CHAPTER 6
IMPLEMENTATION OF GA BASED FACIAL EXPRESSIONAL BSS

6.1 PREAMBLE

Facial expressions recognition system implementation for genetic algorithm based this chapter. This section gives the organization of the chapter. Section 6.2 discusses the geometric face model. This section also discusses the smoothing and thresholding, tracing head and face boundaries, locate facial features and face boundary repairing. Facial features based on geometric face model in discuss Section 6.3. This section also focus feature vector points of the spatio-temporal model and geometric face model based on Gabor filter. In section 6.4 facial geometric evaluation of the expression and section 6.5 mapping of facial geometry to its expression with genetic algorithm presented.

6.2 GEOMETRIC FACE MODEL

Facial geometric feature extraction of human face includes two threshold, they are: high-threshold image for tracing head boundary and low-threshold image for scanning face boundary. The facial geometric experimentation applied x- and y-projections to extract facial features such as eyes, nose and mouth. With low contrast of chin some face images cannot detect its boundary completely. A geometric face model then has been applied to locate facial features whereas Elliptic models to trace face boundary. The
Gabor filter algorithm has been adopted to locate the positions of two eyes. To be refer the Figure 6.1 the scheme of two threshold method of facial features.

![The Scheme of Two Threshold Method of Facial Feature](image)

**Figure 6.1 The Scheme of Two Threshold Method of Facial Feature**

Experimental results show that this proposed method is as good as other methods. Thresholding is performed to transform the gray-level edge images into binary. The high threshold value is determined by choosing all the high intensity pixels that occupy 5% of the entire pixels. The low threshold value is decided by choosing all the high intensity pixels that occupy 25% of the entire pixels. The high thresholded image is used to obtain
the head boundary and the low thresholded image is used to produce the face boundary. These thresholding percentages are determined based on the empirical data in order to achieve better results.

The thresholding edge image is used to trace head boundary, face boundary and facial features including eyes with eyebrows, nostrils and mouth. Head boundary is the outer profile of head including shoulders. Face boundary is the face contour that excludes hair and shoulders. Face boundary use rectangular boxes to location of the face as shown in Figure 6.2.

![Figure 6.2 Rectangular Boxes to Location of the Face Boundary](image)

6.2.1 Smoothing and Thresholding

In this scheme of two threshold method of facial feature, the first step is to reduce noise by using a $3 \times 3$ median filter and identify the edge detected is applied. The edge output appears too thin and the top-face boundary is too weak to be detected in the later thresholding procedure. Image edges and select the maximum as the edge strength and using the large sizes for edge detection (Shin and Chuang 2004).
6.2.2 Tracing Head and Face Boundaries

In order to trace the head boundary, divide the high-thresholded image into left and right halves. The scan of the edge image from top to bottom, the first layer of the contour occurred is the head boundary and the second layer of the contour occurred is the face boundary. For tracing the head boundary, a starting point is located as the first white pixel on the first layer of the left half. From the starting point, trace the left and right profiles of head. Because the outer border of the first layer is shifted outwards from the actual boundary for a few pixels p, to be adjust the edge of the left half to the right and the edge of the right half to the left by p pixels respectively. Because some face profiles disappear in the high thresholded image, the low thresholded image is used to trace face boundary. The head borders are removed and a morphological opening is used to eliminate unnecessary noises. After that, the image is scanned from four directions (right to left, left to right, top to bottom and bottom to top) to produce the face boundary.

6.2.3 Locate Facial Features

In order to identify facial features, first extract their images. The images are extracted by overlaying the face boundary on the binary edge image and converting all the white pixels in the binary edge image that are on or outside the face boundary to black. After that, apply x- and y-projections to locate facial features. In the candidate image, use x-projection to obtain the facial features’ horizontal locations and y-projection to obtain their vertical locations. By combining the horizontal and vertical locations, can be obtain four rectangular boxes: two for eyes, one for nostrils and one for mouth.
6.2.4 Face Boundary Repairing

Sometimes, the chin edge is too low-contrasted to be completely detected by edge detection, use of two approaches to repair the chin line of face boundary. In the first approach, utilize the center point of chin (that is, the average point of the available chin edge pixels) as the initial point in the grayscale image to trace the chin line.

(1) **From the center point of the chin to its right:** Let the gray level of the center point of the chin be $f(x, y)$. Choose the $\text{Max} \{f(x+1, y+1), f(x+1, y), f(x+1, y-1)\}$ to be the next connected point and repeat the procedure until it reaches the right part of the face boundary. As an example, Figure 6.3(a) shows an image of facial features candidates, Figure 6.3(b) shows the unrepaired face boundary and Figure 6.3(c) shows the repaired face boundary.

(2) **From the center point of the chin to its left:** Choose the $\text{Max} \{f(x-1, y+1), f(x-1, y), f(x-1, y+1)\}$ to be the next connected point and repeat the procedure until it reaches the left part of the face boundary.

![Figure 6.3](image_url)  
(a) An image of facial features candidates, (b) the unrepaired face boundary, (c) shows the repaired face boundary
6.3 FACIAL FEATURES BASED ON GEOMETRIC FACE MODEL

The geometric facial features of the five steps of the procedure. The first one is get the images of the input to be the camera, the second input images applying the Sobel operation process. Third one is converting the thresholding of the operations and fourth is positions of the images to be head or face. Finally the applying geometric face model, these procedures of geometric face features as shown in Figure 6.4.

![Figure 6.4 The procedural of geometric face features](image)

6.3.1 Feature Vector Points of the Spatio-Temporal Model

Facial feature point tracking is followed by a spatio-temporal representation of the face, which is based on geometric relationships using Euclidean distance between feature points, as illustrated in Figure 6.5. Each
geometric parameter is used to create a set of 15 Spatio-temporal features for each image. The components of the feature vectors are created by taking the difference between the geometric coefficients for each frame and the geometric coefficients of the first frame. Such dynamic characteristics provide shape independence; the work presented herein focuses on dynamic characteristics of expressions. For scale normalisation, all the components of the vectors are further divided by the corresponding coefficients from the first frame. Using the spatially localised geometric facial model shown in Figure 6.5 for the representation of expressions, allows robust handling of partial occlusion. Whenever one or several face regions such as the mouth or an eye become occluded (for example, by a hand), some geometric parameters are lost but the model is not compromised entirely (Shih et al. 2004).

**Figure 6.5** Geometric facial model used to produce 15 spatio-temporal feature vectors
Matlab based implemented of Gabor filters with modified facial geometric feature method was deployed. The execution time is 5 to 6 seconds for the geometric face model to process the images of sample face database. The geometric extraction system successfully detected the eye and mouth regions using the extracted ravines, obtained by the proposed algorithm. Experimental results show that this algorithm can perform the extraction of human head, face and facial features successfully and demonstrate better results in head boundary tracing and facial feature detection.

6.3.2 Geometrical face Model based on Gabor Filter

The facial features candidates are too points, they are x- and y-projections. Under the location of geometric face model to locate facial features. The model utilizes the designing objects are eyes, nostrils and mouth. Assume that in most of faces, the vertical distances between eyes and nose and between eyes and mouth are proportional to the horizontal distance between the two centers of eyes. Referring to the Figure 6.6 let the distance between the two centers of eyes to be D. The facial model of geometric feature distance of two subjects is:

1. The vertical distance between two-eyes and the center of mouth is D.
2. The vertical distance between two-eyes and the center of the nostrils is 0.5D.
3. The width of the mouth is D.
4. The width of nose is 0.6D.
5. The vertical distance between eyes and eyebrows is 0.3D.
In facial feature extraction, a Gabor filter, named after Dennis Gabor, is a linear filter used for edge detection. Frequency and orientation representations of Gabor filter are similar to those of human visual system, and it has been found to be particularly appropriate for texture representation and discrimination. In the spatial domain, a 2D Gabor filter is a Gaussian kernel function modulated by a sinusoidal plane wave. The Gabor filters are self-similar, all filters can be generated from one mother wavelet by dilation and rotation.

Its impulse response is defined by a harmonic function multiplied by a Gaussian function. Because of the multiplication-convolution property (Convolution theorem), the Fourier transform of a Gabor filter’s impulse response is the convolution of the Fourier transform of the harmonic function and the Fourier transform of the Gaussian function.
where $x' = x \cos \theta + y \sin \theta$ and $y' = -x \sin \theta + y \cos \theta$

In this equation, $\lambda$ represents the wavelength of the cosine factor, $\theta$ represents the orientation of the normal to the parallel stripes of a Gabor function, $\psi$ is the phase offset, $\sigma$ is the sigma of the Gaussian envelope and $\gamma$ is the spatial aspect ratio, and specifies the ellipticity of the support of the Gabor function. A set of Gabor filters with different frequencies and orientations helpful for extracting useful geometric features from the facial image.

Gabor filters are directly related to Gabor wavelets, since they can be designed for a number of dilations and rotations. However, in general, expansion is not applied for Gabor wavelets, since this requires computation of bi-orthogonal wavelets, which may be very time-consuming. Therefore, usually, a filter bank consisting of Gabor filters with various scales and rotations is created. The filters are convolved with the signal, resulting in a so-called Gabor space. This process is closely related to processes in the primary visual cortex.

The Gabor space is very much useful in image processing applications of facial expressional recognition. Relations between activations for a specific spatial location are very distinctive between objects in an image. Furthermore, important activations can be extracted from the Gabor space in order to create a sparse object representation.
For particularly difficult cases such as poor lighting and shadows, to be locate of two eyes using Gabor filter and then apply the elliptic model to extract face boundary. The procedure of locating facial features by the geometric face model is illustrated in Figure 6.7. The three steps to locating two eyes are:

1. Apply Gabor filter to the original image.
2. Apply Gaussian weighting to the filtered image.
3. Locate peaks in the image and find the locations of eyes.

Figure 6.7 Locate of Two Eyes using Gabor Filter

Expressional invariants of face using facial action units (behavioural patterns) initially taking 30 facial action units, 20 units known for its anatomic basis and 10 units focused on emotion, the next mode handles the single action units. The number of units combines to get collective behavioural patterns. Combinatorial action units modify the appearance of ones with which they co-occur. Recognition of action unit combinations makes human-like perceptual judgments, even if it is modified by their occurrence in novel patterns. Separate rigid (head motion) from non-rigid (expression) motion in spontaneous facial behaviour, head tracker events is generated. The tracker precisely estimates 6 degrees of freedom of head
motion movement in the horizontal and vertical planes that is translation, movement toward and away from the camera (that is, scaling and rotation). Face image is stabilized, by warping each frame to a common orientation and size.

6.4 FACIAL GEOMETRIC EVALUATION OF BEHAVIOURAL EXPRESSION

The physiological geometric face consists of necessary components that denote a high-level description of a face and its contents. The focus is on the use of left and right eyes and mouth in 2D although generic physical components contain Eyes, Eyebrow, Mouth, Nose, Hair and Face boundary / outline. The reason to extract these three aspects is that their extraction or detection has now become well developed so these components play a reliable and stable role in the recognition stage.

Assume that edges / boundaries of these three geometric components have been obtained. The absolute and relative positions of the three geometric components are so important that they need to be calculated and stored in this application. In addition, in order to enhance the face recognition the region outlined by the weight centers of these three organs needs to be evaluated regarding its intensity and color histogram. This histogram (with the calculated mean and variance values) especially helps reduce misclassification rates in the case of facial rotation.

The face boundary variation of neutral to happiness is shown in Figure 6.8(a) specified by regions R1 and R2. The R1 region shows the cheeks with moderate changes and eyebrows are relaxed. The R2 region shows that the mouth is open and mouth corners pulled back toward ears. In general happiness expressions change to the geometric features of the eyes sparkle, skin under eyes wrinkled, mouth drawn back at corners.
Figure 6.8(a) Facial Geometric Feature Extraction in Happiness Expression

The face boundary variation of neutral to sadness is shown in Figure 6.8(b) specified by regions R1 and R2. The R1 region indicates inner eyebrows which bent upward and eyes are relaxed. R2 region depicts the nose elongation and R3 region shows upward movement of upper lip. In general sadness expression changed the geometric features of mouth with depressed corners, and raised inner eyebrows corners (low spirits).

Figure 6.8(b) Facial Geometric Feature Extraction in Sadness Expression

The face boundary variance related to fear expression is depicted in Figure 6.8(c). In the R1 region eyebrows are raised and pulled together. The inner eyebrows are bent upward. In R2 region eyes are tense and alert for neutral and fear expressions respectively and the cheeks are elaborate to both sides. R3 region indicates mouth is open and upper and lower lip is expanded.
The fear expression had variation of geometric features in most parts of the faces that is eyes, mouth, lips and eyebrows.

Figure 6.8(c) Facial Geometric Feature Extraction in Fear Expression

Anger expression variance to neutral faces is depicted in Figure 6.8(d) with regions R1 and R2. The R1 region shows that inner eyebrows are pulled downward and eyes are wide open. In case of R2 region nose part is slightly changed and in R3 region lips are pressed against each other with exposed teeth. As a whole anger expression cause changes in the facial parts such as raised nostrils, compressed mouth, furrowed brow, wide open eyes and erect head.

Figure 6.8(d) Facial Geometric Feature Extraction in Anger Expression
R1, R2 and R3 regions indicated in Figure 6.8(e) shows the expressional variation due to surprise compared with neutral face. The R1 region shows raised eyebrows and R2 region shows wide open upper eyelids and R3 region indicates open jaw. Surprise expression made the changes to the geometries of eyebrows, mouth, eyes and lips.

![Figure 6.8(e) Facial Geometric Feature Extraction in Surprise Expression](image)

Figure 6.8(e) Facial Geometric Feature Extraction in Surprise Expression

Figure 6.8(f) shows the changes caused due to disgust expression on the face with respect to neutral expressions. Eyebrows and eyelids are slightly closed in R1 region and nose shrinkage is shown in R2. The upper lip is raised and bent upward as indicated by R3. Disgust expression changes causes variation of physiological features with geometric differences in eyebrows, mouth, eyes and lips.

![Figure 6.8(f) Facial Geometric Feature Extraction in Disgust Expression](image)

Figure 6.8(f) Facial Geometric Feature Extraction in Disgust Expression
In the expressions of feature extracted eyes from faces as well as the mouth extraction. The modified canny edges detector in the MATLAB to applied extract edges / contours from a face image. This is followed by the dilation and erosion operation for connected curves. An eye / Mouth detection algorithm is used to extract these three features. Physiological evidence can be used in this Eye / Mouth extraction stage for the purpose of simplicity. For instance, the position of the left eyebrow is about one fourth of the facial width.

The proposed physiological based geometric scheme was deployed for face component shape recognition. In the experiments preprocessing for obtaining good faces was performed. Faces were extracted by this research work, these images were cropped in order to create a $32 \times 32$ size. The image is represented as a 1024 dimensional vector and the classical geometric based algorithms used $32 \times 32$ dimensional matrix. The purpose of this evaluation is to train the face recognition systems and a new face image is projected to ‘d’ dimensional subspace and the nearest neighbor classifier was applied for face identification. Figure 6.9 shows quantification of intensities expression of happiness.

![Figure 6.9](image.png) **Figure 6.9** Quantification of Intensities of Happiness Expression
6.5 MAPPING OF FACIAL GEOMETRY TO ITS EXPRESSION WITH GENETIC ALGORITHM

Evaluation of facial geometric features and behavioural pattern for facial expression are mapped to its respective cause (expressions like happiness, sadness, fear, anger, surprise and disgust) and effect (change in the geometric shape on eye and lip) using genetic algorithm. In iterative genetic algorithm process a chromosome of length of 8 bits and a population of 30 are chosen in this test environment. The expression invariant is represented as chromosome of a fixed length and population, with suitable crossover probability and mutation probability. Fitness function is evaluated to measure the performance or fitness of an individual chromosome with specific expression action units (happiness, sadness, fear, anger, surprise and disgust) to its geometric shapes being restored.

The facial expression results from one or more motions or positions of the muscles of the face. These movements convey the emotional state of the individuals to observers. Facial expression is a form of nonverbal communication. It is a primary means of conveying social information among humans but also occur in most other mammals and some other animal species.

Human beings can consider a facial expression as a voluntary action. However, as expressions are closely tied to emotions they are more often involuntary. It can be nearly impossible to avoid expressions for certain emotions even when it would be strongly desirable to do so. A person who is trying to avoid an insult finds it highly unattractive and may nevertheless show a brief expression of disgust before being able to reassume a neutral expression. The close link between emotion and expression can also work in the other direction being observed that voluntarily assuming an expression can actually cause the associated emotion. As faces have only a limited range of movement expressions relied upon fairly minuscule differences in the
proportion and relative position of facial features, reading them requires considerable sensitivity. Some faces are often falsely read as expressing some emotion even when they are neutral because their proportions naturally resemble another face assuming some emotion.

Experiments were performed on colored as well as grayscale image databases. The neutral face to expressions of the face to be source image is depicted in Figure 6.10(a) to 6.10(g). The database consists of color image sequences depicting the six facial expressions happiness, sadness, anger, fear, surprise and disgust along with its extraction of geometrical features on sideward. This database was used to test the accuracy of the facial expression recognition algorithm. In the following graphs, depicted the accuracy obtained in the conducted tests.

![Figure 6.10 Experimental of one Facial Expressions of the Image Database](image)

Among the different biometric techniques, facial expression recognition is one of the most reliable and efficient systems in hand held devices such as Laptop and Palmtop. Its great advantage is that it does not require aid from the test subject which needs special devices in case of finger print systems as the present laptop contain inbuilt camera for image acquisition. Properly designed facial expression systems installed in airports, multiplexes and other public places can detect presence of criminals among the crowd. The behavioural traits as registered in the genetic (properties)
alleles mapped by the geometry of the face gives a clear recognition even when the human attitude change cause facial morphological change.

Discussion of the experimentation is carried out on developing a systematic pattern of the face expressions which is a basis for automatic extraction of specific features, such as changes of contours of eyes, eyebrows, forehead, nose tip, chin and cheek and a basis for the classification of emotional facial expressions. The emotional expressions are classified based on the defined points on specific locations of the contour. The graph of the contour is rotated to some fixed position. The points correspond to the peaks and the valleys in the graph. It offers the possibility to use Mathematical Tool MATLAB to locate maximum and minimum points or points of extreme curvature in an automatic way.

The proposed model adopt the geometrics of the face based on their expressions a behavioural biometric trait. The visual details of the geometrics as captured in standard digital or scanned images play vital role in the recognition system. This technique of mapping geometrics to the behavioural traits in the allele (properties) of gene turns the unique lines, patterns and spots apparent in a person’s face into mathematical space. Tests have shown that with the addition of geometric behavioural analysis, the performance in recognizing faces can be increased from 20 to 25 percent.

6.5.1 Genetic Algorithm Implementation

Genetic algorithms are simple to implement, but their behaviour is difficult to understand. In particular it is difficult to understand why these algorithms frequently succeed at generating solutions of high fitness when applied to practical problems. The Building Block Hypothesis (BBH) consists of:
a. A description of a heuristic that performs adaptation by identifying and recombining ‘building blocks’, that is, low order, low defining-length schemata with above average fitness.

b. A hypothesis that a genetic algorithm performs adaptation by implicitly and efficiently implementing this heuristic.

The variant algorithm simplest represents each chromosome as a bit string. Typically, numeric parameters can be represented by integers, though it is possible to use floating point representations. The floating point representation is natural to evolution strategies and evolutionary programming. The basic algorithm performs crossover and mutation at the bit level. Other variants treat the chromosome as a list of numbers which are indexes into an instruction table, nodes in a linked list, hashes, objects, or any other imaginable data structure. Crossover and mutation are performed so as to respect data element boundaries. For most data types, specific variation operators can be designed. Different chromosomal data types seem to work better or worse for different specific problem domains.

When bit strings representations of integers are used, Gray coding is often employed. In this way, small changes in the integer can be readily effected through mutations or crossovers. This has been found to help prevent premature convergence at so called Hamming walls, in which too many simultaneous mutations (or crossover events) must occur in order to change the chromosome to a better solution. Other approaches involve using arrays of real-valued numbers instead of bit strings to represent chromosomes. Theoretically, the smaller the alphabet, the better the performance, but paradoxically, good results have been obtained from using real-valued chromosomes.
A very successful (slight) variant of the general process of constructing a new population is to allow some of the better organisms from the current generation to carry over to the next, unaltered. This strategy is known as elitist selection. Parallel implementations of genetic algorithms come in two flavours. Coarse grained parallel genetic algorithms assume a population on each of the computer nodes and migration of individuals among the nodes. Fine grained parallel genetic algorithms assume an individual on each processor node which acts with neighboring individuals for selection and reproduction. Other variants, like genetic algorithms for online optimization problems, introduce time-dependence or noise in the fitness function.

Genetic algorithms with adaptive parameters Adaptive Genetic Algorithms (AGAs) is another significant and promising variant of genetic algorithms. The Probabilities of Crossover (PC) and Probabilities of Mutation (PM) greatly determine the degree of solution accuracy and the convergence speed that genetic algorithms can obtain. Instead of using fixed values of pc and pm, AGAs utilize the population information in each generation and adaptively adjust the pc and pm in order to maintain the population diversity as well as to sustain the convergence capacity. In adaptive genetic algorithm, the adjustment of pc and pm depends on the fitness values of the solutions. In Clustering-based Adaptive Genetic Algorithm (CAGA), through the use of clustering analysis to judge the optimization states of the population, the adjustment of PC and PM depends on these optimization states.

It can be quite effective to combine genetic algorithm with other optimization methods. Genetic algorithm tends to be quite good at finding generally good global solutions, but quite inefficient at finding the last few mutations to find the absolute optimum. Other techniques (such as simple hill climbing) are quite efficient at finding absolute optimum in a limited region.
Alternating genetic algorithm and hill climbing can improve the efficiency of genetic algorithm while overcoming the lack of robustness of hill climbing.

This means that the rules of genetic variation may have a different meaning in the natural case. For instance, provided that steps are stored in consecutive order, crossing over may sum a number of steps from maternal DNA adding a number of steps from paternal DNA and so on. This is like adding vectors that more probably may follow a ridge in the phenotypic landscape. Thus, the efficiency of the process may be increased by many orders of magnitude. Moreover, the inversion operator has the opportunity to place steps in consecutive order or any other suitable order in favour of survival or efficiency. Population-based incremental learning is a variation where the population as a whole is evolved rather than its individual members.

In this Table 6.1 gene property mapping values of face expressional parameter indicates the mapping sequence of face with the gene property functions. In this table calculate the various values for mapping the facial expressions. In each and every human facial expression depends on their creation and the table is being calculated with 50 human faces and their frequency expressions like happiness, sadness, fear, anger, surprise and disgust are being tabulated in the table. Human face with the highest happy expression will be having the lowest of all expressions.
Table 6.1  Mapping of Gene Property Values on Facial Expression

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<th>S-Surprise</th>
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Mapping of facial geometry to its expressions with genetic algorithm implying geometric face expression offers two additional advantages: optimal based techniques for dimensionality reduction is derived from genetic algorithm model and the computational efficiency is improved by adding a whitening procedure after dimension reduction. Again the proposed geometric algorithm outperforms other methods due to faster convergence and less error rates.
Genetic Algorithm is deployed for finding the characteristic matching points. The coordinates of those points can then be used to classify an emotional expression and to characterize a general expression. The characteristic points are the beginning of the forehead line, eyebrow, crust and turf below the eyebrow, nose end point, lip elevations, cheek breadth and chin tip. If the contour is changing, the characteristic points are also changes.

In systematic pattern from the characteristic points, a set of features is calculated, such as distances between the points, angles between them and areas of some triangles formed by some of these points. To evaluate the facial recognition, a relationship is established between the characteristic geometric points of the face and its expressional features stored in the allele (property) of genes. Each gene can have hidden and exposed property in which the expressional features are kept based on instance of notion of the face. Comparison is made by analyzing the position of characteristic points in relation to the original position of the normal face by observing whether the point was going up, down, back or front, compared to the normal face position stored in the genetic property.

The higher geometric to lower facial expressional dimension reduction problem for face recognition is carried out with genetic algorithm. When the number of facial samples is less than the image dimension (total number of pixel), within the class Scatter Matrix (SW) is singular and fisher face for dimension reduction of SW is employed with genetic algorithm so that it becomes nonsingular. The method is to select the largest nonzero eigenvalues and the corresponding eigenvectors for the genetic value of the gene set generated for every expressional relating to geometric shape of any input facial sample.
Image database has been created with 7.2 Mega Pixel Sony Cyber Shot-Digital Camera with facial picture resolution of 624 * 864 of 24 bit color depth. Human faces of 63 individuals were photographed under same lighting conditions, among these 21 for men and 42 for women. Each individual is photographed with six different expressions that is, happiness, sadness, fear, anger, surprise and disgust. In these 63, 4 men and 9 women facial images with six expressions were discarded due to irrational expressions compared to other sample human facial images. The final sample database of human facial image data set used for the experimentation contained (50 individuals * 6 different expressions) 300 images as a valid database. In the final data set 17 men and 33 women faces with six expressions were sampled for this facial expressional recognition system. In GA based facial expressional recognition system is able to detect both men and women facial expressions more accurately compared to the work of (Avraam Kasapis 2003), which is more suited to the facial expression of men. The database comprises of 24 individuals of six expressions in color images and 26 individuals of six expressions in gray scale images.

The accuracy of GA based facial feature extraction for colored and grayscale images is shown in Figure 6.11. In case of colored images, the lip enhancement transform was applied to the images. An average accuracy of 92.2% was obtained for grayscale image database (data size = 26 images). In case of color image database, a slightly better accuracy of 95.4% was obtained (data size = 24 images). The marginal improvement of the performance for the color images is due to the expressional ranges measured in color quantization. Color value quantization improves the level of gene properties mapping expressional characteristics to the geometric shape. This improvement is due to the sharp color edges on the facial geometry when compared to improper and blunt edges of gray scale images. The sharp color
edges gave discrete value range of the gene mapping property for expressional recognition system.

![Figure 6.11 Accuracy for Facial Feature Extraction](image)

**Figure 6.11 Accuracy for Facial Feature Extraction**

Facial expression recognition of each grayscale image sequence in the database depicted one of the expression classes (happiness, sadness, fear, anger, surprise, disgust and against neutral). The first image in the sequence was a neutral image. Confidence level of each expression was calculated for each of the subsequent images against the neutral image. The calculated vector of confidence levels was added to give total confidence for each of the expressions. Expression having the highest total confidence level was declared as the expression of the sequence. On a test set of 50 human faces (300 images) an accuracy of 95.4% was achieved for color and 92.2% for gray scale images. The previous work (Avraam Kasapis 2003) has reported an accuracy of 67.5% for 240 training facial images with only four expressions of human individuals. The feature point extraction using feed forward and back ward neural network propagation training model. The holistic approach has reported an accuracy of 89% as shown in Figure 6.12.
Figure 6.12 Accuracy for Color Image Sequences

Mapping of facial geometry to its expressions with genetic algorithm implying geometric face expression offers two additional advantages: optimal based techniques for dimensionality reduction is derived from genetic algorithm model and the computational efficiency is improved by adding a whitening procedure after dimension reduction. Again the proposed geometric algorithm outperforms other methods due to faster convergence and less error rates.

In previous work of (Avraam Kasapis 2003) used NN training data set to achieve the recognition of facial samples used classifier in facial expressional variant of individual human faces. The database used 15 gray scale image of facial recognition in four expressions, such as happiness, sadness, angry and neutral. This four expressions used best weight initialization scheme and an optimal selection of NN parameters, achieved generalization accuracy of 67.5% average to detect facial expressional recognition. The improvement of our GA based facial expression recognition used six different expressions of facial feature extraction. In addition, as shown in Figure 6.13 our work utilize the gene mapping which contributes more number of discrete characteristic points deployed in the facial
recognition, but in NN method less number of characteristic points were generated depend on the strength of training data set.

![Figure 6.13 Comparative Performance of NN and GA Based Facial Expression Recognition](image)

**Figure 6.13 Comparative Performance of NN and GA Based Facial Expression Recognition**

Experimental results as show in Figure 6.13 indicate that almost 30% of improvement is achieved in GA based facial expression recognition compared with previous NN facial recognition model (Avraam Kasapis 2003). In terms of recognition rate measured in percentage of accuracy in GA based facial expressions recognition. This shows encouraging research proceedings in the direction of behaviour map to geometric features.