FACE RECOGNITION WITH GABOR PHASE

A Thesis by

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The following faculty members have examined the final copy of this thesis for form and content, and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Electrical Engineering.

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DEDICATION

To my parents, and teachers

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ABSTRACT

Face recognition is an attractive biometric measure due to its capacity to recognize individuals without their cooperation. This thesis proposes a method to dynamically recognize a facial image with the help of its valid features. To validate a set of feature points, the skin portion of the facial image is identified by processing each pixel value. Gabor phase samples are examined, depending on whether they are positive or negative at each filter output, and feature vectors are formed with positive or negative ones along with the spatial coordinates at the validated feature points. The collection of feature vectors is referred to as the feature vector set.

The face recognition system has two phases: training and recognition. During the training phase, all images from the database are automatically loaded into the system, and their feature vector set is determined. When the test image arrives at the system, the feature vector set of the test image is compared with that of database images. Feature vectors are location-specific, and thereby similarities between the feature vectors of the test image and database images are calculated, provided that they are from the same spatial coordinates. Once spatial coordinates are matched by using exclusive-OR (X-OR) operation, the similarity is calculated from the values of the feature vector. Simulations using the proposed scheme have shown that precise recognition can be achieved.

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Chapter 1

Introduction and Preview

1.1 Introduction

Individuals can be recognized by human beings using a set of physical or behavioral characteristics. These characteristics are referred to as biometrics and are used as a form of access management and control. Behavioral biometrics, such as voice, gait and typing rhythm, are related to the behavior of a person. Physiological biometrics, which are related to the shape of the body, include fingerprint, face recognition, DNA, hand and palm geometry, and iris recognition.

Human beings can identify features and recognize individuals with relative ease. Understanding the human mechanisms employed to recognize different individuals constitutes a challenge for researchers and is important because the same underlying mechanisms could be used to build a system for the automatic identification of individuals by machine. Due to advances in image processing methods, the automatic recognition of individuals based on their biometric characteristics has attracted the attention of many researchers.

Face recognition, which has both commercial and law enforcement applications, is emerging as an active research area. Implementation of this technology includes several disciplines, such as image acquisition, image processing, and pattern recognition. Applications include access control, video surveillance, airport screening, and smart cards.

1.1.1 Significance of Face Recognition

With the increased importance of security, identification and authentication methods have developed into a key technology in various areas. Requirements for reliable personal identification in computerized access control has resulted in an increased interest in biometrics.

Automatically identifying or verifying an individual by a physical characteristic or personal trait is preferred in biometric identification. An automatic system means the system should identify or verify a human characteristic or trait quickly with little or no intervention from the user.

Many biometric systems have been developed for automatic recognition. One system is the hand key, which uses the three-dimensional shape of a person's hand to distinguish people. This system takes approximately two seconds to capture the side and top views of a hand positioned in a controlled capture box, and certain measurements are used to generate a set of geometric features to build an efficient feature vector. This system has the capacity to store as many as twenty thousand different hands.

With its unique characteristics, finger print recognition is another well-known biometric measure. In iris recognition, like fingerprints, it has been observed that the iris of the eye displays patterns and textures unique to each human and remains stable. Speech recognition also offers one of the most natural and less obtrusive biometric measures, where a user is identified through his or her spoken words.

Although these biometrics deliver very reliable performance, the human face recognition method remains an attractive biometric because of its advantages. Face recognition when compared to other biometric technologies does not require test subject cooperation. For example, human intervention is required for iris or finger print recognition; that is, subjects must look into an eye scanner or place their finger on a finger print reader. The advantage of face recognition is that, the subject can be identified by simply passing him or her in front of a surveillance camera. In addition, low-cost hardware has fueled the research in face recognition.

1.2 Thesis Overview and Contribution

From a given still picture or video, facial images of individuals are extracted to identify one or more persons using a stored database of faces. The face recognition application covers both controlled and uncontrolled environments. An environment consisting of uniform background with frontal and profile photographs and identical poses among the participants is referred to as a controlled environment. General face recognition, a task that is done by humans in daily activities, is done in an uncontrolled environment, which may include background along with facial images and features that are not necessary for face recognition.In this thesis, these features are referred to as valid features.

Detection and extraction of a face from a still picture or video is done using a combination of OpenCV technology and Java code. Recognition of facial images is characterized by two important criteria:(1) feature detection and (2) feature validation. Previous work on feature detection includes the use of grey levels and the detection of edges and corners. Features, by definition, are perceptually interesting locations in the image. In facial image, the features could be eyes, nose, mouth, moles and scars. The identification of these features automatically will improve the recognition rate. The second criterion, that of feature validation, is equally important in facial recognition. This includes considering those feature points that are only in the region of interest, which is on the facial part but not at the edges (for example, hair and background). Feature vectors are formed from Gabor samples at the feature points. Feature validation removes unwanted feature points, thereby reducing the computing complexity.

In this work, the combination of feature extraction, feature validation, and score for symmetry calculation are used to determine how close the test image is with images in the facial database for facial recognition.

1.3 Thesis Outline

This thesis is divided into five chapters. Chapter 1 provides an introduction to facial recognition, feature extraction, and the validation mechanism. Chapter 2 summarizes the literature on both human and machine recognition of faces. Chapter 3 discusses the proposed algorithm based on the Gabor phase. Chapter 4 describes the simulation setup followed by obtained results. Finally, the conclusion and scope of future work is presented in Chapter 5.

Chapter 2

Literature Survey

Face recognition systems have been a popular research topic for many years. A general understanding of the human capacity for recognizing familiar faces should be a good starting point for such a system. Many trials have been made to model the capability of humans in recognizing individuals. For example, humans can easily identify people who belong to their own race and place, while they take some time to identify people from different ethnic groups and locations. Efforts have been made to model this capability by building up the average face from a facial database and performing a recognition.

Research using face variations was fueled by Bruce [3], whose work includes super imposing the low-spatial-frequency components of one picture over the high-frequency components of another picture. The resultant image resembles the second picture at closer distance and the first picture from a farther distance. This researches involved high data storage and processing, and further work was done to minimize the data through which the image was represented. Instead of representing and storing the whole face image, this face-recognition work was done by taking samples at fixed locations that were expected to have high facial content. Although the results from these methods were satisfactory, the statical assignment of feature points does not indicate the feature present on the face and result may differ from one person to another. Further work was aimed at identifying the high feature content in the human face automatically and extract those features and use them for face recognition.

2.1 Related Work

The techniques for recognizing individuals go back to the previous century where the French used measurements on face and length of fingers to recognize their prisoners.

Benson and Perrett [4]and Sir Francis Galton [5] initiated research into recognizing individuals. Many experiments and measurements have been made conducted, including the following primary measures of length and breadth of the head, and length of the foot. Galton proposed method focused on measuring the distance between the important facial features such as eye corners, mouth corners, nose tip, etc.

With the advancement in computers, the work by Blesoe [6] included a human operator to manually locate points on the face and enter their position on the computer. The nearest neighbor calculation was done to identify the person. Since this method includes the human, variations in head rotation, tilt, image quality, and contrast can be maintained.

Advancements in image processing contributed to this research includes detecting the fiducial points by edge detectors [7] and recognition by computing the Euclidean distance. Facial image data are always high dimensional and require considerable computing time for classification. The linear discriminate technique is thus important in extracting effective discriminative features and reducing dimensionality of an image. Two of the most well-known methods are Eigen face and Fisher face [8].

The Eigen faces method, proposed by Turk and Pentland [9], is based on Karhumen - Loeve expansion and is motivated by Sirovitch's [10] work for efficiently representing pictures of faces. This method uses the total scatter matrix as the production matrix. It cannot, however, make use of pattern-separable information like the Fisher criterion, and its recognition effect is not ideal when the size of the sample set is large [11].

The Eigen system has a problem with faces scaled larger or smaller than the original data set, and also the image background can have a sufficient effect on performance. The face recognition in real time is performed by suppressing the background by using a two-dimensional Gaussian function. This work is quite popular and was very seminal due to its ease of implementation in the field of face recognition. The capabilities of the Eigen face method was extended to three-dimensional object recognition by Murase and Nayar [12].

The facial image can be regarded as the gradual changing signal. Jing et al. [13] showed that Fourier analysis is an effective analysis tool for facial images. Lower-frequency bands contain most facial discriminating features, while high-frequency bands contain noise. Jing et al. [13] presented a Fourier- linear discrimination analysis (LDA) method, which combines the Fourier transform and a two-dimensional discrimination transform, their results showed that the LDA in the Fourier domain was significantly more robust to variations in lighting when compared to the LDA that was applied directly to the intensity images. This method achieved good results for face and palm print recognition.

A discriminant wavelet method for face recognition, proposed by Chein and Wu

[14], extracted linear discriminative features from a specific level of low-frequency sub-images of wavelet decomposition. The appearance-based algorithm suffered much from small facial variations, such as expression, illumination, and pose. Hence, face representation become a key issue for successful recognition systems. Gabor features and local binary patterns [15] were very successful in this area.

Gabor feature representation has achieved great success in face recognition even with its high dimensionality. High dimensionality is due to multi-scale and multi-oriented Gabor filters. Elastic bunch graph matching [16] extracts Gabor features from several local landmarks and then constructs a graph over the landmarks. Another technique, Gabor-Fisher Classifiers (GFC) [17], adopts the Fisher discriminate analysis (FDA) to reduce the dimensionality of raw Gabor features.

The work on biologically based face recognition includes the way in which face images are processed between the retina and primary visual cortex. This was modeled using the log-polar transformation and Gabor filtering [18].

2.2 Gabor Wavelets and their Significance

Dennis Gabor first proposed that a one-dimensional signal must necessarily be quantized so that no signal or filter could occupy less than a certain minimal area in a time-frequency domain. The Gaussian modulated complex exponentials, however, provided the best tradeoff between time resolution and frequency. The original functions are generated by varying the frequency of the modulating wave and with fixed Gaussian function.

Rediscovered two-dimensional Gabor filters, which are multi-scale and multi-orientation kernels, are now being used extensively in various computer vision applications. The Gabor features of an image is obtained by convolving image $I(\overrightarrow{x})$ where $\overrightarrow{x} = (x, y)$ with a set of Gabor filters [19]:

$$J_j(\overrightarrow{x}) = \int I(\overrightarrow{x}')\psi_j(\overrightarrow{x} - \overrightarrow{x}')d^2\overrightarrow{x}' \quad (2.2.1)$$

Keeping this in mind, Gabor filters [19] can be defined as

$$\psi_j = \frac{k_j^2}{\sigma^2} \exp\left(\frac{-k_j^2 x^2}{2\sigma^2}\right)(\exp(i\overline{k_j}\overline{x}) - \exp(\frac{-\sigma^2}{2})) \quad (2.2.2)$$

The shape of the plane waves with the wave vector, restricted by a Gaussian envelope function. A discrete set of five different frequencies and eight orientations are defined as

$$\overline{k_j} = (k_{jx}, k_{jy}) = (k_v \cos\phi_w, k_v \sin\phi_w) \quad (2.2.3)$$

Where

$$k_v = 2^{(\frac{(v+2)}{2})}\pi \quad (2.2.4)$$

$$\phi_w = w \times \frac{\pi}{8} \quad (2.2.5)$$

$$j = w + 8v \quad (2.2.5)$$

The set of five different frequencies and eight orientations is represented in Figure 2.1. Image processing using Gabor filters is chosen for its biological relevance and technical properties. The spatial receptive field structure of a simple cell in the primary visual cortex [16] is modeled by each member of this family of Gabor wavelets. When the image is convolved with multi-oriented and scaling Gabor filters,

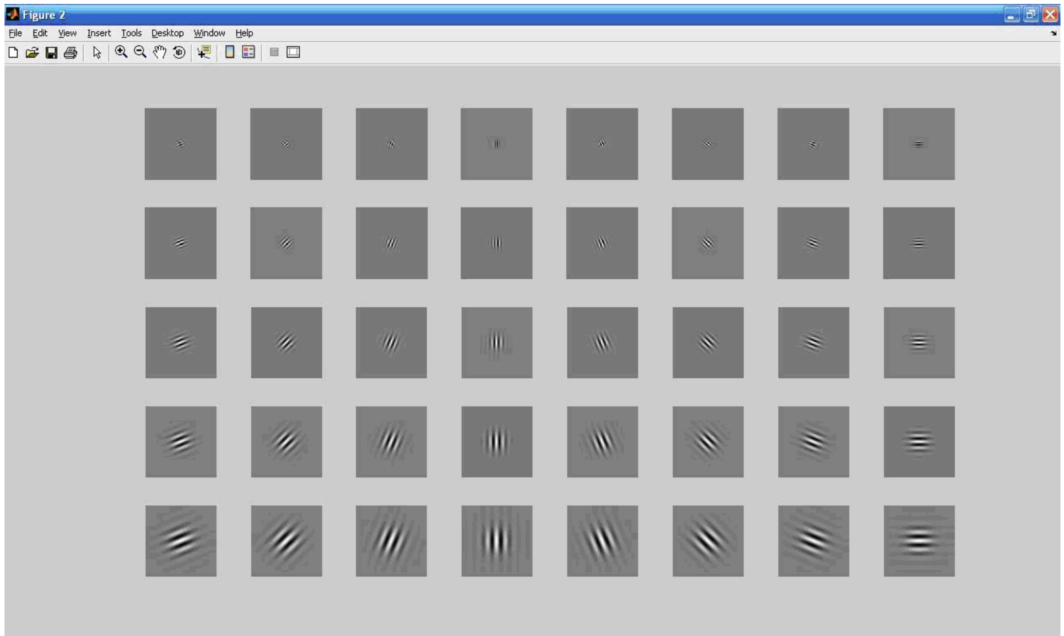

Figure 2.1: Ensemble of Gabor wavelets

they respond to short lines, line endings, and sharp changes in the curvature. This information corresponds to salient features in an image; hence, the convolution results in a low-level feature map of the intensity of image.

2.3 Gabor Filters in Medical Imaging

Medical image registration is a large field and is of considerable importance in detailed diagnosis. A new method by measuring similarity between feature regions in two images is built with a wavelet network based on Gabor functions. This method is capable of dealing with image registration in the presence of illumination changes. With better intensity pattern function approximation, this technique is best for registering images from endoscopy.

2.4 Gabor Filters in Image Registration

A small number of feature points is located in two images from the frame, and the rotation between the two frames is estimated, using an illuminant direction estimation method. By pairwise matching of the detected feature points, an initial estimate of translation and scaling is obtained. This method is most reliable than the correlation matching method.

This thesis presents the face recognition algorithm with a combination of Gabor filters for feature point selection and facial extraction for validation along with single-bit similarity matching.

Chapter 3

Proposed Model for Face Recognition

3.1 Introduction

The objective of this algorithm is to automatically identify the unique points of interest in the required region of the face. The points of interest, or feature points, are obtained by locating the maximum peaks from each of the Gabor filter responses. The feature points thus obtained are validated by estimating the facial region. Gabor phase samples at these validated feature points are analyzed, depending on whether the Gabor phase samples are positive or negative feature vectors when positive ones or negative ones are generated. These feature vectors with single-bit values are used to find similarity between the test image and the database images.

A block diagram representing the proposed method is shown in Figure 3.1. The system is equipped with a Gabor filter to decompose the facial image, so that both the magnitude and phase value matrices are calculated for each orientation and scale of the filter. Feature points are calculated by determining the peaks from each Gabor filter output. These peaks in the magnitude value of Gabor filter output constitute

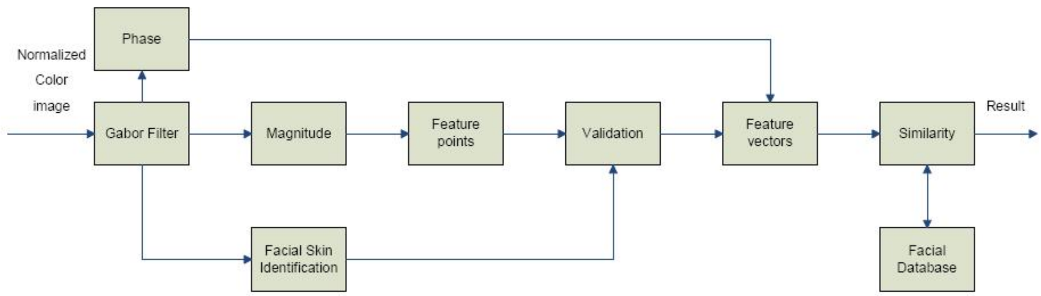

Figure 3.1: Block diagram of proposed model

the high energy information on the facial image. This also includes the features of the face, like hair, which are not required for facial recognition. General face recognition is done in the uncontrolled environment. The facial image thus obtained may contain some background information. This attracts the Gabor filter, resulting in feature points formed at this background and adding to the interested facial region. Thus, validation is required for the formed feature points. Feature points obtained from each filter are assembled into a feature point set. To validate the feature points from the feature point set, the skin portion in the facial image is identified by processing each pixel value of the facial image. Thus, the region of interest representing the facial part is obtained and is used to validate the feature points. Gabor phase samples are examined, depending whether they are positive or negative at each filter output, and the feature vector is formed with positive ones or negative ones along with the spatial coordinates at the validated feature points. The collection of feature vectors is referred to as a feature vector set.

The face recognition system has two phases: training and recognition. During the training phase, all images from the database are automatically loaded into the system, and their feature vector set is determined. When the test image arrives at the system, the feature vector set of the test image is compared with that of database images. Feature vectors are location-specific, and thereby similarities between feature vectors of the test image and database images are calculated, provided that both are from the same spatial coordinates. Once spatial coordinates are matched by an exclusive-OR (X-OR) operation, the similarity is calculated from the values of the feature vector.

3.2 Decomposition of Facial Image

Gabor wavelets are multi-scale and multi-orientation filters. The beauty of Gabor filters is that when an image is convolved with the Gabor filters with a specific orientation, the filter accentuates those features, which are in that orientation and smoothes the other features. This directional-filtering capability is used in face recognition to extract the features present on the face. With an orientation and scaling sensitivity, the Gabor decomposition can be considered as a directional microscope. In normal images, the short lines, line endings, and sharp changes respond to this decomposition. As a result, peculiar features like moles and scars respond to these filters on a facial image. Thus, effort is made to improve the dynamism in the system.

On passing the image to the Gabor filter, the real and imaginary values obtained are used to determine the magnitude and phase information. The magnitude and phase values, which are calculated for each Gabor filter, are used in the recognition. The average pixel value from the magnitude output is calculated and used as the threshold value to determine the feature points. The magnitude value of each Gabor filter is logically divided into small blocks. The maximum pixel value or peak value is obtained by scanning each block. If the maximum value from each block is greater than the threshold value, the location of the maxima is stored as a feature point.

Thus, this process is repeated for each Gabor filter. The set of such maxima's are named as feature points and stored as a feature point set. These points, by default, constitute the high-information content on the face, like eyes, nose, dimples, scars, and mouth. Since these features are dynamically extracted but not statically assigned, the number of features is not fixed to every image. Such features gained, represent the diverse facial characteristics. Thus, the determination of feature points can be mathematically represented [19] as

$$R_j(x_0, y_0) = Maximum(R_{jw}(x, y)) where R_{jw}(x, y) \in w \tag{3.2.0}$$

$$R_j(x_0, y_0) > \frac{1}{WH} \sum_{x=1}^{W} \sum_{y=1}^{H} R_j(x, y) \tag{3.2.0}$$

where W and H are the width and height of the Gabor image, and respectively R_j is the response of the face image to the j^{th} Gabor filter.Block size w must be chosen small enough to identify important features.

A feature set is formed for the face by repeating above process to each Gabor filtered image. The Gabor phase has more discriminative information than the magnitude information. The Gabor phase information is more efficient when compared to the phase of the fast Fourier transform for its multi-resolution and multi-orientation. This information is also successfully used in iris recognition systems. Work on Gabor phases [20] proves that phase information of the same person under different illuminations and at different backgrounds are almost the same. The Gabor phase is tolerant of illumination variations while maintaining the same discriminative ability. The change of a Gabor phase value from positive to negative, or vice versa, indicates a change in the image.

Assuming that the Gabor wavelet is GW, the Gabor phase is calculated from the obtained real value R(GW) and imaginary Im(GW) value by,

$$\Phi = \tan^{-1}\left(\frac{Im(GW)}{R(GW)}\right) \tag{3.2.0}$$

$$\begin{aligned} Gaborsample &= 1,\ if\ \Phi\ \geq\ 0 && (3.2.1)\\ &= 0,\ otherwise && (3.2.2)\end{aligned}$$

3.3 Identifying the Region of Interest

This step focuses on removing the information other than the facial part in a given image image that is not required for recognition, thus facilitating further processing and increasing the robustness. Feature points are validated by identifying the face in the given image. A validation matrix of size equal to that of the facial image is constructed indicating the facial part. This is achieved by processing the image independent of identification of features simultaneously so that image is not distorted and produce false results. The facial part is calculated by the following: (1) blurring the image, (2) calculating the log likelihood of each pixel and then the threshold the result to decide skin or non-skin, and (3) constructing the validating matrix by taking pixels representing the facial part as ones and rest of them as zeros. Eliminating the non-facial pixels also eliminates the eyes and lips, which are important for face recognition. Therefore filling the gaps is an important task, which is achieved by scanning the validation matrix horizontally and vertically, identifying the borders of the face, and replacing the zero-value pixel within the facial borders to a non-zero value of one.

The feature matrix formed by the ensemble values from the Gabor filter magnitude response is thus overlapped with the validation matrix to obtain the valid feature points or points of interest on the face; other points from the feature matrix are eliminated by rounding them to zero. Thus, this step reduced to a greater number of feature vector formations. Figure 3.2 [1] shows the steps in feature point validation.

3.4 Formation of Feature Vector

From the coordinates of valid feature points, the computed Gabor phase samples are extracted, and a feature vector is constructed at the corresponding feature points. The coordinates of the feature point are also included in the feature vector. The coordinates included will be used at the time of similarity calculation. The size of the feature vector is directly proportional to the number of Gabor filters.

3.5 Similarity Calculation

The similarity calculation is done with the nearest-neighbor classifier. In this method, the test image is compared sequentially with each image in the database. Initially the feature vectors for the test image are calculated, and then they are compared with the stored feature vectors in the database. Similarity between the test image and the database images is calculated in following steps:

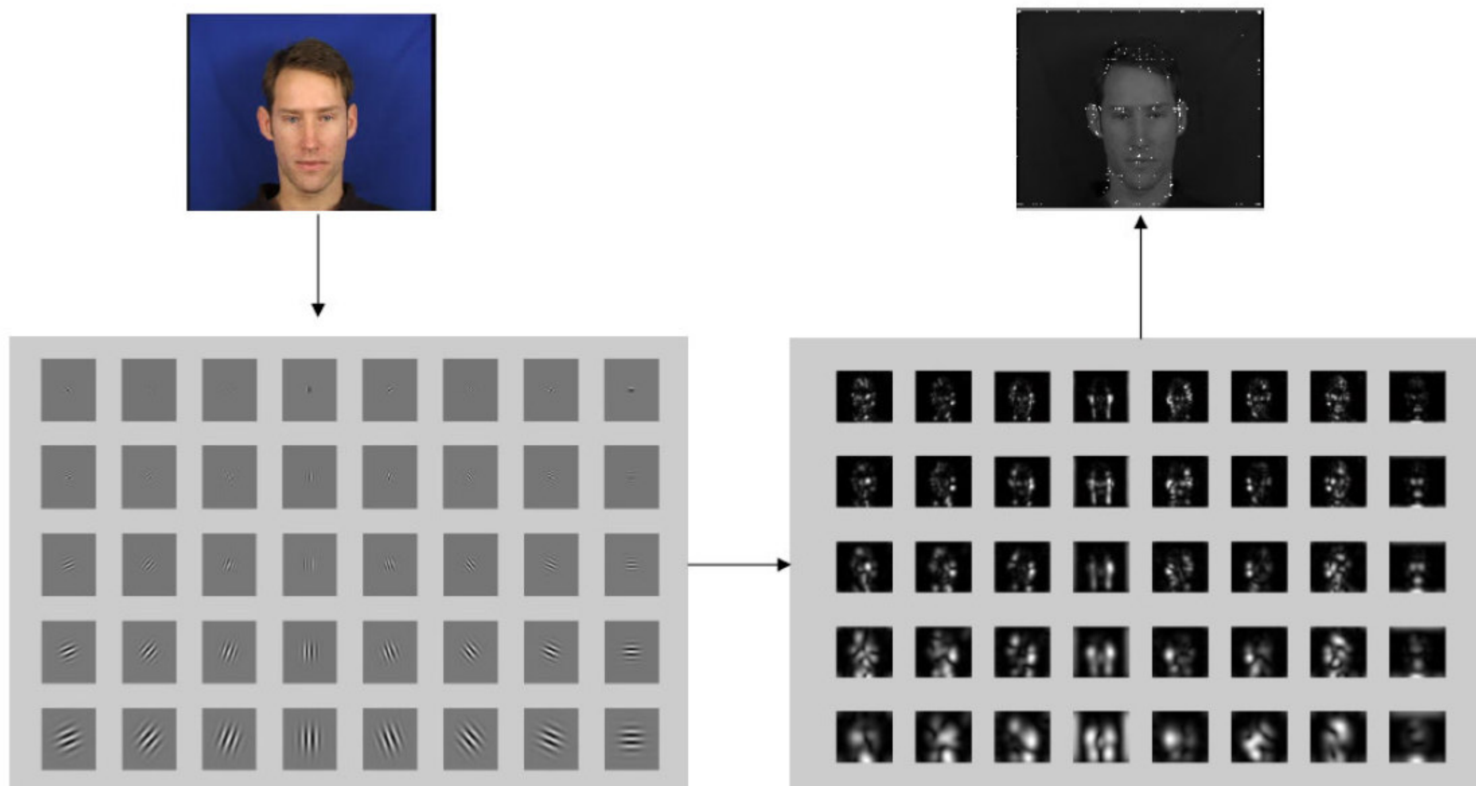

Figure 3.2: Obtaining feature points from Gabor filter, facial image is from M2VTS [1] database

3.5.1 Feature Matching

The feature vector is the collection of Gabor samples at the corresponding feature point. Since Gabor samples are location-specific, it is important to match the coordinates of the feature point before matching the Gabor samples. In this stage, the geometrical locations of the feature points on the test subject and the corresponding image in the database are compared. After the comparisons, the feature points that are common to both images are determined as the matched feature points.

3.5.2 Feature Vector Comparison

Then the sign changes in the Gabor samples are matched, which is a single-bit comparison. All positive Gabor phase samples are taken as positive one, and all the negative phase samples are taken as negative one. The feature vector consists of either one or zero. Each feature vector of the test image is compared with the feature vectors stored in the database. The similarity is calculated by the X-OR operation on the corresponding bits from the feature vectors. The identical bits as an input to the X-OR result in zero as output, and different inputs result in one as output. In other words, success in the comparison results in zero output whereas one is the result of failure. The resultant row matrix of the X-OR operation is the collection of these zeros and ones. The sum of all elements of this matrix is calculated. The sum indicates the total value of dissimilarities between the feature vectors of the test image and the database image. The process is repeated sequentially for all matched feature vectors.

3.5.3 Score Calculation

The term score is introduced to match the maximum number of matched feature vectors and the sum of dissimilarities among the feature vectors. Both these values are important for symmetry calculation. The sum of total dissimilarity of the image with the corresponding image of the database is called the score. The score value should be minimal for a successful match. For example, considering the twenty-four Gabor filters and that the test image has eleven features to be matched with the database images, when the test image arrives at the comparator for symmetry calculation with the image in the database, it has three possibilities.

Completely Matched Condition

This condition arises when the test image exactly matches the image in the database. That is, both the coordinates and content of feature vectors are matched. In other words, if all the eleven features are matched, then the score value is zero. Thus a zero value signifies a exact match.

Partially Matched Condition

This condition arises if only some of the feature points are matched. Assuming that only six feature points are matched and the similarity is calculated between only six feature vectors, then these feature vectors are compared, the maximum sum of dissimilarity and similarity are given by zero and twenty four for each feature vector. Assume that the resultant sum of dissimilarities between these six feature vectors is 'S'. The other five feature points of the test image are considered to be dissimilar to the images in the database. Since we are considering the twenty-four filters, the total dissimilarity results in a sum of twenty-four per each dissimilar feature vector, and a total of 120 for five feature vectors. Thus, the score for this partially matched condition is defined as the sum of the dissimilarities of the matched six-feature vectors and the unmatched five-feature vectors:

$$\text{Score} = \text{S} + (\text{unmatched feature vector dissimilarity})$$

The score value gives the relation between the maximum number of feature vectors matched with Gabor samples.

Completely Unmatched Condition

This condition arises if none of the feature points are matched, and thus the maximum score for all feature vectors are considered. In this example, the value of 264 as the score value, is considered.

Once the test image arrives at the system and the steps are followed, the algorithm should display the possible matches of test image from the facial database. The database image having the least score is a close match with the test image. The database images with ascending scores should be displayed as a result.

Chapter 4

Simulation Results and Analysis

4.1 Introduction

The performance of system can be evaluated by a set of metrics that includes the number of matched feature points and least score among the matching points. This represents the similarity of the test image to the image in the database.

The proposed method was tested on color facial databases with variations in facial expressions. The facial databases used in this thesis were from the AR Facial database [2]. This database comes with images with occlusions and changes in facial expression. The availability of this database provides an opportunity to check the performance of the algorithm using a standardized data set and test procedure.

4.2 Simulation Logic

The simulation was done in Matlab. In the main program, the input image was passed through the Gabor filter and skin detector. In the Gabor filtering process, the image was passed through twenty-four filters, and the resultant output of both real and imaginary values of the image was saved in the three-dimensional matrix.

An magnitude value was calculated for each filter output, and processed to obtain the peaks, or point of interest or feature point. This processing included dividing the image into blocks and identifying the maximum peaks from each block. Thus, the obtained feature points from all the Gabor filters were saved as a two-dimensional matrix for a particular image.

In the skin detector [21] process, the output was expected to be a two-dimensional matrix, with all ones in the facial region and all zeros in the non-facial region. The facial region is referred to as the region of interest. Any irregularities in the output were processed before the Gabor feature set is validated. Irregularities were due to the presence of zeros in the region of interest.

The two-dimensional matrix obtained from the skin detector [21] process was overlapped with the two-dimensional feature set matrix, rounding the non-facial features to zero. The coordinates of each feature point from the feature set were obtained, and corresponding sign of the Gabor phase sample from each filter output was loaded. Thus the collection representing the sign of the Gabor samples along with the location information was stored as a one-dimensional matrix called the feature vector.

The feature vectors at all the feature points were calculated, and the complete feature vector set was passed back to the main program. This feature vector set is a two-dimensional matrix including all the feature vectors of the image processed.

In the training phase, all the database images were processed automatically by scanning the database folder for images. The two-dimensional feature vector set that was obtained for each database image was stored in the three-dimensional matrix. The size of the matrix depends upon the number of the Gabor filters used, number of feature points obtained, and number of images in the database.

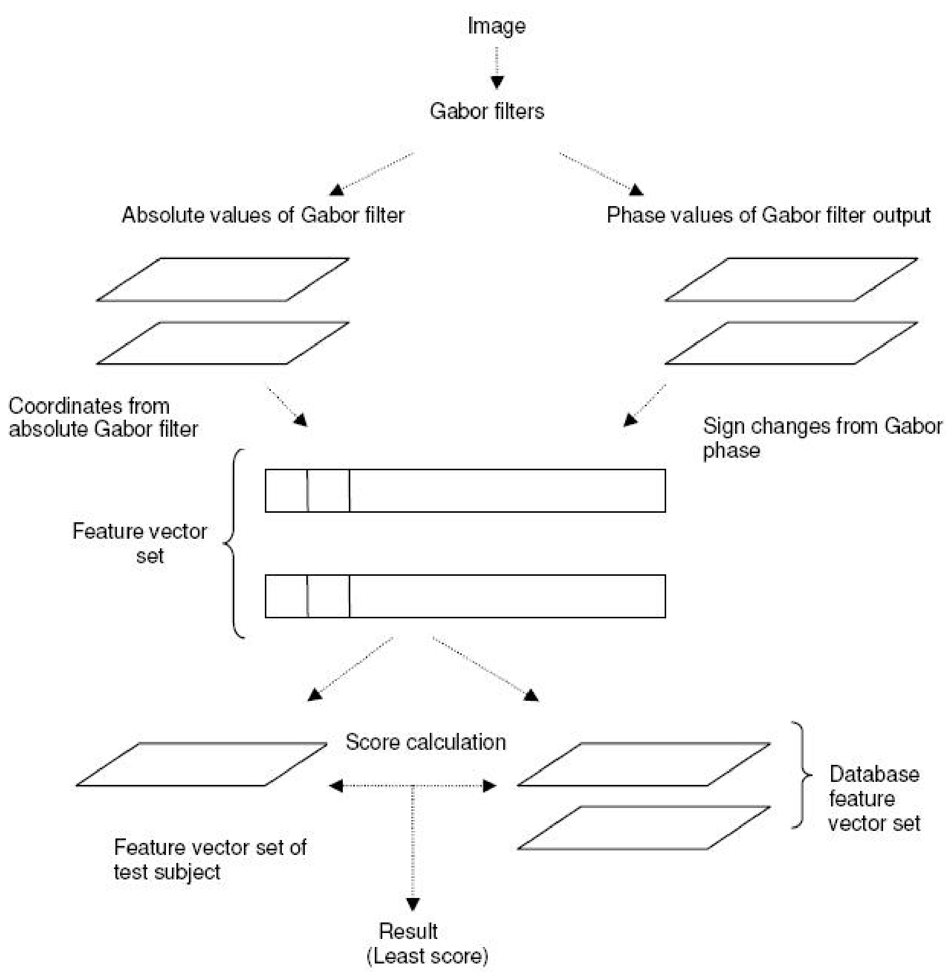

Figure 4.1: Simulation logic

In recognition phase, the two-dimensional feature vector set was calculated for the test subject and compared with each stored feature vector set of the database image. The score value of test subject with respect to each image was sequentially stored in an array.

The resultant matrix is the collection of all database image indices and corresponding score values. The score values were sorted in ascending order, and the top six file names, depending on the indices of the resultant sorted matrix, were displayed.

4.3 Performance in Facial Extraction

The peaks thus obtained from Gabor filters are spread throughout the image. Feature points are also formed at redundant locations, which are not useful for recognition. These features are ignored by developing the region of interest around the facial area. As observed, the redundant feature points were reduced by validating with the region of interest. Figure 4.2 [1] describes the reduction in the feature points with the increase of Gabor filter dimensionality.

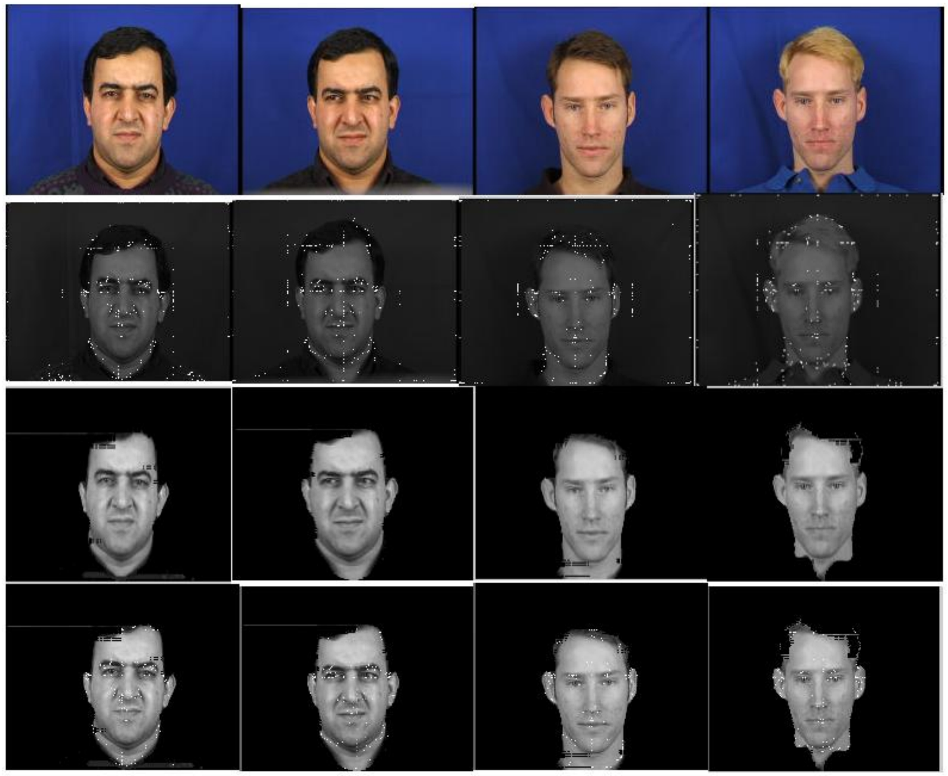

Figure 4.2: Steps in validating the feature points using facial images from M2VTS [1] database

4.4 Feature Vector Formation

The Gabor filter is provided in equation (2.2.2). A reduced facial image of size 60 $\times$ 83 pixels as shown in Figure 4.3(a), was convolved with the real and imaginary values of the filter. Magnitude and phase components were computed according to equation (3.2.0), and the values were stored in a three-dimensional matrix of size equal to $60 \times 83 \times 24$ (size of picture $\times$ number of Gabor filters). For each Gabor filter output, the average value of pixels was computed. Those pixel values greater

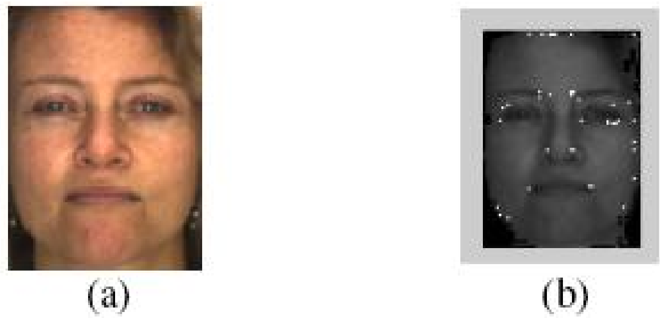

Figure 4.3: Facial image from AR [2] database(a)original facial image (b) image with formed feature points

than the average value represent the high-energy content in the face. It was observed that optimum recognition was achieved by setting the threshold value equal to twice the average value. Twenty-four Gabor filters were considered, and each filter output obtained was logically divided into smaller blocks of size 8×10. Feature points were obtained by comparing the Gabor filter output with the threshold. The coordinates of each feature point were stored in a two-dimensional matrix, using which feature vector is generated. For example, in Figure 4.3(b), the feature points are located at (24, 22), (24, 34), (24, 35),...... etc.

For each feature point, the corresponding phase component was examined. When the phase was positive, it was represented with a value of 1. If the phase was negative it was represented with -1.

The phase samples at the coordinates (24, 22) from each filter are as follows:

[-2.4314, -0.4439, -2.2038, -2.5463, -2.6845, -2.2495, 3.1285, 2.6929, 0.8060, 0.4077, 0.0457, -0.9915, -0.6601, -0.6931, -1.6268, -2.6645, 0.4389, 0.3711, 0.2657, 0.1189, -0.0462, -0.2227, -0.3886, -0.4672].

The feature vector formed with the feature coordinates along with the phases corresponding to the filter. For example at the coordinate (24, 22), the feature vector is given by

[24, 22, -1, -1, -1, -1, -1, -1, 1, 1, 1, 1, 1, -1, -1, -1, -1, -1, 1, 1, 1, 1, -1, -1, -1, -1].

The complete feature vector set for Figure 4.3(b) is given by

[2,18,-1,-1,-1,-1,-1,-1,1,1,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,1,1,1,1,1]

[2,23,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[2,26,-1,1,-1,-1,-1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[2,27,-1,1,-1,-1,-1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[2,28,-1,-1,-1,-1,-1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[2,34,-1,1,-1,-1,-1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[2,58,1,1,1,-1,-1,1,-1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]

[24,22,-1,-1,-1,-1,-1,-1,1,1,1,1,1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1, -1]

[24,34,-1,1,-1,-1,-1,1,1,1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1]

[24,35,-1,1,-1,-1,-1,1,1,1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1]

[25,26,-1,1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1]

[25,34,-1,1,-1,-1,-1,1,1,1,1,1,1,1,1,1,-1,1,1,1,1,1,1,1,-1,-1]

[26,22,-1,1,-1,-1,-1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1,1,1,-1,-1,-1]

[27,37,-1,-1,-1,-1,-1,1,1,1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1]

[28,56,-1,1,-1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,-1]

[29,10,1,1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,1,1,1,1,1,-1,-1,-1]

[29,50,-1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1]

[30,8,-1,1,-1,-1,-1,1,1,1,1,1,1,1,1,-1,-1,-1,1,1,1,1,1,-1,-1,-1]

[35,7,-1,-1,-1,-1,-1,-1,1,1,-1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1]

[35,38,-1,-1,-1,-1,-1,1,1,1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,-1]

[35,48,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,1,1,1,1,-1,-1,1,1,1,1,1,1]

[35,52,-1,1,-1,-1,-1,1,1,1,-1,1,1,-1,-1,1,1,1,-1,1,1,1,1,1,1,1]

[35,58,-1,1,1,-1,1,1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,-1]

[36,48,-1,-1,-1,-1,-1,1,1,1,-1,-1,1,-1,1,1,1,1,-1,1,1,1,1,1,1,1]

[36,50,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,1,1,1,1,-1,1,1,1,1,1,1,1]

[36,51,-1,1,-1,-1,-1,1,1,1,-1,1,1,-1,1,1,1,1,-1,1,1,1,1,1,1,1]

[43,58,-1,1,1,-1,1,1,-1,1,1,1,1,1,1,1,1,-1,1,1,1,1,1,1,1,-1]

[46,25,-1,1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1]

[46,34,-1,-1,-1,-1,-1,-1,1,1,1,1,1,1,1,-1,-1,-1,1,1,1,1,1,-1,-1,-1]

[46,35,-1,-1,-1,-1,-1,1,1,1,1,1,-1,-1,1,1,-1,-1,1,1,1,1,1,-1,-1,-1]

[46,58,-1,1,1,-1,1,1,-1,1,1,1,1,1,1,1,1,-1,1,1,1,1,1,1,1,-1]

[57,58,-1,1,1,1,1,1,-1,1,1,1,1,1,1,1,1,-1,1,1,1,1,1,1,1,-1]

[60,41,-1,-1,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1]

[60,42,-1,-1,-1,-1,-1,-1,-1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1]

[61,18,-1,1,-1,-1,-1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,-1,-1]

[68,6,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,-1,-1,-1,-1,-1,-1]

[68,54,-1,1,1,-1,1,-1,-1,1,1,1,1,1,1,1,-1,-1,1,1,1,1,1,1,-1,-1]

[72,10,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1,-1,1,1,1,1,-1,-1,-1,-1,-1]

4.5 Simulation

Two sets of simulations were done on the AR facial database [2]. Images in this database feature frontal view faces with different facial expressions, and pictures were taken under strictly controlled conditions.

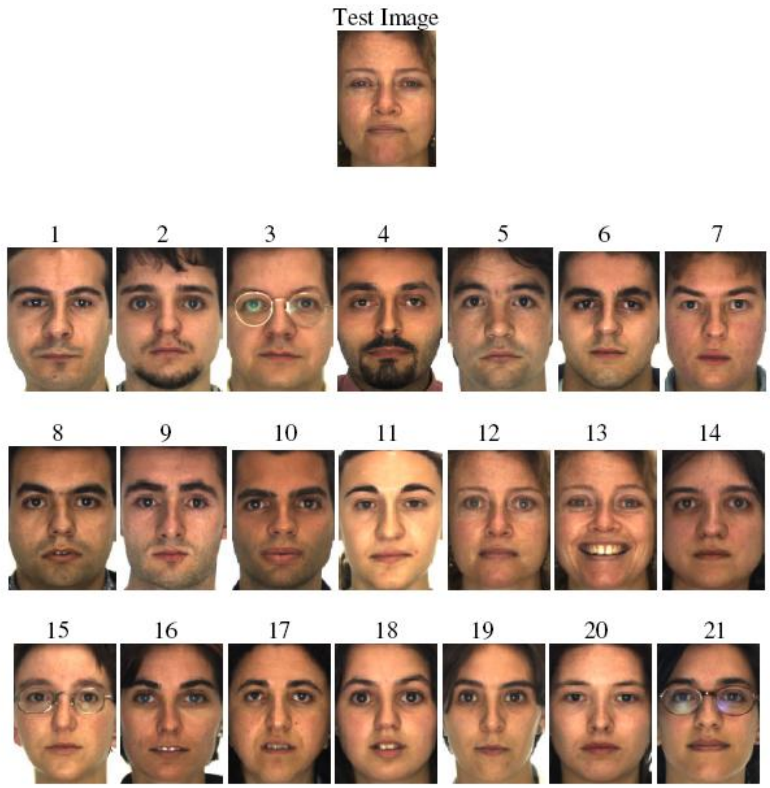

Figure 4.4: Facial images from the AR database [2]

4.5.1 Simulation I

The first simulation included fewer images in the AR facial database [2] in order to easily represent the entire tabular column of scores in this report. This image database includes facial images of different men and women, as shown in Figure 4.4. The test subject had different facial expression from the images in the database.

Table 4.1: Table of Matched Features and Score

Image No	No. Matched Features	Sum	Score
12	16	109	637
13	12	54	678
1	9	64	760
17	7	19	763
20	7	27	771
6	6	15	783
7	5	12	804
3	5	22	814
14	5	22	814
11	4	8	824
19	4	9	825
18	4	14	830
15	4	21	837
10	4	24	840
16	4	28	844
9	3	15	855
8	3	16	856
5	3	18	858
21	3	24	864
2	2	9	873
4	1	7	895

It is observed that top two images extracted from the database are facial images of the same person with different expressions, as shown in table 4.1.

4.5.2 Simulation II

The second simulation included fifty male and female facial images with six facial expressions. Since the database includes six facial expressions for each person, the top six results of the sorted matrix output were considered. The simulation was repeated for a different number of Gabor filter outputs and different database sizes. It was observed that for a smaller database size, all six images related to the test image showed up in the top six results of the sorted matrix. As the database size increased, four images related to the test subject were in the top six of the sorted matrix. This result was continuous for different Gabor filters and for different database sizes.

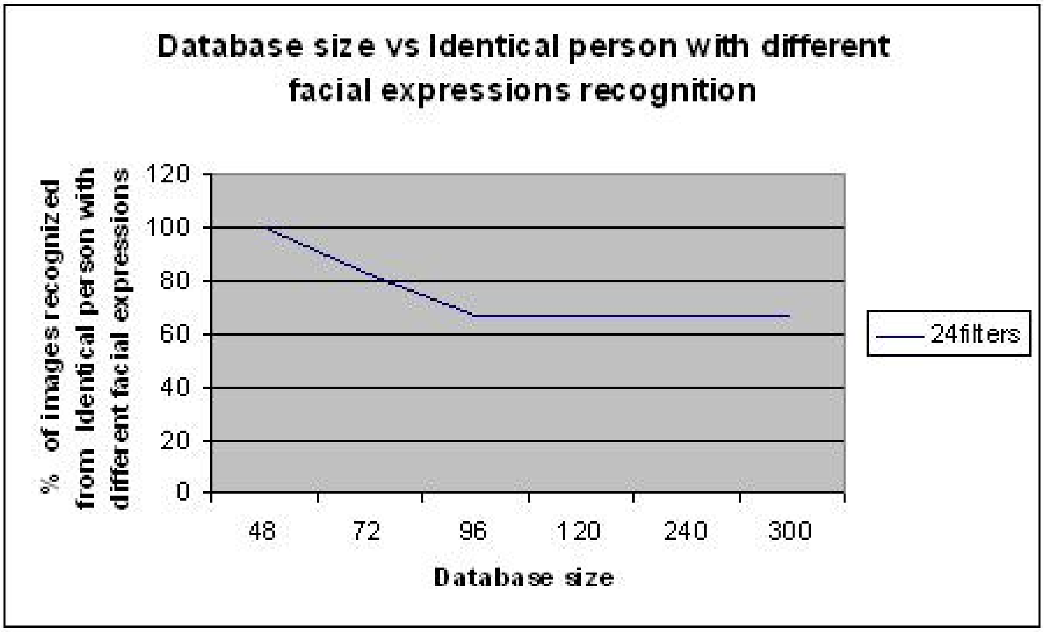

Figure 4.5: Variation in recognition with change in database

First, these simulations were done on the individual women and men databases. The graph in Figure 4.5 represents the outputs for different Gabor filters with a different set of databases individually of men and women. Then the simulations were done by combining both the men and women databases. Results were the same and it was observed that face recognition is highly dependent on the number of feature points. When face was effectively represented by feature points, the recognition rate remained the same, even if the database size is increased.

Chapter 5

Conclusion and Future Work

5.1 Conclusion

The face recognition algorithm based on the Gabor phase and automatic face extraction was proposed. This system is equipped with automatic feature point detection by using Gabor magnitude responses. The feature points were obtained by dividing the entire Gabor magnitude responses logically into smaller blocks. The average pixel value for each magnitude response was computed, and twice the average was considered as the threshold value. If the maximum or peak value of the pixel was greater than the threshold value, it was considered as feature point. The skin portions of an image were calculated, and the feature points belonging to the skin region were only considered. Lastly, the similarities of test image with database images were calculated using the X-OR operation. The score value is the sum of the results from the X-OR operation and sum of the unmatched feature vectors. The minimum score value gives the closest match. The simulations were done by using different database sizes. The results obtained are identical, and it is observed that face recognition using this technique is highly dependent on the number of feature points. When the face is effectively represented by feature points the recognition rate remains the same, even if the database size is increased.

5.2 Future Work

This work assumes that both the test image and database image are identically oriented. In the future, the algorithm could be modified to identify the change in orientation between the test and database images, and recognition could be performed by changing the test image orientation according to the database image.

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