contour. Thus, from the viewpoint of frequency analysis, global features should mainly correspond to the lower frequencies, while local features should be of high frequency and dependent on position and orientation in the face image. Considering that, in this paper, global information is represented as the Fourier coefficients in low frequency band, and local information is encoded as the responses of multi scale and multi orientation Gabor wavelets. It is known that the Gabor wavelet is a Gaussian modulated Fourier transform. Therefore, it can be tuned to extract global (usually low frequency) features by increasing the bandwidth and the radius of its Gaussian modulator. However, doing like this is not as computationally desirable as using Fourier transform directly. Specifically, we hope the global features should be compact and orientation-independent.



Extraction of Local Gabor Features:

In recent years, face descriptors based on Gabor wavelet transform (GWT) have been recognized as one of the most successful face representation methods. Gabor wavelets are in many ways like Fourier transform but have a limited spatial scope. 2-D Gabor wavelets are defined as follows

$$\psi_{u,v}(z) = \frac{\|k_{u,v}\|^2}{\sigma^2} e^{(-\|k_{u,v}\|^2\|z\|^2/2\sigma^2)} \left[e^{i\vec{k}_{u,v}z} - e^{-\sigma^2/2}\right]$$



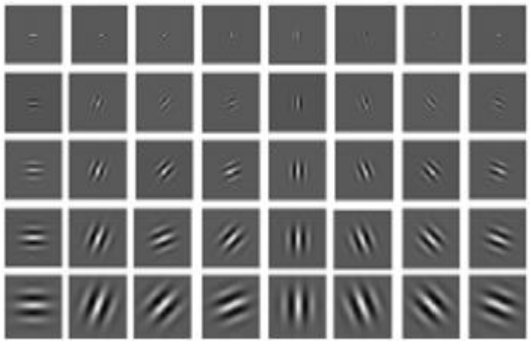
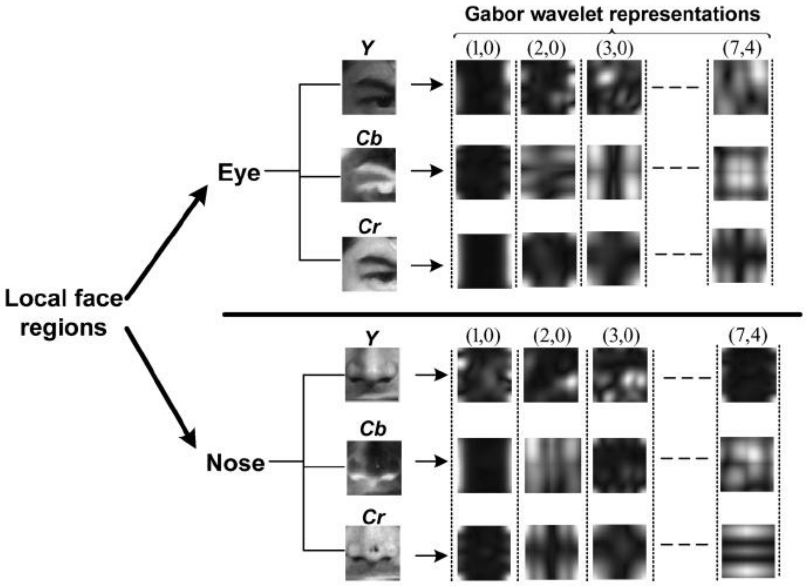


Figure 4: Global feature extraction by 2D – DFT

The frequency, gives the orientation. As can be seen from the definition, Gabor wavelet consists of a planar sinusoid multiplied by a 2-D Gaussian. The Gaussian insures that the convolution is dominated by the region of the image close to the center of the wavelet. That is, when a signal is convolved with a Gabor wavelet, the frequency information near the center of the Gaussian is encoded and frequency information far away from the center of the Gaussian has a negligible effect. Therefore, compared with Fourier transform which extracts the information in the whole face region, Gabor wavelets only focus on some local areas in the face and extract information of specific scale and orientation within these local areas.



Principal Components Analysis (PCA):

PCA commonly referred to as the use of Eigen faces, with PCA, the probe and gallery images must be the same size and must first be normalized to line up the eyes and mouth of the subjects within the images.

The PCA approach is then used to reduce the dimension of the data by means of data compression basics2 and Reveals the most effective low dimensional structure of facial patterns. This reduction in dimensions removes information that is not useful4 and precisely decomposes the face structure into orthogonal (uncorrelated) components known as Eigen faces. Each face image may be represented as a weighted sum (feature Vector) of the Eigen faces, which are stored in a 1d array. A probe image is compared against a gallery image by measuring the distance between their respective feature vectors. The PCA approach typically requires the full frontal face to be presented each time; otherwise the image results in poor performance 4 the primary advantage of this technique is that it can reduce the data needed to identify the individual to 1/1000th of the data presented.

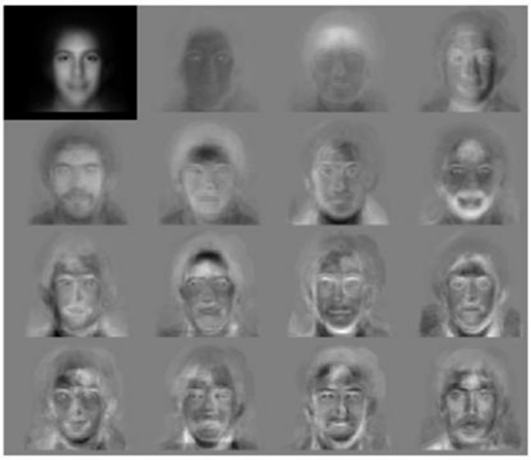


Figure 5: Standard Eigen faces: Feature vectors are derived using Eigen faces

Linear Discriminant Analysis:

LDA is a statistical approach for classifying samples of unknown classes based on training samples with known classes. This technique aims to maximize between-class (i.e., across users) variance and minimize within-class (i.e., within user) variance. In Figure 6 where each block represents a class, there are large variances between classes, but little variance within classes. When dealing with high dimensional face data, this technique faces the small sample size problem that arises where there are a small number of available training samples compared to the dimensionality of the sample space

Figure 6: Example of Six classes using LDA

VI. Conclusion

To this end, under the framework of local pattern encoding, we have proposed two effective color local texture features, i.e., CLBP and CLGW. Furthermore, in order to combine multiple color local texture features, we have suggested the feature-level fusion approach, which maximizes their complementary effect in the context of FR. We experimentally reveal that color FR methods based on CLBP and CLGW significantly outperform the methods relying only on texture or color information. One particularly important result is that our color local texture features allows for a significant improvement in the FR accuracy when recognizing face images taken under a severe change in illumination (at least, in the data sets used in our experimentation), as well as for low-resolution face images, as compared with their gray scale counterparts. In addition, comparative experimental results show that color FR methods using color local texture features yield better or comparable FR performance compared with those obtained using other recent advanced color FR methods.

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