A REVIEW ON FEATURE EXTRACTION TECHNIQUES IN FACE RECOGNITION

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ABSTRACT

Face recognition systems due to their significant application in the security scopes, have been of great importance in recent years. The existence of an exact balance between the computing cost, robustness and their ability for face recognition is an important characteristic for such systems. Besides, trying to design the systems performing under different conditions (e.g. illumination, variation of pose, different expression and etc.) is a challenging problem in the feature extraction of the face recognition. As feature extraction is an important step in the face recognition operation, in the present study four techniques of feature extraction in the face recognition were reviewed, subsequently comparable results were presented, and then the advantages and the disadvantages of these methods were discussed.

KEYWORDS

Face Recognition Systems &Feature Extraction

1. INTRODUCTION

Face recognition is an active research area with a wide range of applications in the real world. In the recent years, a defined face recognition pipeline, consisting of four steps i.e. detection, alignment, representation, and classification has been presented. In the detection step the place of the image including face is found. The alignment step ensures the detected face is lined up with a target face or a model. In the representation step the detected face is described in a way that several descriptions with certain aspects about the detected face are presented. Finally, the classification step determines whether a certain feature corresponds with a target face or a model [1]. Face recognition techniques are divided into Geometric and Photometric approaches. Geometric approaches consider individual features such as eyes, nose, mouth and a shape of the head and then develop a face model based on the size and the position of these characteristics. In photometric approaches the statistical values are extracted, subsequently, these values are compared with the related templates. A large number of researches have been devoted to feature extraction based on Gabor filter [2,3]. A face representation using the Gabor filter, has been of focal importance in the machine vision, image processing and pattern recognition [4]. In the face recognition, the feature representation of a face is a critical aspect. If representation step does not perform well, even the best classifiers cannot produce appropriate results. Good representations are those that on one hand minimize intra-person dissimilarities, on the other hand maximize differences between persons. Additionally, a significant representation should be fast and

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compact [4]. There are several views related to the classification of the feature extraction methods. One possible classification divides the feature extraction methods into Holistic Methods and Local Feature-based Methods. In the first method the whole face image is applied as an input of the recognition operation similar to the well-known PCA-based method which was used in Kiby and Sirovich [5] followed by Turk and Pentland [6]. In the second method local features are extracted, for example the location and local statistics of the eyes, nose and mouth are used in the recognition task. EBGM methods are included in this category[7].

Lades et al. [8] suggested a face recognition system based on DLA (Dynamic Link Architecture) platform, using extracting Gabor jets from each node over the rectangular grid to recognize faces. Wiskott et al. [9] expanded DLA and introduced EBGM (Elastic Base Graph) method based on a wavelet to recognize the face. However, both LDA and EBGM have a high computational cost. Although the Gabor filters are computationally expensive due to a high dimension of the feature vector the results obtained from them are robust [10]. T.Ojala et al. [11] introduced an original LBP operator which is regarded as a strong tool for describing the image texture. The main proportion of this study is devoted to the feature extraction techniques as follows:

The first technique addresses a new algorithm using the neural network which is trained by extracted features of the Gabor filters [10]. The second technique uses ten 2-D Gabor filters to extract reduced 3-D feature vectors, and then a classifier is applied to perform matching. Finally, the face recognition ends with a face verification method based on a set threshold [12]. In the third technique a face graph is represented to describe a face. The Gabor filter performs on nodes (coordinates of the nodes), at the end, the minimum average distance classifier corresponds each face graph with the faces in the data base and matching or not matching is decided upon [7]. In the fourth technique the face region is divided into small regions (blocks), and then a Local Binary Pattern (LBP) operator produces binary pattern histograms. By connecting these binary patterns to each other the enhanced feature histograms are generated [13].

The rest of the present study is organized in the following order: to obtain a better understanding of the feature extraction in the face recognition techniques in section 2 the feature extraction techniques were reviewed and elaborated, following comparing those techniques in section 3 and results are presented in section 4.

2. REVIEW ON TECHNIQUES

This section reviews the techniques used for the feature extraction in the face recognition and their related performance characteristics in detail.

2.1. First Technique

The Gabor filter, an image processing tool, applied broadly to the feature extraction, stores the information about the digital images [14]. This technique addresses a new algorithm using a neural network which is trained by the extracted features of the Gabor filters. The novel approach of this technique is scaling RMS contrast and presenting fuzzily skewed filtering. Initially the original images are converted into the gray-level images and cropped into 100×100 pixel images. By determining the centre of the two eyes for each face, then the face images are rotated [2]. The pre-processing phase of the related technique has three steps: contrast and illumination equalization, histogram equalization and fuzzy filtering [2].

2.1.1. Contrast and Illumination Equalization

RMS measuring is of great interest in the related area because it produces an appropriate recognition performance. Moreover it uses fuzzily skewed filtering to suppress the noise in the images [10].

Due to the different lighting conditions, the images might have a poor contrast, therefore all of the images are processed with the same illumination and the same RMS contrast to reach a significant representation. RMS contrast is the standard deviation of the illumination, Equation (1) shows RMS.

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

$$g = \alpha f + \beta \qquad (2)$$

Where x_i is a normalized gray-level value, $0 < x_i < 1$ and $\overline{x}$ is the mean normalized gray-level values [10]. Taking the related definition into account, all of the images are stored with the same illumination and contrast. In Equation (2) α and β are respectively the image contrast and illumination which can either increase or decrease. f shows the original image and g is a new image [10].

2.1.2. Fuzzily Skewed Filtering

It should be noted that sometimes different sources make an imperfection on the images, i.e. details of the image representation with a high frequency are disturbed by the noise [10]. In order to overcome such a disturbance, a new filter namely fuzzily skewed filter which has been used for the noise suppression. It has the advantages of both the median and the averaging filters. The value of each pixel is appointed by setting fuzzy rules and the neighborhood gray-level values of the pixels. There are 3 steps to determine the pixel value [14].

1) Determining an n×n neighborhood for each pixel, and sorting the gray level values in an ascending or descending order.
2) Defining a membership function for the pixels of the neighboring region according to a-c steps [14]:

   a) Pi-shaped membership function is defined.

   b) A value of 0 is assigned to the highest and the lowest gray-level values.

   c) A membership function value of 1 is assigned to the mean value (i.e. averaging on the gray-level values in the neighborhood of the pixels).

3) Returning the highest value of the membership function as an output.
4) Only pixels $2 \times k + 1$ ($k <= \frac{n^2}{2}$) are considered, k is the range value meaning that the number of the pixels that contributed to the skewing process of the stored pixels list.

To obtain a better understanding of the explained steps suppose the following 3×3 neighborhood, as shown in Figure 1:

91	114	175
92	116	176
95	111	182

Figure 1. The 3×3 neighborhood with the gray-level values [10]

Main value: 116, Median value: 114, Mean value: 128

Sorted list: [91, 92, 95, 111, 114, 116, 175, 176, 182]

Membership function value: [0, 0.0018, 0.0286, 0.5635, 0.6864, 0.7622, 0.0409, 0.0302, 0]

Considering the list of the pixel values (the median value is fixed in the centre of the list) {95, 111, 114, 116, 175}, value 116 which has a maximum value of the membership function (0.7622) is selected. Then using a $pi - shaped$ membership function, the fuzzily skewed filter is performed ($Pi - shaped$ membership function is implemented as a combination of $s - curve$ and $z - curve$), they are presented based on Equations (3) and (4), [10].

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

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

Where x_r and x_l are the left and right breakpoints respectively.

2.1.3. Designing Gabor Filter

The Gabor filter is used for extracting the image features [10]. It generates an optimal resolution in the spatial and frequency domain. To operate the Gabor filter, two orientation and frequency parameters are required. The selection of the parameters in the Gabor filter is a critical issue [12]. Therefore in the mentioned technique for reducing the extracted feature vector, 15 Gabor filters (5 orientation parameters and 3 spatial frequency parameters) are applied, see Figure 2, [10].

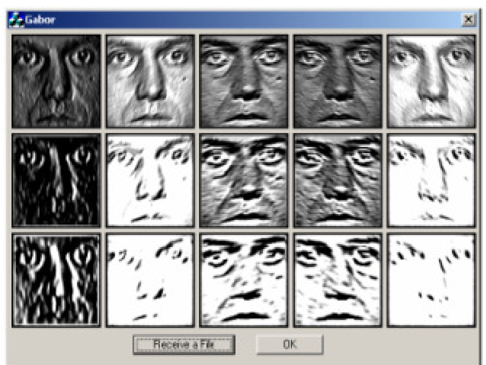

Figure 2. Extracted features of The Gabor filter [10]

A 2-D Gabor filter $\psi_{f,\theta}(x, y)$ can be represented as a complex sinusoidal signal and Gaussian kernel functions [10,14]:

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

$$\begin{bmatrix} x_{\theta_n} \\ y_{\theta_n} \end{bmatrix} = \begin{bmatrix} \sin\theta_n & \cos\theta_n \\ -\cos\theta_n & \sin\theta_n \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} \qquad (6)$$

$$where\ f \in \{0.06\ , 1.0\ , 1.4\}\ and\ \ \theta \in \left\{\frac{\pi}{5}\ , \frac{2\pi}{5}\ , \frac{3\pi}{5}\ , \frac{4\pi}{5}\right\}$$

σ_x and σ_y are the standard deviations of the Gaussian envelope along the x and y dimensions, f is the central frequency of the sinusoidal wave, and θ_n is the orientation value of x, y plane is defined according Equation (7) and p is the number of the orientations [10]:

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

By convolving the face images with the Gabor filters the output of the mentioned Gabor filter is computed by [10], if $f(X,Y)$ is the gray level value of the coordinate (x,y), then the convolution operator is computed by the following Equation (8):

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

where $\otimes$ shows the convolution operator.

2.1.3. Training the Neural Network

The extracted features using the Gabor filter is used to train a neural network. The neural network is trained using Error Back Propagation (EBP) algorithm [10], as shown in Figure 3. The number of the nodes in the input layer of the neural network are equal to the number of the extracted outputs from the Gabor filters and the number of the nodes in the output layer indicate the number of the recognized faces with the neural network, see Figure 4.

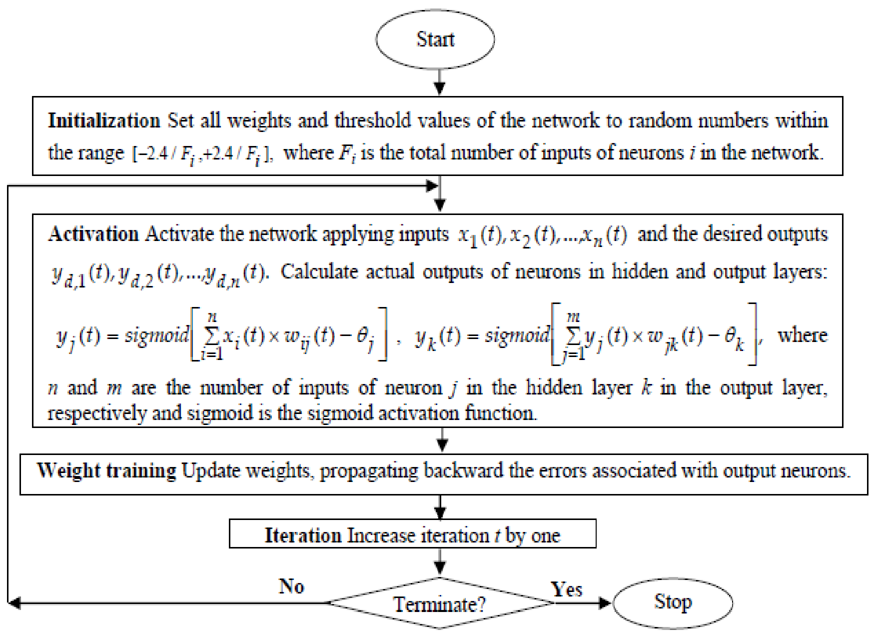

Figure 3. A flowchart for training neural network using Error Back Propagation algorithm [10]

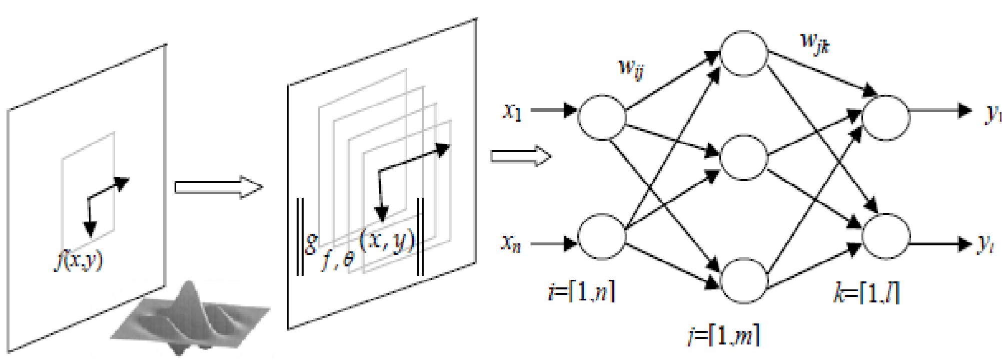

Figure 4. A structure of the used neural network [10]

2.2. Second Technique

This technique introduces a new method based on a 2-D Gabor filter for extracting the reduced 3-D feature vector. Initially all of the images should have the same illumination and the same contrast. So the operation of the histogram equalization is performed on the images. as a result, a satisfactory contrast is provided and the banks of the 2-D Gabor filter (10 filters for the frequency and 5 for the orientation) are used for extracting features [12].

2.2.1. Designing Gabor Filter

Gabor filter is expressed as a band-pass linear filter made of a complex sinusoidal plane of the particular frequency and the orientations modulated by a Gaussian envelop [15]. The shown Gabor filter in Equation (8) presents a group of wavelets containing the orientation and the frequency information of the digital images.

$$G_{\sigma_y,\sigma_x,f_l,\theta_k}(x,y) = exp\left(-\left[\frac{x_{\theta_k}^2}{\sigma_x^2} + \frac{y_{\theta_k}^2}{\sigma_y^2}\right]\right).\cos\left(2\pi f_{ix\theta_k} + \varphi\right) \qquad (8)$$

$Where\ x_{\theta_k} = x\cos\theta_k + y\sin\theta_k$, $y_{\theta_k} = y\cos\theta_k - x\sin\theta_k$, f_i provides the central frequency of the sinusoidal plan wave at an angle θ_k with the x-axis , σ_x and σ_y represent the standard deviation of the Gaussian envelope along the two axes, x and y. With set the phase $\varphi = {}^{\pi}/_{2}$ and compute each orientation as $\theta_k = \frac{k\pi}{n}$, where k=$\{1 , \dots , n\}$.

In order to design an appropriate the Gabor filter for extracting features, the parameters of the Gabor filter should be selected optimally. Therefore the related technique uses some appropriate variance values, a set of radial frequency and a series of orientations. In this technique $\sigma_x = 2$, $\sigma_y = 1$, $f_i \in \{0.75 , 1.5\}$ $and\ n = 5$, which means $\theta_k \in \left\{\frac{\pi}{5}, \frac{2\pi}{5}, \frac{3\pi}{5}, \frac{4\pi}{5}, \pi\right\}$. Therefore, a 2-D Gabor filter bank $\{G_{\theta_k,f_i,2,1}\}$ composed of 10 channels is created. By convolving the face image with each Gabor filter from this set, each face image is filtered, see figure 5. Later the 2-D feature vector $V(x,y)$ is generated containing the optimal features of face image I. Then vector $V(x,y)$ is extended to $V(x,y,z)$ using Equations (9) and (11) having more comprehensive information about an image [13], see Equation (10):

$$V(I)[x,y,z] = V_{\theta(x),f(x),\sigma_x,\sigma_y}(I)[x,y] \qquad (9)$$

Where $x \in [1,x]$, $y \in [1,y]$
and we have:

$$\theta(z) = \begin{cases} \theta_z , & z \in [1.n] \\ \theta_{z-n} , & z \in [n+1 , 2n] \end{cases} \quad , \quad f(z) = \begin{cases} f_1 , & z \in [1.n] \\ f_2 , & z \in [n+1 , 2n] \end{cases}$$

$$V_{\theta(z),f(z),\sigma_x,\sigma_y}(I)[x,y] = I(x,y) \otimes G_{\theta(z),f(z),\sigma_x,\sigma_y}(x,y) \qquad (10)$$

Then the Fast Fourier Transform (FFT) performs a fast 2-D convolution [16] based on Equation (11)

$$V_{\theta(z),f(z),\sigma_x,\sigma_y}(I) = FFT^{-1}\left[FFT(I).FFT(G_{\theta(z),f(z),\sigma_x,\sigma_y})\right] \qquad (11)$$

Subsequently, a 3-D feature vector is generated that represents the characteristics of the face image.

Due to the dimension of the created feature vector which is dependent on the image size, initially a resizing operation should be performed on the images. This technique uses a squared Euclidean distance measure to do it, see Equation (12):

$$d\big(V(I),V(J)\big)=\sum_{x=1}^{X}\sum_{y=1}^{Y}\sum_{z=1}^{2n}|V(I)[x,y,z]-V(J)[x,y,z]|^2 \qquad (12)$$

Where I and J are two face images resized to the same $[X \times Y]$ size.

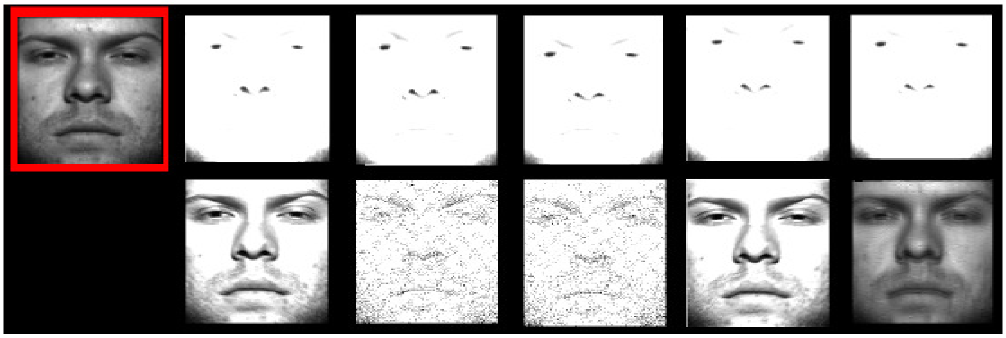

Figure 5. An output of the Gabor filters [10]

2.2.2. Supervised Classification Step

After creating the 3-D feature vectors in the previous stage using the Gabor filter, a supervised classification method is suggested to classify these vectors. This technique applies one of the well-known supervised classification methods i.e. a minimum distance classifier. The minimum average distance classifier is applied to perform matching. In this technique N registered persons are selected to create the training set. Each person of this set is presented by several representations or face template of its own which are included in the training set as shown in Figure 6. Then each face image in the input set is corresponded with all of the face images in the training set using the minimum average distance classifier. The results of the supervised classification with regard to Figures 5 and 6 are provided in Table 1, the minimum average distances generated from the classifier are marked with a star.

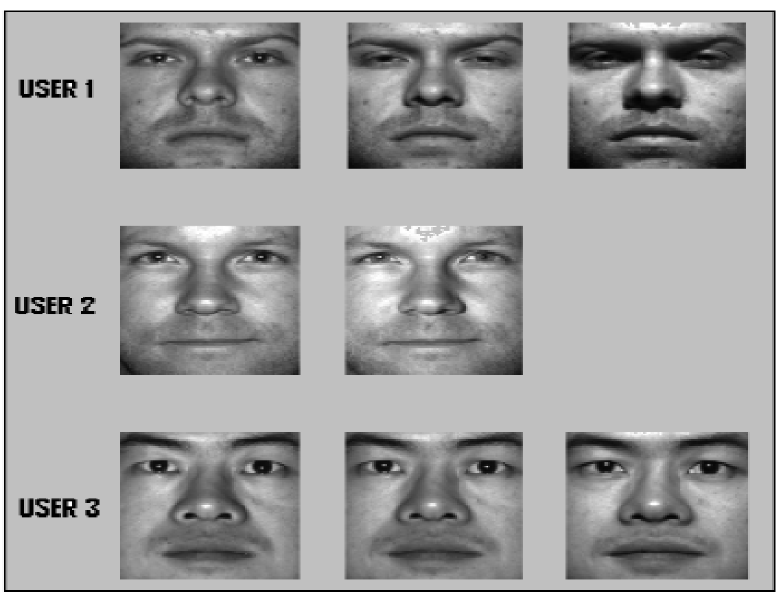

Figure 6. Face training set example [12]

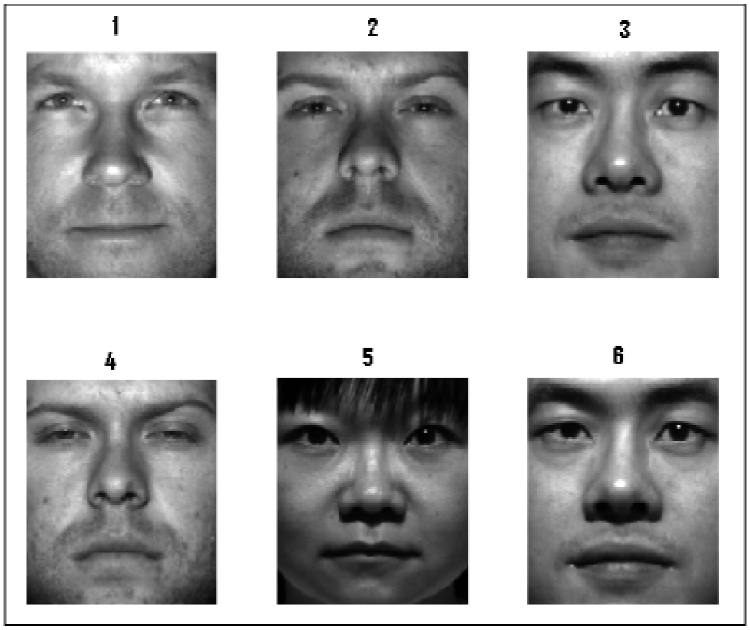

Figure 7. Input images set [12]

Table 1. Results of comparison in supervised classification [12]

	I_1	I_2	I_3	I_4	I_5	I_6
User 1	1.0970	0.6208	1.5475	0.7779	1.6175	1.0379
User 2	0.5581	1.4291	1.7623	1.2103	1.1313	1.2551
User 3	1.2154	1.0946	0.9278	1.2548	1.3562	0.6333

2.2.3. Automatic Face Verification Method

Finally the face recognition ends with a face verification method based on a threshold which determines a positive verification or a rejection [17]. If the assigned average distance corresponding to an image from a class is greater than the threshold T that image is rejected.

2.3. Third Technique

The present technique is an extended form of the EBGM (Extended Bunch Graph) method. EBGM is a technique which uses the Gabor filters for extracting the local information of the images. In the pattern recognition a descriptor is used to represent the features of the image. This method introduces a new technique using local descriptors for the feature extraction [7]. A block diagram of the used algorithm in this technique adopted from [18], has been shown in Figure 8.

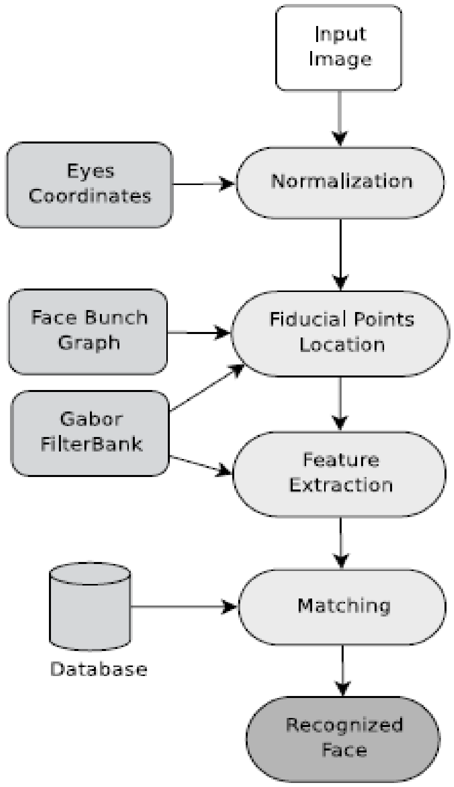

Figure 8. Block diagram of used algorithm in third technique [7]

In the first stage, that is normalization, a transformation is used to adjust all of the images to obtain images with the same size, to this aim, the eye coordinates are located manually. In Fiducial Points Location step, a representative description of the face is needed for automatically locating points on a new face, the description should be generated for a wide range of different forms of the face. The representative description system is named Face Bunch Graph (FBG) [19]. In order to create FBC, sets of face graphs are combined and each FBC node is labeled with a set of jets. Having the coordinates of the eyes, FBC and statistical evaluations, the coordinates of other nodes are produced [14]. Consequently, the final the face graph is created see Figure 9.

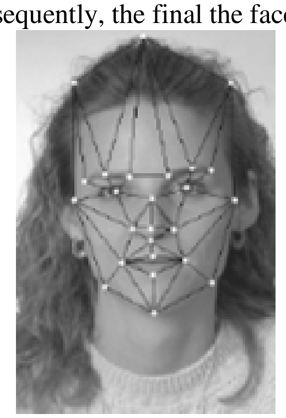

Figure 9. an example of the face Graph [7]

2.3.1. Feature Extraction

Then in the Feature Extraction stage the Gabor filter performs on the nodes (coordinates of the nodes). After that some features are extracted which are referred to "jets" [14]. The produced jets and coordinates of the nodes are stored, the edges of the graph are labeled based on the distance between two nodes [20].

The basic formula of the Gabor filter, a combination of the Gaussian kernel with trigonometric function extracting features, is drawn by Equations (13) and (14), [21].

$$w(x,y) = \mathrm{f}e^{-\frac{x^2+y^2}{2\sigma^2}}(\cos(2\pi f x + \phi) - DC) \qquad (13)$$

$$DC = cos\,\phi e^{-2\pi^2\frac{\sigma^2}{f^2}} \qquad (14)$$

$$Where\ ,\ \begin{cases} x = xcos\theta + ysin\theta \\ y = -xsin\theta + ycos\theta \end{cases}$$

In Equation (14) parameter $\sigma = kf$ ensures that the filter spatial range of action is proportionally limited to the central frequency f. This technique applies five different frequencies and eight orientation parameters, totally 40 filters generated for initializing the parameters of the Gabor filter [14].

2.3.2. Matching Set

After obtaining the face points and the outputs of the Gabor filter the following Equations (15) and (16) are used for matching or not matching the input face with the faces stored in the database [7].

$$L(G,G) = \frac{1}{n}\sum_{i=1}^{n} S_\alpha(J_i, J_i) \qquad (15)$$

$$S_\alpha(J,J) = \frac{\sum_{j=1}^{N} \alpha_j \alpha_j}{\sqrt{\sum_{j=1}^{N} \alpha_j^2 \sum_{j=1}^{N} \alpha_j^2}} \qquad (16)$$

$J_i\ and\ J_i^{'}$ are jets i of the graphs $G\ and\ G^{'}$ respectively, $a\ and\ \alpha\ are$ the results of Gabor filter, $n\ is$ the number of the nodes for each graph and $N\ is$ the number of Gabor filter [21].

2.4. Fourth Technique

This technique introduces a new algorithm of the feature extraction based on the LBP (Local Binary Pattern) operator. Using LBP operator, the features of each image are extracted, in a way that the face image is divided into the small regions (blocks) and then the binary pattern histograms are extracted (a binary code is extracted for each neighboring pixel). T.Ojala et al. [11] introduced the original LBP operator which is regarded as a strong tool for describing image texture. By selecting the 3×3 neighboring region of each pixel with a central value as a threshold and taking the results as a binary number into account, the pixels are labeled [13]. Afterwards, the histograms of the labels are used as an image descriptor in the face recognition, see Figure 10 and Figure 11. Later LBP is extended to operate on the circular regions with different sizes [13]. To indicate the circular regions notation (P, R) is used. By connecting the binary patterns an enhanced feature histogram is generated and the face image is significantly represented [13].

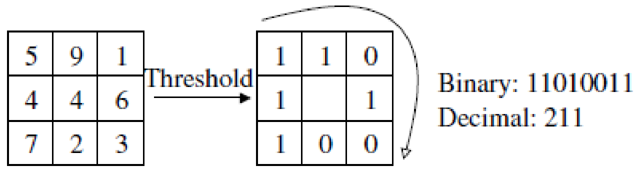

Figure 10. The original LBP operator [13]

The produced histograms contain various information related to all the regions of the face. Notation $LBP_{P,R}^{u^2}$ is used for identifying the LBP operator which the subtitle and superscript respectively indicate a circular region and binary labels (bits 0 and 1), therefore the histogram of the image $f_l(x, y)$ can be defined as Equation (17), [13].

$$H_i = \sum_{x,y} I\{f_l(x,y) = i\} \quad , \qquad i = 0, \dots, n-1 \qquad (17)$$

n is the number of the different labels generated by the LBP operator, based on Equation (18) we have[13]:

$$\mathrm{I(A)} = \begin{cases} 1 & , \quad A \text{ is true} \\ 0 & , \quad A \text{ is false} \end{cases} \qquad (18)$$

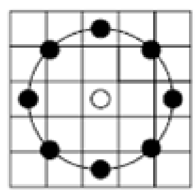

Figure 11. A circular neighborhood region (8,2), [13]

Histogram H_i includes the information about a description of the small patterns such as borders, flat regions, spots, etc. [22].

To achieve an appropriate representation of the face, face spatial information is also stored, therefore the face image is divided into regions $R_i, \dots, R_{n-1}$, and the extended histogram is based on Equation (19), [13] :

$$H_{i,j} = \sum_{x,y} I\{f_l(x,y) = i\}\; I\{(x,y) \in R_j\} \;, \quad i = 0, \dots, n-1 \;\; and \;\; j = 0, \dots, m-1 \qquad (19)$$

The technique represents the description of the face in three different levels. The labels of the histogram contain the information on some patterns at the pixel level, then the labels are gathered in a small area in order to provide some information on regional level, subsequently the regional histograms are connected together to provide an optimal description of the face image [23]. Since some of the regions such as the eyes play more important role than the other regions in the face recognition, the LBP operator can be equipped with a weight parameter [11].

3. COMPARISON OF THE TECHNIQUES

To compare the techniques used for the feature extraction in the face recognition it is important to take some of the databases containing the images under different conditions into consideration, these conditions are summarized below:

F_a : the ordinary face images

F_b : The different expression of the face images

F_c : The condition of the different illumination

DupI, DupII : captured images after several months or years.

Set F_a used as a gallery and one of the sets F_b, F_c, DupI or DupII is as the test set [12]. The comparison results are displayed in Tables 2 and 3.

Table 2. Comparison of the techniques performance on PIE database

Technique name	Correct recognition	Correct rejection
EBGM[7]	75.29	78.32
Log-Polar Gabor[7]	77.38	83.33
RMS scaling Gabor[7]	84.50	87.75

Table 3. Comparison of the techniques performance on FERET database

Technique name	Fb	Fa	DupI	DupII
Weighted-LBP[11]	97	79	66	64
Non-weighted-LBP[11]	93	51	61	50
Optimal-EBGM[11]	90	42	46	24

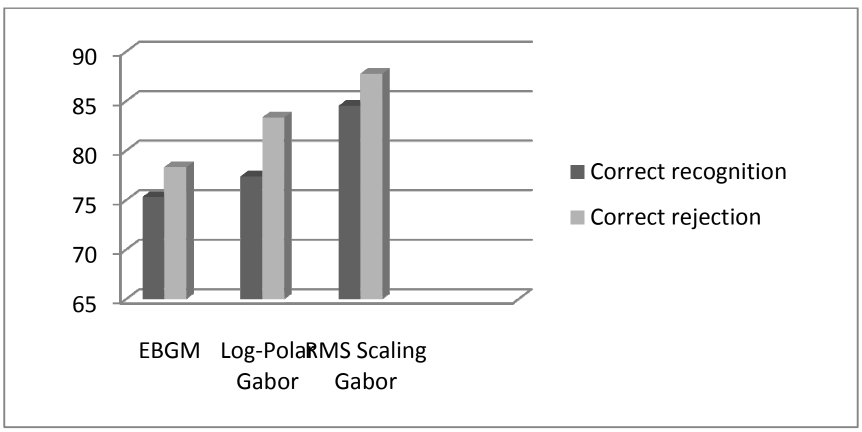

Figure 12. Comparison EBGM, Log-polar Gabor filter and RMS scaling Gabor on PIE database

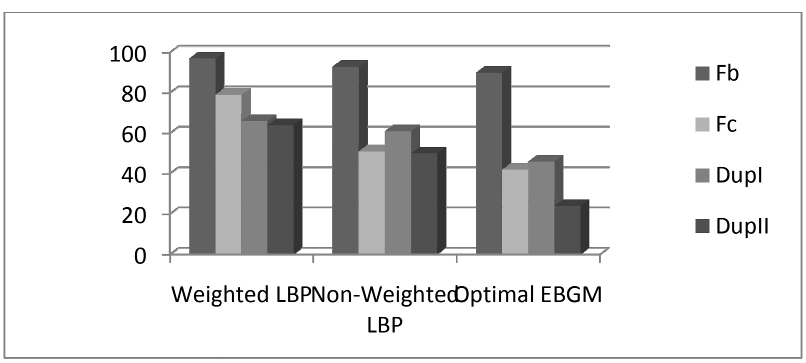

Figure 13. Comparison of weighted-LBP, non-weighted LBP and optimal-EBGM on FERET database

Also in Table 4 the advantages and the disadvantages of mentioned techniques are presented.

4. CONCLUSIONS

As the face recognition systems are widely used in the security scopes, in this study we reviewed four important techniques of the face recognition in the feature extraction phase. With regard to the results obtained from several studies and also comparison made on the performance of four techniques of the feature extraction methods in the face recognition, it is concluded that weighted-LBP has the highest recognition rate compared to the rest of the techniques. Non-weighted LBP has the highest performance in the feature extraction among three techniques EBGM, 10-Gabor filter and the 15-Gabor filter. Although the vector length in 10-Gabor and 15-Gabor filters is long, the extracted recognition rates in these two techniques are higher compared to the EBGM and Optimal-EBGM methods. A further study can be conducted on a dimension reduction of the extracted feature vectors using 10-Gabor and 15-Gabor filters to achieve a higher speed of the recognition operation. On the other hand if the face graph in the Optimal-EBGM method is fully determined automatically then a higher performance is generated.

Table 4. The advantages and the disadvantages of mentioned techniques

Technique name	Advantages	Disadvantages
15-Gabor filter[10]	Using the RMS contrast and the fuzzily filter leads to a high rate of the feature extraction in the face recognition.	A long feature vector causes a low speed in the face recognition.
10-Gabor filter[12]	Use of a small number of the Gabor filters and the automatic-Face verification method causes a higher recognition rate.	A long feature vector causes a low speed in the face recognition and also the detection rate is extremely low for the non-frontal images or the images that are rotated.
Optimal-EBGM[7]	The FBG statistical model provides the semi-automatically generated face graph.	To adjust the nodes of the whole face graph First the eye points should be adjusted manually.
LBP[13]	It only requires one scanning without any need to a complicated analysis in the EBGM method.	The obtained weak results on the DupI and the Fc databases prove that yet the illumination variations are challenging.

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