CHAPTER 4

GEOMETRIC AND BEHAVIOURAL CHARACTERISATION

4.1 PREAMBLE

There are many biometric techniques available based on physiological and behavioural characteristics but the quest for devising an innovative biometric technique is ever lasting and never ending process so as to constantly establish the fool proof of the system. The scopes of investigated nature of biometric physiological and behavioural characters are effective for personal device authenticity. The geometric and behavioural characterization is presented in this chapter. Section 4.2 discusses the asymmetric cryptosystem model and its drawbacks. Section 4.3 presents the concepts hierarchy method. Section 4.4 presents the Geometry and Behavioural characteristics involved in the facial expressional. Finally Section 4.5 discusses the facial expressions recognition method.

4.2 ASYMMETRIC CRYPTOSYSTEM MODEL

The encryption using the module process encryption key confirms the validity of the facial traits that is sent through the encryption module process used by a legitimate user and not using the unlocking key available with the verifier as one can not input directly the secure features to the encryption module which are actually calculated using the facial expressions. Hence the system develops the required asymmetric nature.
The fuzzy vault scheme described previously has a drawback that the verifier is also able to generate the vault pretending to be the actual sender. To alleviate this problem the proposed system adds some extra information in the encrypted facial feature vector which could be easily verified by the laptop user but not replicated for creating a fake vault.

For this purpose the system has used the RSA cryptosystem to design a system as depicted by the Figure 4.1. The system primarily consists of a number of encryption modules linked to the facial template for information transfer. Each module has its own RAS security protocol (128 bit) such that the encryption key is secured with the module and the decryption key and the field is made public by sending it to biometric recognizer. Each module can register a number of users. While registering a user, it generates a secure transformation for that particular user which is kept secure inside the module.

Figure 4.1 The Designing of RSA Cryptosystem Model
The following steps using the asymmetric RSA cryptosystem model applied, modified Fuzzy Vault scheme for facial recognition system:

1. Facial recognition takes the facial expressions of the user and extracts the features from it.
2. Facial features are transformed to secure features using the secure transformation registered with the module.
3. An RSA cryptosystem is initialized having field, encryption key and decryption key.
4. Feature vector is divided into chunks of appropriate length and encrypted using encryption key.
5. Random digits are appended to d which is to be secured in the Fuzzy Vault so that the required value of permissible Error is achieved.
6. Invariant features corresponding to the desired security level are extracted.
7. Modified Fuzzy Vault containing appended d is created over the invariant features.
8. The created Vault is encrypted using the module encryption key and is sent to receiver along with the encrypted facial features and required identifications and values.

The facial recognizer is supplied with the Fuzzy Vault unlocking key that the invariant features corresponding to the desired security level once for all the transaction. To identify the recognized face in the template, the verifier does the following:
1. Decrypt the vault using the publicly available module decryption key.

2. If security level of vault is lesser than security level of verifier generate the new key corresponding to vault security level.

3. Open vault using the key to get facial feature vector decryption key.

4. Decrypt feature vectors using first few desired digits of decryption key.

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4.3 CONCEPT HIERARCHY

In the evaluation of concept hierarchy for facial interpretation image shape filters implemented in MATLAB are used to process human face images and output its results to an application based agent as various shape object classes. The shape object classes are categorized with its hierarchical links. Multiple MATLAB agents are used to process the same image of hierarchical classes. The results of this class hierarchy are then aggregated using object specific shapes to analysis the contents of the facial image. Often it is necessary to pass the same image through a series of hierarchical filters before any deduction can be made. This therefore involves the application
agent planning a set of filters that is applied in some sequence to obtain some meaningful analysis of the image.

Mechanisms for connecting interfaces developed with the Genetic Algorithm Toolkit in Matrix Laboratory (MATLAB) are evaluated. The approach used allows application based genetic algorithm interfaces agents to launch commands on one or more MATLAB interfaces (running locally or remotely). Each MATLAB interface is responsible for receiving a class recognition query and processing on one or more hierarchical classes. The system of concept hierarchy approach for facial shape object categorization is used much in identifying the geometric patterns of face and its expression.

4.4 GEOMETRY AND BEHAVIOURAL CHARACTERISTICS

The main focus of this research work is to exploit the behavioural geometric variation information to cope with multiple facial expressions. The system presented techniques take input of the multiple variant facial images to produce a pair of normalized images depicting frontal pose. Resilient to matching the variations is achieved not only by using a combination of a shape object and class hierarchy of the face, but mainly by using face geometry information and allele of gene mapping variations that inhibit the performance of 2D face recognition. Figure 4.2 as the flowchart of the proposed model of face recognition expressions.

A face normalization approach is proposed which unlike state of the art techniques is computationally efficient and does not require an extended training set. Experimental results on a large data set show that template based face recognition performance is significantly benefited from the application of the proposed normalization algorithms prior to classification.
4.4.1 Geometric Features of Face

Facial geometric factors are considered for the evaluation of identifying its features of shape, size, and length, width between different components of a person’s face such as mouth, nose and eye. The proposed models 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 plays vital role in the recognition system. This technique of mapping geometrics to the behavioural traits in the allele 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 performance in recognizing faces can increase 20 to 25 percent.

The facial expression results from one or more motions or positions of the muscles of the muscles of the face. These movements convey the emotional state of the individuals to observers. Facial expressions are a form of nonverbal communication. They are a primary means of conveying social information among humans but also occur in most other mammals and some other animal species.
Humans can adopt a facial expression as a voluntary action. However because expressions are closely tied to emotion 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 insult to an individual he or she finds highly unattractive might 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 it has been observed that voluntarily assuming an expression can actually cause the associated emotion.

Some expressions can be accurately interpreted even between members of different species anger and extreme contentment being the primary examples. Others however are difficult to interpret even in familiar individuals. For instance disgust and fear can be tough to tell apart. Because faces have only a limited range of movement expressions rely upon fairly minuscule differences in the proportion and relative position of facial features and reading them requires considerable sensitivity to same. Some faces are often falsely read as expressing some emotion even when they are neutral because their proportions naturally resemble those another face would temporarily assume when emoting.

Among the different biometric techniques facial expression recognition is one of the most reliable and efficient system in hand held devices that is Laptop, Palmtop. Its great advantage is that it does not require aid from the test subject that is 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 alleles mapped by the
geometry of the face gives a clear recognition even when the human attitude change cause facial morphological change.

Other biometrics like fingerprints, iris and speech recognition cannot perform this kind of mass scanning. However questions have been raised on the effectiveness of facial recognition software in cases of railway and airport security. The future directions can take towards processing facial image recognition in the mass assembly crowd which involve segregation of individual faces and make it viable for the facial expressional system.

**Geometric feature shape model formula** using head motion also encapsulates partly how humans expression emotion, that is, a person is sadness expressions they tend to move their head less than when someone is happiness expressions. Thus it is considered to generate new sequences with a similar look and feel as the original data, it is important to maintain geometric variation as otherwise it would only be possible to synthesize a static head which has no change in position with respect to time. To build the linear shape model the following stages are performed:

1. Using control point set $XZ$, where $X$ is set of points in object, $Z$ is the number of labeled frames, compute the mean shape.

\[
\bar{X} = \frac{1}{Z} \sum_{i=1}^{Z} X_i
\]  

(4.1)

2. Calculate the covariance, $V_s$ of data $XZ$.

\[
V_s = \frac{1}{Z} \sum_{i=1}^{Z} (X_i - \bar{X})(X_i - \bar{X})^T
\]  

(4.2)
3. Compute shape eigenvectors, $\Phi_S$, and corresponding eigenvalues $\lambda_S$ for the top $i$ principal components of $V_s$, which account for 98% of the variation within the shape data set.

4. Form the linear shape model. With this model any shape in the original data set can be reconstructed:

$$X_i = \bar{X} + \Phi_S b_S(i)$$  \hspace{1cm} (4.3)

where, $b_S(i)$, are the shape responses for each video frame. These are found by projecting the point data, $X_i$, of each image frame, $I_i$, into the lower dimensional ‘emotion space’ defined by $\Phi_S$

$$b_S(i) = \Phi_S^T (X_i - \bar{X})$$  \hspace{1cm} (4.4)

The shape responses $b_S$, from each image frame form the eigen signature of the shape data. For visualisation the only plot the top two eigenvectors of the eigen signature, though in practice more eigenvectors are used. The top two eigenvectors contain the majority of the variance and therefore it is then possible to roughly observe whether different emotion Eigen signatures occupy different areas of emotion space and have different characteristics.

4.4.2 Behavioural Characteristics of Facial Expressions

The human face is capable of producing a large variety of facial expressions that supply important information for communication. With the investigation on the previous studies using video sequences, movements of single region like mouth, eyes, and eyebrows as well as rigid head motion play a decisive role in the recognition of conversational facial expressions.
The system here is flexible but at the same time, realistic computer human faces are used to investigate the expressional behavioural co-action of facial movements systematically.

For the integrated physical behavioural experiments, properties of faces are manipulated in a highly controlled manner. First, single region (mouth, eyes, and eyebrows) of a human face performing six basic facial expressions is selected. The single region as well as combinations of other regions is interrogated for each of the six facial expressions. Participants have been asked to recognize these expressions in the experiments. The findings show that the appropriation of facial expressional behaviour to the physical geometry is a useful tool for the investigation of facial expressions, although improvements have to be made to reach a higher recognition accuracy of certain expressions.

In the view of the six basic emotions such as happiness, sadness, fear, anger, surprise and disgust have been presented by Kanade et al. (2001). Already there is another work which uses neural networks to recognize the human expression was presented by Tian et al. (2001). With this geometric and expressional characteristic, the proposal of this research has made an attempt in constructing a hybrid facial recognition system that utilizes both physiological and behavioural factors with the effect of genetic algorithm. The functional operation of gene with its mutative and crossover functions are evaluated to map the physical facial geometric variation to different expressions of the individual human being. Furthermore, the results shed light on the importance and interplay of individual facial regions for recognition. The perceptual quality of facial expression integration to geometric features with genetic algorithm and gene mapping techniques is investigated to get an improved hybrid facial system recognition rate for the personal device usage to reach a higher level of realism and effectiveness.
The core objective of this research work is to facilitate the implementation of behavioural and physiological characteristic expressions such as happiness, sadness, fear, anger, surprise and disgust in personal devices such as PCs, laptops, PDAs, mobile devices so as to achieve the insensitivity during the time of login in spite of having different levels of expressions along with the accuracy of 95.4% efficiency using genetic algorithm.

The intricate performance objectives of this research works is based on genetic algorithm, a gene operation that is crossover and mutation. The operation is that mapping the geometric structure to facial expressions at various level of hierarchical concept. These emotions are clearly recognized with the accuracy of level and rate of expressions. This model is compatible to the different modes and levels of expressions for the identification of different facial expressions such as happiness, sadness, fear, anger, surprise and disgust at the time of login with the personal devices.

**Behavioural Expressions formula** to extract information about facial expression, each 256 × 256 pixel image I, the image I was convolved with a multiple spatial resolution, multiple orientation set of Gabor filters \( G_{k,+} \) and \( G_{k,-} \). The sign subscript indicates filters of even and odd phase, while \( k \), the filter vector, determines the spatial frequency and orientation tuning of the filter. A description of the complex valued two dimensional Gabor transform is given below. Responses of the filters to the image were combined into a vector, \( R \), with components given by:

\[
R_{K,\pm} (\vec{r}_0) = \int G_{K,\pm} (\vec{r}_0, \vec{r}) I (\vec{r}) \, d\vec{r}
\]  

\[(4.5)\]
where

\[ G_{k,+}(\vec{r}) = \frac{k^2}{\sigma^2} e^{-k^2 \|\vec{r} - \vec{r}_0\|^2} \cos(k \cdot (\vec{r} - \vec{r}_0)) - e^{-\sigma^2/2} \]

\[ G_{k,-}(\vec{r}) = \frac{k^2}{\sigma^2} e^{-k^2 \|\vec{r} - \vec{r}_0\|^2} \sin(k \cdot (\vec{r} - \vec{r}_0)) \]

The integral of the cosine Gabor filter, \( e^{-\sigma^2/2} \) was subtracted from the filter to render it insensitive to the absolute level of illumination. The sine filter does not depend on the absolute illumination level. Three spatial frequencies were used with wave numbers measured in inverse pixels.

\[ k = \left\{ \frac{\pi}{2}, \frac{\pi}{4}, \frac{\pi}{8} \right\} \] (4.6)

The components of the Gabor vector \( R_k \) are defined as the amplitude of the combined even and odd filter responses

\[ R_k = \sqrt{R_{k,+}^2 + R_{k,-}^2}. \] (4.7)

The response amplitude is less sensitive to position changes than are the linear filter responses. To study the similarity space of Gabor coded facial images, responses of filters having the same spatial frequency and orientation preference were compared at corresponding points in the two facial images. The normalized dot product was used to quantify the similarity of two Gabor response vectors. The similarity of two facial images was calculated as the average of the Gabor vector similarity over all corresponding facial points. Since Gabor vectors at neighboring pixels are highly correlated and redundant, it is sufficient to calculate the average on a sparse grid covering the face. This similarity measure is used in the automatic face
recognition system. The filter parameters used here differ from those used in that work. Automatic systems for scaling the face. The 34 node grid used to represent facial geometry and registering a graph approximately with the features of the face. In this study, for higher precision, facial graphs were positioned manually on images of a standard scale.

4.5 FACIAL EXPRESSIONAL RECOGNITION METHOD

The facial expressions as mentioned above are directly proportional to the changes in the facial geometric depiction of any particular expression. Those changes in the geometry are taken as physiological parameter in measuring and recognizing facial expression in the research work. However the expressional geometric changes are due to impact of attitude and behaviour of the individuals. This research work quantifies the attitude and behaviours based on its associated expressions, with the behavioural biometric principles. The behavioural expressions are related to respective geometric changes in the lips, eyes and nose positional spaces, elongation and contraction. The mapping of geometric property with behavioural property results in more robust and adaptable biometric security system with the human of various physics and attitudes.

The facial expressions recognition methods of the reviewing the geometric features and behavioural characteristics. These the steps involved in the methods, that is geometric feature, feature selection of head, feature selection face and template classification as shown in Figure 4.3. Details of these steps in,
Figure 4.3 The Framework of Geometric Feature and Behavioural Expressions Classifier Model

Step 1: Geometric Feature partition

At the beginning, geometric feature should be defined. This involved two factors, that is, the shape and the size of the images. The simplest and most widely used shape of image is rectangular window as shown in Figure 4.4. The size of rectangular areas has direct influence on the number of geometric features and the robustness of the underlying.

![Figure 4.4 The Geometric Feature Identification of the Rectangular Shape in Happiness Expressions](image)

Step 2: Feature Selection of Head

The images half top most position of the head regions are defined, one has to decide how to represent the information of them. This is very critical for the performance of a recognition system. The commonly used
features include gray-value features and a variety of derived features, such as Gabor wavelet. In general, gray-value feature is the simplest feature without loss of texture information, while Gabor features and other derived features are more robust against illumination change and some geometrical translations.

**Step 3: Feature selection of Face**

If the images another half bottom of the position in face of features are generated in the previous step, additional feature selection stage is usually needed for effectiveness and efficiency consideration. Commonly used feature selection method guaranteeing minimal loss of information using PDA, Linear Discriminant Analysis (LDA) can be used for selecting the features with most discriminative power; some local statistics such as the degree of texture variation are also used for feature selection.

**Step 4: Template Classification of the Images**

The final step is face expression identification. Combining geometric and behavioural characteristics classifiers is the most common way for that purpose. In particular, each component classifier is applied on one geometric feature and the final decision is made by recognizing rate of the expressions.

This research work is used to develop a secured biometric facial expressional recognition system to acquire the facial images through digital photographs. The facial biometric process deals with the extraction of features. In the extraction of feature, the geometric facial features are extracted to lay the foundation for template generation. The geometry of the nose, lip and eyebrows are measures with the pixel terms on multiple expressions depicted by the sample images. The geometric association is
made relevant to each and every standard expressions such as happiness, sadness, fear, anger, surprise and disgust. The behavioural geometric mapping is converted into gene value set using the genetic operations of crossover and mutation.

The system model works on the classification of the genetic value sets to form different sets of template classes for various expressions. These template classifiers are depicted for the given sample input image as well. The training samples are generated with different human face of varied nature expressions such as happiness, sadness, fear, anger, surprise and disgust. The recognition is used to evaluate the similarity of the input sample facial image template classifiers with the training sample templates. With the appreciable recognition rate of comparison, the matched image is listed down to show the rate of accuracy in terms of visual and quantified genetic values of the behaviour mapped to geometrics property.