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Research Article

Face Representation using Gabor Volume based Local Binary Pattern

Soju Ravi K[†*]

[†]Department of Electronics and Communication Engineering, LBS College of Engineering, Kasaragod, India

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Abstract

The face images are usually affected by different expressions, positions, occlusions and illuminations. The difference of face image from the same person could be different at positions. The major problem is to extract fair and discriminate features which make the intra person face images compact and provide large margin among the images of different persons. Since individual domains such as space, scale and orientation cannot provide sufficient information to discriminate the face images, a combined information extracted from these domains can provide rich information for representation of face images. Using Gabor filters, images are decomposed into different scale and orientation response. Local Binary Pattern analysis is performed to describe the neighboring relationship of the responses in these domains. Thus the information explored from the domains can give immense clue for face representation

Keywords: *Face recognition, Gabor volume based local binary pattern (GV-LBP) ,Gabor volume representation, local binary pattern*

1. Introduction

Face detection, face recognition and facial expression recognition has turned out to be the key areas of research in face analysis research. This is because of the immense potential of these in application fields such as machine vision, visual surveillance, automation systems, security etc. Of these, face recognition has got utmost importance as well as complexity.

1.1 Face recognition and Biometrics

Face recognition comes in the broad area of biometric systems. The International Biometric group (IBG), the biometric industry's leading independent integration and consulting firm providing broad range of biometric services and solutions since 1996, have evaluated the various biometric schemas and their effectiveness. This includes ease-of-use, cost, distinctiveness (accuracy), and perceived intrusiveness on the user.

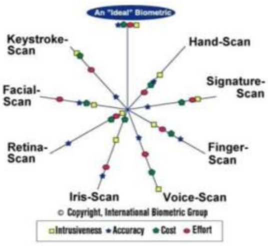

Fig.1 Zephyr Analysis of different biometric systems

*Corresponding author: **Soju Ravi K**

Among the six biometric indicators considered, it has been seen that facial features scored the highest compatibility, in a machine readable travel documents (MRTD) system based on a number of evaluation factors[X. Wang and X. Tang 2004].

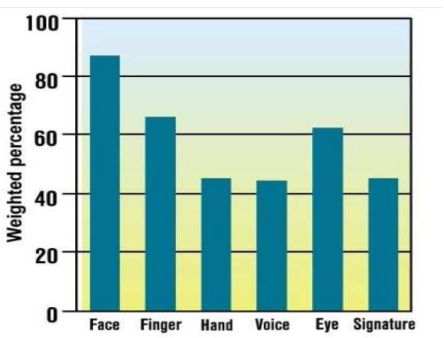

Fig.2 Challenges in face recognition

It has been found that faces are affected by age, facial expression, pose, variations in illumination, nearby clutter, occlusion like presence of scarf, spectacles etc, wide capturing conditions which includes translation, rotation, scale and size. The need to extract unique discriminating features from a face and to increase the margin between the features of faces of different persons has made this area a critical and challenging one. The design of face recognition algorithms that are effective over a wide range of viewpoints is still a major area of research. The reliability of such systems has to be validated by precise testing and verification on real-world datasets. For practical applications, all this has to be done in real-time and in the presence of movement like head motion.

1.3 Categories of Face recognition

Face recognition can be defined as given images of a scene, identify or verify one or more persons in the scene using a stored database of faces. From this definition it can be observed that face recognition problems comes in two categories

Face Verification – verifying the face which has been trained with a training set (fig 3)

Training data Testing Data

Fig.3 Face verification scenario

Face Identification scenario where a face has to be identified among various sets of faces (fig .4)

Training Data Testing Data

Fig.4 Face Identification scenario

2. Literature Survey

Literature already points out the extensive research that has resulted in the development of several approaches based on various models and features.

Image-based face recognition techniques can be mainly categorized into two groups based on the face representation which they use: appearance-based which uses holistic texture features; model-based which employ shape and texture of the face, along with 3D depth information.

2.1 LBP based face description

The LBP operator [W. Zhao,2003] is one of the best performing texture descriptors and it has been widely used in various applications. It has proven to be highly discriminative and its key advantages, namely, its invariance to monotonic gray-level changes and computational efficiency, make it suitable for demanding image analysis tasks. The idea of using LBP for face description is motivated by the fact that faces can be seen as a composition of micro patterns which are well described by such operator.

The LBP method is used for face description. The procedure consists of using the texture descriptor to build several local descriptions of the face and combining them into a global description. The facial image is divided into local regions and texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face. The basic histogram can be extended into a spatially enhanced histogram which encodes both the appearance and the spatial relations of facial regions. As the m facial regions (R0,R1,... Rm-1) have been determined, a histogram is computed independently within each of the m regions. The resulting m histograms are combined yielding the spatially enhanced histogram. The spatially enhanced histogram has size m X n, where n is the length of a single LBP histogram. The LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level, and the regional histograms are concatenated to build a global description of the face. It should be noted that the regions (R0,R1, . . .Rm-1) do not need to be rectangular nor of the same size nor shape and they do not necessarily have to cover the whole image.

Fig 5: A facial image divided into 7 X 7, 5 X 5, and 3 X 3 rectangular regions

Based on the psychophysical findings, which indicate that some facial features (such as eyes) play more important roles in human face recognition than other features, it can be expected that, in this method, some of the facial regions contribute more than others in terms of extra personal variance. Utilizing this assumption, the regions can be weighted based on the importance of the information they contain. The weighted Chi square distance is one distance metric used.

Fig.6: A facial image divided into 7 X 7 windows and the weights set for the weighted Chi square dissimilarity measure. Black squares indicate weight 0.0, dark gray 1.0, light gray 2.0, and white 4.0.

There are some parameters that can be chosen to optimize the performance of the LBP-based algorithm. These include choosing the type of the LBP operator, division of the images into regions, selecting the distance measure for the nearest neighbour classifier, and finding the weights wj for the weighted chi square statistic.

2.2 GV-LBP Scheme

In this project, we propose to explore discriminative information by modelling the neighbouring 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[C. Liu and H. Wechsler2002].

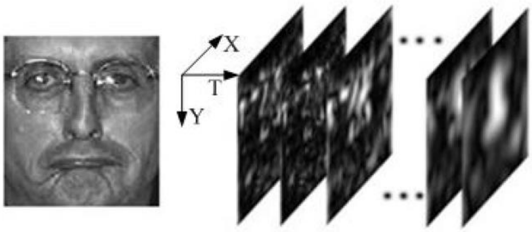

Fig.7: Face image and its corresponding third-order Gabor volume

Analysis can be conducted on XY, XT and YT planes to explore more sufficient and discriminative information for face representation. Conventionally, analysis is done only on the XY plane and the result is used for face recognition. The proposed method takes into account all the three planes and uses it to produce the discriminative information for face recognition. This method is termed GV-LBP-TOP

2.3 GV-LBP-TOP

It can be seen that the existing methods can be applied on XT and YT planes to explore more sufficient and discriminative information for face representation. This techniques is christened GV-LBP-TOP. 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. 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. 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.

2.4 Algorithm of GV-LBP-TOP

1. Compute Gabor face volume by convolving a face image with 40 Gabor filters.
2. Compute GV-LBP-XY, GV-LBP-XT, GV-LBP-YT codes based on XY, XT and YT planes of Gabor volume respectively.
3. Divide the face into several blocks and for each block, compute the local histogram HXY , HXT , HY T respectively and concatenate them into one H = [HXY ,HXT,HY T].
4. Concatenate the local histograms into a single histogram sequence and use the weighted histogram intersection defined in equation given below to derive the dissimilarity score.

$$D(H^1, H^2) = \sum_{i=1}^{n} w_i D(H_i^1, H_i^2)$$

where H^1, H^2 denote the two histogram sequences and we is the weight for the it local histogram pair H_i^1 , H_i^2 .

In this project, we take the similar measure in to set the weights for different blocks. For each block, we first compute the dissimilarity means mime and variations σ2i , σ2 e based on the block, for intra (the same person) and extra (different persons) sample pairs respectively and then the weight for the block can be computed following the fisher criterion as

$$w = \frac{(m_i - m_e)^2}{(\sigma_i^2 + \sigma_e^2)}$$

where mi, σ2i denote the mean and variation of intra sample pairs and me, σ2e are those of extra sample ones.

2.5 LGBPHS Based recognition

Local Gabor Binary Pattern Histogram Sequence (LGBPHS) is actually a representation approach based on multi-resolution spatial histogram [W. C. Zhang,2005]. It combines local intensity distribution with the spatial information, Therefore, it is robust to noise and local image transformations due to variations of lighting, occlusion and pose. Additionally, instead of directly using the intensity to compute the spatial histogram, multi-scale and multi-orientation Gabor filters are used for the decomposition of a face image, followed by the local binary patterns (LBP) operator. The combination of Gabor and LBP further enhances the representation power of the spatial histogram greatly. To construct the LGBPHS model, one does not need a training stage necessarily, which has naturally avoided the generalizability problem. For recognition, histogram intersection is used to measure the similarity of different LGBPHS and the nearest neighbourhood is exploited for final classification. Additionally, considering the fact that different local regions in face image are with different contribution to classification.

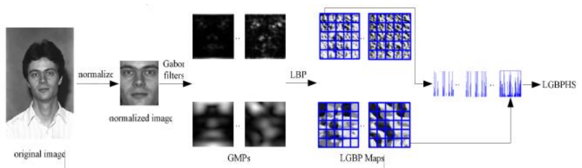

Fig.8: The framework of the proposed LGBPHS face representation approach

This technique is found to be impressively insensitive to appearance variations due to lighting, expression, and aging. Moreover, the modelling procedure of LGBPHS does not involve in any learning process, that is, it is non-statistical learning based. Therefore, the inherited generalizability problem is naturally avoided in this representation approach. The effectiveness of the LGBPHS comes from several aspects including the multi-resolution and multi-orientation Gabor decomposition, the Local Binary Pattern, and the local spatial histogram modelling. LGBPHS actually consists of many pieces of histogram corresponding to different face components at different scale and orientation. Basics of Proposed Scheme The scheme that is proposed in this project uses LBP operator and Gabor wavelets.

2.6 LBP Operator

The operator assigns a label to every pixel of an image by thresholding the 3X 3-neighborhood of each pixel with the centre pixel value and considering the result as a binary number, as shown in the figure.

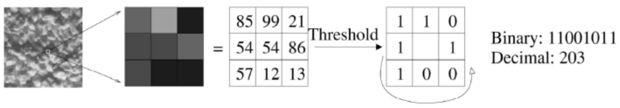

Fig.9: LBP operation

Then, the histogram of the labels can be used as a texture descriptor.

The LBP operator was can be extended to use neighbourhoods of different sizes. Defining the local neighbourhood as a set of sampling points evenly spaced on a circle cantered at the pixel to be labelled allows any radius and number of sampling points. Bilinear interpolation is used when a sampling point does not fall in the centre of a pixel. In the following, the notation (P,R) will be used for pixel neighbourhoods which means P sampling points on a circle of radius of R.

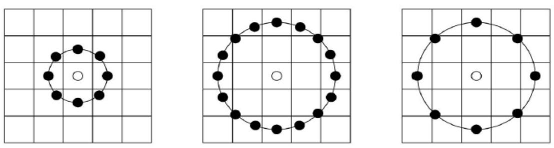

Fig.10: The circular (8,1), (16,2), and (8,2) neighbourhoods

Another extension to the original operator is the definition of so-called uniform patterns. A local binary pattern is called uniform if the binary pattern contains at most two bitwise transitions from 0 to 1 or vice versa when the bit pattern is considered circular. For example, the patterns 00000000 (0 transitions), 01110000 (2 transitions) and 11001111 (2 transitions) are uniform whereas the patterns 11001001 (4 transitions) and 01010011 (6 transitions) are not uniform. In the computation of the LBP histogram, uniform patterns are used so that the histogram has a separate bin for every uniform pattern and all non uniform patterns are assigned to a single bin

2.7 Gabor Wavelets

The Gabor wavelet representation captures salient visual properties such as spatial localization, orientation selectivity, spatial frequency characteristic. Gabor wavelets were introduced to image analysis due to their biological relevance and computational properties. The Gabor wavelets, whose kernels are similar to the 2-D receptive field profiles of the mammalian cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity, and are optimally localized in the space and frequency domains.

The Gabor kernels we used are defined as follows:

$$\psi_{\mu,\nu} = \frac{k_{\mu,\nu}^2}{\sigma^2} \exp\left(-\frac{k_{\mu,\nu}^2 z^2}{2\sigma^2}\right) \times \left[\exp(ik_{\mu,\nu}z) - \exp\left(-\frac{\sigma^2}{2}\right)\right]$$

where μ and ν define the orientation and scale of the Gabor kernels, respectively, z=(x,y) and the wave vector $k_{\mu,\nu}$ is defined as $k_{\mu,\nu} = k_\nu e^{i\phi_\mu}$

where

$$k_\nu = k_{\max}/f^\nu,\ k_{\max} = \pi/2,\ f = \sqrt{2},\ \phi_\mu = \pi\mu/8.$$

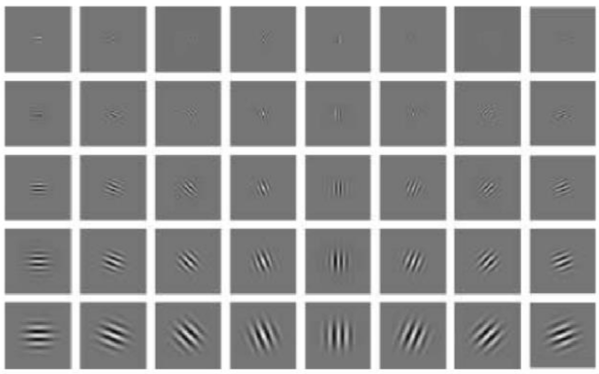

Fig.11: The real part of the Gabor kernels at five scales and eight orientations with the following parameters

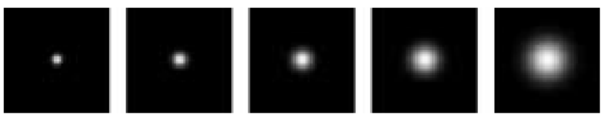

Fig.12: The magnitude of the Gabor kernels at five different scales

Here we use Gabor kernels at five scales $\nu \in \{0,1,2,3,4\}$ and eight orientations $\mu \in \{0,1,2,3,4,5,6,7\}$ with the parameter $\sigma = 2\pi$ 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.

3. Proposed Scheme

For the centred point I, I0 and I4 are the orientation neighbouring points; I2 and I6 are the scale neighbouring ones; I1, I3, I5 and I7 are the neighbouring points in spatial domains. Like LBP, all the values of these points surrounded are compared to the value of the centred point, threshold into 0 or 1 and transformed into a value between 0 and 255 to form the E-GV-LBP value[W. C. Zhang,2006].

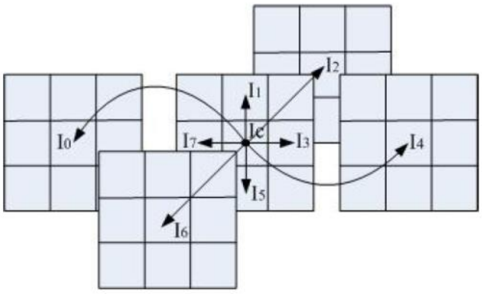

Fig.13 Formulation of E-GV-LBP

The E-GV-LBP value can be found using the given equation

$$E - GV - LBP = \sum_{p=0}^{7} 2^p S(I_p - I_c)$$

where S(IP-IC) is a threshold function defined as

$$S(I_p - I_c) = \begin{cases} 1 & \text{if } I_p - I_c \geq 0 \\ 0 & \text{if } I_p - I_c < 0 \end{cases}$$

4. Details of Proposed Scheme

4.1 Algorithm

1. Compute Gabor faces by convolving a face image with different scales and orientations Gabor filters.
2. Compute effective GV-LBP code introduced on Gabor faces.
3. Divide the face into several blocks and for each block, compute the local histogram H of E-GV-LBP code.
4. Concatenate the local histograms into a single histogram sequence and use the weighted histogram intersection to derive the dissimilarity score.

4.2 Software Requirement

Using MATLAB 7.6.0.324 (R 2008a) version, this project can be implemented. Database Requirement

Several standard databases are available for implementing and testing face recognition problems. The AR database contains occlusions due to eye glasses and scarf. The CMU PIE database is collected with well-constrained pose, illumination and expression. FERET and XM2VTS databases are the two most comprehensive databases, which can be used as a benchmark for detailed testing or comparison. It is proposed to use The FERET database which is one of the largest publicly available databases ,or any Indian data base

This project was done using a database of human face images called Indian Face Database. The database can b e viewed and downloaded at the following web address http://vis-www.cs.umass.edu/~vidit/AI/dbase.html. This database has been created by Vidit Jain and Dr. Amitabha Mukherjee in cooperation with Neeraj Kayal, Pooja Nath and Utkarsh Hriday Shrivastav.

The database of faces contains a set of face images taken in February, 2002 in the IIT Kanpur campus. The database was prepared in the context of a face recognition project carried out in the course Artificial Intelligence in the Computer Science and Engineering Department.

There are eleven different images of each of 61 distinct subjects. For some subjects some additional photographs have been included. All the images were taken against a bright homogeneous background with the subjects in an upright, frontal position. A preview image of the database is shown below.

Fig.14 Preview image

The files are in JPEG format. The size of each image is 640x480 pixels, with 256 grey levels per pixel. The images are organized in two main directories - males and females. In each of these directories, there are directories with name as a serial numbers, each corresponding to a single individual. In each of these directories, there are eleven different images of that subject, which have names of the form abc.jpg, where abc is the image number for that subject. The following orientations of the face : looking front, looking left, looking right, looking up, looking up towards left, looking up towards right, looking down- are present in the database. Various emotions like neutral, smile, laughter, sad/disgust are present in the database.

5. Results

Two common parameters used to measure the performance of the Face Recognition system are Recognition Rate and Recognition Accuracy. Recognition Rate is defined as the percentage of number of faces correctly recognized. It is the ratio of number of faces correctly identified to total number of faces given for identification.

$$\text{Recognition Rate} = \frac{\text{Number of faces correctly identified}}{\text{Total number of faces}} \text{X } 100$$

Recognition accuracy is the number of occurrence of face of a single person identified correctly. It is the ratio of number of occurrence correctly identified to total number of test faces of a single person given for identification multiplied by 100.

Fig.15 Test faces

$$\text{Recognition Accuracy} = \frac{\text{Number of occurence correctly identified}}{\text{Total number of test faces of a single person}} \text{X } 100$$

Table.1 Recognition rate

	Front Faces	Side Faces
Recognition Rate	78.94%	73.68 %

In comparison with other databases, the recognition rate has been improved

Table.2 Comparison for different data base

Georgia Tech Database with 400 images	70%
Indian Database	78.94%

When comparing with other face recognition techniques like Vector Quantization (VQ), Principal Component Analysis (PCA), Local Binary Pattern (LBP), Fischer's Linear Discriminant Analysis (FLDA), it can be seen that GV-LBP-TOP outperforms all other techniques.

Table.3 comparison of different methods

Vector Quantization Techniques with various code book size(avg)	76.7%
PCA	61%
LBP	67.87%
FLDA	70.06%
SRK GV LBP TOP	78.94%

Recognition accuracy is the number of occurrence of face of a single person identified correctly .It is the ratio of number of occurrence correctly identified to total number of test faces of a single person given for identification multiplied by 100.

$$\text{Recognition Accuracy} = \frac{\text{Number of occurence correctly identified}}{\text{Total number of test faces of a single person}} \text{X } 100$$

There are around 61 subjects in the database. Various poses of the subjects under various conditions were used as the test images. It has been found that the average recognition accuracy is 72.72% in the simulations.

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