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On Face Recognition using Gabor Filters

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***Abstract*—**Gabor-based face representation has achieved enormous success in face recognition. This paper addresses a novel algorithm for face recognition using neural networks trained by Gabor features. The system is commenced on convolving a face image with a series of Gabor filter coefficients at different scales and orientations. Two novel contributions of this paper are: scaling of rms contrast and introduction of fuzzily skewed filter. The neural network employed for face recognition is based on the multilayer perceptron (MLP) architecture with backpropagation algorithm and incorporates the convolution filter response of Gabor jet. The effectiveness of the algorithm has been justified over a face database with images captured at different illumination conditions.

***Keywords*—**Fuzzily skewed filter, Gabor filter, rms contrast, neural network.

I. Introduction

FACE representation using Gabor features has attracted considerable attention in computer vision, image processing, pattern recognition, and so on. 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].

This paper proposes a Gabor filter coefficient based 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. This paper also addresses on noisy images and introduces a new filter, named “fuzzily skewed filter” for noise suppression, which swallows the advantages of both the median filter and averaging filter. Despite robustness, Gabor filter based feature selection methods are normally computationally expensive due to high dimensional Gabor features. 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 image pre-processing. Section III describes Gabor filter design. Section IV illustrates construction of the neural network with backpropagation algorithm. The experimental method and results are presented in Section V. Finally, in section VI, the results are discussed, conclusions are drawn and future works are proposed.

II. 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.

Contrast and Illumination Equalization: Contrast is a measure of the human visual system sensitivity. Although the role of contrast is significant in visual processing of computer displays, in almost all of the past literatures address the face recognition process in different lighting conditions with different illumination and contrast. 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]:

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

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(a) Images with different illumination and contrast

(b) Images with same illumination and same rms contrast

Fig. 1 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.

where x_i is a normalized gray-level value such that $0 < x_i < 1$ and $\overline{x}$ 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:

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

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. 1.

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].

Fuzzily Skewed Filtering: Images are sometimes corrupted by various sources of noise. The fine details of the image represent high frequencies which mix up with those of noise. So low-pass filters are used to obliterate some details in the image. This paper introduces a new filter named "fuzzily skewed" filter to suppress the noise.

In the fuzzily skewed filter, fuzzy rules are applied for deciding the gray level of a pixel in the image from the neighborhood of that pixel. This is a variation of the median filter and neighborhood averaging filter. The decision process includes the following steps:

1. The gray values of the neighborhood pixels ($n\times n$ neighborhood) are stored and then sorted in ascending or descending order.
2. Fuzzy membership value is assigned for each neighbor pixel with the following notions:
   i. A Π-shaped membership function is defined.
   ii. The highest and lowest gray values are assigned with the membership value of 0.
   iii. Membership value 1 is assigned to the mean value of the gray levels of the neighborhood.
3. Consider only $2\times k+1$ pixels ($k<=n^2/2$), where k is the range value, that is, the number of participant pixels in the skewing process of the sorted pixels list (these are the median gray value and k previous and forward values of the sorted list.
4. Select the gray value that has the highest membership value and produce it as output.

Example: Let us consider a 3x3 neighborhood with gray levels as follows:

91	114	175
92	116	176
95	111	182

Here,
Original value: 116;
Mean value: 128;
Median value: 114;
Let range value, k=2;

Sorted list: [91, 92, 95, 111, 114, 116, 175, 176, 182];
Membership value: [0, 0.0018, 0.0286, 0.5635, 0.6864, 0.7622, 0.0409, 0.0302, 0];

Therefore, considering the list of pixels (centering the median value) with gray levels {95, 111, 114, 116, 175}, the pixel with gray level 116 will be selected (corresponding to highest membership value of 0.7622).

The membership function employed for the fuzzily skewed filter, as shown in Fig. 2, is a π - shaped curve [10], implemented as a combination of s- curve and z-curve, respectively given by:

$$s(x_l, x_r, x) = \begin{cases} 0, & x < x_l \\ \dfrac{1}{2} + \dfrac{1}{2}\cos\left(\dfrac{x - x_r}{x_r - x_l}\pi\right), & x_l \le x \le x_r \\ 1, & x > x_r \end{cases} \qquad (3)$$

$$z(x_l, x_r, x) = \begin{cases} 1, & x < x_l \\ \dfrac{1}{2} + \dfrac{1}{2}\cos\left(\dfrac{x - x_l}{x_r - x_l}\pi\right), & x_l \le x \le x_r \\ 0, & x > x_r \end{cases} \qquad (4)$$

where x_l and x_r are the left and right breakpoints, respectively.

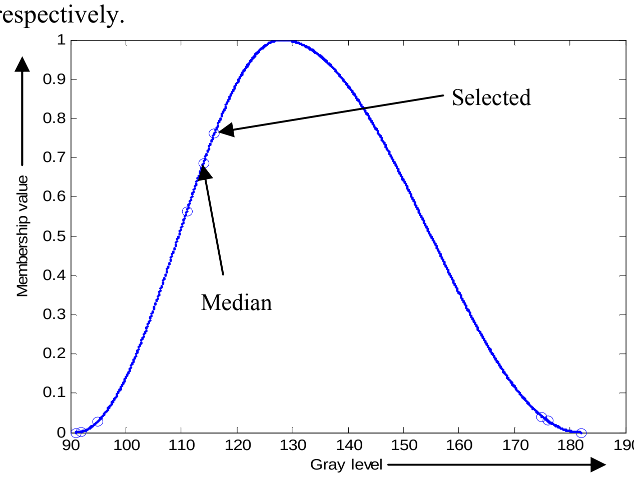


Fig. 2 Membership function for the fuzzily skewed filter

This method incorporates the advantages of both the median filter and averaging filter. For k=0, it acts like median filter and for $k/2<=n^2$, it acts like neighborhood averaging filter. This method can successfully reduce noise that results due to sharp transitions in the gray values, and it does not make any blur in the resultant image as the neighborhood averaging filter does.

III. 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]:

$$\psi_{f,\theta}(x,y) = \exp\left[-\frac{1}{2}\left\{\frac{x_{\theta_n}^2}{\sigma_x^2} + \frac{y_{\theta_n}^2}{\sigma_x^2}\right\}\right]\exp(2\pi f x_{\theta_n}), \tag{5}$$

$$\text{where, } \begin{bmatrix} x_{\theta_n} \\ y_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \tag{6}$$

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:

$$\theta_n = \frac{\pi}{p}(n-1), \tag{7}$$

for n=1,2,…,p and $p \in \mathbf{N}$, 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 θ_n. 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.

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:

$$g_{f,\theta}(x,y) = f(x,y) \otimes \psi_{f,\theta}(x,y) \tag{8}$$

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:

$$\left\|g_{f,\theta}(x,y)\right\| = \sqrt{\Re^2\{g_{f,\theta}(x,y)\} + \Im^2\{g_{f,\theta}(x,y)\}} \tag{9}$$

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:

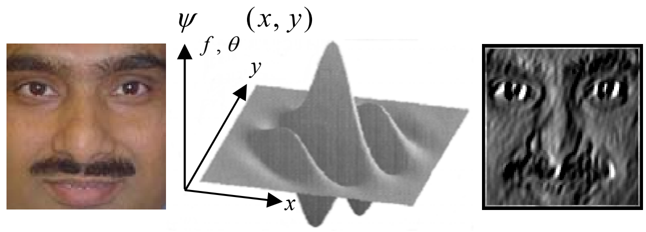


Fig. 3 Convolution result of a face image with a Gabor filter. (a) Face image, (b) Gabor filter (f=0.19,θ=3π/4,σ_x=σ_y=3), (c) Output of Gabor filter

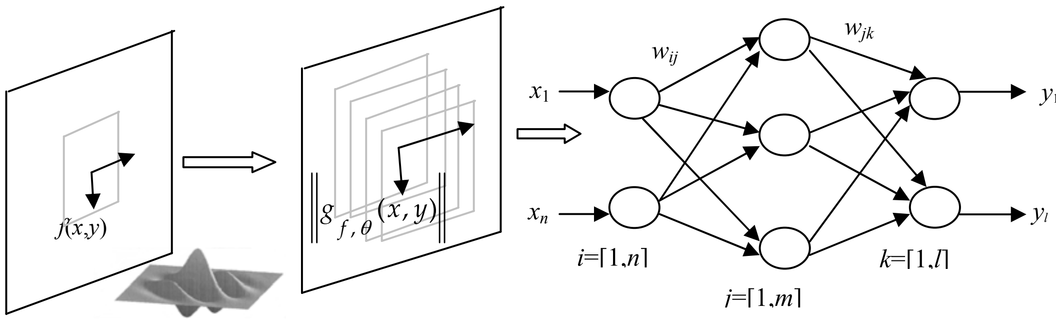


Fig. 4 Network architecture of Gabor based multi-layer perceptron

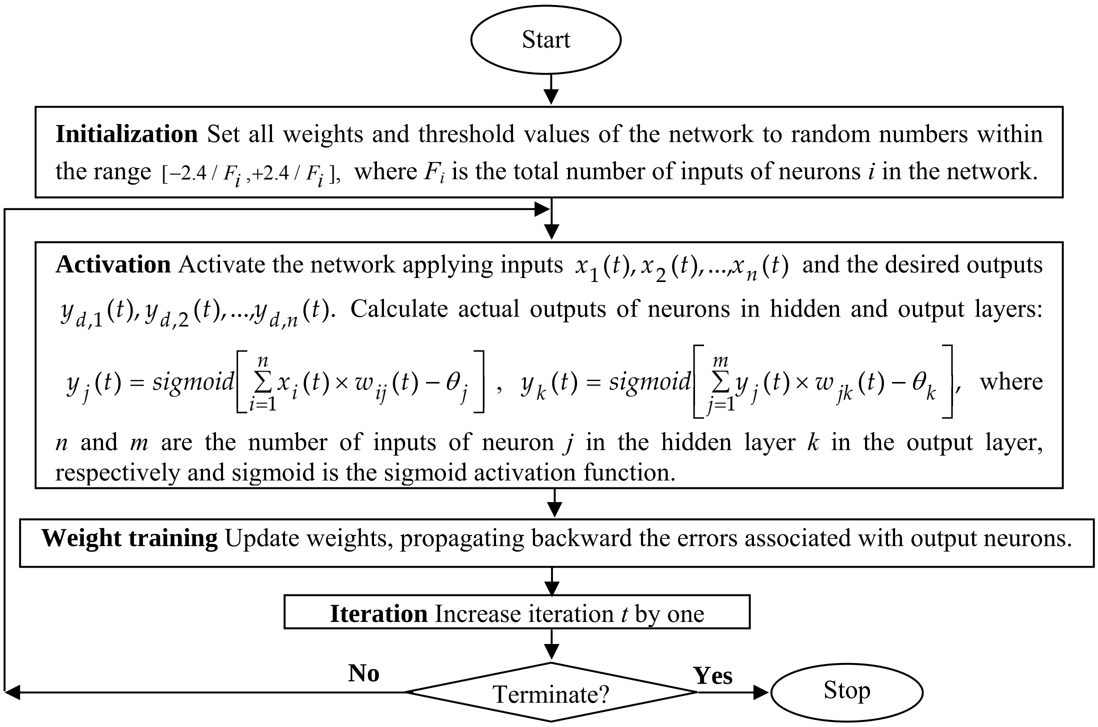


Fig. 5 Flowchart for backpropagation algorithm

$$Q_{f,\theta}(x,y) = \frac{\left\| g_{f,\theta}(x,y) \right\|}{\sum_{\theta \in \Theta} \left\| g_{f,\theta}(x,y) \right\|}. \tag{10}$$

The function $Q_{f,\theta}(x,y)$ takes the value in the range [0,1] and the parameter θ is in $\Theta \equiv \left\{0, \frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}\right\}$.

IV. Gabor Filter Based Neural Network

Face recognition is achieved by employing a multilayer perceptron with backpropagation algorithm. The architecture of the neural network is illustrated in Fig. 4. 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 10,000 and the goal was 0.01. The back-propagation training algorithm is illustrated in a flowchart as shown in Fig. 5.

V. 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 2 different poses and 5 different illumination conditions. 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. 6 shows the results for a typical face image. The output of the Gabor filters was used to train the neural network. The training curve, indicating the gradual reduction in error over several epochs due to backpropagation learning algorithm, is shown in Fig. 7.

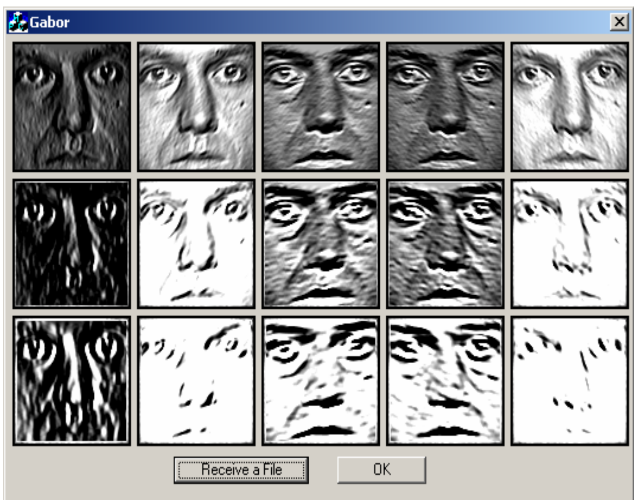


Fig. 6 Gabor filter response of a typical face image

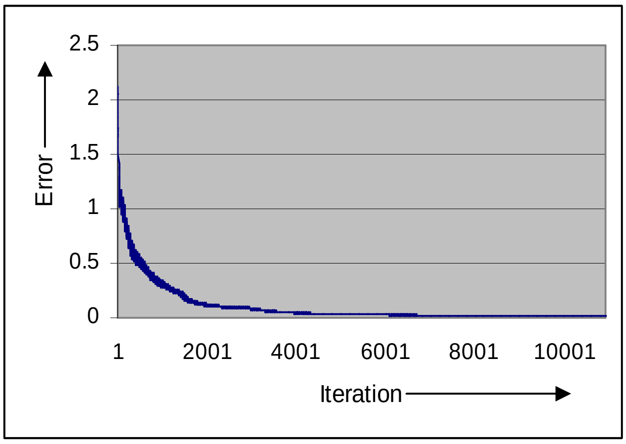


Fig. 7 Error versus iteration

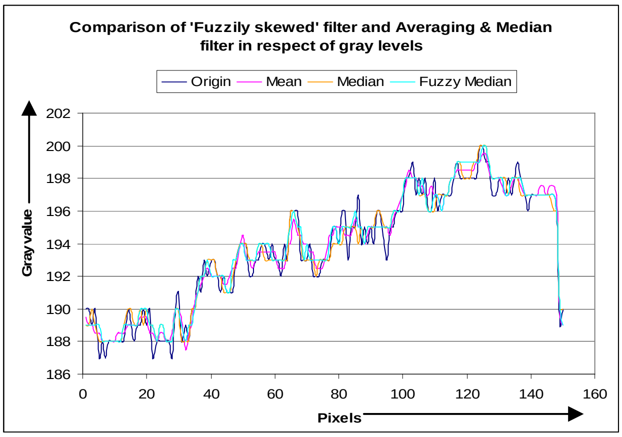


Fig. 8 Fuzzily skewed versus averaging and median filters

The response of the proposed fuzzily skewed filter has been analyzed. A graphical comparison among the 'Fuzzily skewed' filter, averaging and median filters is shown in Fig. 8. The graphical analysis imply that the fuzzily skewed filter snatches the advantages of both the median filter and averaging filter. This method can successfully reduce noise that results due to sharp transitions in the gray values, again, it does not make the resultant image as blur as the neighborhood averaging filter.

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. The performance of the fuzzily skewed filter was evaluated at the noisy environments. For this, two types of artificial noise were added to the images: (i) "Salt and pepper" noise with noise density 0.05, and (ii) Gaussian white noise of mean 0 and variance 0.01, respectively, as shown in Fig. 9. Experimental results demonstrate that our method is capable of recognizing faces in these noisy environments with significant margin.

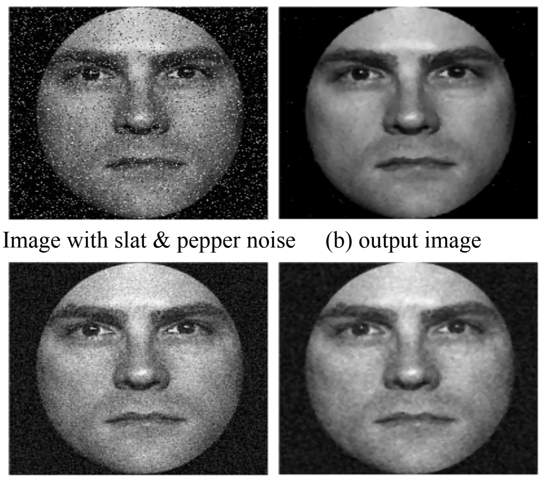
TABLE I
RECOGNITION PERFORMANCE OF THE PROPOSED ALGORITHM

Method	Correct Recognition (%)	Correct Rejection (%)
EBGM	75.29	78.32
Log-polar	77.38	82.33
rms scaling Gabor	84.50	87.75

VI. 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 and noise suppression by employing 'Fuzzily skewed filtering' in the processing step.

A face recognition system should identify a face from a new image despite the variations between images of the same face. A common approach to surmount the impediments in image variations due to changes in the illumination conditions is to use image representations that are relatively insensitive to these variations. Examples of such representations are edge maps, image intensity derivatives, and images convolved with Gabor-like filters. This paper focuses on a pragmatic study that evaluates the effectiveness of the proposed method for facial images at different illuminations. The processing time of Gabor transformation is reduced to less than one second with the image size of 100×100 pixels on a PC with a 1.2 GHz processor. From now on, the effectiveness of the method will be justified by testing it with face images of more persons and of some common databases. 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.



(a) Image with slat & pepper noise (b) output image

(c) Image with Gaussian noise (d) output image

Fig. 9 Noise suppression using Fuzzily skewed filter

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