International Journal of Power Control Signal and Computation (IJPCSC)
Vol. 4 No. 2 April- June -2012

ISSN:0976-268X
Available at : http://ijcns.com

NEURAL NETWORK BASED FACE RECOGNITION USING GABOR TRANSFORM

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***Abstract*—The position, spatial frequency and orientation selectivity properties are believed to have an important role in visual perception. This paper proposes a novel face representation and recognition approach by exploring information jointly in image space, scale and orientation domains. The face image is first decomposed into different scale and orientation responses by convolving multiscale and multiorientation Gabor filters. Second, local binary pattern analysis is used to describe the neighboring relationship not only in image space, but also in different scale and orientation responses. Thus information from different domains is explored to give a novel face image representation for recognition.Neural Networks provide significant benefits in face recognition. They are actively being used for such advantages as locating previously undetected patterns, controlling devices based on feedback, and detecting characteristics in face recognition. It improves the level of accuracy compared with existing face recognition methods.**

***Keywords*—Gabor Volume Based Local Binary Pattern (GV-LBP),Gabor Volume Representation, Local Binary Pattern (LBP).**

I. INTRODUCTION

FACE recognition has attracted much attention due to itspotential value for applications and its theoretical challenges.In real world, the face images are usually affected bydifferent expressions, poses, occlusions and illuminations, andthe difference of face images from the same person could belarger than those from different ones. Therefore, how to extractrobust and discriminant features which make the intrapersonalfaces compact and enlarge the margin among different personsbecomes a critical and difficult problem in face recognition.Up to now, many face representation approaches have beenintroduced, including subspace based holistic features and localappearance features [1]. Typical holistic features include thewell known principal component analysis (PCA) [3], linear discriminate analysis (LDA) [4], independent component analysis(ICA) [5], etc.

PCA provides an optimal linear transformation from the original image space to an orthogonal eigenspace with reduced dimensionality in sense of the least mean square reconstruction error. LDA seeks a linear transformation by maximizing the ratio of between-class variance and within-class variance. ICA is a generalization of PCA, which is sensitive to the high-order relationship among the image pixels.

Recently, Wang and Tang [6] unify PCA, LDA and Bayesian methods into the same framework and present a method to find the optimal configuration for LDA. Yan et al. [7] reinterpret the subspace learning from the viewof graph embedding so that various methods, such as PCA, LDA, ISOMAP , LLE , LPP , NPE MFA etc. can all be interpreted under this framework. Furthere, to handle the nonlinearity in face feature space, the nonlinear kernel techniques (e.g., kernel PCA [8], kernel LDA [9] etc.) are also introduced.

Local appearance features, as opposed to holistic features like PCA and LDA, have certain advantages. They are more stable to local changes such as illumination, expression and inaccurate alignment. Gabor [10], [11] and local binary patterns (LBPs) [12] are two representative features. Gabor wavelets capture the local structure corresponding to specific spatial frequency (scale), spatial locality, and selective orientation which are demonstrated to be discriminative and robust to illumination and expression changes.

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©gopalaxjournals,singapore
ISSN:0976-268X
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LBP operator which describes the neighboring changes around the central point is a simple yet effective way to represent faces. It is invariant to any monotonic gray scale transformation and is, therefore, robust to illumination changes to some extent. Recently, some work has been done to apply LBP on the Gabor responses to obtain a more sufficient and stable representation. Zhang et al. [13] propose LBPs descriptor on Gabor magnitude representation and Zhang et al. [14], perform LBP on Gabor phase information. The global and local descriptors are presented, respectively, and finally fused for face representation. These combinations of LBP and Gabor features have improved the face recognition performance significantly compared to the individual representation.

Combining information from different domains is usually beneficial for face recognition. Recent biological studies indicate that retinal position, spatial frequency and orientation selectivity properties have an important role in visual perception [15]. Therefore, in this paper, we propose to explore information jointly in space, frequency, and orientation domains to enhance the performance of face recognition.

II.CONSTRUCTION OF GABOR VOLUME

A.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 we used are defined as follows:

$$G(X,Y,theta,f)=\exp([-1/2\{(x' / s_x)^2 + (y' / s_y)^2\}]) * \cos(2 * pi * f * x')$$

where,

$x' = x * \cos(theta) + y * \sin(theta);$

$y' = y * \cos(theta) - x * \sin(theta);$

Theta=Orientation of each pixel in source image.

The gabor Filtered Output (G_{w}) contains both real and Imaginary Part.For further analysis, we require magnitude part of the Gabor filtered Output.

$$I_{w} = Root[Re[G_{w}(z)^2] + Im[G_{w}(z)^2]]$$

We consider 5 scales on a geometric grid and 20 Orientations.

Scale f =[0 1 2 3 4]
Orientations or theta =[0 1 2 3 4 5 6 7]

For each scale, we get 8 Orientation output.Totally 40 orientation Gabor output images are obtained.For every image pixel we have totally 40 Gabormagnitude 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.

Then bycombing 40 Gabor magnitude face images with the original space face image to form the Gabor face volume.Therefore, Gabor face volume consists of 40+1 face images.

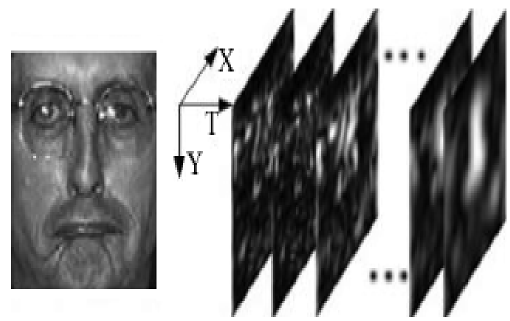

Figure.1 Face image and its corresponding third-order Gabor volume

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

For a face image, the derived Gabor faces are assembled by the order of different scales and orientations to form a third-order volume. The three axes X, Y, T denote the different rows, columns of face image and different types of Gabor filters, respectively. The existing methods essentially applied LBP on XY plane only. It is not sufficient for analysis of face image.Hence we propose the LBP on XT and YT planes to explore more sufficient and discriminative information for face representation.

C.Effective GV-LBP:

Extracting LBP for the 41 Gabor volume images are very complex in terms of number feature vectors.To reduce the complexity of feature vector, we propose Effective GV-LBP for the Gabor volume images

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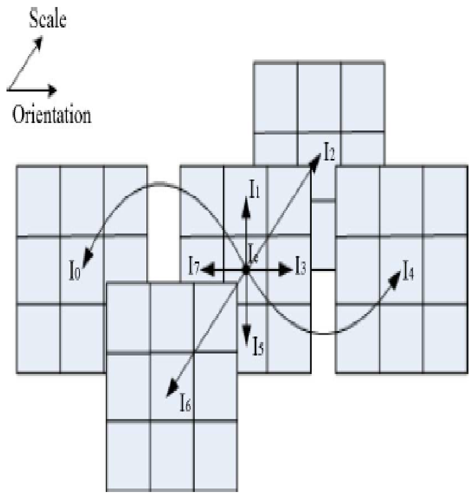

Figure. 2. Formulation of E-GV-LBP.

For the central point ,Ic, I_o and I_4 are the orientation neighboring pixels; I_2 and I_6 are the scale neighboring ones; I_1,I_3,I_5 and I_7 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, thresholded into 0 or 1 and transformed into a value between 0 and 255 to form the E-GV-LBP value.

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

where $S(I_p - I_c)$ is a threshold function defined as

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

D.Statistical Uniform Pattern:

In [12], researchers propose uniform pattern mechanism for LBP code which is robust to noise and improves the recognition performance. In LBP code, the uniform patterns are defined as such code that at most two bitwise transitions from 0 to 1 orvice versa occur when the binary string is considered circular. It is based upon the observation that there are a limited number of transitions or discontinuities in the circular presentation of the 3 *3 texture patterns. Therefore, the uniform patterns occupy a vast majority proportion of all LBP patterns in local image texture. In this paper, we adopt a more general strategy and define the uniform pattern via statistical analysis, according to the occurrence percentage instead of the number of 0–1 and 1–0 transitions for different codings.

III.EXPERIMENTS

Extensive experiments have been carried out to illustrate the efficacy of the proposed method. Specifically, three large publicly available face databases, FERET [16], AR and FRGC ver 2.0 , are used to evaluate the performance of different methods. These face databases contain various changes of face images, including expression, lighting, aging, occlusion etc. The proposed methods, GV-LBP-TOP and E-GV-LBP, have shown their robustness and accuracy in these variations.

***FERET Database*:**

The FERET database is one of the largest publicly available databases. In this experiment, the training set contains 731 images. In test phase, the gallery set contains 1196 images from 1196 subjects. Four probe sets (fb, fc, dup1, and dup2) including expression, illumination and aging variations are used to compare the performance of different methods. All the images are rotated, scaled and cropped into 88* 80 size according to the provided eye coordinates The uniform pattern number and the block size are two parameters that impact the performance of the proposed method. Fig. 3 shows the recognition rate on fb probe set by varying the number of uniform patterns and block size for E-GV-LBP representation on Gabor magnitude and phase responses, respectively.

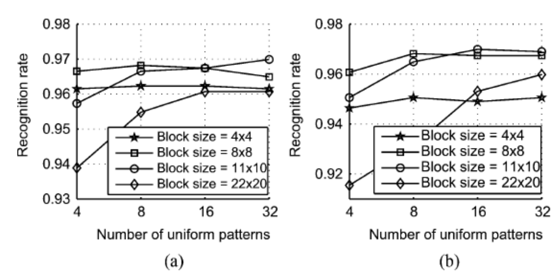

Figure.3.Face recognition rate of E-GV-LBP on fb probe set with different uniform pattern numbers and block sizes:

(a) E-GV-LBP-M and (b) E-GV-LBP-P.

Here, the uniform patterns are computed on the FERET training set and the unweight histogram intersection measure is used. As expected, too large or too small block size would result in a decreased face recognition rate because of the loss of spatial information or sensitivity to local variations. A smaller size of uniform pattern set would lose the discriminative information and a larger one would increase the computational cost. Considering the tradeoff between the recognition rate and computational cost, in the following experiments, the face image is divided into 11 *10 no overlapped blocks with the size of 8* 8, and the number of uniform patterns is set to 8. For the LBP, LGBP, GV-LBP-TOP and E-GV-LBP methods, weighted histogram intersection measure is adopted. The uniform codes of GV-LBP-TOP and E-GV-LBP and the weights of different blocks are statistically calculated on the FERET training set.

IV.RESULTS AND PERFORMANCE EVALUTION

Neural Networks provide significant benefits in face recognition. They are actively being used for such advantages as locating previously undetected patterns, controlling devices based on feedback, and detecting characteristics in face recognition. It improves the level of accuracy compared with existing face recognition methods.

A multilayer feed forward network, consisting of an input layer, three hidden layers and an output layer, is adopted in this paper. The input layer is composed by a number of neurons equal to the dimension of the feature vector (seven neurons). Regarding the hidden layers, several topologies with different nu provided optimal NN configuration. The output layer contains a single neuron and is attached, as the remainder units, to a nonlinear logistic sigmoid activation function, so its output ranges between 0 and 1.

Table 1

Performance Metric	PCA Classifier	NN Classifier
Accuracy Rate	0.764	0.812
DetectionRate (in sec)	0.92	0.76

V. CONCLUSION

This paper proposes two novel face representations. Different from LGBP, we first formulate Gabor faces as a third order volume and then apply LBP operators on three orthogonal planes (GV-LBP-TOP) encoding discriminative information not only in spatial domain, but also in frequency and orientation domains. In order to reduce the computational complexity, an effective GV-LBP (E-GV-LBP) descriptor is further proposed to describe the changes in spatial, frequency and orientation domains simultaneously. The statistical uniform pattern mechanism is proposed to improve the effectiveness and robustness of the proposed representations. Experimental results validate the efficacy of the proposed method.

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