Multimodal Biometric Security using Evolutionary Computation

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Declaration

I solemnly declare that this thesis submitted for the degree of MS Computer Science at the International Islamic University is entirely my own work and has not been previously submitted by me at another University for any degree. It is further certified that, to the best of my knowledge, any ideas, techniques, quotations, or any other material included in my thesis from the work of other people are fully acknowledged according to the standard referencing practices.

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Abstract

Reliable user authentication has become very important with rapid advancements in networking with increased concerns about security. Biometric systems perform recognition with the help of specific physiological or behavioral characteristics(s) of a person. Biometrics establishes identity on the basis of biological characters e.g., structure of your DNA, facial features, voice, gait etc, instead of ID cards, PIN numbers, tokens, passwords, etc. UniBiometrics systems depend on the evidence of only one source of information whereas multibiometric systems consolidate/combine multiple sources of biometric evidences. Multibiometric systems are capable of enhancing the matching performance as they get the evidence presented by different modalities or biological characteristics and the use of multiple body traits improves the identification accuracy significantly. Moreover, they are expected to increase population coverage, prevent spoofing attacks and provide fault tolerance to biometric systems. In this thesis, we have proposed an evolutionary approach to enhance the matching performance of our multibiometric system. The system uses Discrete Cosine Transform at feature extraction level due to its high energy compaction property. The existing methods of Linear Discriminant Analysis and Principal Component Analysis are also used in parallel with DCT in order to compare the three feature extraction methods. LDA being more efficient than PCA as LDA uses both intra-class scatter and inter-class variation whereas PCA only deals with intra-class scatter. However, DCT offers far less computational complexity than the other two methods. Three biometric traits i.e. face, iris and ear have been used which are fused at feature level and genetic algorithm has been incorporated for feature vector optimization. Classification is performed through the Bayesian classifier. Results have been computed on the basis of Error Equal Rate (EER) values and ROC curves which have shown that the use of Discrete Cosine Transform with genetic algorithm has significantly improved the performance of our multibiometric system.

Keywords: Multimodal, Biometrics, Discrete Cosine Transform (DCT), Linear Discriminant Analysis (LDA), Principal Component Analysis (PCA), feature level fusion, Genetic Algorithm (GA), Bayesian Classifier

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Chapter 1
Introduction

1.1 Introduction to Biometric Systems

Biometric systems perform recognition of individuals on the basis of their physical and/or behavioral traits. Some commonly used traits are fingerprint, face, iris, retina, palm print, voice pattern, signature, gait, etc. Most biometric systems will serve one of the two purposes: identification or verification/authentication. Biometric systems provide several advantages over the traditional methods. Biometric traits cannot be easily copied, shared, distributed or forged. Biometric systems also provide the convenience in a sense that the user is no more required to design or remember passwords. Multibiometric systems consolidate multiple sources of biometric evidences. The integration of evidences is known as fusion. The information from multiple sensors, multiple samples or multiple traits of an individual is consolidated by the multibiometric system using various algorithms deployed on the same biometric trait.

The fundamental requirement for various operations using biometrics is to verify an individual's identity. In order to provide the genuine individual with the desired privileges given that they are provided at the correct time by having authenticated access, three approaches are available to establish an individual's identity [16]. The said methods used in various real life applications for verifying individual's identity include:

- *Something you have:* Desired privileges can be accessed by the user when he/ she possess some physical objects like, keys, identity card, smart card, etc., and these are shown to the authorities to get access of something or to be identified.
- *Something you know:* When the user already knows some predefined objects like passwords and these objects are entered in order to verify the individual.
- *Something you are:* A user can have access to a desired service with the help of measurable biometric traits (some examples are given in figure 1.1).

The application of biometrics in the processes of human identification and/or verification has some significant advantages over the other two methods. This is due to the fact that biometric traits are complex enough to share or steal and at the same time it is almost impossible that these traits cannot be forgotten or lost. Thus it can be stated that a higher security level can be achieved using biometrics for person identification/verification. There are several biometric traits which are used in various applications. Some examples of biometric traits are given in figure 1.1.

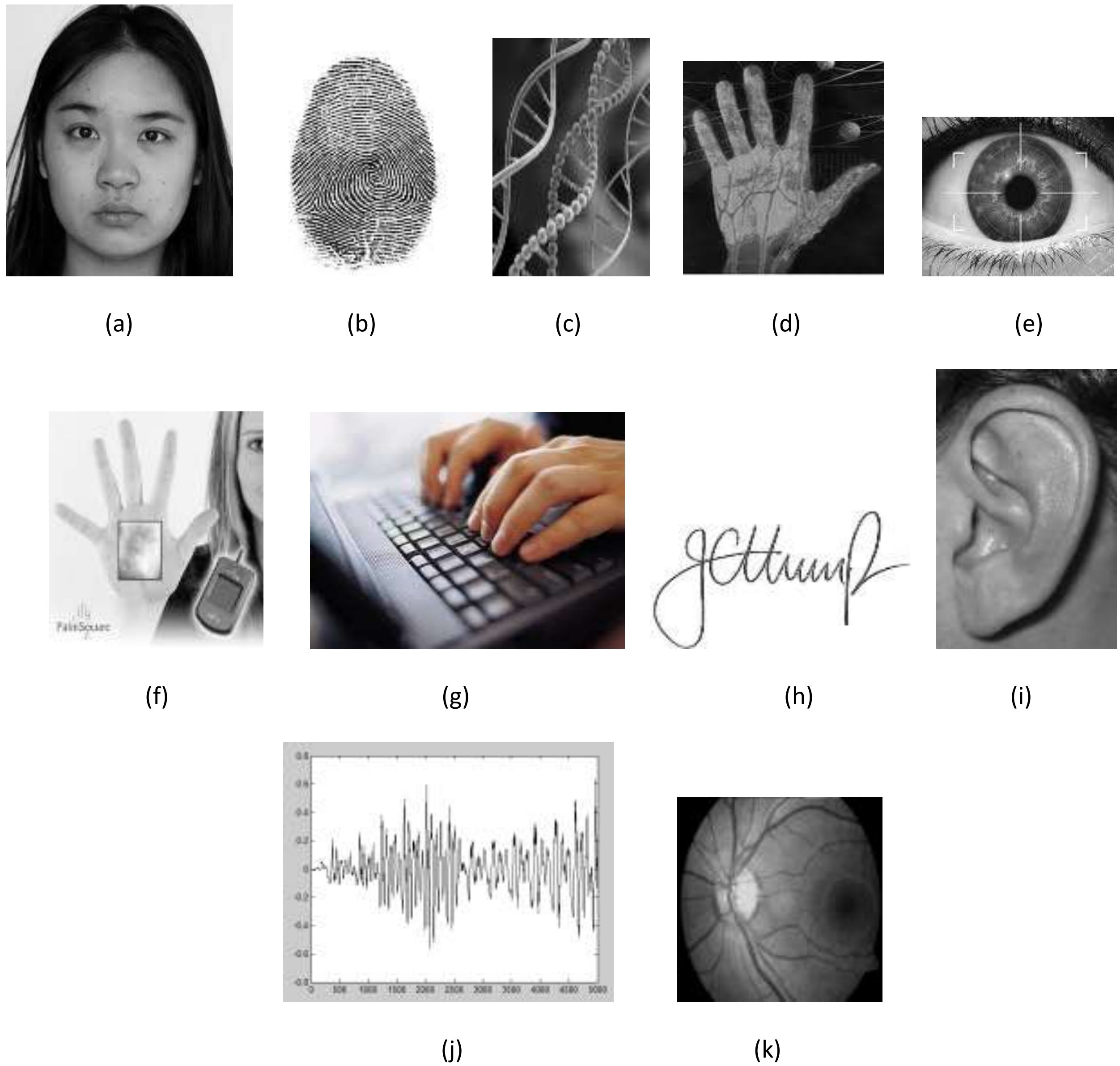


Fig. 1.1: Different Biometric Traits (a) Face, (b) Fingerprint, (c) DNA, (d) Hand veins, (e) Iris, (f) Palmprint, (g) Typing, (h) Signature, (i) Ear, (j) Voice, and (k) Retina

1.2 Biometric System Functional Processes

A biometric system involves the following three main functional processes [15]:

— Enrollment Process:

In enrollment process, a subject presents his/her biometric characteristics to the sensor along with his/her non-biometric information. Non-biometric information related to subjects could be name, social security number, driver license's number, etc. Biometric features extracted from the captured sample and the non-biometric information is enrolled in the database.

— Verification Process:

In a verification process, the claim of the person is checked whether he/she is the same person that he/she claims to be. The user who wishes to be recognized provides some objects which could be a Personal Identity Number (PIN), a username or a smartcard and also submits his biometric information through some sensors like camera, microphone or fingerprint detector etc. The system then compares the extracted template (from the captured sample) with the already enrolled template linked to the claimed identity from the database (1:1 matching) and determines whether the claim is true or false. When a user is willing to be recognized or verified, identity verification is used and this is known as positive recognition.

— Identification Process:

In an identification process, it is to be checked that that a particular person is? In this process, an individual is recognized by first capturing and then extracting the person's biometric features for finding a match with all the stored user templates in the enrollment database (1:M matching). When a user is not willing to be recognized, identification is used and this is known as negative recognition.

The significance of identification process lies mostly in negative recognition when the user tries to avoid being found out who he is. Some examples of such applications are background checks, criminal identification or preventing terrorists from entering certain areas. One of the major contribution of biometrics is the negative recognition that cannot be provided with the existing, traditional recognition methods such as passwords, PIN, tokens which can only work for positive recognition.

1.3 Desirable Properties of Biometric Traits

Some desirable properties of biometric characteristics for good subject discrimination and reliable recognition performance are described below [17]:

— *Universality*: Every individual must have the specific biometric characteristic.

— *Uniqueness*: The characteristics of each individual must be satisfactorily distinguishable among the whole enrolled database of all the individuals.

— *Permanence*: The biometric characteristics are required not to vary with time, for example, appearance of wrinkle in overage can be a problem.

— *Measurability*: It should be possible to acquire the characteristics without causing too much difficulty. The captured images or data must be suitable for future processing.

From an application point of view, following properties should also be taken into account.

— *Performance*: The required recognition accuracy in an application should be achievable using the characteristics.

— *Acceptability*: Acceptability refers to the willingness by the subject to present his biometric characteristics.

— *Spoof Resistance:* This refers to how difficult it is to use manufactured article (for example, fake fingers) for physiological traits and impersonation (for example voice tampering) for behavioral traits.

1.4 Biometric System Operations

There are three basic elements in a biometric system; 1) a sensor that captures the user's biometrics characteristics; 2) a software or feature extractor which is used to convert this raw data from the sensor to digital form for comparing with data already enrolled in the database, and 3) a database, which stores the processed digital biometric data.

All the biometric systems consist of four steps that are listed as under:

- *Capture*: A sensor (for example, a camera for capturing face, iris or ear images) is deployed at the start of the biometric system. It collects the sample(s) of biometric features like fingerprint, voice etc of the person who wants to have access to a desired privilege.

- *Extraction*: The samples obtained from the sensors are incorporated into the feature extraction software and a template is generated. The unique features for each individual extracted by the system are then converted into a digital biometric code. This code is then stored into the database as the biometric template for that individual.

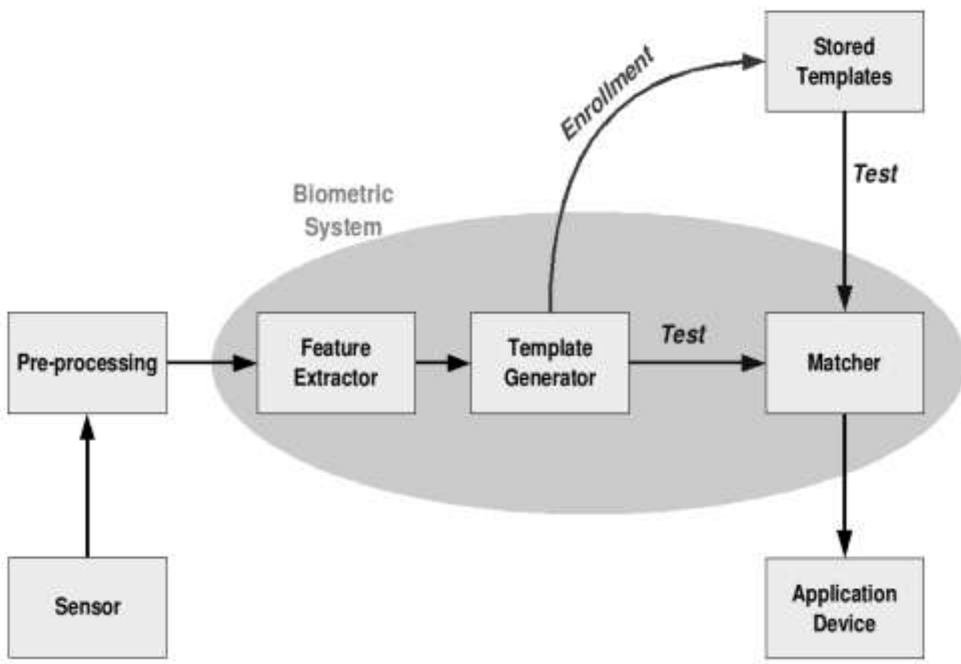


Fig. 1.2: Working of a Biometric System [18]

- *Comparison*: When a person needs to be verified, the above processes are repeated in order to generate a new template for that person. The generated template is then used to find a match with all the stored user templates in the enrollment database.
- *Match/non-match*: Finally the system outputs whether the new generated template at runtime matches with one of the template from the database or not. In this way a match/non-match or simply identified/unidentified is declared by the biometric system.

1.5 Advantages of Biometric Systems

Several advantages are offered by the use of biometrics for identification as well as verification purposes. Here we have the person as the key so the problem of remembering password is eliminated. Each body part of every individual is unique among the whole population and this unique identity is employed in the biometric system to activate/deactivate or lock/unlock something.

- Increased security – Provide a convenient way of implementing security.

- Decrease hoax attacks by using different methods and materials in construction of the biometric system. For example reduction in ID fraud, buddy punching, etc.
- Problems of lost IDs and forgotten passwords can be eliminated by using physiological biometric traits. For e.g. preventing unauthorized use of ID cards.
- No need to administer passwords, so reducing password management costs.
- Passwords are no more required to be remembered which are at a threat of sharing or observance.
- With the use of biometrics it has become possible, to automatically determine WHO has done something, WHAT has been done, WHEN something has been done and WHERE something did happen!
- Biometrics employed in attendance system offer considerable cost and time savings.
- An individual can be directly connected to a transaction without requiring another individual for his/her verification.

1.6 Limitations of Biometric Systems

Biometric security systems actually have an individual's biometric traits in a sense they are attacking the privacy of the individual, so therefore there are a number of concerns relating to it. Among the population, it is not necessary that all the people are willing to register for some application on the basis of their biometric traits, for example one may not feel comfortable giving their DNA or personal information to the biometric system stored in a database beyond his/her control. Moreover a high level security must be employed in the biometric system because if personal information is stolen, it may results in devastating effects on the particular individual's life. Also if the biometric system has stopped working suddenly, it cannot recognize/identify the individual. Furthermore the identity of the person may be completely lost.

So biometric systems are still having the following challenges to deal with:

- Noise in sensed data causes accuracy reduction
- Non-universality increases failure to enroll error (FTE)

- Lack of Individuality/Uniqueness increases False Accept Rate (FAR)
- Intra Class variation increases the False Reject Rate (FRR)
- Inter Class similarity increases FAR
- Openness to circumvention by spoofed attacks commonly for voice and signature

1.7 Application of Biometric Systems

Because of reliable identification and verification provided by the use of biometric systems, they have been installed in a variety of applications. Some of them are listed as under [19]:

- Biometric systems are used widely in commercial applications in the areas such as Internet access, computer network login, e-commerce, physical access control, ATMs or credit cards, mobile phones, managing medical records, Personal Digital Assistant (PDA), distance learning, etc.
- Government applications use biometric systems for making national ID cards, driving license, passports, social security numbers (SSN), welfare expenditure codes, border passage system, etc.
- Forensic applications make use of biometric systems for corpse identification, parenthood determination, criminal investigation, terrorist identification, etc.

(a)

(b)

(c)

(d)

(e)

(f)

Fig. 1.3: Biometric applications (a) Immigration and Naturalization service Passenger accelerated service system (INSPASS), based on hand geometry for individual recognition at US airports deployed to minimize the immigration processing time, (b) Fingerprint-based door lock to limit access to certain premises, (c) Fingerprint-based point of sale (POS) terminal for verifying customers before taking payment from their credit cards in retail shops, restaurants and cafeterias, (d) Fingerprint verification system employed for computer login (e) Hand geometry system for immigration and security uses Express Card entry kiosks deployed on airport in Israel(f) Iris recognition system used as border control system at London’s Heathrow airport.

1.8 Thesis Motivation

Reliable identity establishment/conformance is becoming critical in a variety of applications. Examples of those applications may include computer resources sharing connected via a network, performing remote financial transactions, border security control, and forensic applications. Traditional methods of establishing identity are either knowledge based systems (e.g., passwords) or possession based systems (e.g., ID cards). Individuals have certain distinct physiological and behavioral traits that are used by biometric systems for reliable authentication. Biometric systems provide better security and greater convenience than the traditional systems.

Our motivation for working on this project comes from the fact that in near future biometric systems will be supplementing or replacing the traditional systems in many applications. Most of the biometric systems presently being used are unimodal biometric systems typically making use of a single biometric trait for recognition purpose. There are several limitations of such systems and some of these can be resolved by employing multibiometric systems that consolidate/combine numerous sources of information based on biometric traits. Multibiometric systems offer the advantage of improving the matching accuracy of the biometric system [19]. They also address challenges such as non-universality, noise, susceptibility to spoof attacks and large intra-class variations.

1.9 Thesis Contribution

In this thesis, we addressed three issues in the design of multibiometric systems.

- Three feature extraction methods are used to compute the feature vector of each biometric trait (face, iris, and ear). DCT, LDA and PCA methods are used for feature extraction. The energy compaction property of DCT makes it the efficient method among the existing approaches of PCA and LDA. At this level, the accuracy of the unimodal systems is computed in terms of EER.
- Three fusion methods are implemented in order to fuse the feature vectors for making multimodal biometric system. ‘sum’, ‘min’ and ‘mul’ fusion methods are used for fusion. It has been seen that we get different results for same feature vectors fused by using different fusion methods. Here the EER values and the ROC curves are computed to check the efficiency of multimodal biometric systems.
- For achieving desired level of efficiency of our multimodal biometric system, the proposed method then implements genetic algorithm for feature vector optimization. The use of GA improves the performance of each feature extraction method.

Experiments have been performed for calculating the accuracy and efficiency of the proposed method. Matlab R2012a, on windows 7, has been used to implement this project. Finally the accuracy is computed for the three feature extraction methods with and without the implementation of genetic algorithm.

1.10 Thesis Layout

Chapter 2 gives the detailed description of the Multibiometric Systems. The advantages of multibiometrics over UniBiometrics have been discussed. The different feature extraction techniques used in biometrics are described like PCA, LDA and DCT. Also the various fusion level methods are discussed in detail.

Chapter 3 deals with the literature review. Recent techniques in UniBiometrics and multibiometric systems have been studied and analyzed.

Chapter 4 describes in detail the proposed solution for making a more accurate multibiometric system with better recognition ability.

Chapter 5 describes the experiments performed for finding the accuracy of UniBiometrics system and multimodal biometric system. ROC curves and EER values validate the experiments performed with and without the use of genetic algorithm.

Chapter 6 finishes the thesis and gives some future implementation of our proposed method in the field of multibiometrics for individual's identification.

Chapter 2
Multimodal Biometric Systems

2.1 Introduction to Multibiometric Systems

Those systems which aim at determining the identity of an individual by combining facts of biometric information/traits from multiple sources are known as multibiometric systems [20]. The use of multibiometric systems for identification or verification can eliminate most of the limitations caused by UniBiometrics systems. This is due to the fact that different biometric sources generally reimburse for the inherited problems of the other biometric traits [21]. Therefore, a multibiometric system has several advantages over UniBiometrics systems. The problems of UniBiometrics systems can be efficiently dealt with the implementation of multibiometric systems as described below:

- With the help of an effective fusion method applied for consolidating different biometric information/traits can result in significantly enhancing the recognition effectiveness of the multibiometric system.
- The use of multibiometric systems can efficiently reduce the errors of FAR and FRR by addressing the non-universality problem. For example, due to an accidental cut on finger print ridges, it would be difficult to enroll a person in a finger print system. However, if multibiometric system is used, other biometric traits like face, voice, ear, iris, etc. can be employed to identify the individual.
- Multibiometric systems offer a flexible environment for user identification/verification. For example, if a user registers into the system using various biometric traits, it is possible using a multibiometric system that at the runtime only a few of the traits can be used for matching for checking the authenticity of the user. Thus multibiometric system provides a convenient way of authentication both for the system and the user.
- Employing multiple sources of information greatly reduce the bad effects of noise in raw data. While capturing a particular biometric information/trait, if the sample is not of sufficient quality, the samples of other sources may still present enough distinguishing information in order to identify that individual.
- As it is not easy to hack/spoof multiple biometric templates at the same time so multibiometric systems offer resistance against spoof attacks more than the UniBiometrics systems. Moreover, a user challenge response technique can be deployed by a multibiometric system at runtime during capturing of the biometric trait. This can be

implemented by taking only some of the traits in a random order so that it can be ensured that a live user is interacting with the system.

- Multibiometric systems provide template security by consolidating the biometric information from various sources using some fusion methods.

Multibiometric systems also have some of the drawbacks in comparison with UniBiometrics systems.

- As they use multiple sources of information so for capturing different biometrics, different instruments are required making the system more expensive.
- More storage space and resources for computation are required by a multibiometric system as compared to UniBiometrics systems.
- Multibiometric systems need more user time during enrollment at image acquisition stage causing difficulty for the user.
- For combining the information obtained from multiple sources, an appropriate technique must be followed as different fusion techniques cannot result in providing equal accuracy of a multibiometric system. Different subsets of biometric traits are fused with different fusion methods, one fusion method cannot be applied to all the subsets of biometric traits, so the choice of fusion method is a crucial step.

2.2 Nomenclature of Multibiometric Systems

A multibiometric system relies on the biometric information provided by multiple sources. Depending on the nature of these sources, a multibiometric system can be categorized into the following five categories [9] as illustrated in figure 2.4:

2.2.1 Multi-sensor systems

Multi-sensor systems exploit several sensors to get images of a single biometric trait of an individual [9]. For example, a face detection system may use different cameras fixed at different position from face to capture the front, left or right side image of face of an individual; a camera with varying frequencies may be used to take images of the face, iris or ear; or an optical sensor may be employed to acquire fingerprint image of an individual. The employment of multiple sensors in a multibiometric system can result in achieving related information that can significantly improve the identification prospective of the system. As an example, images of a person captured in varying illumination, or images captured in infrared light can give different information resulting in improvement or may be reduction in recognition accuracy. Similarly, a 2D face authentication system can be made more efficient by using a 3D camera for face images employing the shape information of the individual's face.

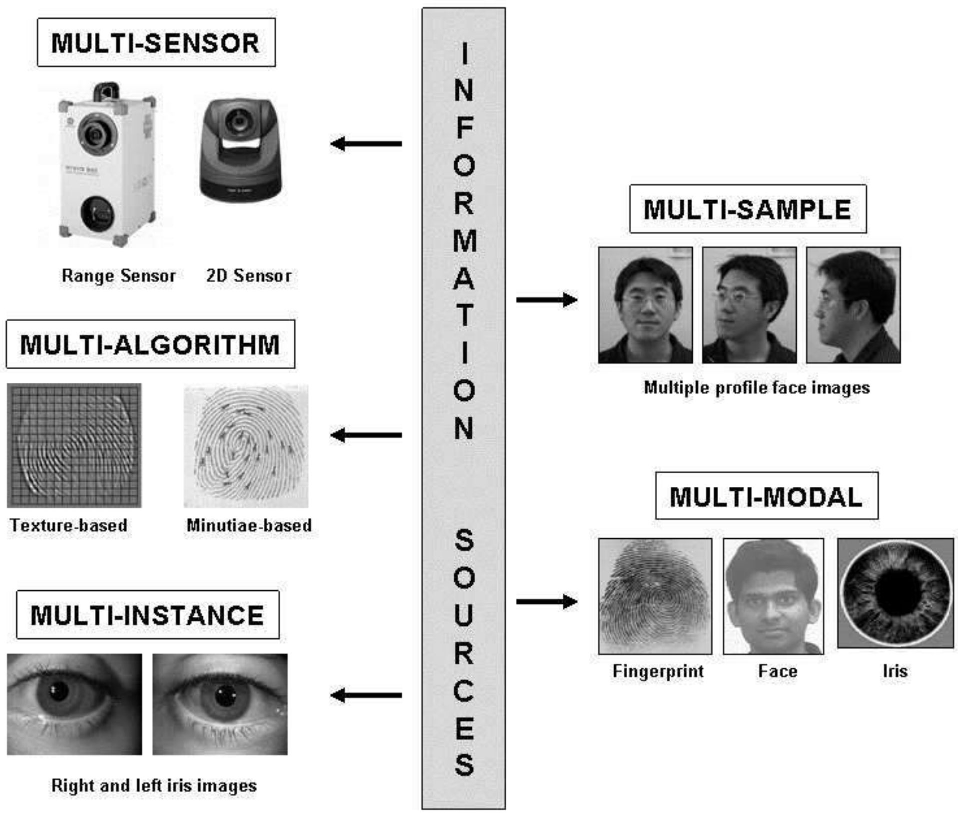


Fig. 2.1: Information sources for biometric fusion [9]

2.2.2 Multi-algorithm systems

Sometimes more than one feature extraction method applied on the one biometric data may result in considerable recognition accuracy of the multibiometric system. Multi-algorithm systems employ different algorithms or feature extraction methods and each algorithm produces a feature vector. These feature vectors are combined using particular fusion technique. They are cost-effective in a sense that they do not require much hardware (sensors) compared to other categories of multibiometric systems. However on the other hand, time and computational complexity are increased due to the use of various feature extraction and identification modules in the system. For example Sabareeswari et al [13], have proposed a multimodal biometric system using signature, face and ear biometric traits using two feature extraction methods of FLD (Fisher's Linear Discriminant) and PCA (Principal Component Analysis).

2.2.3 Multi-instance systems

A multi-instance system attempts to exploit multiple images of a single biometric trait. They are also called multi-unit systems [9]. For example, the system captures images of both index fingers or both irises of an individual for identity verification. These systems are more cost effective as only one sensor can be used to take the multiple images of a single biometric trait sequentially. As an example, Jacob et al [52] have used multi-instance, unimodal biometric system implementing nine images of fingerprints for each individual for verification purpose.

2.2.4 Multi-sample systems

In a multi-sample system, more than one sample of the same biometric trait is taken from a single sensor to get images/samples with variation in illumination, position and/or expression that can occur in the trait [9]. For example, for a face identification system, the front image as well as left and right side face images are captured in order to deal with the variation in the facial pose and expression. Similarly, a small size fingerprint sensor is used to get various fingerprint regions with different orientations which are then stitched together using image mosaicing technology to get a complete fingerprint image. In a multi-sample system, a crucial step is finding the number of samples to be used in the system. Also it is significant that the samples obtained must present the variability among samples for one individual as well as the uniqueness of the individual's biometric data [9].

2.2.5 Multimodal systems

A Multimodal system declares identity of an individual based on the factual information provided by more than one biometric trait. For example, the old multimodal systems mostly use face and voice biometric features for identification and/or verification purposes as listed in Table 2.1. Better results can be achieved when uncorrelated traits e.g., fingerprint and face are employed as compared to correlated traits e.g., voice and lip movement [9]. The main disadvantage of these systems is the high cost of setting up these systems as multiple sensors are required for capturing multiple biometric traits. The significant advantage of these systems is that accuracy can be drastically enhanced by using more number of traits. This is the reason we are proposing a multimodal biometric identification system for achieving better results. The number of traits used in a particular verification scenario can be restricted by real-life consideration such as enrollment time of the whole population, the cost of deployment, throughput time according to various implemented algorithms, predictable error rate, etc.

2.3 Feature Extraction Methods

Feature extraction is a method employed for the purpose of dimensionality reduction, in pattern recognition and image processing. When the raw data entering into an algorithm is a large vector, then for earning time computation this data will be changed into a reduced set of features, which is also termed as feature vector. The process of transforming data into a set of features is called feature extraction [22]. It is necessary that the extracted features are chosen carefully, so that they may have the ability to extract the information from the input data for performing the desired task of identification/verification. Thus it reduces the complexity of the system by using reduced number of features instead of the full size input data.

A feature is function of measurement, that is capable of uniquely specifying some biometric property of an object/individual, and is calculated in a way that it can measure some valuable properties/characteristics of the individual/object [24]. Features can be classified into various categories according to the information provided by them:

- General features: These are application independent features for example color, quality, and form or shape. They are subdivided into the various classes; pixel-level features, global features, and local features. Pixel-level features are obtained at pixel level, e.g. color, location, etc. Global features are computed over the whole image or a cropped area of the original image. Local features are obtained by subdividing the image with the help of segmentation and/or edge detection.
- Application specific features: As the name implies, these features depend on the type of application for which they are generated for example human face, iris, ear, and other intangible features like voice, gait or lip movement etc [24].

A multibiometric system based on domain-specific features result in better performance as compared to general features. However, if expert knowledge is not available general features can be used. The examples of such general dimensionality reduction methods include Principal component analysis, Multifactor dimensionality reduction, Multilinear subspace learning, Linear discriminant Analysis, Latent semantic analysis, Nonlinear dimensionality reduction, Kernel PCA, Multilinear PCA, etc.

2.3.1 Principal Component Analysis

Principal Component Analysis is a statistical method in which one-dimensional as well as multi-dimensional data is analyzed. PCA monitors association between various dimensions of the given data and extracts principal dimensions, where the variation among the whole data is at peak [13]. The significance of PCA is that it determines those features that can describe most of the variation in the data by using only a small number of features. The PCA matrix consists of the eigen-values which are obtained from the covariance matrix **S** and hence it takes long time making it computationally expensive [25].

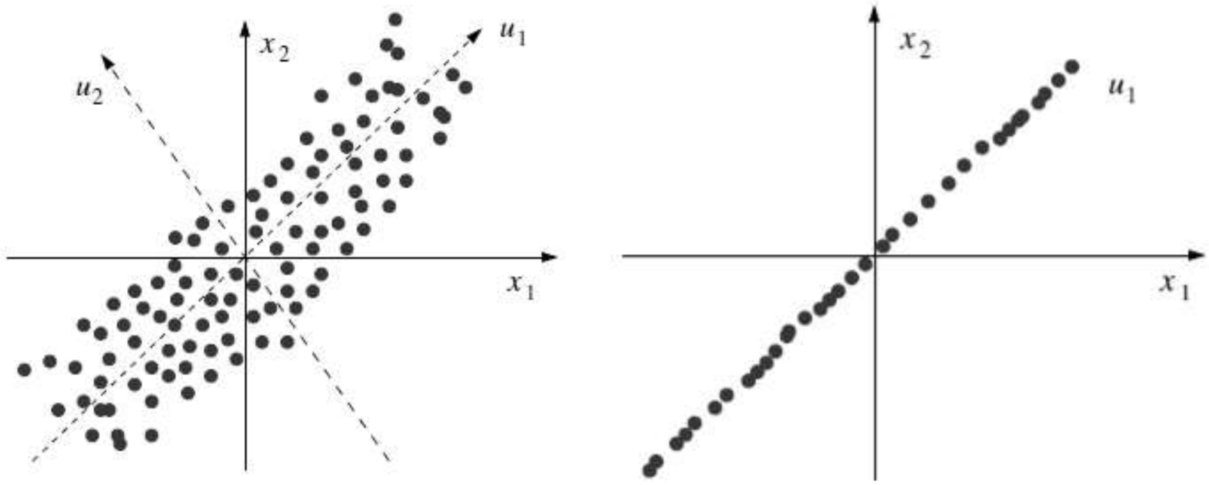
$$w \leftarrow eig\_decomposition(S = \sum_{i=1}^{n} (x_i - m)(x_i - m)^T) \tag{2.1}$$

where n represents the number of instances, $\mathbf{x}_i$ is the i^{th} instance, and **m** represents the mean vector of the input data.

Following algorithm depicts the process of obtaining principal components from a given input data:

1) First of all covariance matrix S is calculated from the given input data.
2) The eigenvectors and eigen-values of this covariance matrix S are then computed and sorted in a descending order with respect to the eigen-values.
3) A specific number of components from the eigenvectors are selected and a new matrix is formed.
4) Lastly, the product of the original space the obtained new matrix is computed, that results in dimensionality reduction.

For defining a threshold, the principal axis describes the required collective percentage of variance. This percentage defines the total number of components, chosen for making the new matrix.



(a) (b)

Fig. 2.2: The PCA model, (a) 2D space illustrating the geometric representation of principal eigenvectors, (b) 1D reconstruction (projection of the data) using the first principal component [15].

2.3.2 Linear Discriminant Analysis

Linear discriminant analysis (LDA) is also a statistical method like PCA and is most commonly employed in the fields of pattern recognition, image processing and machine learning to find a combination of features that are capable of distinguishing two or more classes of objects. The resultant set of features can be deployed as a linear classifier in an application. A LDA classifier is most commonly used as a dimensionality reduction method as well as a classification method.

LDA forms a subset of dependent variables representing a set of other features. LDA and PCA are similar in the sense that both of them search for a set of features that has the ability to explain the whole data significantly. LDA can clearly create the difference between the defined classes. On the other hand PCA cannot explain difference in classes.

During image acquisition, much of the variation is data is produced due to the changing illumination, position and expressions of the individual. In these conditions PCA cannot give highly consistent results [13]. To overcome this problem, LDA may be used to produce a subspace projection matrix. The LDA method takes advantage by utilizing within-class information and in this way it can significantly reduce variation within each class. However, it may still maximize class separation. The following equations show the scatter matrices, which shows the within class (S_W), between-class (S_B), and total distributions (S_T).

$$S_W = \sum_{i=1}^{C} \sum_{T_k \epsilon X_i} (Tk - \varphi_i)(Tk - \varphi_i)^T \tag{2.2}$$

$$S_B = \sum_{i=1}^{C} |X_i|(\varphi_j - \varphi)(\varphi_j - \varphi)^T \tag{2.3}$$

$$S_T = \sum_{n=1}^{M} (T_n - \varphi)(T_n - \varphi)^T \tag{2.4}$$

here the average of each individual class X_i is $\varphi_i = (\frac{1}{|X_i|}) \sum_{T_i \in X_i} T_i$ and the average image vector of the complete training set is $\varphi = \left(\frac{1}{M}\right) \sum_{n=2}^{M} T_n$ [13].

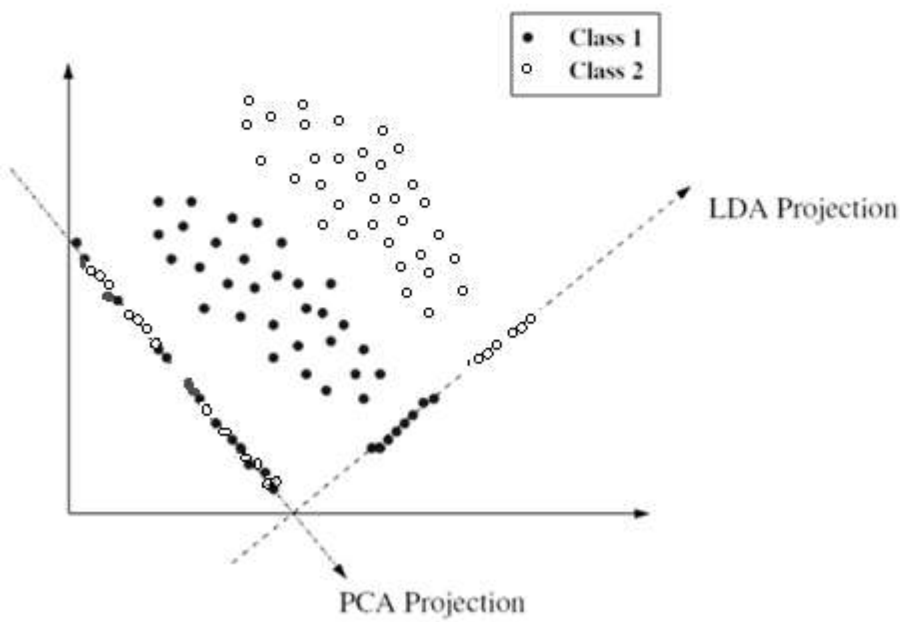


Fig. 2.3: An example of LDA and PCA projections for two classes [15]

2.3.3 Discrete Cosine Transform

Coding transformations are based on the fact that a pixels in an image must have a relationship with its adjacent pixels. As an example of the just stated fact, we have seen that in a video transmission, the adjacent pixels in successive frames show a high degree of association with each other. Therefore, this king of association between pixels can be utilized to predict a pixel from its adjacent pixels. Mapping of this correlated data into uncorrelated coefficients is called transformation. This transformation must be capable of exploiting the fact that an individual pixel contains relatively small information i.e., contribution of a pixel in an image or a sample can be predictable using its adjacent pixels [23]. Transform coding is an essential element of present-day image/video processing applications.

Discrete Cosine Transform (DCT) is one of the coding transformation method that has emerged as the tool for image transformation in visual applications in the last decade. It has been extensively used by video coding standards, i.e., JVT, MPEG, etc.

The Discrete Cosine Transform (DCT) attempts to transform the input image data into a form where coefficients have no correlation. Thus each of the resultant transform coefficients can be programmed separately without the loss of accuracy to be achieved during compression. This section illustrates the concept of DCT computation for image processing in detail and its important properties [23].

For computing DCT, the equation below shows vs (k), which are DCT coefficients and the sequence u (n) as a vector of an image. The output v(k) can be obtained by applying DCT as a transformation matrix to this image vector [20]. The DCT transformation matrix, C = {c (k, n)}, is defined as:

$$c(k,n) = \begin{cases} \frac{1}{\sqrt{N}} \; k = 0, 0 \le n \le N-1 \\ \sqrt{\frac{2}{N}} \cos\left(\frac{(2n+1)\pi k}{2N}\right) \; 1 \le n \le \mathrm{N}-1, 0 \le \mathrm{n} \le \mathrm{N}-1 \end{cases} \qquad 2.5$$

here *k* and *n* represent the row and column indices, respectively. Using above equation, the DCT of the sequence u (n) can be computed as:

$$\mathrm{v} = C\mathrm{u} \qquad 2.6$$

In order to get the original image back we can reverse the process by using inverse discrete cosine transform. It is employed to obtain *u (n)* from *v (k)* as defined by:

$$u(n) = \sum_{k=0}^{N-1} \alpha(k) v(k) \cos\left(\frac{(2n+1)\pi k}{2N}\right) \; 0 \le n \le N-1$$

2.7

By arranging Eq. 2.6, the inverse discrete cosine transform, u, of a vector v is obtained by taking the inverse of matrix C. Mathematically, the inverse discrete cosine transform is obtained from the following equation:

$$u = C^{-1} v \tag{2.8}$$

The above definitions describe that by applying the discrete cosine transform to an input image vector, we can decompose it into a summation of basic cosine series [20]. Eq. 2.7 shows that u(n) can be constructed again by adding the cosine sequences. The summation of cosine sequences is weighted by the DCT coefficients. These basic sequences of the DCT are the rows of the matrix C.

In the paper [20], two methods of feature extraction have been used, i.e., PCA and DCT. Comparison is performed on the basis of number of coefficients used and the size of database. They have shown that PCA takes more computation time for processing coefficients during the enrollment stage as compared to DCT. However, once the enrolled database has been computed, PCA uses very less time during the matching process of input image coefficients with the enrolled database as compared to DCT. The cumulative recognition accuracy has been computed which shows that the DCT outperforms the PCA method as shown in Fig 2.3.

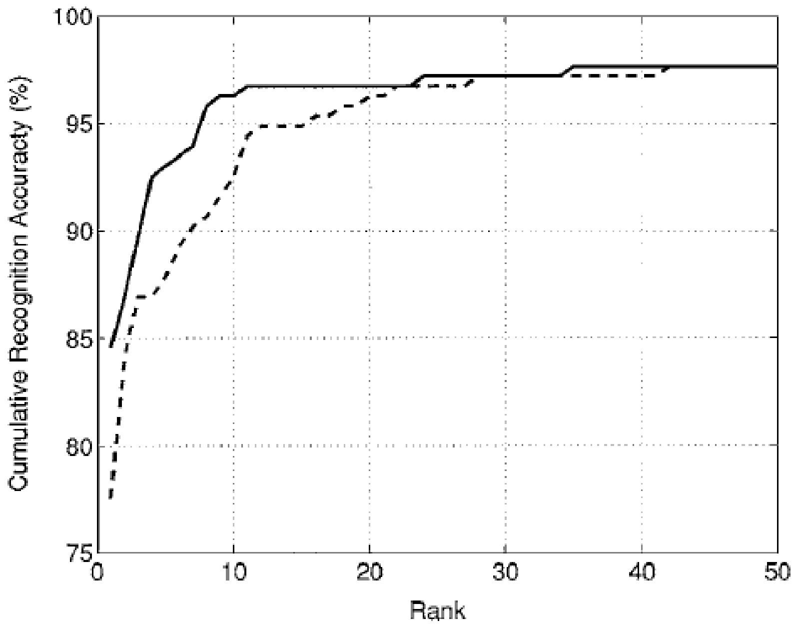


Fig. 2.4: Comparison of DCT and PCA in terms of Cumulative recognition accuracy as a function of rank for the CIM face database. (- DCT, - - PCA) [20]

2.4 Levels of Fusion in Multibiometrics

Before implementing the fusion process, it is essential to find out the type of information that needs to be combined/ consolidated. The level of information decreases after each step of processing in different element of a multibiometric system [19]. The richest source of information is contained in the raw data captured form the sensors whereas the final decision provided by the biometric system just contains an abstract level of information.

There are two basic levels of fusion i.e., pre-classification (fusion before matching) and post-classification (fusion after matching). These fusion levels are further subdivided. Fusion before matching has two subdivisions i.e., sensor level fusion and feature level fusion. Fusion after matching is subdivided into score level fusion, rank level fusion and decision level fusion [19]:

2.4.1 Fusion before Matching

2.4.1.1 Sensor Level Fusion

The raw data that is just captured by one or more sensors is consolidated. This is called sensor level fusion. This level of fusion cannot be performed on two different biometric traits. It is the limitation of this fusion that it can only be used when we have multiple instances of the same trait captured from single sensor, or multiple samples of the same trait captured from multiple sensors. For example, various 2D face images acquired from multiple sensors positioned at left, right and front of the face can be stitched to make a 3D image of the individual's face [21]. It is an essential point in sensor level fusion that various samples must be well-suited and the association between points in the original samples must be known before applying fusion.

2.4.1.2 Feature Level Fusion

Feature vectors created by various information sources are integrated in feature level fusion into a new feature vector. For homogeneous feature sets (multi-instance systems), for example, multiple images of a person's hand geometry, first the weighted average of the individual feature vectors is computed and then the resulting feature vectors are fused [27]. For non-homogeneous feature sets, (multi-modal system), for example, features of different biometric traits like face, iris, and ear, a single feature set can be obtained by concatenation of the biometric feature vector.

Dimensionality reduction scheme like feature selection/transformation is applied to obtain a minimal feature set. The key advantage of the feature level fusion is that it facilitates the removal of correlated feature values improving recognition accuracy. Feature level fusion is difficult to be employed for the following causes [28]:

1) The feature vectors obtained for multiple biometric traits might be incompatible for fusion. For example, the eigenvectors of face and the minutiae set of fingerprints.
2) By concatenating two or more feature vectors, the resultant vector might have very large dimensions and this might cause dimensionality problem. In such cases, when sufficiently large numbers of training samples are not available, increasing number of features result in performance degradation.
3) Access to the feature vector might not be provided in most cases by commercial biometric system vendors.
4) More complex matching algorithms might be required to work on concatenated feature vectors.

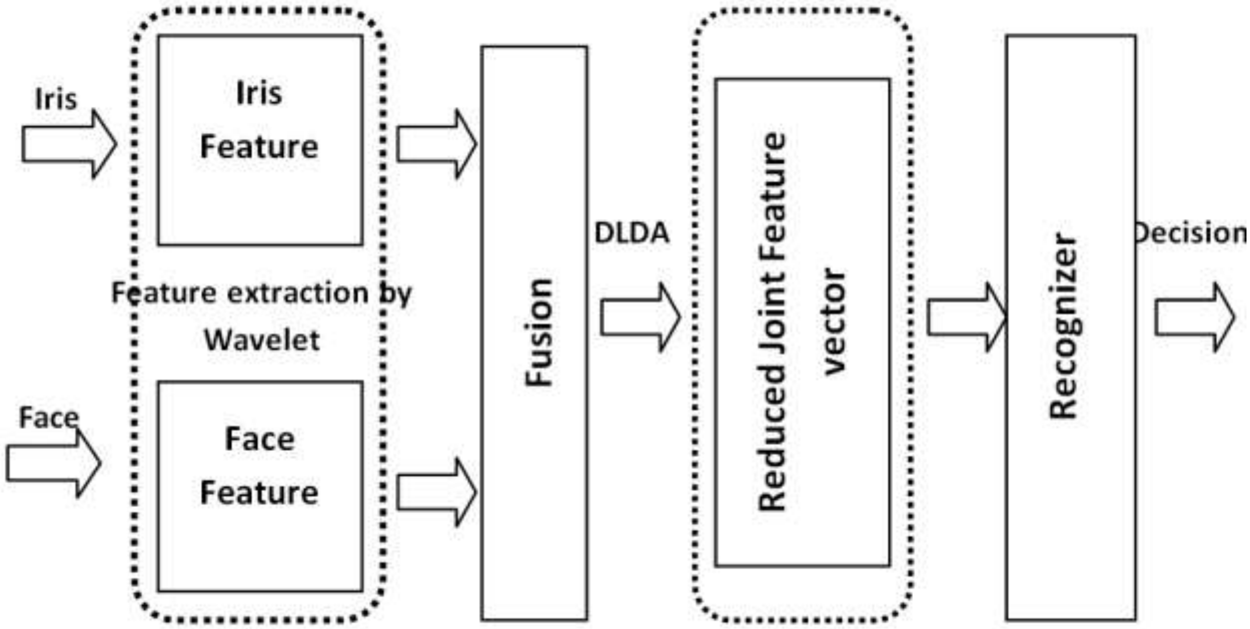


Fig. 2.5: Example of feature level fusion using face and iris biometric traits [19].

2.4.2 Fusion after Matching

2.4.2.1 Score Level Fusion

Different biometric matchers provide match scores representing the relationship between the input and the stored template vectors from the database. These match scores are consolidated to reach the final recognition decision. After the sensor level and feature level information, highest level of information is contained by the match score about the input biometric sample. Fusion at this level provides the best swap over between the available information content and convenience of fusion. Therefore, this scheme is extensively studied in literature. This level of fusion is also called measurement level fusion or confidence level fusion.

Fusion methods at score level have been further subdivided into three kinds [19]: transformation, density and classifier-based techniques.

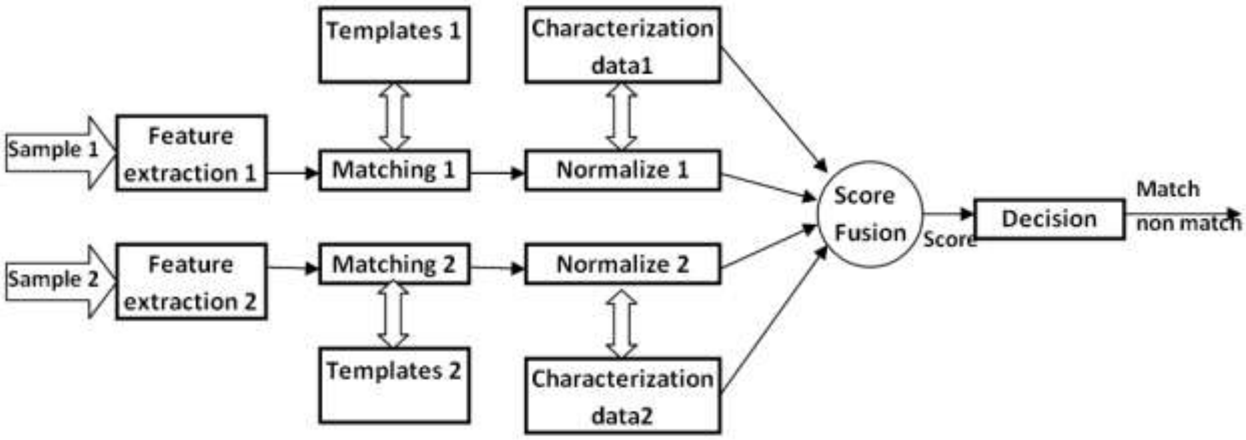


Fig. 2.6: Match score level fusion [19]

2.4.2.2 Rank level Fusion

A rank is associated in the rank level fusion with each biometric trait at every module of the biometric system. The higher rank assigned to a biometric trait indicates a better match [19]. Rank level fusion requires combining the multiple ranks of individual biometric subsystems to determine a new rank for each biometric trait. The decision is made according to the new ranks for all identities. Ranks reveal more information for determining the best match and provide less information as compared to the match scores.

There are three methods usually used to consolidate the ranks allocated by each biometric matcher. Those are the logistic regression, the borda count, and the highest rank method. Logistic regression is the most efficient among the three methods.

2.4.2.3 Decision Level Fusion

Decision level fusion is employed when the final recognition decision by each of the individual biometric recognition system is available at hand. Most of the commercial off-the-shelf (COTS) biometric systems use this level of fusion. They are designed in such a way that the user can see only the final decision of the individual biometric matchers. In this case, only decision level fusion can be employed feasibly. Decision level fusion can be incorporated using the methods like majority voting, ‘and’ and ‘or’ rules, Bayesian decision fusion, weighted majority voting, the Dempster-Shafer theory of evidence, etc [21].

Table 2.1: Examples of multimodal systems

Modalities	Authors	Level of Fusion	Fusion Methodology
Face and voice	[33]	Match score;	HyperBF; Rank Geometric weighted average
	[35]	Match score	Min, Max, Sum, Product and Median rules
	[29]	Match score	SVM; multilayer perceptron; C4.5 decision tree; FLD; Bayesian classifier
	[31]	Match score	Bayesian theory
Face, voice and lip movement	[2]	Match score	Weighted sum rule at Decision level fusion; majority voting
Face and fingerprint	[38]	Match score	Product rule
	[32]	Match score	Sum rule, Weighted sum rule
Face, fingerprint and hand geometry	[47]	Match score	Decision trees; Sum rule; linear discriminant function
Face, fingerprint and voice	[34]	Match score	Likelihood ratio
Face and iris	[37]	Match score	Sum rule; weighted sum rule; FLD; neural network
Face and gait	[46]	Match score	Sum rule
	[48]	Match score	Sum and product rules
Face and ear	[39]	Sensor	Concatenation of raw images
Face and Palm print	[41]	Feature	Feature Concatenation
Fingerprint, hand geometry and voice	[42]	Match score	Weighted sum rule
Fingerprint and hand geometry	[30]	Match score	Reduced multivariate polynomial model
Fingerprint and Voice	[43]	Match score	Functional link network
Fingerprint and signature	[45]	Match score	SVM (quality measures incorporated)
Voice and signature	[36]	Match score	Weighted sum rule

Summary

The design of multibiometric system usually depends on various aspects such as capturing and processing of input samples, sources of information, and fusion level scheme. In the last decade, a lot of work has been done by using different taxonomic architectures of multibiometric systems and the efficiency of a particular method depends on the specific application for which the biometric system has been deployed. The chapter discusses various feature extraction methods and different levels of fusion employed by multibiometric system in order to efficiently consolidate multiple biometric feature vectors in a way of providing minimum loss of information content. Table 2.1 summarizes some of the work in the field of multibiometrics depending on the sources of information used.

From these tables, it is obvious that the match score level fusion has been studied and practiced extensively by the biometrics experts. However, informal methods of normalization have been employed by these match score level fusion strategies for finding weights of each biometric trait used. Also the feature level fusion has not been broadly studied. Hence, our thesis aims at developing a structure for feature level fusion in multibiometric systems.

Chapter 3
Literature Review

3.1 Overview of the Existing Methods

Hong et al [1] described a bimodal biometric system using fingerprint and face biometric traits. The system utilized the minutiae-based fingerprint and PCA based face recognition system. Fusion at the decision level has been used. PCA is deployed in those systems where a smaller number of artificial variables are to be formed from the observed variables obtained during image analysis. The artificial variables are called principal components of the original image. These components are then used for prediction of other variables in the next stages of the identification system. The authors have compared the unimodal systems for their biometric traits with the multimodal biometric system obtained after fusion. With 0.01% FAR, the unimodal face systems attained FRR of 61.2% and for fingerprint unimodal system the achieved FRR is 10.6%. However the multimodal approach outperformed the unimodal approach by resulting in FRR of 6.6% for the same value of FAR.

Limitation of the system is that decision level fusion assumes that the matching values of faces are numerically independent and have no correspondence with the matching values of fingerprints. While the assumption is valid for fingerprints and faces, it may not be true for other biometric characteristics.

Frischholz et al [2] proposed a multimodal approach for commercial purposes named BioID. The system uses three biometric traits i.e., face, voice and lip movement for individual verification. Face images and lip movement were captured during a video progression and the voice is taken from an audio device. According to the security level, experiments on 150 persons produced good results with an FAR value below 1%.

The classification process implemented by the authors can lead to insecurity which is the major drawback of BioID. After preprocessing of a runtime pattern of the three biometric templates ranked scalar products are obtained and the highest rank suggests the resulting class. This policy is termed as winner-takes-all. As this policy always results in a classification because it never rejects a pattern so the authors accounted for the second highest scalar product. They provided a rule that if the difference between the highest and the second highest ranked output is smaller than a specified threshold, the pattern will be rejected otherwise accepted. Judgment on the classification result is based on the fact that if the difference between the two highest scalar products is approaching to zero, the two people are impossible to distinguish, and the therefore this proposed method of classification leads to “insecurity.”

Object recognition systems widely use appearance-based methods [3]. PCA and LDA are the most implemented appearance based methods and have been confirmed to be useful for many applications for example face recognition. It is generally taken that LDA would always performed better than PCA, however there are systems that suggest otherwise based on the application scenario.

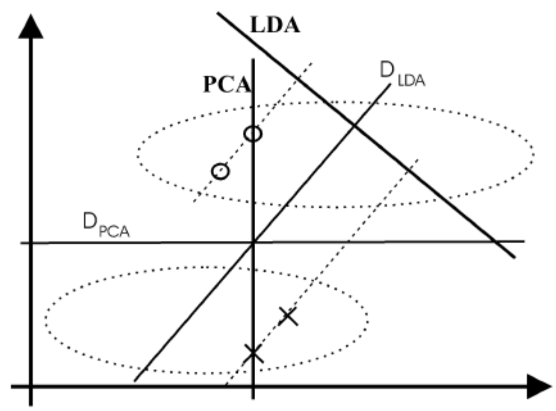


Fig. 3.1: Two different classes shown by the two Gaussian-like distributions, two samples per class provided to the learning procedures, PCA or LDA. Classification result produced by PCA using only one eigenvector is more than that produced by LDA. DLDA and DPCA are the decision thresholds suggested by using nearest-neighbor classification [3].

The figure above shows that the PCA might outperform LDA when we are dealing with small number of samples per class or secondly, when the training data non-uniformly samples the fundamental distribution. In many of the practical applications, and especially face recognition, we cannot predict/know beforehand the underlying distributions for the various classes. So, for practical applications it would be difficult to determine whether the available training data is sufficient for the job or not.

Fierrez-Aguilar et al [4] suggested a multimodal approach using three biometric trait i.e., face, fingerprint, signature. The face system is based on selection of global features and minutiae are extracted for the fingerprint system. The signature system uses HMM modeling of sequential functions combined together with the help of fusion methods. Two score level fusion methods have been used i.e., support vector machine (SVM) and the sum-rule which are implemented both as user-free and user-reliant methods. The EERs of the unimodal systems for face, the online signature, and the finger print verification systems were 10%, 4%, and 3%, respectively. However the multimodal system fused with the sum-rule, the SVM user-free, and the SVM user-reliant approaches achieved EERs of 0.5%, 0.3%, and 0.05%, respectively. The stated results showed that the multimodal system has outperformed all the unimodal biometric systems.

Disadvantage of the paper is that these values are calculated by using a database of only 50 individuals which cannot prove good for real-life applications comprising of huge databases.

Kumar et al [5] developed a bimodal approach using two biometric traits i.e., palm print and hand geometry. These biometric traits are fused at two fusion levels; at the feature level fusion by concatenation of the feature vectors as well as at the match score level fusion by using max fusion rule. Only the fusion approach at the matching score level outperforms the unimodal systems. The palm print performs better than hand geometry unimodal system. The palm print the best among the two unimodal approaches gained a FAR of 4.49% at an FRR of 2.04%. However the fusion of these unimodal systems resulting in a multimodal approach performs better by achieving a FAR of 0% at a FRR of 1.41%.

The advantage of the paper is that only one sensor is used to get the images of both biometric traits hence making the proposed method user-friendly as the user does not face the inconvenience of going through multiple sensors for capturing multiple images for other multibiometric systems. The authors have stated the drawback because of user-involvement at the image acquisition stage that some users could not touch their palm/fingers on the imaging board properly causing FTE (Failure-to-Enroll) error. These images were removed. Out of 500, 28 such images were identified and discarded. This causes performance degradation.

In the same year Heseltine et al [6] investigated the three face recognition methods; the eigen-face method, the direct correlation method, and fisher-face method or Fisher's Linear

Discriminant (FLD), when applied during the pre-processing step. The optimum image pre-processing techniques were used which showed that the FLD method has the lowest EER (17.8%), performing better than the other two methods. FLD consumes less time in computation however it was slightly better than direct correlation with an EER 18.0%. The Eigen-face method showed the least accuracy with an EER 20.4%.

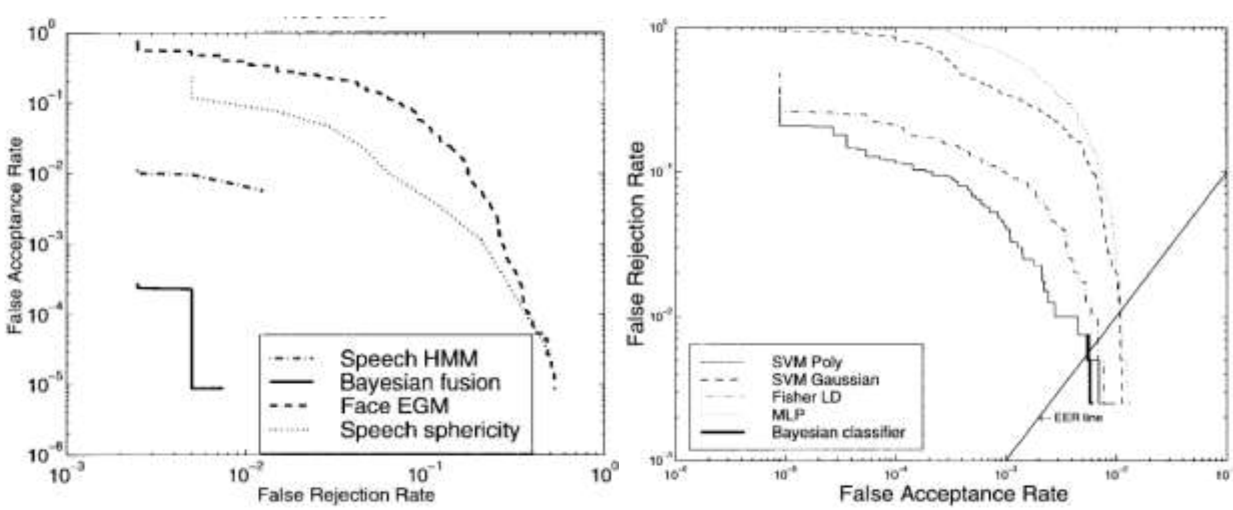
The advantage of the paper lies in the use of FLD which uses its property of utilizing within class information, as it reduces variation within each class and at the same time maximizing class separation. In other words, it tries to reduce FAR. The limitation of the paper is that the authors were still unable to identify which preprocessing methods have enhanced which specific features and when a given preprocessing method performs most efficiently.

Toh et al. [7] proposed a multimodal biometric system based on three biometric traits; hand geometry, fingerprint, and voice. These traits have been fused at the match score level with weighted sum rule. They took the multimodal decision problem at match score fusion as a two-stage problem i.e., learning and decision. Experiments performed on the unimodal biometric systems of fingerprint, speech, and hand-geometry confirmed that only local learning can enhance verification ERRs to almost 50%.

In 2005, Snelick et al. [8] developed a bimodal multibiometric system based on fingerprint and face biometric traits. These systems are fused at match score level. Three fingerprint recognition systems and one face system were used for implementing the proposed the method. The EERs of the best fingerprint system and the face recognition system were 2.16% and 3.76%, respectively, while the multimodal system developed through the max fusion rule on normalized scores attained an EER of 0.63%.

Their work has shown that Counter-of-the-shelf (COTS) multimodal biometric system using fingerprint and face biometric traits outperform the unimodal COTS systems. However, the accuracy of the proposed COTS multimodal system is not better than the non-COTS existing multimodal systems developed by others.

Ross et al [9] described the methods for efficiently consolidating different sources of biometric information. They have proposed that early fusion methods are expected to perform better than delayed fusion methods or simply feature level fusion can perform better than score-level and decision level fusions. However, prior to implementation of fusion methods it is not possible to estimate the performance gain achieved through each of the methods. They have compared unimodal biometric systems of face and voice modalities with their multimodal counterparts. And results have shown the improved performance with multimodal biometric system. The figure 3.2 (a) shows the ROC curves of the unimodal and multimodal systems fused through Bayesian fusion technique. Part (b) shows the performance of different classifiers for the multimodal system. Roc curves show that Bayesian classifier has outperformed the other methods of SVM Poly, SVM Gaussian, Fisher Linear Discriminant and Multilinear Principal Component Analysis.



(a) (b)

Fig. 3.2: Performance comparison of (a) unimodal and multimodal biometric systems, and (b) classification methods [9]

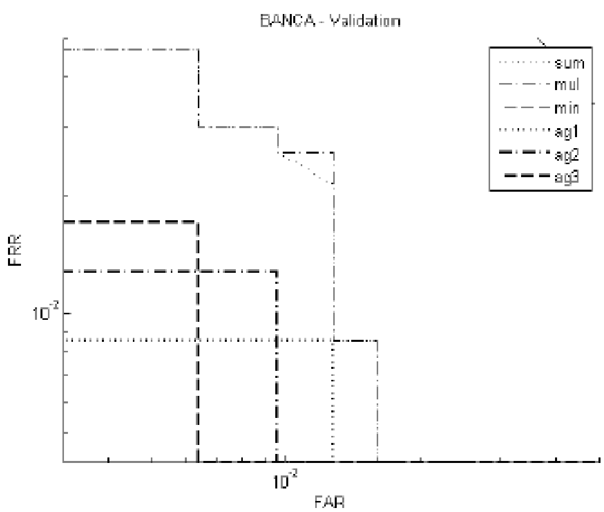
A new unimodal approach for efficient individual identification has been introduced in 2009 by Kumar et al [10] using Knuckle Codes. The preprocessed knuckle images are employed to generate Knuckle Codes with the help of localized Radon transform that clearly show random curved lines and wrinkles. The similarity between two Knuckle-Codes is calculated from the least matching distance which results due to noisy data like variations resulting from positioning of fingers. The practicability of the proposed approach is checked on a database of finger knuckles from 158 subjects. Experiments showed an EER of 1.08% and rank one recognition rate of 98.6%, therefore proved that the proposed method can be used for human identification.

Various fusion methods can be implemented on UniBiometrics systems for generating multimodal biometric systems. The fusion can be applied by using different algorithms on the same biometric trait. For example, Hocquet et al in 2007 [11] worked with three different keystroke which are fused together in order to get a decrease in error equal rate (EER). The limitation here is that less than 40 subjects have been used in the database. In the same year, Teh et al [12], developed a fusion approach with two keystroke systems. These systems are fused on the whole by using weighted sum rule. However, information about assigned weights and their computation is not listed. Also the system is implemented by using only 50 subjects. They also proposed that fusion methods can be implemented on different biometric traits to improve the biometric verification.

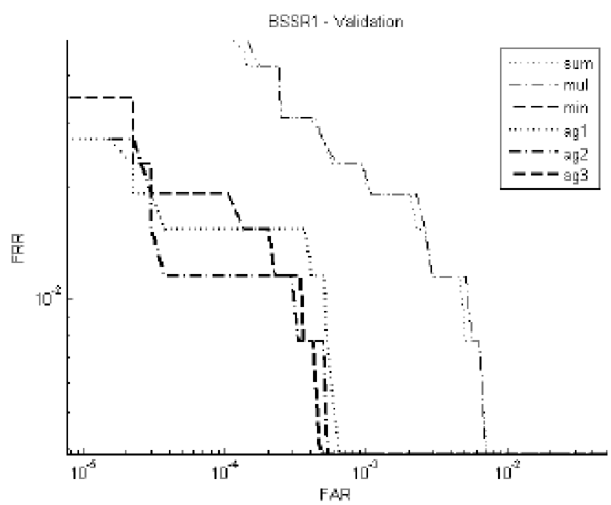
In 2010 Sabareeswari et al [13] proposed a multimodal biometric system using three biometric traits i.e., face, ear and signature. The proposed system utilizes two techniques at the feature extraction level; PCA and FLD (Fisher's Linear Discriminant) for identity authentication. The proposed system implemented the novel rank level fusion method for consolidating the three different biometric matchers. Three methods have been used for combining the ranks of individual matching biometric systems. They are the logistic regression, the highest rank and the Borda count. Results have shown the better performance of logistic regression among the three rank level approaches.

The advantage of the method is that even with low quality image data for the face, signature and ear traits, fusion of three unimodal systems enhances the overall performance of the multibiometric identification system. One of the limitations of the paper is that the use of signature verification is a time-consuming process for the user in real time situations. For the purpose of person identification, selection of signature biometric identifier is inappropriate as signatures are used normally for verification purposes. Another limitation is that the authors have incorporated PCA and FLD based global features only, however if local features were extracted from the images, performance could be enhanced.

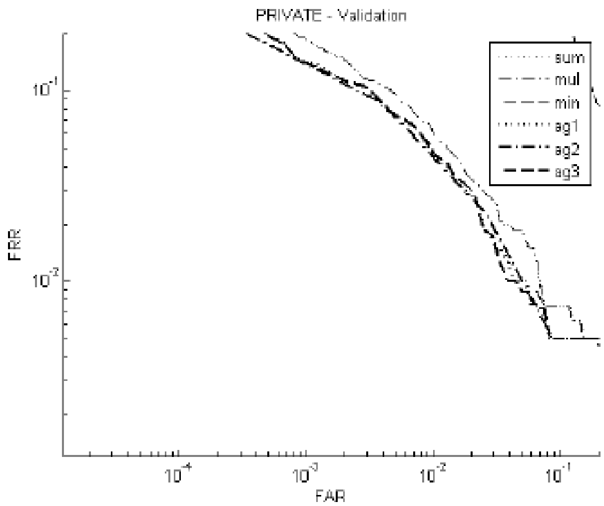
In the same year Giot et al [14] have presented a multimodal biometric system that focused on two important considerations in the field of multibiometrics. They have proposed a high-speed EER calculating method and two fusion techniques which are optimized through genetic algorithm. Five different biometric systems have been used to test the developed EER calculating method and a comparison is made with the existing methods. Three multibiometrics (two real and one virtual) databases have been deployed. Fusion has been performed at the match score level and has been validated on the databases. Their method is superior to other methods because it uses less time and give accurate results in terms of EER. These results have proved that fewer impostors can be accepted as well as fewer authentic users can be rejected by using this system. Furthermore better security can be achieved for the verification process. Best gain calculated on three databases is 78% whereas the least is 28%.



(a)



(b)



(c)

Fig. 3.3: ROC Curve of proposed fusion functions on the three databases (a) BANCA (b) BSSR1 (c) PRIVATE [14].

The advantage of the proposed method is to reduce the computation time of the genetic algorithm because its fitness function is calculating the EER. Results have shown that the fusion functions along with the use of genetic algorithm have outperformed the existing fusion functions i.e., sum, min and product. Limitation of the paper is that the ROC curve is not precise due to computing time earning. Table 3.1 gives the comparison of EER on three different datasets.

Table 3.1: EER and Time Gain by using the proposed EER calculating method [14]

Function	Train EER	Test EER	Gain (%)
BANCA			
(5): ga1	**0.0032**	0.0091	**61.29**
(6): ga2	**0.0032**	0.0091	41.84
(7): ga3	0.0037	**0.0053**	43
BSSR1			
(5): ga1	0.000596	**0.0038**	**78.32**
(6): ga2	**0.000532**	**0.0038**	64.77
(7): ga3	0.000626	**0.0038**	28.49
PRIVATE			
(5): ga1	0.019899	0.0241	**77.66**
(6): ga2	**0.019653**	0.0244	46.5
(7): ga3	0.020152	**0.0217**	55.03

Jacob et al [52] proposed a unimodal multi-instance approach for finger prints implemented by feature level fusion. The proposed system aims that the feature level has better performance than the matching score on the basis of their processing time. Nine randomly selected multi-instance images undergo thinning process twice, once using Hilditch's algorithm and second time using Hit and Miss Algorithm. Correlation based feature extraction is used and for finger matching, cross correlation motivated by square Euclidean distance has been employed. Final decision is made by comparing the fusion results with a set threshold.

The above systems proved that feature level fusion proved to be much effective in terms of availability of raw materials and performance if multiple traits of the same biometric are used. Secondly, the processing time has been reduced as normalization for the same biometric feature vectors is not required as they are already compatible for fusion purpose. There are several limitations of the proposed method. If fingerprint orientations are a little misplaced the system cannot generate accurate results i.e., it has the problem of lack of uniqueness/individuality. Also the cross correlation technique sometimes caused problems in matching like nonlinear distortions, variation in skin condition and finger pressure.

In the thesis [15], a new multimodal recognition system is proposed which combines the evidences from face and fingerprint biometric traits. Fusion of these traits is made at the decision level. In this approach, the two biometric classifiers are independently so that class specific information can be accessed for enhancing performance. Results have shown that the proposed methodology outperforms the existing state-of-art fusion techniques.

LDA and Non-Parametric LDA have been employed for providing class specific information. Face biometric classifier is good at providing this background information. Due to the presence of high sensitivity of minutiae points, fingerprint biometric classifier cannot provide this information hence cannot identify and individual's identity properly.

Fusion is applied on the two biometric classifiers using sum rule. The authors have also proposed a method of Multiple Classifier Combination (MCC). Experiments have proved that the proposed method (LDA and Nonparametric LDA) outperforms the on hand fusion techniques like sum and product rules, Dempster-Shafer theory and decision template. Their results are presented in table 3.2 below.

Table 3.2: Performance/Accuracy (%) of multimodal biometric databases calculated with different fusion methods [15].

$TestSet$	Sum	Max	Min	Product	DT	DS	P_{LDA}	P_{NLDA}
$Test_{11}$	93.00	92.67	88.00	92.33	83.00	82.33	96.00	**97.67**
$Test_{12}$	88.75	88.33	70.83	81.67	78.33	80.83	92.50	**92.92**
$Test_{13}$	87.22	85.56	65.56	78.33	77.22	82.22	91.11	**92.78**
$Test_{14}$	91.11	84.44	62.78	78.89	80.00	85.55	**94.44**	92.78
$Test_{21}$	92.67	86.00	81.67	91.33	85.00	84.67	98.33	**98.67**
$Test_{22}$	85.83	80.83	69.17	77.08	83.75	83.75	96.25	**97.08**
$Test_{23}$	85.56	82.22	64.44	74.44	79.44	79.44	**96.67**	**96.67**
$Test_{24}$	88.89	78.89	65.00	76.67	80.56	87.22	**97.22**	**97.22**

3.2 Problem Statement

Sabareeswari et al [13] proposed a multimodal biometric system using three biometric traits i.e., face, ear and signature that have been fused at the rank level. The proposed system utilizes two techniques at the feature extraction level; PCA and FLD (Fisher's Linear Discriminant) for identity authentication. It has been observed that the use of signature verification is a time-consuming process for the user in real time situations. For example if a person is to be identified, it should be the responsibility of the organization to identify that person without user involvement in order to speed up the identification process. In other words, user-involvement reduces the time efficiency of the identification process and causes delay

Secondly, the authors have implemented PCA and LDA based global features only. They have shown the superiority of FLD over PCA that has already been proved. Furthermore, it has been observed that the existing methods of PCA and LDA do not perform equally well in case of different fusion techniques and with different datasets. So a new approach with different biometric traits (fusion of which have not yet been studied) is required to overcome the problems faced by PCA and LDA systems.

Summary

Although rapid progress has been observed in the development and deployment of biometric systems for identification/verification and authentication purposes in the past few decades, a number of research issues in biometrics still require a lot of expert's attention. The error rate of the biometric systems cannot have zero value due to the factors of intra-class variations and inter-class similarity. Furthermore, the high failure rates (FTER and FTCR) also limit the use of biometric systems in various applications.

Solutions for approaching the error rates to zero in biometrics include the development of new sensors that can reliably, conveniently and securely capture the biometric traits of an individual. Also biometric system performance can be increased by the development of efficient matching algorithms, selecting best fusion strategies for consolidating evidence from multiple biometric sources in order to reduce the limitations caused by using individual sources and the development of methods for template security of the multibiometric systems. In this thesis, we focus on biometric systems that integrate evidence obtained from multiple biometric traits for efficient human identification. Multibiometric systems provide many advantages that can reduce the problems caused by the commonly-used UniBiometrics systems. This thesis mainly deals with two crucial matters in the design of a multibiometric system, namely, feature extraction methodology, and feature vector optimization.

Chapter 4
Proposed Methodology

4.1 Introduction

A new multimodal biometric system is proposed that reduces user involvement at the identification stage to make the process of identification as fast as possible in everyday life. For that reason, the traits of signature, palm print, finger prints, keystrokes and voice cannot be utilized as they take a lot of user's time in scanning of these traits. Instead iris, face and ear images are to be incorporated in the system so that computation time can be minimized.

Secondly, Discrete Cosine Transform (DCT) is employed along with the old techniques of feature extraction like PCA and FLD. Genetic Algorithm (GA) is used for feature vector optimization after feature fusion from the three traits (face, ear, and iris). Selected features are then incorporated into a classifier that classifies and shows the result. The classifier confirms the identity of the person and outputs as "identified" or "unidentified".

4.2 Proposed flow of work

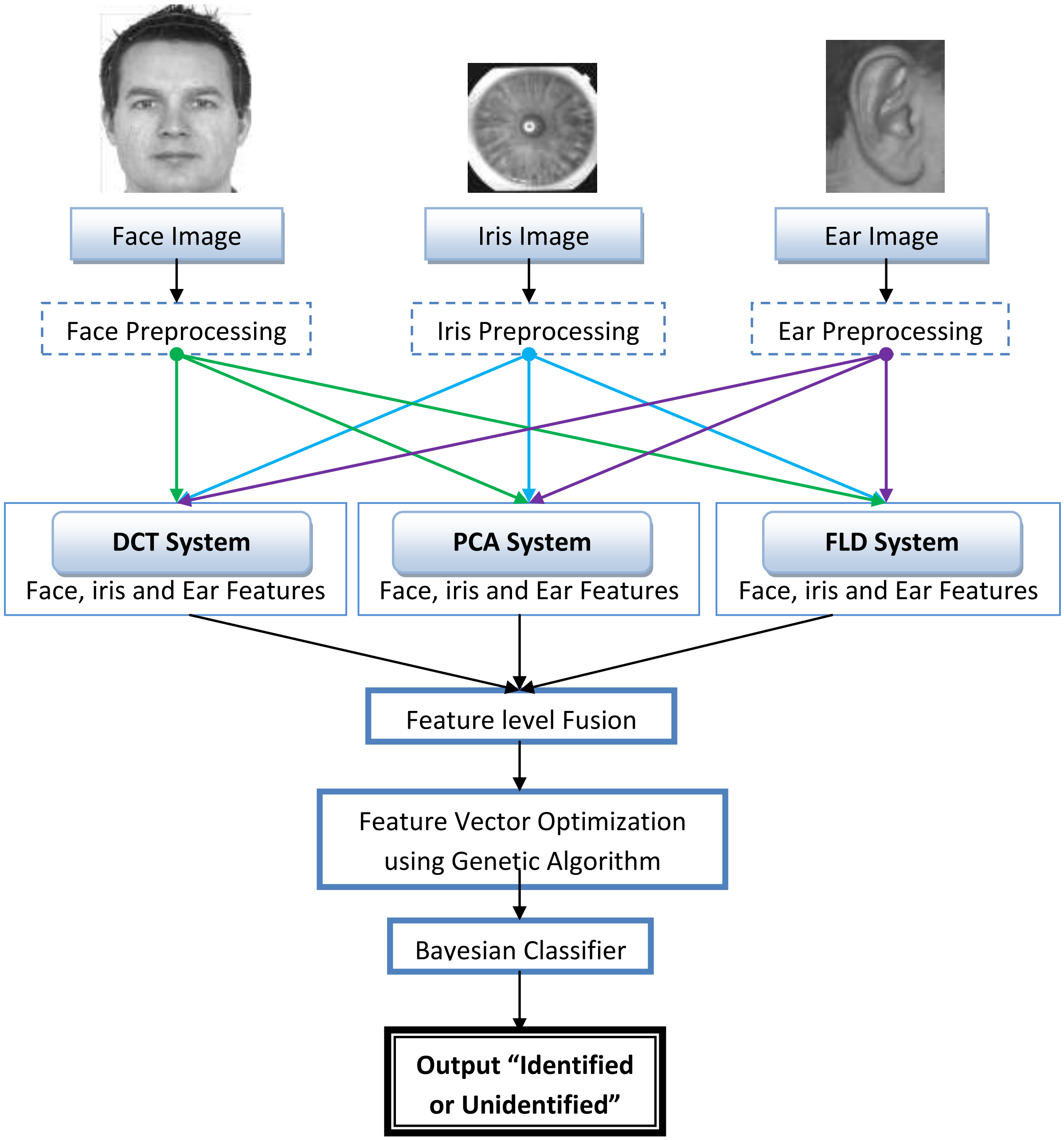


Fig. 4.1: Flowchart of the Proposed Solution

The flowchart of the proposed work has been shown in figure 4.1 above. According to the figure, images of the three databases (face, iris and ear) are sent to the preprocessing step. Due to the unavailability of the biometric traits for a single person, we have implemented a virtual database by pairing the three sets of face, iris and ear datasets.

4.3 Image Preprocessing

Introduction of an image pre-processing step can radically reduce error rates. It has also been observed that different image pre-processing techniques influence each subsequent method differently. The results produced by some image processing techniques can be unfavorable e.g., blurring, smoothing, hue representations and comprehensive normalization, and others are generally beneficial e.g., sharpen, detail, edge, enhance. Some image preprocessing techniques may decrease error rates for some methods while increasing error rates for others.

In our proposed method, the images from the three datasets have been preprocessed by using 2-D Gaussian low pass filter and laplacian of Gaussian filter. The results of image preprocessing are shown in fig. 4.2 below. First the colored image is converted into a gray scale image. The gray scale image is introduced into the Gaussian filter. This filter produces a blurred image. Then this blurred image is passed through the laplacian of Gaussian (log) filter that will enhance the areas of depressions and elevations. This 'log' filter image is added to the blurred image. The resultant image is now preprocessed and will enter to the feature extraction stage.

(a) (b) (c)

(d) (e)

Fig. 4.2: Preprocessing Results (a) Original Image, (b) Gray-scale Image, (c) Blurred Image using Gaussian filter, (d) 'Log' filter Image, and (e) Final Image from (c) and (d)

4.4 Feature Extraction Methods

The goal of the feature extraction method is to extract characteristic features from noisy images that are capable of distinguishing two or more images and at the same time provide invariance with respect to image orientation for the same image. We have used three methods for feature extraction; DCT, LDA and PCA.

4.4.1 Implementation of DCT

DCT is incorporated into the system because of its strong energy compaction property for most accurate feature selection. There are several other advantages offered by DCT which include:

- Provides good cooperation between computational complexity and energy packing capability
- The energy packing property of DCT is the best among all the other unitary transforms
- Ability to pack most of the information into as fewest number of coefficients as possible
- Builds the best sub-image estimate and, thus, the smallest reconstruction errors

DCT is a data independent feature extraction method as compared to the KLT which is data dependent. Since DCT has less computational complexity to other transforms, therefore we have used it to extract the features of face, iris and ear images in the proposed system.

Multidimensional DCT is computed on the same lines as one-dimensional definitions: they are simply computed along each dimension and then separable product is implemented. For example, a two-dimensional DCT of an image or a matrix is calculated by simply finding DCT along one dimension i.e., rows and then along the other dimension i.e., columns (or vice versa). Mathematically, the 2-dimentional DCT is given by the formula:

$$X_{k_1,k_2} = \sum_{n_1=0}^{N_1-1} (\sum_{n_2=0}^{N_2-1} x_{n_1,n_2} \cos[\frac{\pi}{N_2}\left(n_2+\frac{1}{2}\right)k_2]) \cos\left[\frac{\pi}{N_1}\left(n_1+\frac{1}{2}\right)k_1\right] \tag{4.1}$$

$$X_{k_1,k_2} = \sum_{n_1=0}^{N_1-1}\sum_{n_2=0}^{N_2-1} x_{n_1,n_2} \cos\left[\frac{\pi}{N_1}\left(n_1+\frac{1}{2}\right)k_1\right] \cos[\frac{\pi}{N_2}\left(n_2+\frac{1}{2}\right)k_2] \tag{4.2}$$

Eight of the total DCT coefficients for the three biometric identifiers are taken as a feature vector representing the face image, a feature vector representing the iris image and a feature vector representing the ear image. DCT is most efficient in terms of time complexity among the three feature extractors being used. Its time complexity is $O(n^2)$.

4.4.2 Implementation of LDA

The key idea behind LDA is to find the subspace that is capable of distinguishing different images by maximizing intra-class variation, while minimizing the inter-class variation. The eigenvectors for LDA are computed by calculating the eigenvectors of S_w^{-1} (within class variation) and S_b (between class variation). Here, S_b and S_w are the between-class and within-class variation matrices defined as:

$$S_w = \sum_{i=1}^{C} \sum_{x_k \in C_i} (x_k - m_i)(x_k - m_i)^T \tag{4.3}$$

$$S_b = \sum_{i=1}^{C} n_i (x_k - m_i)\,(x_k - m_i)^T \tag{4.4}$$

where n_i shows the number of training samples in i^{th} class and m_i, the mean image for i^{th} class.

We have employed LDA on the face, iris and ear datasets and the eigenvector of length eight is computed. It is important to mention here that LDA feature vector takes the highest computation time as compared to PCA and DCT methods. It is one of the drawbacks of LDA. LDA has $(mnt + t^3)$ time complexity and requires $O(mn + mt + nt)$ memory, where m is the number of samples, n is the number of features and $t = min(m, n)$.

4.4.3 Implementation of PCA

PCA aims at finding the best set of sub-space projections in order to maximize intra-class scatter among all the images. For this purpose, a set of Eigen-faces from the eigenvectors is computed. The eigenvectors of the total scatter matrix S_t is defined as:

$$S_t = \sum_{i=1}^{N} (x_i - m)\,(x_i - m)^T \qquad 4.5$$

where m represents the mean image of the sample set x. For dimensionality reduction, a subset k (where k < m) of the eigenvectors $U = [u_1, u_2, \cdots u_k]$ related to first k highest Eigen-values of S_t are chosen as eigenvector values.

The PCA is applied on the face, iris and ear dataset and the eigenvector of length eight is computed. PCA uses less time as compared to LDA for computing eigenvector on the same dataset. This is due to the fact that the time complexity of PCA, $O(n^3)$, is less than LDA.

4.5 Feature Vector Normalization

Normalization is the method of changing the location and range parameters of the score distributions so as to transform them into a common domain. A scale parameter determines the statistical dispersion of the probability distribution. A larger scale parameter implies a more spread out distribution and a smaller scale parameter implies a more concentrated distribution.

For example, if two matchers had score values in the range [0, 10] and [0, 1000], the normalization technique can be applied and the scores can be transformed into a common range [0, 1].The location parameter determines where the origin will be located and can be either positive or negative. The location parameter is used to shift a distribution in one direction or another. The prediction of location and range parameters for a specific score distribution must be efficient and robust for producing good normalization results [10]. Efficiency means the closeness of the obtained predicted values to the optimal prediction and Robustness means the insensitivity to outliers when the distribution is already known.

We have used *z-score* normalization technique. It is implemented by taking arithmetic mean and standard deviation of the score values. It performs well when the variance and average of score distribution are known. If this prior knowledge is not available, the mean and standard deviation of the score values are required to be computed from given data at that time. The normalized scores are given by

$$s'_k = \frac{s_k - \mu}{\sigma} \qquad 4.6$$

where σ represents standard deviation and μ, the arithmetic mean. For the feature vectors of our three dataset, we have computed the average and variance first and then normalized them using the above equation of z-score normalization.

4.6 Feature Level Fusion

The finest among the three outputs of the each identifier is selected. Now these three features are fused together. This process is called feature level fusion. In this kind of fusion, the feature vectors created by various biometric algorithms (DCT, PCA, and LDA) are consolidated into a single feature vector by applying appropriate feature level fusion methods. The benefit of feature-level fusion is finding the correlated values produced by different algorithms and thus determining a prominent set of features that can enhance identification accuracy [18]. Ben-Yacoub et al. [29] developed a bimodal biometric system using face and voice biometric traits. They have explained the use of several fusion strategies, such as multilayer perceptrons, support vector machines (SVM) and tree classifiers.

The fused feature vector can be generated by combining the best feature vectors of face, iris and ear among the three feature extraction systems and doing feature selection on the concatenated vector. Also, the feature sets being fused reside in commensurate vector space. Probabilistic rules have been used which are product rule, min rule, and sum rule.

- Product rule (mul rule) performs best as described by [19] in situation when unlike biometric traits of a user (e.g. face, ear, iris) are independent of each other. When input feature vectors Z is entered into the matching algorithm I (i = 1, 2, 3... M)
  where M shows total number of classifiers, the equation generates extracted feature vector, x_i. W_j stands for the class j (j = 1, 2, 3... m), where m shows total number of classes. P $(w_j|x_i)$ stands for the posteriori probability of the input feature vectors Z that belongs to class w_j, given the feature vector x_i. Input feature vectors Z is finally allocated to the class c that belongs to 1, 2... m.

$$c = argmax_j \prod_{i=1}^{M} P(w_j|x_i)$$

4.7

- Min rule can produce degraded performance in the presence of noise (i.e., outliers). Then the input feature vectors Z is allocated to class c such that

$$c = argmax_j min_i P(w_j|x_i) \tag{4.8}$$

- Sum Rule produces good fusion results as it is a smoothing operation. The input feature vectors Z is assigned to class c such that

$$c = argmax_j \sum_{i=1}^{M} P(w_j|x_i) \tag{4.9}$$

4.7 Feature Vector Optimization using GA

Next the feature vector is now passed into the GA for optimization that repeatedly processes the fused vector and selects most suitable features from the fused feature vector and discards the others.

4.7.1 Genetic Algorithm

A genetic algorithm (or short GA) is a search operation employed to find fairly accurate solution to optimization problems. They belong to a specific class of evolutionary algorithms that have designed its techniques motivated by the concepts of evolutionary biology such as mutation, selection, inheritance, crossover, and recombination.

Algorithm is started with some vector set of solutions which is called the initial population of the algorithm. The set of solution is represented by chromosomes. The solutions of one population are obtained and are utilized in formation of a new population. This is encouraged to reveal the fact that the new population will be capable of producing better results than the old one. Those solution sets, which are selected to generate new offspring, are selected according to their fitness (designed by the fitness function) – New solutions (offspring) have more chances to reproduce if they are more appropriate.

This process is repeated again and again until some stopping criteria, (for example specified number of generations) is met.

The figure below describes in detail the various steps involve in processing genetic algorithm:

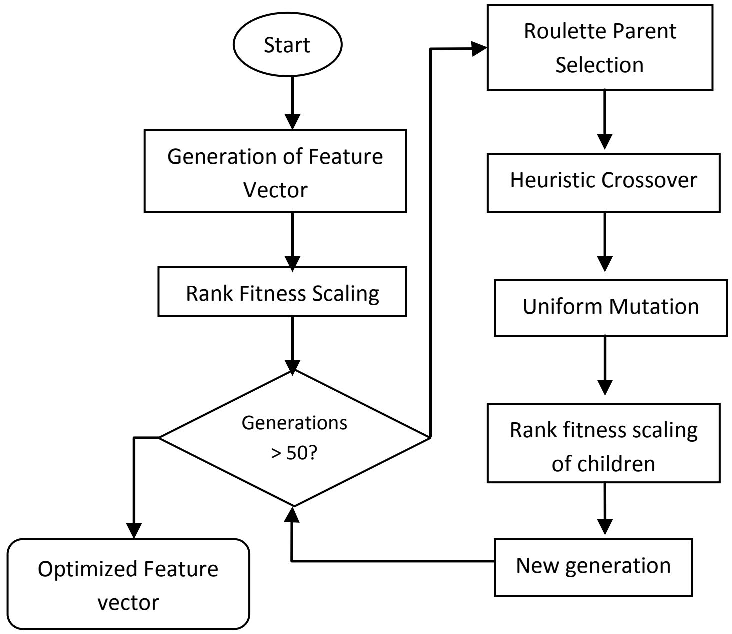


Fig. 4.3 Genetic Algorithm process flow

We have implemented genetic algorithm on the multimodal system gained after fusion of biometric traits. The feature vector obtained by three fusion functions is then incorporated in the genetic algorithm in order to produce more accurate scores for classification. The parameters selected for the algorithms are described in the table 4.1.

Table 4.1: Parameters of Genetic Algorithm

Parameter	**Value**
Population instances	100
Generations	50
Fitness Scaling	Rank
Selection	Roulette
Mutation	Uniform
Crossover	Heuristic

4.8 Classification using Bayesian Classifier

Now the selected GA vector is introduced into the classifier that matches the GA vector to all the vectors in the database. Therefore Bayesian classifier is incorporated which gives the output by comparing the result from GA optimized output with the database. The system finally suggests that the person (to be identified) is “identified” or “Unidentified”. This step completes the identification process of our proposed system.

4.8.1 Bayesian Classifier

Bayesian classifiers are used for classification in many applications as they offer many advantages. They are based on probability theory. They can take into account both the expert opinion and data at the same time to construct models. They offer backward reasoning (prediction of inputs when outputs are given), in addition to forward reasoning (prediction of outputs when inputs are given). They also provide support when data is missing during learning as well as classification. Bayes theorem establishes a connection between the probabilities of A and B, denoted here by P(A) and P(B), and the conditional probabilities of A on B and B on A, P(A|B) and P(B|A) [42]. Mathematically, the theorem is implemented by the following equation:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{4.10}$$

Summary

This chapter discusses our proposed method in order to solve the problems of selection of feature extraction method and feature vector optimization, described in the last chapter. DCT has been proposed as a feature extraction method because of its energy compaction property and reduced computation time. The old techniques of feature extraction like PCA and LDA have also been employed at feature extraction level in order to have a comparison between the proposed and the existing methods.

Before the implementation of fusion methods it was necessary that the feature vectors must be normalized. For this reason, z-score normalization is done on each of the feature vectors of face, iris and ear trait. Z-score normalization arranges the data to a common range for fusion in next level. The normalized feature vectors so obtained are then combined using sum, min and product. At this level three multimodal systems have been achieved based on DCT, PCA and

LDA. Next Genetic Algorithm (GA) is employed for feature vector optimization to enhance the efficiency of the three multimodal systems. For classification Bayesian classifier has been implemented using supervised learning. The classifier confirms the identity of the person.

Chapter 5
Experimental Results

5.1 Introduction

Experiments have been performed to determine the accuracy of our proposed method. This chapter discusses various scenarios for performing experiments at four different levels. At first, the unimodal biometric traits are compared after the feature extraction to test the efficiency of each biometric trait. Secondly, the fusion methods of ‘sum’, ‘min’ and ‘mul’ for the three biometric traits of face, iris and ear have been compared to get the effectiveness of the multimodal biometric system. Next the feature extraction methods of DCT, LDA and PCA are compared for both unimodal and multimodal systems. Also the use of genetic algorithm for better performance of the multimodal system has been analyzed. Finally the accuracy is computed for the three feature extraction methods with and without the implementation of genetic algorithm.

5.2 Datasets

We have used face, iris and ear biometric traits for our multimodal biometric system. In a multi-biometric system, it is possible sometimes that the database employed is not the true database. True database is the one which has more than one biometric trait for each individual. Instead, the database is a virtual database which contains records that are created by properly pairing a user from one unimodal database (e.g., face) with a user from another database (e.g., iris). Due to the unavailability of the biometric traits for a single person, we have implemented such a database by pairing the three sets of face, iris and ear datasets. In this way, a triplet set of 100 is formed from three datasets (face, iris, and ear) or we can say that a dataset of 100 individuals with face, iris, and ear images has been used for performing our evaluation according to the proposed methodology given in last chapter. The details of the datasets are listed as under:

5.2.1 AMI Ear database [50]

It consists of ear images collected from students, teachers and official staff at ULPGC, Spain. The images have been taken in an indoor environment. The database was acquired from 100 different subjects, all of them in the age range of 19-65 years.

— The database was acquired from 100 different subjects and 7 images per individual.
— Size of the images is 492 x 702, having JPEG file format
— Among seven images of each individual, there is 1 image of left ear and 6 images of right ear with orientations: up, down, left, right and zoom

5.2.2 Faces94 Dataset [49]

A sequence of 20 images is taken when a subject is asked to speak while sitting at a fixed distance from the camera. The speech introduces variation in facial expressions. Database description is as under:

— Total number of subjects is 153; female (20), male (113), male staff(20)
— Image resolution is 180 × 200 pixels with JPEG format

The detail of variation in individual's images is given below:

— The background is plain green
— Very minor variations seen in the attributes like head in turn, tilt and slant position
— lighting variation is not introduced while taking the images
— Considerable facial expression changes as speech has been introduced

5.2.3 MMU2 Iris Database [48]

MMU2 iris database has a total of 995 iris images. These images were taken using Panasonic BM-ET100US camera with an operating range of 47-53 cm. These iris images were taken from volunteers with different nationality and age. They are natives of Europe, Asia, Africa and Middle East.

— The database was made from 100 different subjects and 10 images per individual
— 5 images each of left and right eye have been included
— Size of the images is 320 × 238, having Bitmap file format

5.3 Performance Measures

The following performance measures have been used to estimate the effectiveness of our proposed method [51]:

— *False Accept Rate (FAR):* It is a measure of the likelihood that the biometric system wrongly accepts the input user to a non-matching user template in the enrollment database. It measures the percentage of impostor users which are wrongly accepted.

$$\text{FAR} = \frac{\text{Number of imposter transaction attempts accepted}}{\text{Total number of imposter transaction attempts}}$$

6.1

— *False reject rate (FRR):* It is a measure of the likelihood that the biometric system is unable to find a match between the input user and a matching user template in the enrollment database. It measures the percentage of genuine users which are wrongly rejected.

$$\text{FRR} = \frac{\text{Number of genuine transactions attempts rejected}}{\text{Total number of genuine transaction attempts}}$$

6.2

— *Receiver operating characteristic (ROC):* The ROC plot is a visual display of the graph between the FAR and the FRR. A threshold determines proximity of the input to a template in order to consider the input as a match. If the value of the threshold is decreased, the FAR increases and FRR reduces. Similarly, a higher threshold will decrease the FAR and at the same time increases the FRR. The closer the ROC curves to the origin, the better the system.

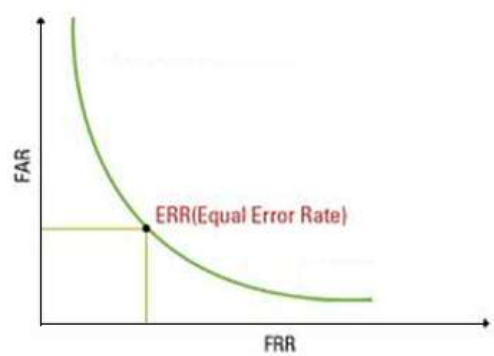


Fig. 5.1: ROC Curve

— *Equal error rate (EER):* It is the value obtained from the ROC curve where the values of FAR and FRR are equal. The EER attempts to exploit the accuracy of different biometric systems using the ROC curves. In general, the lower the EER, the more accurate the results.

$$EER = \begin{cases} \dfrac{FAR(t_1) + FRR(t_1)}{2} & if\ FAR(t_1) - FRR(t_1) \leq FAR(t_2) - FRR(t_2) \\ \dfrac{FAR(t_2) + FRR(t_2)}{2} & otherwise \end{cases} \quad 6.3$$

Where $t_1 = \max_{t \in S}\{t | FRR(t) \leq FAR(t)\}$ and $t_2 = \min_{t \in S}\{t | FRR(t) \geq FAR(t)\}$.

— *Accuracy (ACC):* the accuracy is the proportion of true results i.e., both the number of genuine accepted and number of imposters rejected in the population. It is a parameter of the test.

$$\text{ACC} = \frac{\text{Number of genuines accepted} + \text{Number of imposters rejected}}{\text{Number of genuine transactions} + \text{Number of imposter transactions}} \quad 6.4$$

5.4 Experimental Results

5.4.1 Results of Unimodal Biometrics

The three set of images (face, iris and ear) are introduced to each of the three feature extraction models (DCT, LDA and PCA). In this way, three feature scores are obtained for each of the three models e.g. face score, iris score, and ear score for DCT model and similarly for the other two models. At this level, the scores are compared to find out three things: Which biometric trait is more efficient in identification of a person? Which feature extraction model outperforms the other models?

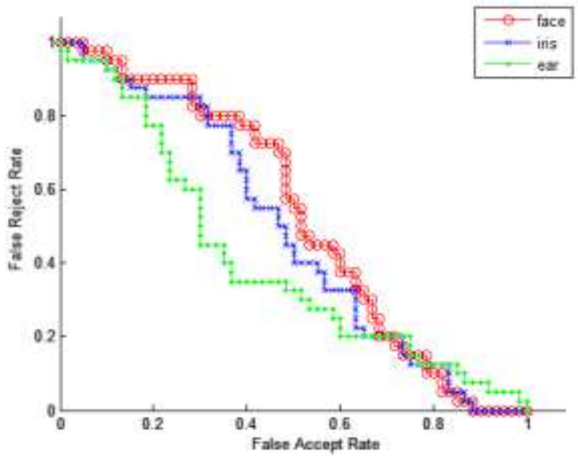
The EER of each feature extraction method of each database is presented in Table 5.1. We see that the proposed method of DCT produces results that are better than the existing methods in case of iris and ear biometric traits. However the best result is shown by LDA using face biometric trait with the least error. At this level, we are only comparing unimodal biometric system and the existing methods do perform better for unimodal systems but in case of multimodal system (that is demonstrated next) these existing methods cannot perform well. In order to reduce spoof attacks, implementation of multimodal system is preferred.

Table 5.1: Performance (EER) of three feature extraction methods for face iris and ear biometric traits

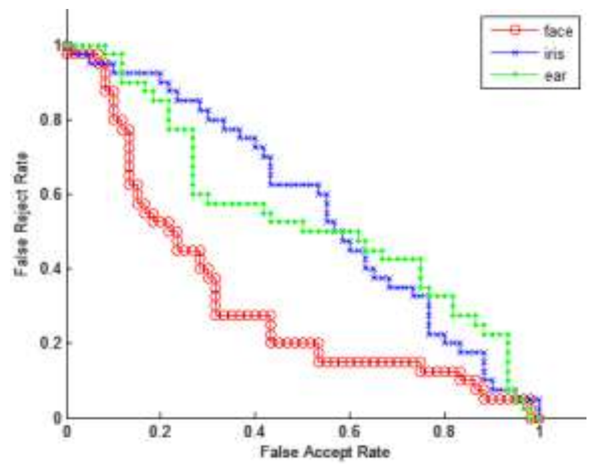
Feature Extraction Method	**Error Equal Rate (EER)**		
	Face	**Iris**	**Ear**
PCA	0.5542	0.5083	0.4333
LDA	0.3458	0.5750	0.5083
DCT	0.5333	0.4667	0.4000

Figure 5.2 shows the ROC curves of feature extraction methods implemented on the face, iris and ear datasets separately as individual biometric systems. Here the ear features have the best EER value in case DCT because the closer the graph to the origin the better the performance of the biometric trait. LDA is giving better performance in case of face features and PCA curve is showing overlap of all the traits, ear being the better.

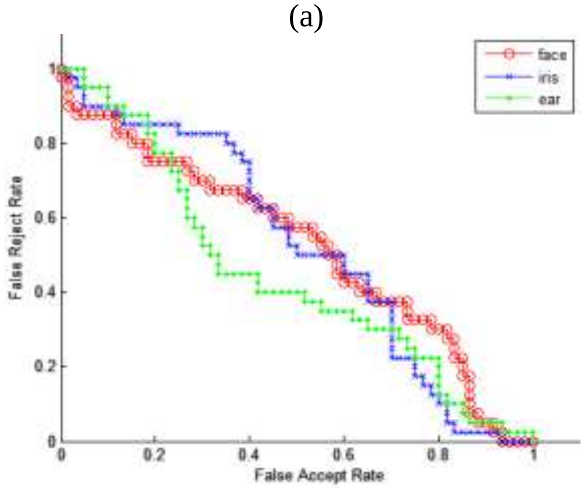
It has been seen that each biometric trait has its advantages and limitations, and a single trait can never meet all the requirements effectively such as efficiency, practicality and expenses at the same time. Therefore, we can say that there is no universally best accepted biometric trait; search for best biometric trait is still going on. Also the selection of particular biometric trait depends on the nature and requirements of the particular application for which the trait is to be employed.



(a)



(b)



(c)

Fig. 5.2: ROC performance curve of face, iris and ear biometric traits using (a) DCT, (b) LDA, and (c) PCA

5.4.2 Results of Multimodal Biometrics

Three fusion techniques (‘sum’, ‘min’ and ‘mul’) are used for combining the feature scores of the biometric traits. This is done for finding the efficiency of our proposed multimodal biometric system. As we have used logistic regression method, so weights to the three biometric traits have been assigned; 0.3, 0.4 and 0.3 are assigned to face, iris and ear respectively. A lower value of weight is assigned to the more accurate biometric trait (the face and ear matcher being more accurate here). Therefore, the results here can be expected to be more influenced by the ranks assigned by the face and ear scores which is the case.

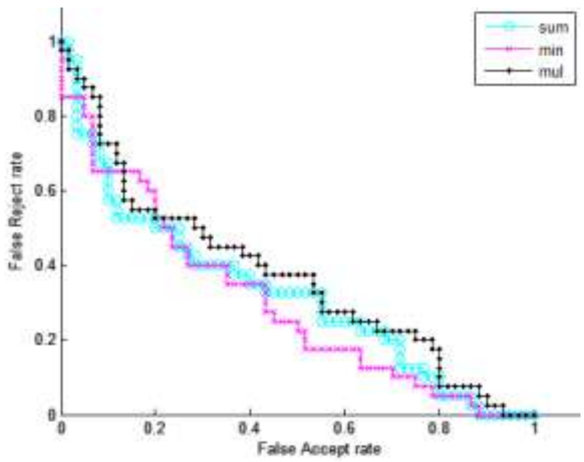
Table 5.2 gives a comparison of the performance measure (EER) of these fusion techniques for the feature extraction methods with and without using genetic algorithm. We see that the genetic algorithm has reduced the EER value to a much greater extent. However, the proposed DCT method is giving accurate results in both cases (with and without GA). The best results with lowest EER are produced by DCT with ‘mul’ fusion technique.

Table 5.2: Performance (EER) of three fusion techniques for PCA, LDA and DCT

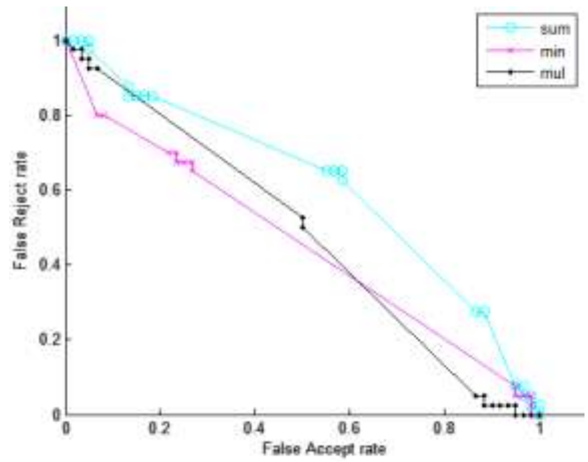
Feature Extraction Method	**Error Equal Rate (EER)**		
	Sum	**Min**	**Mul**
Without GA			
PCA	0.5083	0.5083	0.4875
LDA	0.5083	0.4625	0.4625
DCT	0.3792	**0.3667**	0.4125
With GA			
PCA	0.0643	0.0952	0.2929
LDA	0.2310	0.7381	0.5000
DCT	0.0524	0.0214	**0.0143**

Figure 5.3 shows the performance of two multimodal biometric systems: one without genetic algorithm and the other with genetic algorithm. The fusion techniques (sum, min and mul) have been compared for each feature extraction method (DCT, LDA, and PCA). Figure 5.3 (b, e) gives the comparison between two LDA systems one without genetic algorithm and the other with genetic algorithm, respectively. The straight lines in (b) show that the imaginary values accounted by LDA have not been properly calculated. This problem has been overcome by still

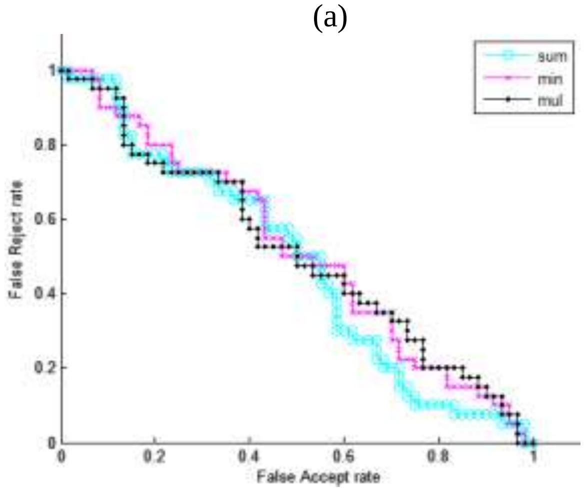
having low EER values. This defect has greatly been reduced by the implementation of genetic algorithm on this method as shown by (e).



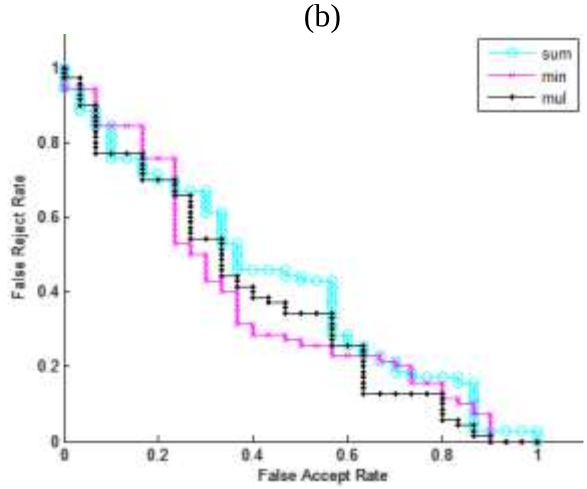
(a)



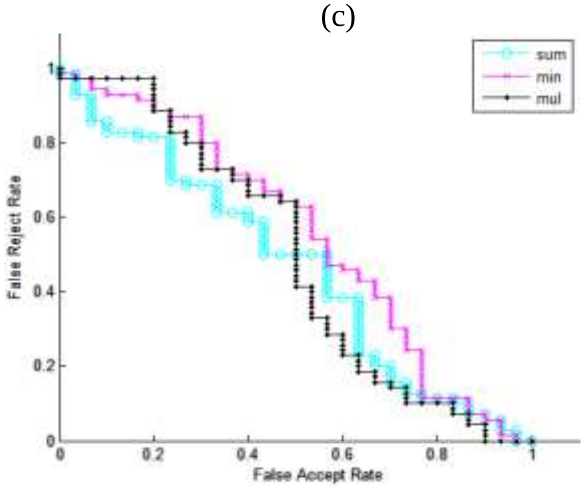
(b)



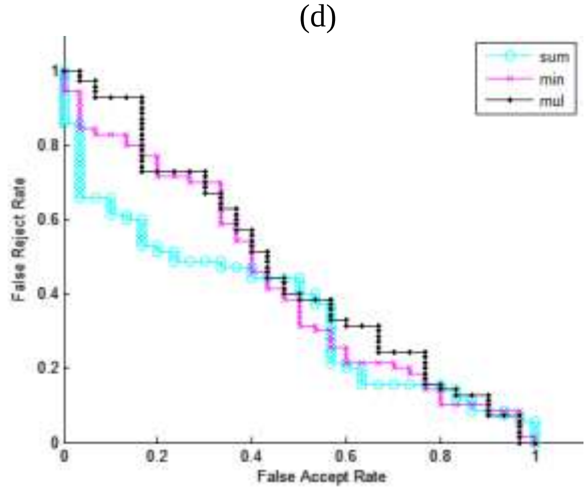
(c)



(d)



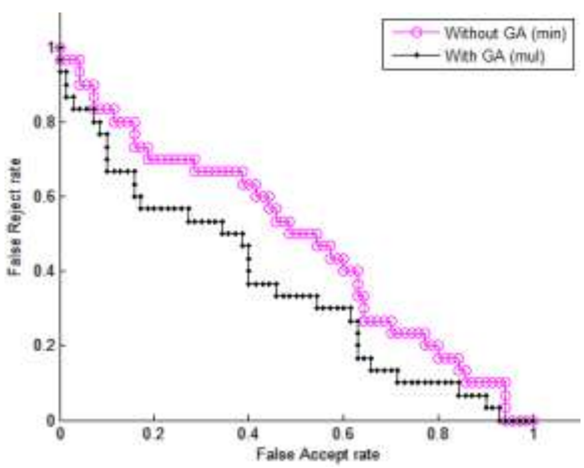
(e)



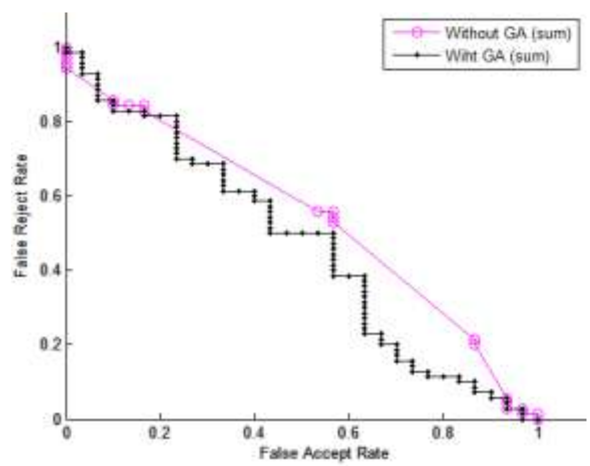
(f)

Fig. 5.3: ROC performance curves of 'sum', 'min' and 'mul' fusion techniques using (a) DCT, (b) LDA, (c) PCA, (d) DCT with GA, (e) LDA with GA, and (f) PCA with GA

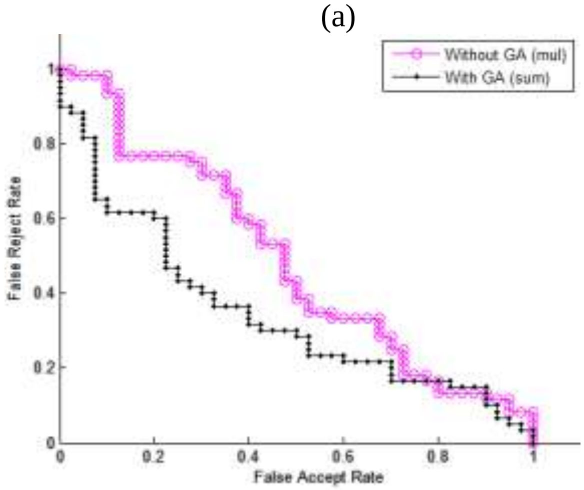
The figure 5.4 shows the comparison between best fusion techniques in all feature extraction methods. We can see that genetic algorithm reduces the EER value in case of each method. Using DCT the 'mul' fusion technique performs the best when genetic algorithm is employed as shown in (a). Similarly using LDA and PCA, 'min' and 'mul' fusion techniques are producing good results respectively. The straight line in (b) showing LDA curve becomes straight as the curve proceeds downwards. This is because here the complex values are not accurately evaluated and effected the results badly. However, the error rate is still very low so this defect can be neglected.



(a)



(b)



(c)

Fig. 5.4: ROC Performance curves of Best Fusion technique in terms of EER with and without the use of Genetic Algorithm using (a) DCT, (b) LDA, and (c) PCA

5.4.3 Results of Feature Extraction Methods

Figure 5.5 shows a comparison between the best feature extraction methods on the basis of 'sum', 'min' and 'mul' fusion techniques. The EER as well as the ROC show better performance of DCT over the other two methods among all the fusion techniques.

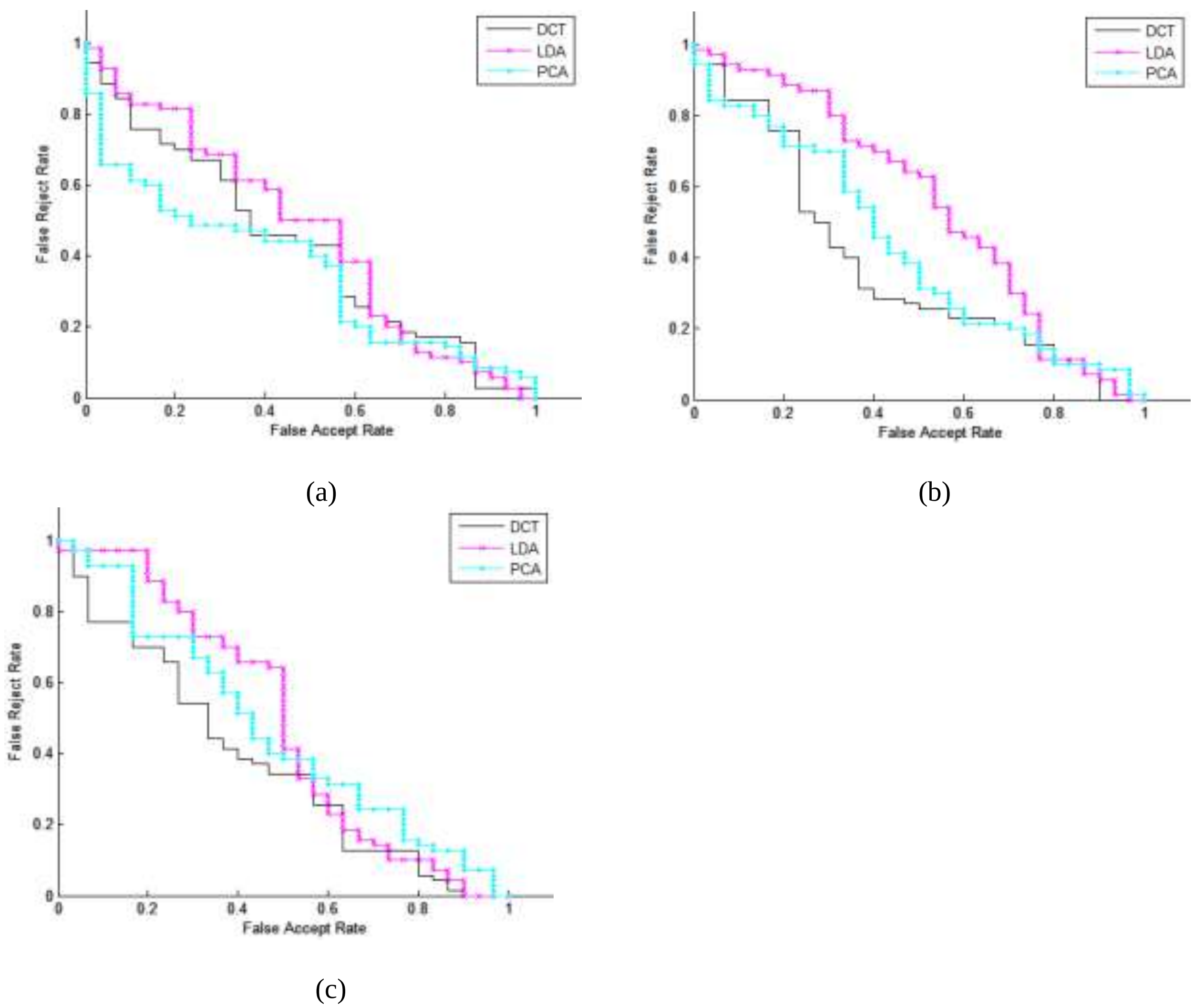


Fig. 5.5: ROC Performance curves of feature extraction methods using (a) 'sum', (b) 'min' and (c) 'mul'

We then selected the best fusion methods in each of the feature extraction methods with the lowest EER values; The DCT and LDA with 'mul', and the PCA with 'min'. They are compared by the ROC curves as shown in the figure 5.6 below. DCT is producing better results here as well. LDA and PCA are overlapping but still PCA produced better results here than LDA.

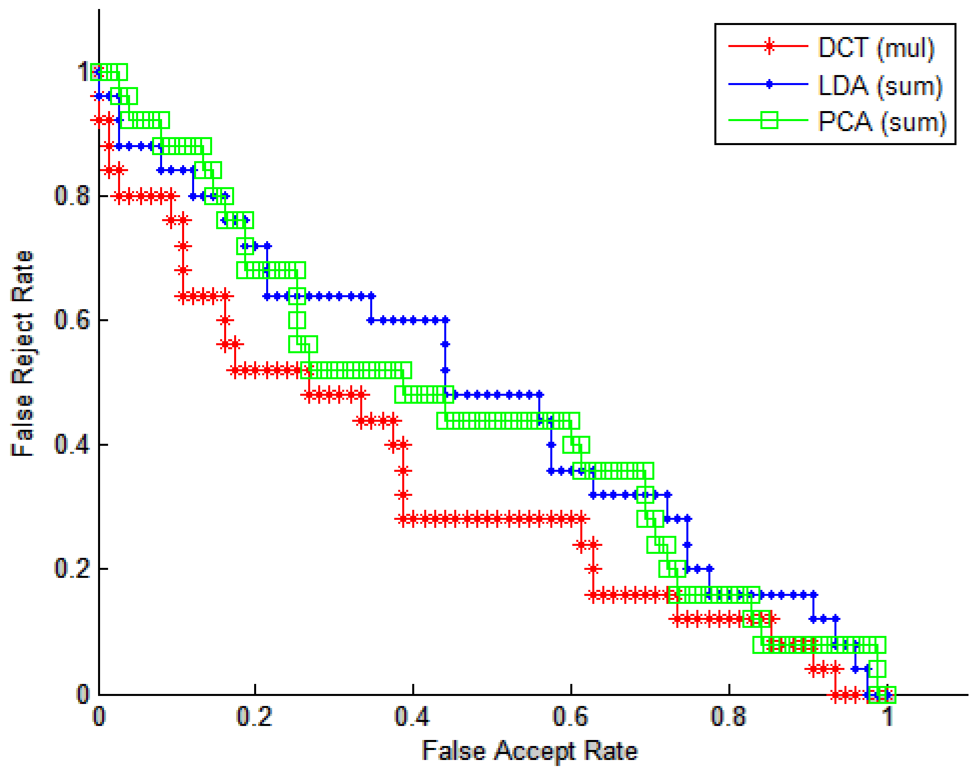


Fig. 5.6: Comparison of the Best fusion techniques of the three feature extraction methods

To our knowledge, we can say now that the DCT with genetic algorithm has produced the better results as individual biometric and as multimodal biometric systems. However multimodal biometric systems always perform better than individual biometric systems.

The feature extraction methods are also compared in terms of time complexity. For our database with 100 images each of face, iris and ear, making a total of 300 images, the DCT is using less time as compared to the other existing methods of LDA and PCA as shown in figure 5.7. This is due to the fact that the DCT is far less computationally complex than PCA and LDA. The complexity of 2D-DCT is $O(n^2)$ whereas for PCA and LDA it is $O(n^3)$ and $O(mnt+t^3)$ respectively where m is the number of samples, n is the number of features and $t = min(m, n)$.

Table 5.3: Time Consumption by feature Extraction methods

Feature Extraction Method	Time Complexity	Time (seconds) used by 300 images
PCA	$O(n^3)$	16.793765
LDA	$O(mnt+t^3)$	27.393744
DCT	$O(n^2)$	8.794472

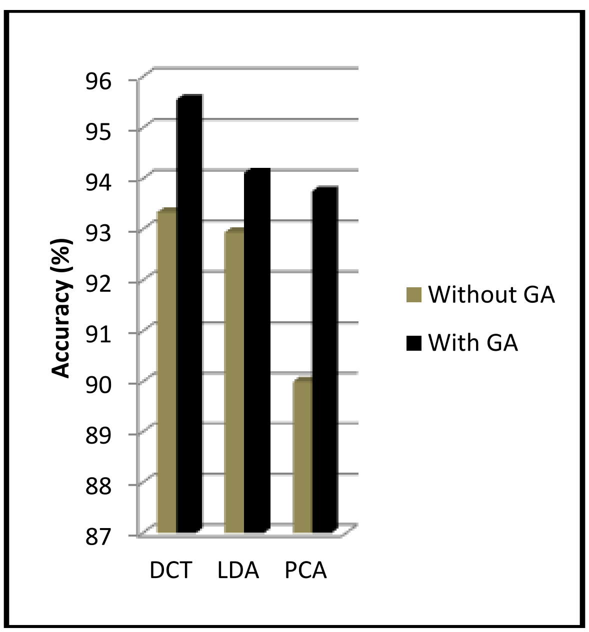
5.4.4 Classification Accuracy Measurement

The multimodal systems have been classified by using Naive Bayesian Classification Model. The accuracy has been computed by the confusion matrix produced in each case of fusion technique before and after implementing genetic algorithm as shown in figure 5.8. In each case the accuracy of the multimodal system has been greatly enhanced by the use of genetic algorithm. The classification accuracy values of simple multimodal system and GA multimodal system are listed in table 5.3.

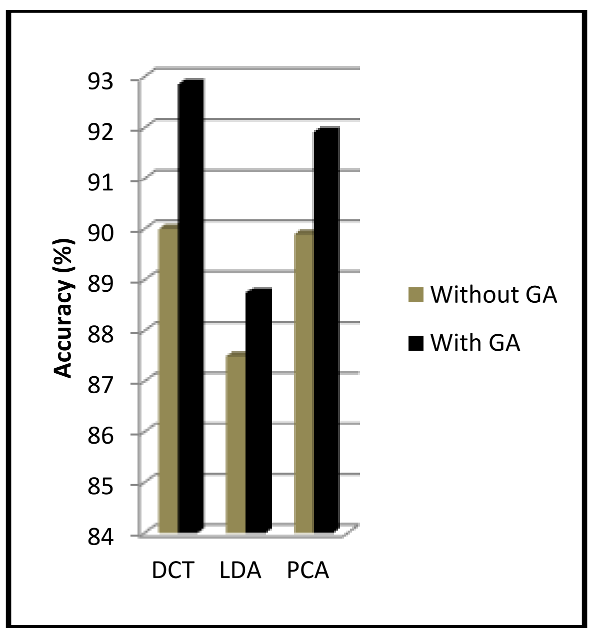
In case of ‘sum’ and ‘mul’, the DCT and LDA perform well as compared to PCA whereas in case of ‘min’, PCA outperforms LDA. So with different fusion methods, PCA and LDA are performing differently. However, DCT performs better in all cases irrespective of the fusion technique being implemented as shown by the bar graphs in figure 5.8.

Table 5.4: Accuracy of the simple multimodal systems and the GA multimodal systems

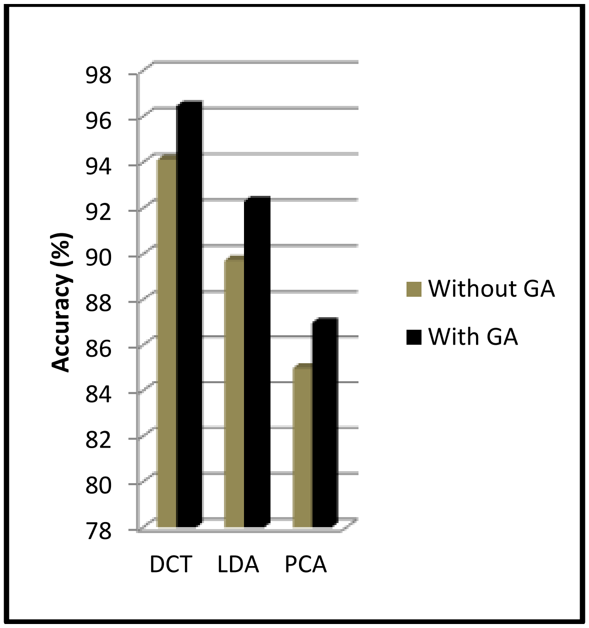
Feature Extraction Method	Accuracy (%)		
	Sum	Min	Mul
Without GA			
PCA	90.00	89.89	85.00
LDA	92.94	87.50	89.74
DCT	93.33	90.00	**94.11**
With GA			
PCA	93.75	91.91	87.00
LDA	94.11	88.75	92.30
DCT	95.55	92.85	**96.47**



(a)



(b)



(c)

Fig. 5.7: Bar graph showing accuracy of fusion techniques with and without the use of Genetic Algorithm for (a) sum, (b) min, and (c) mul

Summary

An illustration of experiments being performed to calculate the efficiency and accuracy of the proposed method is described. The chapter discusses different scenarios for performing experiments at four different levels. At first, the unimodal biometric traits are compared after the feature extraction to test the efficiency of each biometric trait. Here it has been seen that ear and face biometric traits are performing well as compared to iris. For this reason, when these biometric traits are fused for making a multimodal system the weight of iris is set higher than face and ear trait. Higher weight is set for those traits that produce less accurate results. In this way, contribution of iris trait towards multibiometric results is reduced.

Secondly, the fusion methods of ‘sum’, ‘min’ and ‘mul’ for the three biometric traits of face, iris and ear have been compared to get the effectiveness of the multimodal biometric system. Next the feature extraction methods of DCT, LDA and PCA are compared for both unimodal and multimodal systems. Also the use of genetic algorithm for better performance of the multimodal system has been analyzed. Finally the accuracy is computed for the three feature extraction methods with and without the implementation of genetic algorithm. The final classification results have shown that the accuracy of LDA and PCA depends on the fusion method being used, as in case of ‘min’, PCA has shown improved accuracy than LDA. In sum and product fusion methods, LDA shows enhanced performance than PCA. However, the accuracy of the proposed DCT method has outperformed LDA and PCA in all case of fusion methods.

Chapter 6
Conclusion and Future Work

6.1 Introduction

Efficient identity management system has become very important in this highly interconnected world with increased concerns of identity fraud and national security. Biometric systems provide a greater degree of security and user convenience than the traditional authentication methods. Moreover, biometric systems also provide negative recognition and non-repudiation that traditional systems don't. Multibiometric systems, if properly designed, are able to increase the matching accuracy of a recognition system as they, consolidate the evidences from different biometrics, increase population coverage and prevent spoofing attacks.

6.1 Conclusion

In this thesis, we have developed a new approach to enhance the recognition accuracy of proposed multibiometric system. The system uses Discrete Cosine Transform at feature extraction level due to its high energy compaction property and reduced computation time. The existing methods of Principal Component Analysis and Linear Discriminant Analysis are also used in parallel in order to compare the three feature extraction methods. Three biometric traits are used; face iris and ear. It has been seen that each biometric trait has its own advantages and limitations, and a single trait can never meet all the necessary requirements effectively such as efficiency, practicality and expenses at the same time. Therefore, we can say that there is no universally best accepted biometric trait; search for best biometric trait is still going on. Also the selection of particular biometric trait depends on the nature of the particular application for which the trait is to be employed.

The results prove the increased performance of DCT over the other state of the art methods. Three biometric traits i.e. face, iris and ear have been used which at fused at feature level to make the system a multimodal biometric system. ROC curves in terms of FAR and FRR has shown the better performance of our proposed DCT method for feature extraction.

It has been seen that after normalization of the feature vector, the different fusion techniques implemented on the three systems (DCT, LDA and PCA) perform differently. So we cannot summarize that which fusion method performs well for all systems. Genetic algorithm incorporated for feature vector optimization has produced greater accuracy as compared to the simple (without GA) methods; the highest classification accuracy being achieved is 96.47% by the DCT feature extraction method using 'mul' fusion technique. The use of Discrete Cosine Transform with genetic algorithm has significantly improved the performance of our multibiometric system.

6.2 Future Work

The accuracy of biometric technology depends on the accuracy and number of records within the databases. Therefore if the data capturing module is not efficient, which is most of the case, then required accuracy of identification cannot be met. So a lot of work is still required in the area of multibiometrics to reduce the effects of noisy data and to increase template security.

The work presented in this thesis can be extended:

- By implementing different variation of PCA and LDA like Multilinear PCA, kernel PCA, Independent Discriminant Analysis, etc.
- By using the energy compaction property of DCT on a feature extraction method of LDA, and PCA. In this way the feature vector of LDA and PCA systems would be optimized by DCT.
- By employing various fusion techniques in parallel and concatenating the resultant vectors.
- By implementing fusion at various levels described in chapter 2 for making a comparison on the multibiometric system. For example, fusion at the rank level can be implemented and the methods of logistic regression, borda count and highest rank can be compared.

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Glossary

This section lists acronyms that frequently appear in the thesis.

DCT Discrete Cosine Transform

LDA Linear Discriminant Analysis

PCA Principal Component Analysis

GA Genetic Algorithm

ROC Receiver Operating Characteristic

EER Error Equal Rate

PIN Personal Identity Number

ROI Region of Interest

DNA De-oxyribo Nucleic Acid

FAR False Accept Rate

FRR False Reject Rate

IR Infra Red

SVM Support Vector Machines

HMM Hidden Markov Model

ACC Accuracy

KLT Karhunen Loeve Transform

JPEG Joint Photographic Experts Group (image file format)

PNG Portable Network Graphics (image file format)

RGB Red Green Blue

COTS Counter-of-the-Shelf

FTE Fail To Enroll

FMR False Match Rate

FNMR False Non-Match Rate

DWT Discrete Wavelet Transform

PDA Personal Digital Assistant

MCC Multiple Classifier Combination

FTER Failure to Enroll Rate

FTCR Failure to Capture Rate

JVT Joint Video Team