Neural Network based Face Recognition with Gabor Filters

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Abstract:
Gabor-based face representation has achieved enormous success in face recognition. This research addresses a hybrid neural network solution for face recognition trained with Gabor features. The system is commenced on convolving a face image with a series of Gabor filter coefficients at different scales and orientations. The neural network employed for face recognition is based on BAM for dimensional reduction and multi-layer perception with backpropagation algorithm for training the Gabor features. The effectiveness of the algorithm has been justified over a face database with images captured at different illumination conditions.
Keywords:
Gabor filter, rms contrast, neural network, BAM.

1. INTRODUCTION

fACE representation using Gabor features has occupied an emerging research area in numerous commercial and law enforcement applications. The principal motivation to use Gabor filters is biological relevance that the receptive field profiles of neurons in the primary visual cortex of mammals are oriented and have characteristic spatial frequencies. Gabor filters can exploit salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristics [1]-[2]. Considering these overwhelming capacities and its great success in face recognition, this paper addresses Gabor features to represent the face image and produces recognition task in tandem with neural network.
A fair amount of research works have been published in literature for Gabor based image recognition. Lades et al. developed a Gabor wavelet based face recognition system using dynamic link architecture (DLA) framework which recognizes faces by extracting Gabor jets at each node of a rectangular grid over the face image [3]. Wiskott et al. subsequently expanded on DLA and developed a Gabor wavelet-based elastic bunch graph matching (EBGM) method to label and recognize facial images [4]. 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. Liu and Wechsler have developed a Gabor feature based classification protocol using the Fisher linear discriminant model for dimension reduction [5]. Shan et al. have developed an enhanced fisher model using the AdaBoost strategy for face recognition [6]. Zhang et al. proposed a face recognition method using histogram of Gabor phase pattern [7]. Al-Amin et al. developed a multi-layer perceptron with backpropagation algorithm based neural network based Gobor filter method for face recognition [8].
This paper proposes a Gabor filter coefficient based hybrid neural network approach for face recognition. Since rms contrast is sensible for image representation, attempts are focused on rms scaling. The scaling of rms contrast produces better recognition performance. Despite robustness, Gabor filter based feature selection methods are normally computationally expensive due to high dimensional Gabor features. That's why the binary versions of the Gabor images performed by patterning has been employed as the input layer of neural network. To reduce feature dimension, this paper uses 15 Gabor filters; 3 for scaling and 5 for orientations.
The rest of the paper is organized as follows. Section II describes the over all system architecture and Section III image pre-processing. Section IV describes Gabor filter design. Section V describes the patterning technique. Section VI illustrates the construction of the hybrid neural network combining BAM with multilayer perceptron. The experimental method and results are presented in Section VII. Finally, the results are discussed, conclusions are drawn and future works are proposed in section VIII.

2. SYSTEM ARCHITECTURE

The system proposed in this research is designed for recognition of face images. The system consists of five modules: a) Face extraction b) Face preprocessing c) Facial feature extraction using Gabor filter d) Binarization using patterning e) Face recognition using BAM and back propagation algorithm (BPNN). The overall system architecture is shown in Fig. 1.

3. IMAGE PRE-PROCESSING

The original images are first converted into gray scale images. Pointing the centers of two eyes on each face image, all images are properly rotated, translated, scaled and cropped into 100×100 pixels. Images are then subjected to some image pre-processing operations. The image pre-processing phase includes contrast and illumination equalization, histogram equalization, and fuzzy filtering.

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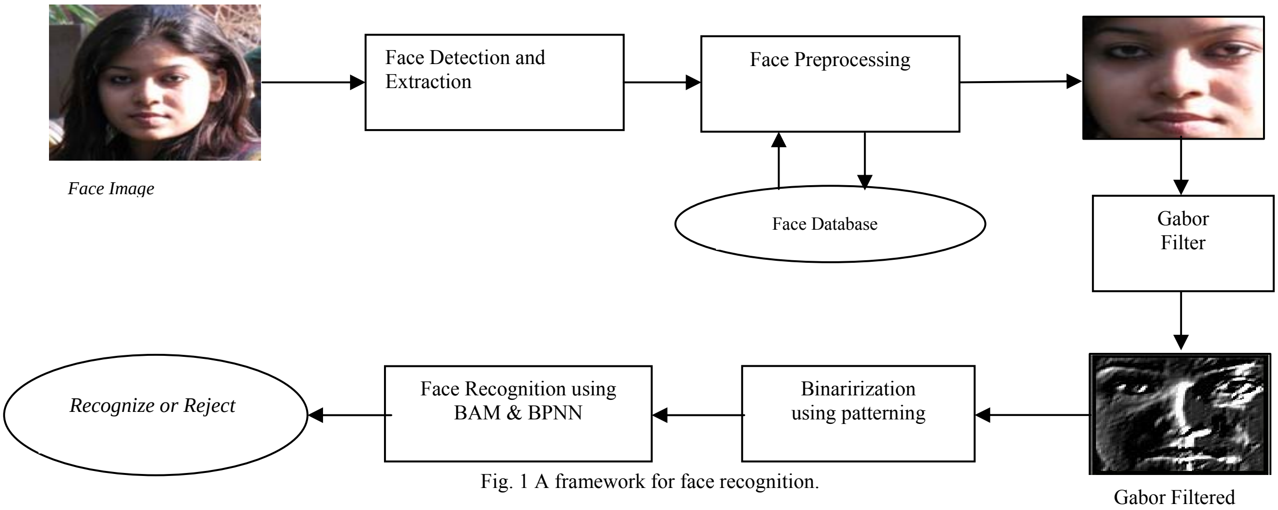

Fig. 1 A framework for face recognition.

Contrast and Illumination Equalization: Contrast is a measure of the human visual system sensitivity. To achieve an efficient and psychologically-meaningful representation, all images are processed with same illumination and rms contrast.
The rms (root mean square) contrast metric, equivalent to the standard deviation of luminance, is given by [8]:

$$C_{rms} = \left[\frac{1}{n} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right]^{1/2} \quad (1)$$

where x_i is a normalized gray-level value such that $0 < x_i < 1$ and $\bar{x}$ is the mean normalized gray level. With this definition, images of different human faces have the same contrast if their rms contrast is equal. The rms contrast does not depend on spatial frequency contrast of the image or the spatial distribution of contrast in the image. All images are maintained with the same illumination and same rms contrast using the following equation:

$$\mathbf{g} = \alpha\,\mathbf{f} + \beta \quad (2)$$

where α is the contrast and β is the brightness to be increased or decreased from the original image f to the new image g. The values of α and β are chosen empirically. The illumination and rms contrast equalization process is illustrated in Fig. 2.
Histogram Equalization: The face images may be of poor contrast because of the limitations of the lighting conditions. So histogram equalization is used to compensate for the lighting conditions and to improve the contrast of the image [9].

(a) Images with different illumination and contrast.

(b) Images with same illumination and same rms con trast.

Fig.2 Illumination and rms contrast equalization. Images were captured at illumination angles of -38.4º, -21.6º, -0.2º, 20.6º, 37º, respectively, all images at a pose of 0º (Courtesy: University of Hull, UK).

4. DESIGNING GABOR FILTER

Gabor filter works as a bandpass filter for the local spatial frequency distribution, achieving an optimal resolution in both spatial and frequency domains. The 2D Gabor filter $\psi_{f,\theta}(x, y)$ can be represented as a complex sinusoidal signal modulated by a Gaussian kernel function as follows [11]:

$$\psi_{f,\theta}(x, y) = \exp\left[-\frac{1}{2} \left\{ \frac{x_{\theta_n}^2}{\sigma_x^2} + \frac{y_{\theta_n}^2}{\sigma_y^2} \right\} \right] \exp(2\pi f x_{\theta_n}), \quad (3)$$

$$\text{Where, } \begin{bmatrix} x_{\theta_n} \\ y_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \quad (4)$$

σ_x, σ_y are the standard deviations of the Gaussian envelope along the x- and y-dimensions, f is the central frequency of the sinusoidal plane wave, and θ_n the orientation. The rotation of the x-y plane by an angle θ_n will result in a Gabor filter at the orientation θ_n. The angle θ_n is defined by:.

$$\theta_n = \frac{\pi}{p}(n-1) \quad (5)$$

for n=1,2,…,p and $p \in$ N, where p denotes the number of orientations.

Design of Gabor filters is accomplished by tuning the filter with a specific band of spatial frequency and orientation by appropriately selecting the filter parameters; the spread of the filter σ_x, σ_y, radial frequency f, and the orientation of the filter θn.

The Gabor representation of a face image is computed by convolving the face image with the Gabor filters [12]. Let f(x,y) be the intensity at the coordinate (x,y) in a gray scale face image, its convolution with a Gabor filter $\psi_{f,\theta}(x,y)$ is defined as:

$$g_{f,\theta}(x,y) = f(x,y) \otimes \psi_{f,\theta}(x,y) \quad (6)$$

where $\otimes$ denotes the convolution operator. Fig. 3 illustrates the convolution result of a face image with a Gabor filter. The response to each Gabor kernel filter representation is a complex function with a real part $\Re\{g_{f,\theta}(x,y)\}$ and an imaginary part $\Im\{g_{f,\theta}(x,y)\}$. The magnitude response $\left\| g_{f,\theta}(x,y) \right\|$ is expressed as:

$$\left\| g_{f,\theta}(x,y) \right\| = \sqrt{\Re^2\{g_{f,\theta}(x,y)\} + \Im^2\{g_{f,\theta}(x,y)\}} \quad (7)$$

This research uses the magnitude response $\left\| g_{f,\theta}(x,y) \right\|$ to represent the features. To reduce the influence of the lighting conditions, the output of Gabor filter about each direction has been normalized. In the sequel, a transformation $Q_{f,\theta}(x,y)$ to which $\left\| g_{f,\theta}(x,y) \right\|$ is subjected is given by:

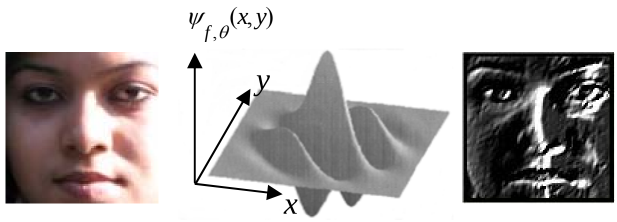

Fig. 3 Convolution result of a face image with a Gabor filter. (a) Face image, (b) Gabor filter (f=0.19,θ=3π/4,σx=σy=3), (c) Output of Gabor filter.

$$Q_{f,\theta}(x,y) = \frac{\left\| g_{f,\theta}(x,y) \right\|}{\sum_{\theta \in \Theta} \left\| g_{f,\theta}(x,y) \right\|}. \quad (8)$$

The important issue in the design of Gabor filters for face recognition is the choice of filter parameters. This research organizes 15 Gabor channels consisting of five orientation parameters $\theta \in \left\{0, \frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}\right\}$ and three spatial frequencies $f \in \{0.06, 1.0, 1.4\}$, respectively.

5. BINIRIZATION USING PATTERNING

Patterning involves replacing each pixel by a pattern taken from a ‘binary font’.Consider the following 3x3 font pattern, as shown in Fig. 4. These fonts are used to print an image consisting of ten gray levels. Since we are using replacing each pixel by a 3x3 block of pixels, both the width and the height of the image is increased by a factor of 3. The algorithm for the patterning process is given below and the output of a typical face image is shown in Fig. 5.

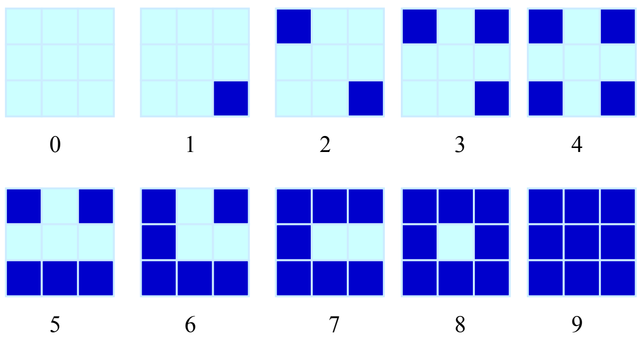

Fig. 4 Binary fonts for generating patterns.

(a) Original image (b) Patterned image

Fig. 5 Patterning process.

Algorithm 1 patternHalftone(im, font)
INPUT: Grayscale image img and a set of font patterns
OUTPUT: BW halftone of the input
Let output be an "empty" image for every pixel P in img
let F be the font that most closely approximates the actual gray-level of P replace pixel P with font F in the output image return output

6. FACE RECOGNITION USING NN

Face recognition is achieved by employing a hybrid neural network, consisting of two networks, (i) Bidirectional Associative Memory (BAM) for dimensional reduction of the feature matrix to make the recognition faster and more efficient, and (ii) Multilayer Perceptron with backpropagation algorithm for training the network. The architecture of the hybrid neural network is illustrated in Fig. 6. The first layer, called Gabor layer, receives the Gabor features. The number of nodes in this layer is, obviously equal to the dimension of the feature vector incorporating the Gabor features. The number of nodes in the output layer equals to the number of individual faces the network is required to recognize. The number of epochs for this experiment was 40,000 and the minimum error margin was 0.001.

7. Experimental results and performance

In order to evaluate the effectiveness of the proposed method, experiments were carried out for real images at different illumination conditions. We used CMU Pose, Illumination, and Expression (PIE) database [13] and selected 200 images of 40 individual subjects with two different poses and five different illumination conditions.

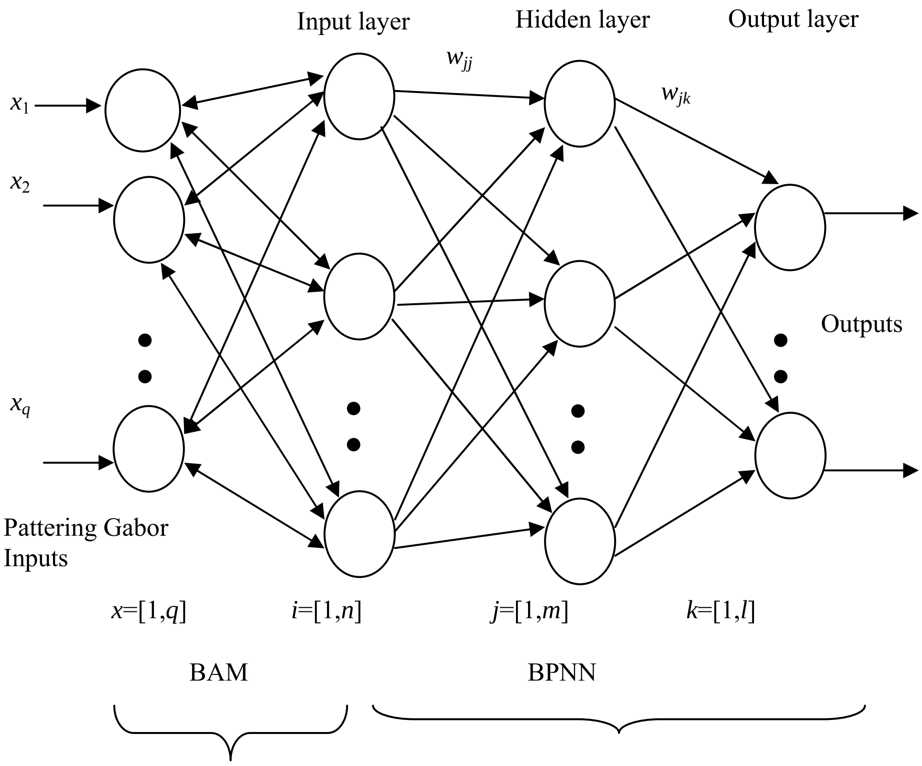

Fig. 6 Hybrid neural network.

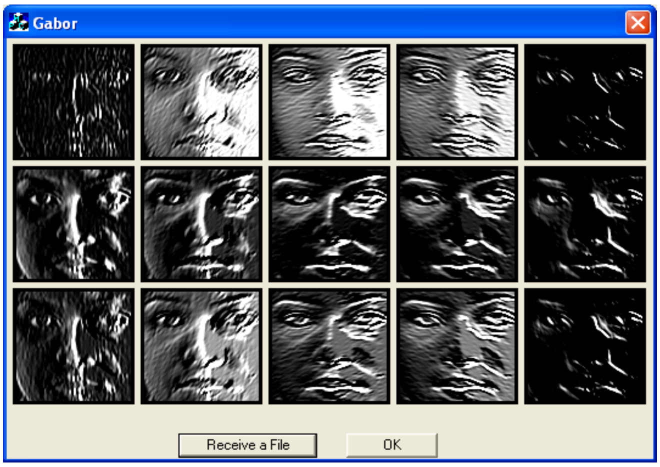

Fig. 7 Gabor filter response of a typical face image.

Half of the images in the database were used as a training dataset and the remaining images were used as probe images in the recognition test. All images were subjected to Gabor filters and were convolved with 15 Gabor filters. To each face image, the outputs were 15 images which record the magnitudes of the Gabor filter responses. Fig. 7 shows the results for a typical face image. The output of the Gabor filters were used to train the neural network. The training curve, indicating the gradual reduction in error over several epochs due to hybrid neural network, as well as BPNN learning algorithm, is shown in Fig. 8. Comparing the performance of two networks BPNN and Hybrid network, Fig. 8 reveals that the proposed hybrid network takes less iteration than BPNN in completion of the training process.

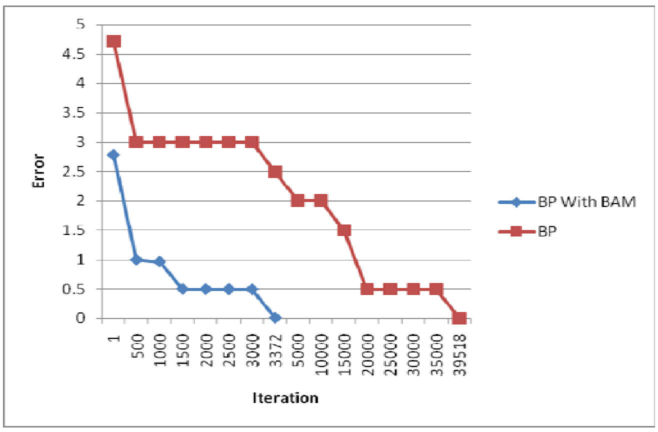

Fig. 8 Error versus iteration.

Finally, the effect of the proposed algorithm on the performance of face recognition has been analyzed. In order to evaluate the method for contrast equalization, we performed a comparison among our proposed system (rms scaling Gabor), the Elastic Bunch Graph Matching (EBGM), and the log-polar Gabor methods. The comparison results for the average recognition rates using different methods are furnished in Table I.

TABLE I Recognition PERFORMANCE OF THE PROPOSED ALGORITHM

Method	Correct Recognition (%)	Correct Rejection (%)
EBGM	75.29	78.32
Log-polar	77.38	82.33
Neural net based Gabor	81.50	82.75
Hybrid net based Gabor	84.50	85.50

8. Conclusion

This paper presents a neural network based face recognition system using Gabor filter coefficients that can cope with illumination changes. The recognition performance has been improved substantially due to implication of contrast equalization using the rms value of the image pixels. Application of a hybrid network (BAM and BPNN) rather than BPNN takes less iteration to train and less time to recognize faces. Since each pixel of the magnitude response of Gabor filter corresponds to a Gabor feature, the number of Gabor features for each sample is 100×100×15=150,000. Therefore, our next step will be to improve the algorithm which would be able to employ more complex classifiers and distance measures to represent Gabor faces with spatial and frequency features.

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