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Face Recognition Using Gabor Volume Based Local Binary Pattern

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***Abstract*— The image space, scale and orientation domains can give valuable clues not seen in either individual of the domains. First we decomposed the face image into different orientation and scale by Gabor filter. Second, we combine local binary pattern analysis with Gabor. It gives a good face representation for recognition. Then we classify in discriminant based up on median histogram distance. The face images are usually affected by different expression, poses, illuminations and occlusions. Although the existing methods perform well under certain conditions, occlusions are still remaining as challenging problem. The proposed method median histogram distance deals this problem. This way, informations from different domains are explored to give a good face representation for recognition. Extensive experimental results on Yale database shows the significant advantages of the method.**

***Index Terms*— Effective Gabor Volume Based Local Binary Pattern (E-GV-LBP), Face recognition, Gabor, Local Binary Pattern (LBP).**

I. INTRODUCTION

Facial recognition [1] is for automatically identifying or verifying a person from a digital image or a video frame from a video source. Face Recognition has become important because of the potential value for applications and its theoretical challenges. Today, face recognition technology is being used to combat passport fraud, support law enforcement, identify missing children, and identify fraud. There are so many challenges in face recognition. Some of them are 1) Illumination variances, 2) Occlusions and 3) Different expressions and poses. The facial images are affected by brighten or darken light called as illuminations. The images of face, obtained by covering face with extra accessories like sunglass or clothes, covering by hands are known as occlusions. The images of face are obtained by rotating face up or down or right or left or up or down side called as poses. The images of face of a person who is in emotional mode (anger, happy, sad, fear, etc) called as different expressions. Already there are some approaches which are 1) feature based face recognition and 2) appearance based face recognition. The feature based face recognition extracts the geometrical relationship and other parameters of face features, such as eyes, nose, mouth and chin, for matching. It is sensitive to expression and pose changes. The appearance based face recognition include the well known Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), Elastic Bunch Graph Matching (EBGM) [6], ICA [5], etc.

PCA, commonly referred to as use of eigenfaces [4]. The PCA [7] approach is then used to reduce the dimension of the data by means of data compression basics and reveals the most effective low dimensional structure of facial patterns. LDA is statistical approach which gives large variance between classes, but small variance with in classes. EBGM is used to represent face by graph in which nodes are fiducially points and described by a set of Gabor wavelet responses [8], [9], [12]. In the EBGM algorithm, the face is represented as a graph, each node of which contains a group of coefficients, known as jets. However, both LDA and EBGM require extensive amounts of computational cost.

II. RELATED WORK

A. Gabor filter

Gabor filter capture the local structure in image space, scale and orientation. Here we use Gabor filters of multi-scale and multi-orientation which have been extensively and successfully used in face recognition to encode the local structure attributes embedded in face images. Gabor filter (kernels) with orientation μ, scale υ are defined as

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

Where z = (x , y), wave vector $k_{\mu,\upsilon}$ is defined as $k_{\mu,\upsilon} = k_{\upsilon} e^{i\varphi_{\mu}}$

Where $k_{\upsilon} = k_{max}/f^{\upsilon}$, $k_{max} = \pi/2$, $f = \sqrt{2}$, $\varphi_{\mu} = \pi\mu/8$.

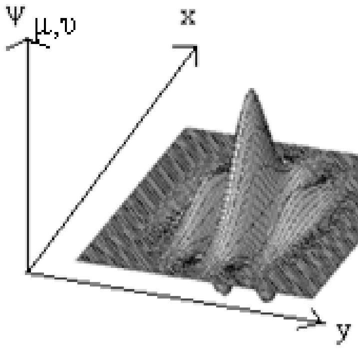


Fig:1 Gabor Filter

Each kernel is a product of a Gaussian envelope and a complex plane wave. These representation results display scale, locality, and orientation properties corresponding to those displays by the Gabor wavelets.

B. Weighted Histogram Intersection

The textures are modeled with volume local binary patterns (VLBP) [3], which are an extension of the LBP operator widely used in ordinary texture analysis, combining motion and appearance. LBP [10], [11] operator label to every pixel of an image by thresholding the 3x3-neighborhood of each pixel with the center pixel value and considering the result as a binary number. E-GV-LBP is the combination of volume local binary pattern and Gabor. The weighted histogram intersection is used to measure the weighted dissimilarity of different faces with E-GV-LBP histogram sequences. This method is suitable only for illumination, different expression and poses but not suitable for occlusion.

III. PROPOSED WORK

The results of weighted histogram intersection and the works so far done are not effective for recognition of the occlusions affected faces. Hence we propose new method median histogram distance.

A. Median Histogram Distance

The effective formulation of GV-LBP (E-GV-LBP) which encodes the information in image space, scale and orientation simultaneously. By encoding Gabor phases (Gp) through local binary patterns and local histograms, we have achieved very impressive recognition results, which are comparable to those of Gabor magnitudes (Gm)-based methods [2].

The fig:2 shows the definition of E-GV-LBP coding. I_c is central point, I_o and I_4 are the orientation neighboring pixels; I_2 and I_6 are the scale neighboring pixels. The Effective formulation of GV-LBP histogram is used to represent faces and in face recognition phase. It is also used to measure median of different histogram sequences that can be formulated as

$$D(H^1, H^2) = median[\sum_i \; d(H_i^1, H_i^2)]$$

where H^1, H^2 denote the two histogram sequences. The histogram intersection is used as the dissimilarity to measure different face images

$$d(H^1, H^2) = \sum_i \min(h_i^1, h_i^2)$$

where H^1, H^2 are two histograms and h_i^1, h_i^2 denote the ith bin value.

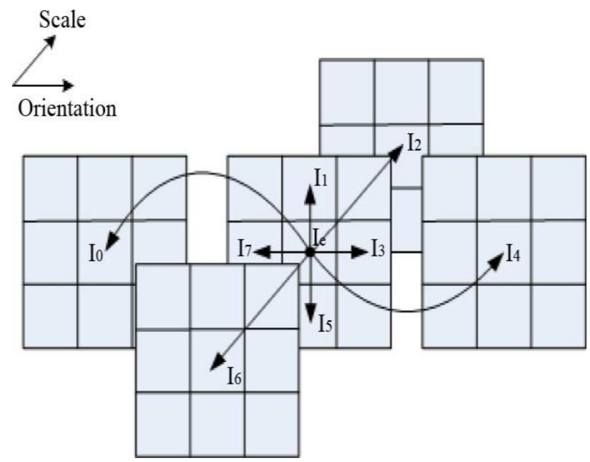
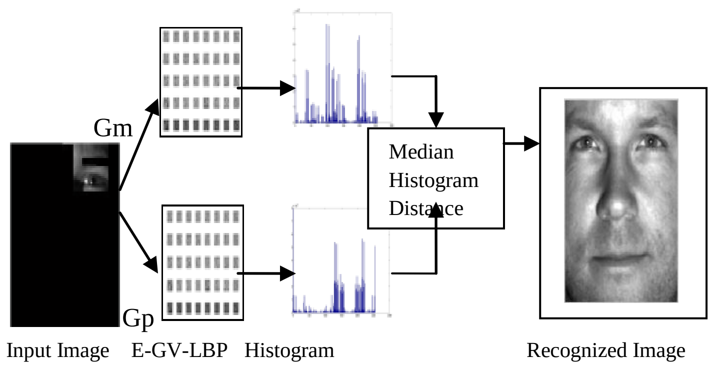


Fig:2 Formulation of E-GV-LBP



Gm-Gabor Magnitude,

Gp-Gabor Phase

Fig: 3 The framework of the proposed median histogram distance

Algorithm

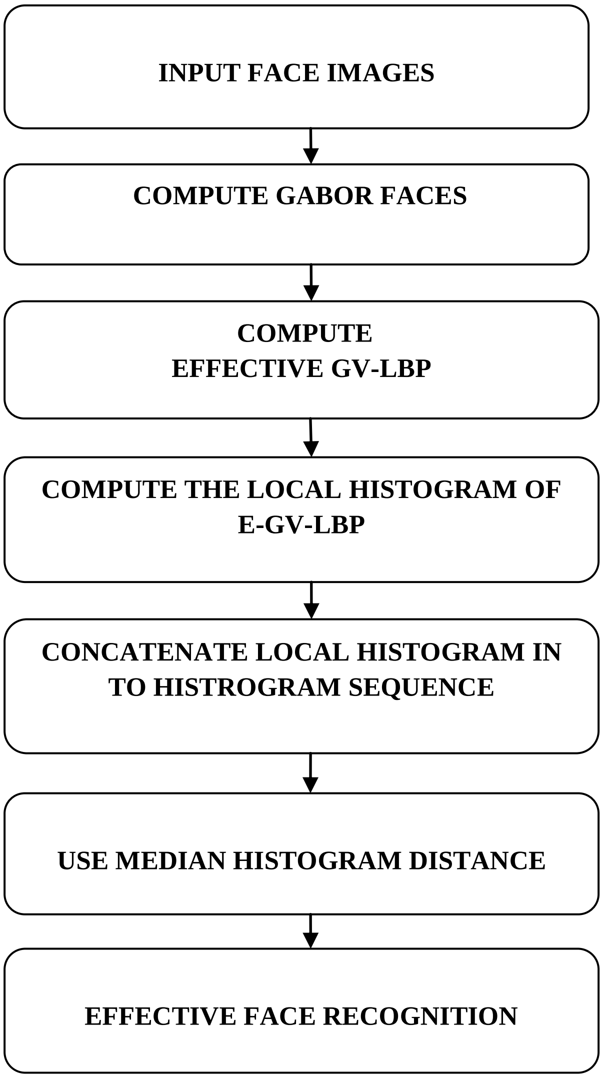
Step1: Compute Gabor faces by convolving a face image with different scales and orientations Gabor filters.

Step 2: Compute Effective GV-LBP code on Gabor faces.

Step 3: Divide the face into several blocks and for each block, compute the local histogram H of E-GV-LBP code.

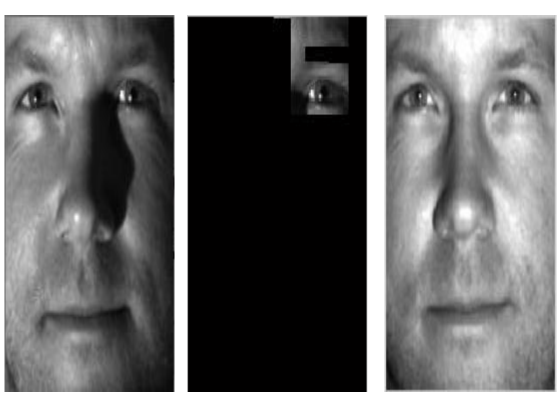
Step 4: Concatenate the local histograms into a single histogram sequence and use the method median histogram distance, as defined in above equation to derive the dissimilarity score.

Flowchart



IV. RESULT

Original image Input Image Recognized Image



The results obtained are efficacy in median histogram distance for less than 80% occluded images. The table 1 shows the accuracy rate of weighted histogram intersection and median histogram distance.

TABLE:1
PERFORMANCE COMPARISON

Image	Old Method (Weighted Histogram Intersection)	New Method(Median Histogram Distance)
20% Occluded Images	60%	95%
50% Occluded Images	55%	90%
80% Occluded Images	46%	85%

V. CONCLUSION

In this paper, we proposed a method median histogram distance. It gives the efficacy result for less than 80% occluded image. We use an effective GV-LBP descriptor of histogram sequences in median histogram distance. It gives compact face representation and improve efficacy of face recognition.

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