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Facial Feature Extraction Based on Local Color and Texture for Face Recognition using Neural Network

S.Cynthia Christabel
Sethu Institute of Technology.
Kariapatti.

M.Annalakshmi
Sethu Institute of Technology.
Kariapatti.

Mr.D.Prince Winston
SSCE
Aruppukottai.

Abstract: For the purpose of face recognition (FR), the new color local texture features, i.e., color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP), are being proposed. The proposed color local texture features are able to exploit the discriminative information derived from spatiochromatic texture patterns of different spectral channels within a certain local face region. Furthermore, in order to maximize a complementary effect taken by using color and texture information, the opponent color texture features that capture the texture patterns of spatial interactions between spectral channels are also incorporated into the generation of CLGW and CLBP. In addition, to perform the final classification, multiple color local texture features (each corresponding to the associated color band) are combined within a feature-level fusion framework using Neural Network. Particularly, compared with gray scale texture features, the proposed color local texture features are able to provide excellent recognition rates for face images taken under severe variation in illumination, as well as some variations in face images.

Keywords: Color face image identification, Gabor Transform, LBP, DWT, GRNN.

1. INTRODUCTION

In pattern recognition and computer vision due to the wide range of applications includes video surveillance, biometric identification, and face indexing in multimedia contents. As in any classification task, feature extraction is of great importance. 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. There has been a limited but increasing amount of work on the color aspects of textured image analysis. Results in these works indicate that color information can play a complementary role in texture analysis and classification/recognition, and consequently, it can be used to enhance classification/recognition performance. In the paper "Classification with color and texture: Jointly or separately", an empirical evaluation study is performed which compares color indexing, gray scale texture, and color texture methods for classification tasks on texture images data set taken under either constant (static) or varying illumination conditions. Experimental result shows that, for the case of static illumination condition, color texture descriptors generally perform better than their gray scale counterparts. In the paper "Experiments in color texture analysis", three gray scale texture techniques including local linear transform, Gabor filtering, and co-occurrence methods are extended to color images. The paper reports that the use of color information can improve classification performance obtained using only gray scale texture analysis techniques.

In the paper "Perceptually uniform color spaces for color texture analysis: An empirical evaluation", incorporating color into a texture analysis can be beneficial for classification /recognition schemes. In particular, the results showed that perceptually uniform color spaces and Hue, Saturation, and Value (HSV) perform better than Red, Green, and Blue (RGB) for color texture analysis. Following the aforementioned studies, it is natural to expect better FR performance by combining color and texture information than by using only color or texture information. However, at the moment, how to effectively make use of both color and texture information for the purpose of FR still remains an open problem. The objective of this paper is to suggest a new color FR framework, which effectively combines color and texture information, aiming to improve FR performance. The main contributions of the paper are:

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

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

2. EXISTING RELATED WORK

There are two main applications where extraction of facial features can play an important role. They are Gender Classification and Face Recognition.

Face Recognition Methods

Face recognition is one of the biometric methods of identifying individuals on the basis of prior knowledge about facial features and structure. Face recognition draws attention as a complex task due to noticeable changes produced on appearance by illumination, facial expression, size, orientation and other external factors. The paper deals with various techniques and methodologies used for resolving the problem .We discuss about appearance based, feature based, model based and hybrid methods for face identification. Conventional techniques such as Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Independent Component Analysis (ICA), feature based Elastic Bunch Graph Matching (EBGM) and 2D and 3D face models are well-known for face detection and recognition.

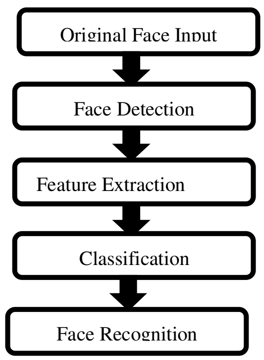

Fig 1. Feature Extraction Applications

Introduction to Face Recognition System

Face detection and recognition has emerged as an active area of research in fields such as security system, videoconferencing and identification. As security deserves prime concern in today's networked world, face recognition can be used as a preliminary step of personal identity verification, facial expression extraction, gender classification, advanced human and computer interaction. It is a form of biometric method utilizing unique physical or behavioral characteristics.

Face recognition is considered to be a complex task due to enormous changes produced on face by illumination, facial expression, size, orientation, accessories on face and aging effects. The difficulty level increases when two persons have similar faces. Usually, face recognition systems accomplish the task through face detection, facial feature extraction and face recognition.

Face Recognition –Different Approaches

Generally, face identification technique can be considered as image based or feature based. The image based methods uses predefined standard face patterns whereas feature based techniques concentrate on extracted features such as distance between eyes, skin color, eye socket depth etc. More specifically, face recognition techniques fall in three categories, holistic, feature based model based and hybrid approaches.

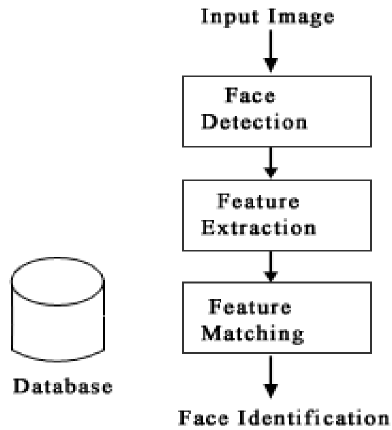

Fig 2. Face Recognition System

Holistic Approach

In holistic or appearance based approach, the whole face region is considered as the input data to the face recognition system. Examples are Eigen faces, fisher faces, probabilistic Eigen face etc. These techniques help to lower the dimensions of the dataset without tampering the key characteristics. Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Independent Component Analysis (ICA) are the most widely used holistic methods.

Feature Based Approach

The heart of any feature based algorithm is the localization and extraction of features on the face. Dynamic link structure and Hidden Markov Model methods belong to this category.

Hybrid Approach

Human perception system recognizes faces using local facial features and the whole face region information. The hybrid method is more akin to human perception system since it is influenced by both feature based and holistic methods. This approach is most effective and efficient in the presence of irrelevant data. The key factors affecting performance depend on the selected features and the techniques used to combine them.

Feature based and holistic methods are not devoid of drawbacks. Feature based method is sometimes badly affected by accuracy problem since accurate feature localization is its very significant step. On the other hand, holistic approach uses more complex algorithms demanding longer training time and storage requirements.

3. PROPOSED WORK

The proposed color FR system model using color local texture features consists of three major steps: color space conversion and partition, feature extraction, and combination and classification. A face image represented in the color space is first translated, rotated, and rescaled to a fixed template, yielding the corresponding aligned face image. Subsequently, the aligned color image is converted into an image represented in another color space. Note that not only conventional linear or nonlinear color spaces (e.g.YC_bC_r, or L*a*b*) but also new color spaces devised for the purpose of FR can be used for color space conversion. Each of the color-component images of current color model is then partitioned into local regions.

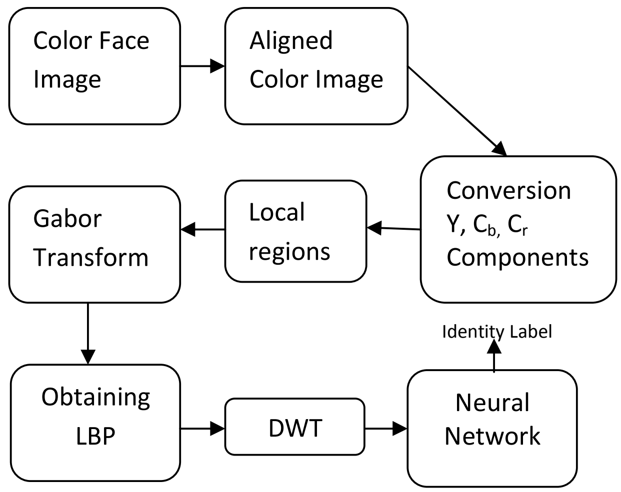

Fig.3. Proposed color gender classification system model based on color local texture features.

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

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

GABOR FEATURE

Gabor Faces

Gabor filters, which exhibit desirable characteristics of spatial locality and orientation selectively and are optimally localized in the space and frequency domains, have been extensively and successfully used in face recognition. The Gabor kernels used are defined as follows:

Where and define μ & υ the orientation and scale of the Gabor kernels, respectively=(x, y), and the wave vector is defined as,

The Gabor kernels are all self-similar since they can be generated from one filter, the mother wavelet, by scaling and rotating via the wave vector. Hence, a band of Gabor filters is generated by a set of various scales and rotations. In this paper, we use Gabor kernels at five scales and eight orientations with the parameter to derive the Gabor representation by convolving face images with corresponding Gabor kernels. For every image pixel we have totally 40 Gabor magnitude and phase coefficients, respectively, that is to say, we can obtain 40 Gabor magnitude and 40 Gabor phase faces from a single input face image.

The Local Binary Pattern (LBP)

The local binary pattern operator is defined as a grey-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. Through its recent extensions, the LBP operator has been made into a really powerful measure of image texture, showing excellent results in many empirical studies. The LBP operator can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its invariance against monotonic grey level changes. Another equally important is its computational simplicity, which makes it possible to analyze images in challenging real-time settings. The LBP method and its variants have already been used in a large number of applications all over the world.

Gabor Volume Based LBP on Three Orthogonal Planes (GV-LBP-TOP)

LBP is introduced as a powerful local descriptor for micro features of images. The basic LBP operator labels the pixels of an image by thresholding the 3 3-neighborhood of each pixel with the center value and considering the result as a binary number (or called LBP codes). Recently, the combination of Gabor and LBP has been demonstrated to be an effective way for face recognition.

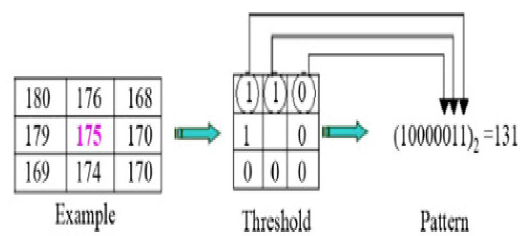

Fig.4. Basic LBP operator

This proposes to explore discriminative information by modeling the neighboring relationship not only in spatial domain, but also among different frequency and orientation properties. Particularly, for a face image, the derived Gabor faces are assembled by the order of different scales and orientations to form a third-order volume, where the three axes X, Y, T denote the different rows, columns of face image and different types of Gabor filters, respectively.

It can be seen that the existing methods essentially applied LBP or LXP operator on XY plane. It is natural and possible to conduct the similar analysis on XT and YT planes to explore more sufficient and discriminative information for face representation. GV-LBP-TOP is originated from this idea.

It first applies LBP analysis on the three orthogonal planes (XY, XT, and YT) of Gabor face volume and then combines the description codes together to represent faces. Fig. 3 illustrates examples of Gabor magnitude and phase faces and their corresponding GV-LBP codes on XY, XT, and YT planes. It is clear to see that the codes from three planes are different and, hence, may supply complementary information helpful for face recognition. After that, three histograms corresponding to GV-LBP-XY, GV-LBP-XT, and GV-LBP-YT Codes are computed as

$$Hj(i) = \sum I(fj(x,y) = l), l = 0,1,.,.,L_j - 1$$

in which is an indication function of a Boolean condition and expresses the GV-LBP codes in th plane (: XY; 1: XT; 2: YT), and is the number of the GV-LBP code.

The GV-LBP-TOP histogram is finally derived by concatenating these three histograms to represent the face that incorporates the spatial information and the co-occurrence statistics in Gabor frequency and orientation domains and, thus, is more effective for face representation and recognition.

Effective GV-LBP

The aforementioned GV-LBP-TOP is of high computational complexity. The Length of the histogram feature vector and the computational cost are threefold compared to those of LGBPHS, so it is not very efficient in practical application. To address this problem, this paper proposes an effective formulation of GV-LBP (E-GV-LBP) which encodes the information in spatial, frequency and orientation domains simultaneously and reduces the computational cost. For the central point, and are the orientation neighboring pixels; and are the scale neighboring ones; and are the neighboring pixels in spatial domains. Like in LBP, all the values of these pixels surrounded are compared to the value of the central pixel, threshold into 0 or 1 and transformed into a value between 0and 255 to form the E-GV-LBP value.

$$E - GV - LBP = \sum_{p=0}^{7} 2^p S\,(Ip - Ic)$$

The E-GV-LBP codes based upon 40 Gabor magnitudes and phase faces for an input face image. The histogram features are then computed based upon the E-GV-LBP codes to provide a more reliable description as

$$H(i) = \sum_{x,y} I(f(x,y) = i), l = 0,2,.,.,L - 1$$

Where I (.) □ {0, 1} is an indication function of a Boolean condition and f (.) denotes the E-GV-LBP codes, and L is the number of the E-GV-LBP codes.

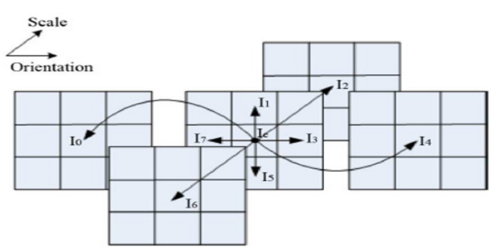

Fig 5. Formulation of E-GV-LBP.

NEURAL NETWORK CLASSIFIER

For each image the DWT analysis is performed on the LBP of the obtained features and the wavelet coefficients (five level decomposition is performed) are normalized, then it is trained using General Regression Neural Networks (GRNN). GRNN is one of the type neural networks that can be used for prediction. In this work GRNN is used to predict the in between training data values
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4. RESULTS & DISCUSSION

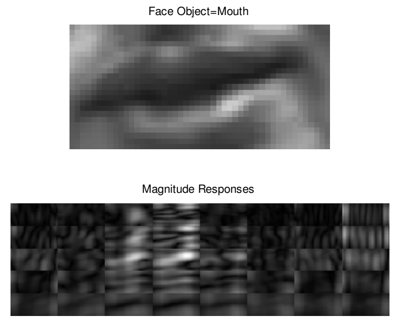

Fig.6. Magnitude Responses of Face Object – Mouth

This figure shows the magnitude responses of Face Object – Mouth under the feature extraction of the color local Gabor wavelets.

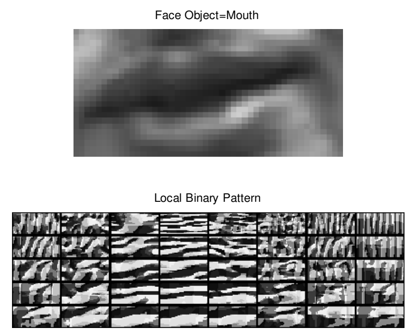

Fig.7. Local Binary Pattern of Face Object – Mouth

This figure shows the local binary pattern of Face Object - Mouth under the feature extraction of the color LBP.

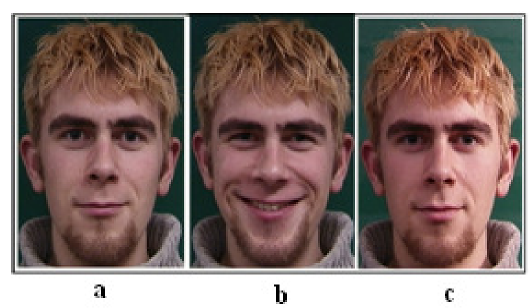

Fig.8.a. Sample Image in the training database, Fig.8.b. Sample Expression Variation Image in the test database, Fig.8.c. Sample Illumination Variation Image in the test database

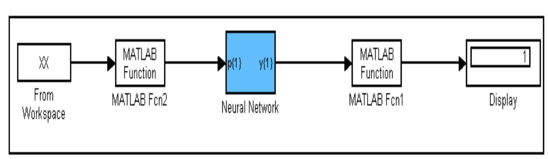

Fig.9. MATLAB Simulink diagram of the Neural Network Classifier

5. CONCLUSION

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

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