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A MULTIMODAL BIOMETRIC SYSTEM BASED ON RANK LEVEL FUSION

MONWAR, MD. MARUF

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A MULTIMODAL BIOMETRIC SYSTEM BASED ON RANK LEVEL FUSION

by

MD. MARUF MONWAR

A THESIS

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled "A Multimodal Biometric System based on Rank Level Fusion" submitted by Md. Maruf Monwar in partial fulfilment of the requirements of the degree of Doctor of Philosophy.

*Supervisor, Dr. Marina Gavrilova,
Department of Computer Science*

*Dr. Jon George Rokne,
Department of Computer Science*

*Dr. Yingxu Wang,
Department of Electrical and Computer Engineering*

*Dr. Hung-Ling (Steve) Liang,
Department of Geomatics Engineering*

*External Examiner, Dr. Piotr Porwik,
Department of Computer Science, University of Silesia,
Katowice, Poland*

Date

Abstract

In recent years, biometric based security systems achieved more attention due to continuous terrorism threats around the world. However, a security system comprised of a single form of biometric information cannot fulfill users' expectations and may suffer from noisy sensor data, intra and inter class variations and continuous spoof attacks. To overcome some of these problems, multimodal biometric aims at increasing the reliability of biometric systems through utilizing more than one biometric in decision-making process. In order to take full advantage of the multimodal approaches, an effective fusion scheme is necessary for combining information from various sources. Such information can be integrated at several distinct levels, such as sensor level, feature level, match score level, rank level and decision level. In this doctoral research, I present a new methodology based on fusion at the rank level, which is a relatively new approach compared to others, to combine multimodal biometric information from three biometric identifiers (face, ear and iris).

I investigate different rank fusion methods, such as highest rank, Borda count and logistic regression. I introduce a novel rank fusion algorithm based on Markov chain which significantly increases the recognition performance of the multimodal biometric system, can handle partial ranking lists, and satisfies the Condorcet criteria essential for fair ranking process.

In order to increase the processing speed and to obtain the level of confidence of recognition outcomes of the multimodal biometric system, I further employ fuzzy logic based fusion for biometric authentication. The fuzzy fusion method is based on fuzzy logic and uses match score and rank information of the multimodal biometric system.

The experiment results tested within different multimodal biometric database framework show superiority of the proposed approaches to other biometric information fusion methods. The developed system can be effectively used by security and intelligence services for controlling access to prohibited areas and protecting important national or public information.

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Dedication

*To my beautiful wife, **Nahid***

and

*my little princess, **Rushama***

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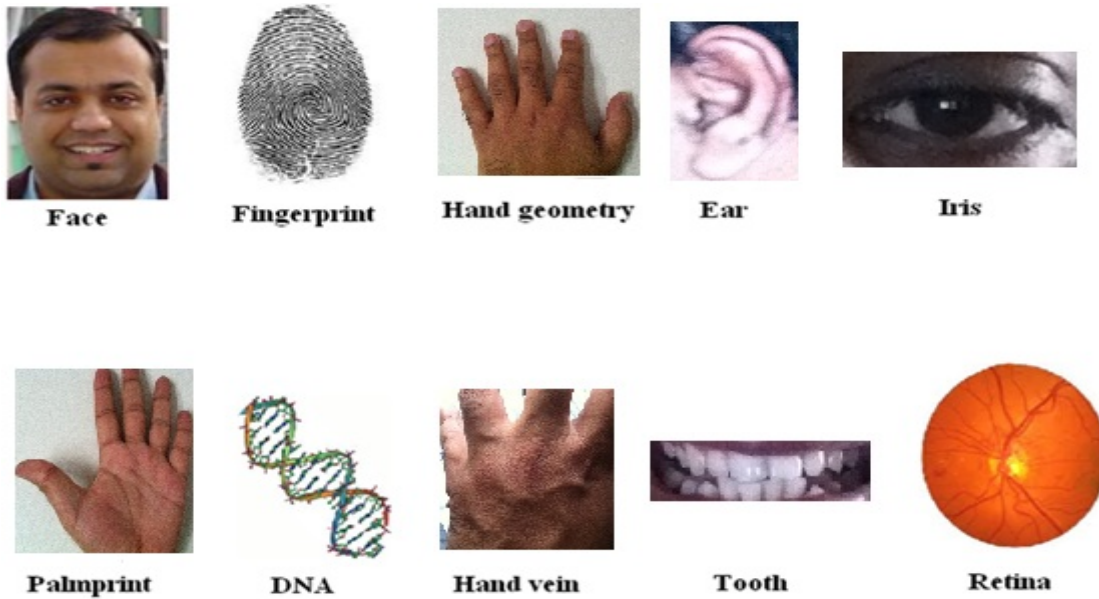
List of Symbols, Abbreviations and Nomenclature

Symbol	Definition
CMC	Cumulative Match Characteristics
CMU	Carnegie Mellon University
CT	Computed Tomography
DBMS	Database Management System
EER	Equal Error Rate
FAR	False Accept Rate
FLDA	Fisher's Linear Discriminant Analysis
FRGC	Face Recognition Grand Challenge
FRR	False Reject Rate
FTCR	Failure-to-Capture Rate
FTER	Failure-to-Enroll Rate
GAR	Genuine Accept Rate
HD	Hamming Distance
HMI	Human Media Interaction
ICA	Independent Component Analysis
KDDA	Kernel Direct Discriminant Analysis
LDA	Linear Discriminant Analysis
MRI	Magnetic Resonance Imaging
MSU	Michigan State University
PCA	Principal Component Analysis
PIE	Pose, Illumination and Expression
PSO	Particle Swarm Optimization
ROC	Receiver Operating Characteristics

CHAPTER ONE: INTRODUCTION

Controlling access to prohibited areas and protecting important government and civilian properties are among the main activities of national and international security organizations. Similarly, with the advancement of large-scale networks (e.g., social networks, e-commerce, e-learning) and the growing concern for identity theft problems, the design of appropriate personal authentication systems is becoming more and more important. Usually, person authentication for access control to a prohibited area or for identification in different networks or social services scenarios (e.g., banking, welfare disbursement) is done using biometric systems. A biometric system is defined as “a system which automatically distinguishes and recognizes a person as individual and unique through a combination of hardware and pattern recognition algorithms based on certain physiological or behavioral characteristics that are inherent to that person” [DunY09]. Some of the physiological characteristics that are now used for biometric recognition include face, fingerprint, hand-geometry, ear, iris, retina, DNA, palmprint, hand vein etc. Voice, gait, signature, keystroke dynamics are examples of behavioral characteristics used for biometric recognition. Recently, soft biometric characteristics, such as, gender, weight, height, eye color, ethnicity, age, scar, marks etc. are started to be used in person recognition along with some physiological or behavioral characteristics. The choice of different biometric characteristic(s) in a biometric system depends on that particular application scenario. Figure 1.1 shows physiological, behavioral and soft biometric characteristics which can be used in biometric systems for person authentication.

Physiological biometric identifiers



Behavioral biometric identifiers



Soft biometric identifiers

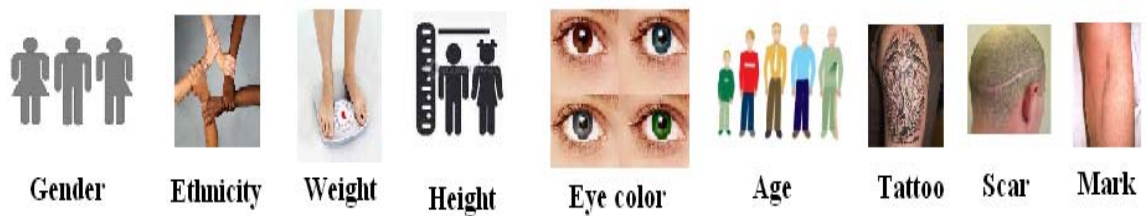


Figure 1.1: Various physiological, behavioral and soft biometric identifiers (sources: Wikipedia [Wiki], Google Image [ImaG]).

This thesis makes a contribution in biometric research domain, specifically in improving recognition performance of a biometric system using more than one biometric characteristic. Motivations for this research are provided in the next section.

1.1 Challenges in Biometric Systems

In recent years, biometric systems have been successfully deployed in a number of real-world applications (e.g., airports, amusement parks, banks, defence establishments etc.) with some biometrics offering reasonably good performance. However, even the most advanced biometric systems to date are still facing numerous problems associated with a variety of factors including data, algorithm used and system design [Bube03]. Generally the following factors are the main drawbacks of biometric systems:

Noisy data: Noisy data (unwanted data without meaning associated with the data) is one of the common problems of biometric systems. Usually, biometric data get affected by noise at the time of acquisition. Using defective or improperly maintained sensors or data acquisition devices is frequently responsible for noisy biometric data. Noise can also be included in the biometric data if the data acquisition process is not fully correct. For example, capturing voice biometric data in a noisy environment (i.e. during heavy rain etc.) will result in a noisy voice signal enrolment. Noisy biometric data can result in poor recognition performance compared to a good quality biometric data [ChDJ05].

Non-universality: Universality is one of the basic requirements for a biometric trait. A biometric trait is said to be universal if all members of the target population can be enrolled in the biometric system. Not all biometric traits are truly universal [Jain05].

For example, a blind person cannot present his/her iris or retina in front of the sensors or an illiterate individual cannot provide signature for biometric authentication.

Lack of individuality: This problem occurs with most of the biometrics traits used in human recognition. If the feature sets of a particular biometric trait obtained from two different subjects are similar, then it is difficult to make distinction between those two subjects. This is called lack of individuality problem in biometrics domain and as a result false recognition rate can be higher in this scenario [Jain05]. For example, due to genetic factors, the facial appearance of a father and a son can be quite similar. This can limit the discrimination capability of a face-based biometric authentication system [GoMM97].

Intra-class variation: This is the problem where two feature sets (for enrollment and for authentication) acquired from an individual are not distinguishable. This can occur due to any sensor related issue or due to changes in the environmental conditions and inherent changes in the biometric trait. Biometric datasets with large intra class variations results in lower recognition performance [UIRJ04].

Susceptibility to circumvention: This problem occurs when an impostor presents a fake biometric sample to the system. For example, study [MMYH02] showed that circumventing a biometric system is possible by using gummy fingers.

Privacy: Privacy is another problem associated with biometric systems since a biometric trait is a permanent link between a person and his identity [JaRN11]. The acquired biometric trait can be easily prone to abuse which violates a person's right to privacy [BCPR04]. Thus, strong data security in biometric system is important.

For the above mentioned problems and thus for the higher recognition errors, biometric system cannot be employed as a standalone system in such environments where

the strict level of security is demanded [Jain05]. Solutions to some of these problems could be found by using updated hardware, using robust algorithm for comparison or employing liveness detection technique, however such solutions are costly and time consuming. Very recently, another solution using multimodal biometric systems and integrating information from different sources emerged. Multimodal biometric systems consolidate biometric identifiers from multiple biometric sources and can significantly improve the recognition performance of a biometric system in addition to improve population coverage, deterring spoof attacks, and reducing the failure-to-enroll rate [RoNJ06]. One of the most important factors in designing a multimodal biometric system is which information needs to be fused and how fusion can occur [RoNJ06], which is the main focus of this thesis.

1.2 Contribution of the Thesis

In this thesis, I propose a method to increase the performance of a multimodal biometric security system which uses multiple biometric trait. The main contribution lies in the efficient consolidation of information obtained from different biometric traits. I propose a novel rank level fusion method based on Markov chain and fuzzy logic based fusion method for multi-biometric information fusion. The detailed contributions of this thesis are summarized below:

- In this doctoral thesis, I develop a multimodal biometric system based on face, ear and iris biometric traits to meet the recent extensive security requirements and demands for high performance. This system can alleviate most of the drawbacks associated with unimodal biometric systems mentioned in section 1.1.

- The main feature of multimodal biometric system is information fusion – that is, what information needs to be consolidated and how. Different multi-biometric information can be consolidated, such as information obtained in sensor level, feature information, matching scores, rank information and decision information. Among these fusion methods, sensor level fusion and feature level fusion methods have not been used extensively due to limited access to such information [Jain05]. Match score level fusion methods are very popular with developers and also has been extensively investigated by biometric researchers as some of the earlier methods. But match score fusion approach needs normalization of the outcomes of unimodal matchers which is computationally extensive. Moreover inappropriate choice of normalization technique can degrade the system performances [RoNJ06]. Decision level fusion approaches are too abstract and used primarily in the commercial biometric systems where only the final outcomes are available for processing [RoNJ06]. Thus in this doctoral research, I use rank level fusion which is relatively new approach compared to others and still remains understudied. In this thesis, I develop a new method based on fusion at the rank level and combine multimodal biometric information from three biometric identifiers (face, ear and iris).

- In the context of rank level fusion method, I investigate different rank fusion strategies, such as highest rank method, Borda count method and logistic regression method. I introduce a new rank level fusion algorithm; the Markov chain [Mark'06] based rank fusion, in this thesis. This Markov chain based rank fusion method significantly increases the recognition performance of the multimodal biometric system,

can handle partial ranking lists and satisfies the Condorcet criteria [Cond1785], which is essential for fair ranking process.

- In order to increase the processing speed and to obtain the level of confidence of recognition outcomes of the multimodal biometric system, I employ fuzzy logic [Zade65] based fusion for biometric authentication. The fuzzy fusion method is based on fuzzy logic and uses match score and rank information of the multimodal biometric system. Further, more information in terms of confidence level about the outcomes can be obtained through this fusion method.

- I develop and test a multimodal system on a variety of multimodal database framework. Presented results clearly demonstrate the advantages of proposed methodology over other multimodal biometric systems.

1.3 Proposed Methodology

In this thesis, the main goal is to evaluate the performance of the multimodal biometric system based on rank level fusion and fuzzy logic based fusion compared to unimodal biometric systems and other multimodal systems. As biometric identifiers, face, iris and ear, all from the facial region, are used. Face is the most common biometric identifier and is used by most of the biometric researchers for identity authentication [BCPR04]. Due to ease in availability, universality, uniqueness, measurability, difficult to circumvention and authentication performances, face is more acceptable than other biometric characteristics [FDHZ04]. The complex iris (annular region of the eye bounded

by the pupil and the sclera) texture carries very distinctive information useful for personal recognition [Daug04][RoNJ06]. Thus, iris recognition is the best authentication process available today. Acquiring iris images is a costly process, but the characteristics, such as stability, uniqueness and flexibility make iris recognition is a good choice for person authentication [Daug00]. Although ear is not a frequently used biometric trait [BurB98], but I choose this trait because I want to use biometrics from the similar region of the human body keeping in mind that, it will help me to create the real time multimodal biometric security system in future. After classification of these unimodal identifiers by three different classifiers, Markov chain rank fusion approach (which consolidates rank information obtained from three different classifiers) will be applied to get the final authentication decision. In another experiment, I employ fuzzy logic based fusion which will operate on elements presented in the individual ranking lists and their respective matching scores.

1.4 Organization of the Thesis

The thesis has been structured in the following way. Chapter 1 describes the general problem statement and the thesis contributions along with description of biometric systems.

Multimodal biometric systems and their possible fusion strategies are described in chapter 2. This chapter also discusses the designing issues involved in multimodal system development process.

Several biometric systems have been developed with different biometric traits and with different fusion mechanisms. In chapter 3, previous research on information fusion and on unimodal and multimodal biometrics are reviewed.

The proposed system for rank fusion and for fuzzy logic based fusion is illustrated in chapter 4. All three unimodal matchers for face, ear and iris are also described in details in this chapter.

Chapter 5 describes rank fusion and fuzzy fusion strategies for proposed multimodal biometric system. Highest rank method, Borda count method, logistic regression method, the novel Markov chain based rank fusion method and fuzzy logic based fusion method are described in this chapter.

Chapter 6 shows the outcomes of the experiments performed on different database frameworks. The experimental overview and the databases are also discussed.

Chapter 7 summarizes the thesis and the contribution and presents some concluding remarks. Possible future directions of this research are also discussed in this chapter.

CHAPTER TWO: OVERVIEW OF MULTIMODAL BIOMETRIC SYSTEMS

The optimal biometric system is one having the properties of distinctiveness, universality, permanence, acceptability, collectability, and security [RoNJ06]. But there is no single biometric identifier which has all of these properties. As a solution, multiple biometric identifiers are used in a single system which is commonly known as multimodal biometric system. For example, a multimodal system may use both face recognition and iris recognition to authenticate a person. Due to reliable and efficient security solutions in the security critical applications, multimodal biometric systems recently emerged in biometric community as an alternative to the traditional unimodal systems.

This chapter starts with the definition, functionalities and performance of biometric systems and continues by describing multimodal biometric systems' functionalities and fusion methods.

2.1 Biometric Systems and Functionalities

The word 'Biometric' is a composite word coming from two Greek words 'bios' (life) and 'metron' (measure). Biometric is sometimes defined as a research area focused on measuring and analyzing a person's unique characteristics [MMJP09]. Biometric authentication offers a reliable solution to the problem of establishing identity of a person utilizing his/her physiological or behavioral biometric characteristics. The advantage of these biometric traits over a token-based or a password-based system is that unlike in those systems, these traits cannot be lost, stolen or shared [RoNJ06]. Biometrics can also

provide negative identification functionality where the goal is to establish whether a certain individual is indeed enrolled in the system although the individual might deny it [Scho]. Due to these advantages, in recent years, biometric systems are adopted by many government and civilian applications [WJMM05].

A typical biometric system operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template feature set in the database [JaRP04]. Thus, biometric system components can be divided into four main modules according to their functionalities. These modules are sensor module, feature extraction module, matching module and decision module [JaFR07]. Sensor module acquires the biometric data from the source, i.e., from an individual, through a variety of instruments, such as, camera, fingerprint sensor, speaker etc. based on the type of biometrics. The feature extraction module extracts features from the acquired biometric trait, which ideally should be unique for each person (extremely small inter-user similarity) and also invariant with respect to changes in the different samples of the same biometric trait collected from the same person (extremely small intra-user variability). The feature set obtained during enrollment is stored in the system database as a template. The matching module matches the feature set extracted from biometric sample during authentication to the template and determine the degree of similarity (dissimilarity) between the two feature sets. The authentication decision is taken at the decision module based on this degree of similarity/dissimilarity. Another important component of all biometric systems is the system database, where all the extracted feature sets (templates) stored for comparison. Further, in some biometric systems, a quality check module also incorporated after the

sensor module [JaFR07] into the system to ensure the quality of the acquired biometric samples. If the acquired biometric samples do not satisfy the required criteria, they are re-acquired from the user.

A biometric system can be used for person verification or person identification. Person verification answers the question, “Am I who I claim to be?” and is the process of establishing the validity of a claimed identity by comparing a verification template to an enrollment template [RoNJ06]. Verification requires that an identity be claimed, after which the individual’s enrollment template is located and compared with the verification template. Thus the comparison needed for verification is termed as one-to-one comparison [JaFR07]. During verification, usually some knowledge about the identity (such as ID) is given to the system along with the biometric identifier. This additional factor uniquely presents an enrolled identity and extracted biometric features to the system database and hence an associated biometric machine representation (feature set) [BCPR04]. Verification is used in day-to-day life where most people with whom we do business or deal with verify our identity (e.g., banking, social services etc.).

Biometric identification establishes a person's identity by answering the question “Whose biometric data is this?” [JaRP04]. To do so, an identification system performs matches to test person’s identity against multiple biometric templates. Thus, in identifications system, matching is one-to-many matching [JaFR07]. In [JaFR07], the authors mentioned two types of identification systems: positive identification and negative identification. They define positive identification systems as those systems which are designed to find a match in a biometric authentication system to answer the question “Who am I?”[JaFR07]. An example of a positive identification system would be

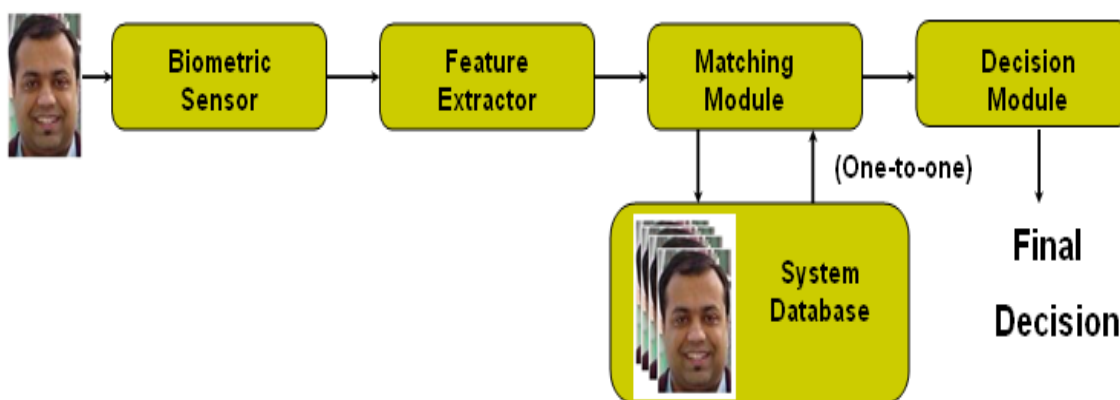
an access control system in an office setup to confirm that the employee is on the designated access list of the office. Negative identification [JaFR07] systems ensure that a person is not present in the database. This can be used in benefits programs to prevent users from enrolling under different names.

For both verification and identification, successful biometric enrollment is necessary [DunY09]. Biometric enrolment is the process of registering subjects in biometric databases. Figure 2.1 illustrates biometric enrolment, biometric verification and biometric identification processes.

Biometric Enrolment



Biometric Verification



Biometric Identification

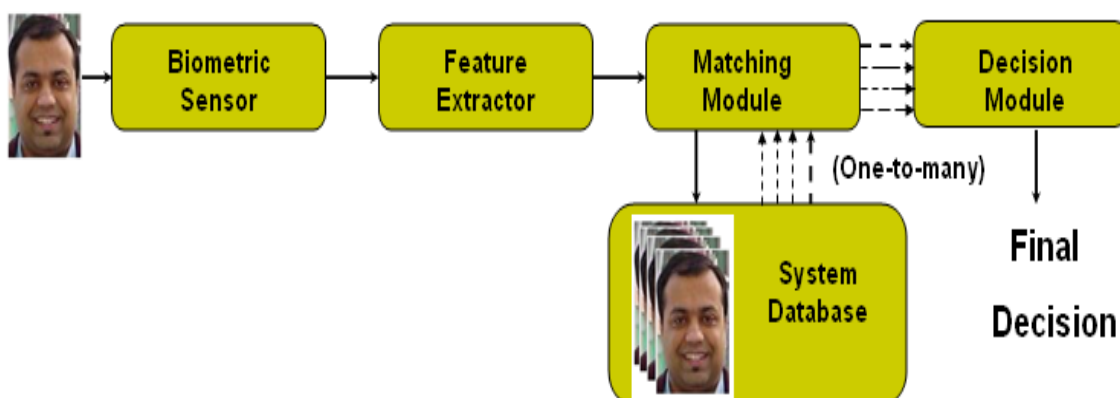


Figure 2.1: Biometric enrolment, biometric verification and biometric identification (adopted from [RoNJ06] and [BCPR04]).

2.2 Performance Metrics of Biometric Systems

Expressing the performance of a biometric system requires some parameters. A decision made by a biometric system is either a “genuine individual” type of decision or an “impostor” type of decision [RoNJ06]. For each type of decision, there are two possible outcomes, true or false. Therefore, there are a total of four possible outcomes: a genuine individual is accepted or a genuine match occurred, a genuine individual is rejected or a false rejection occurred, an impostor is rejected or a genuine rejection occurred and an impostor is accepted or a false match occurred [RoNJ06]. The confidence associated with different decisions may be characterized by the genuine distribution and the impostor distribution, which are used to establish two error rates [JaFR07]:

i) False accept rate (FAR), which is defined as “the probability of an impostor being accepted as a genuine individual” [RoNJ06]. That is, in a biometric authentication system, the FAR is computed as the rate of number of people is falsely accepted (false people are accepted) over the total number of enrolled people for a predefined threshold.

iii) False reject rate (FRR), which is defined as “the probability of a genuine individual being rejected as an impostor” [RoNJ06]. That is, in a biometric authentication system, the FRR is computed as the rate of number of people is falsely rejected (genuine people are rejected) over the total number of enrolled people for a predefined threshold.

FAR and FRR can be changed by a significant amount depending on the threshold used in the system. If a lower threshold is used in a similarity based biometric matching system, then the FAR will be higher and the FRR will be lower. Similarly, if a higher threshold is used in a similarity based biometric matching system, then the FAR will be

lower and the FRR will be higher. Sometimes another term Genuine Accept Rate (GAR) is used to measure the accuracy of a biometric system [RoNJ06]. It is measured as the rate of number of people is genuinely accepted (genuine peoples are accepted) over the total number of enrolled people for a predefined threshold. In other words, GAR can be obtained by subtracting the number of falsely rejected people from the total number of genuine people.

Two other types of failures are also possible in a practical biometric system. Failure-to-Enroll Rate (FTER) is “the proportion of individuals who cannot be enrolled in the system” [BCPR04]. This error can occurs if an individual cannot interact correctly with the biometric user interface or if the biometric samples of the individual are of very poor quality, thus the sensor or feature extractor may not be able to process these samples. Failure-to-Capture Rate (FTCR) is “the fraction of authentication attempts in which the biometric sample cannot be captured” [Rene04].

The values of these performance metrics are usually plotted in different graphs or curves to represent the recognition accuracy of the biometric system. The most commonly used plotting curve is the Receiver Operating Characteristics (ROC) curve [Egan75], which is used mostly for biometric verification. ROC curves plot FAR against the corresponding FRR for any threshold. Another commonly used curve is Cumulative Match Characteristics (CMC) curve [MooP01] which is mainly used for biometric identification. CMC curves show the chance of a correct identification within the top ranked match results. A good system will start with a high identification rate for low ranks identities [DunY09].

The performance of a biometric system may also be expressed using Equal Error Rate (EER) which refers to that point in a ROC curve where the FAR equals the FRR. A lower EER value thus indicates better performance [RoNJ06].

2.3 Advantages of Multimodal Biometric Systems

The advantages of multimodal biometric systems stem from the fact that there are multiple sources of information. The most prominent implications of this are increased and reliable recognition performance, fewer enrolment problems and enhanced security [RosJ04].

2.3.1 Increased and Reliable Recognition Performance

As multimodal biometric systems use more than one biometric trait, hence each of those traits can offer additional evidence about the authenticity of any identity claim. For example, the gaits (the patterns of movements of the limbs) of two persons of the same family (or coincidentally of two different persons) can be similar. In this scenario, a unimodal biometric system based only on gait pattern analysis may result in false recognition. If the same biometric system also includes fingerprint matching, the system would results in increased recognition rate as it is very unlikely that two different persons have same gait and fingerprint patterns.

Another example of increased and reliable recognition performance of multimodal biometric systems is ability to effectively handle the noisy or poor quality data. When the biometric information acquired from a single trait is corrupted with noise, the availability of other traits may aid in reliable determination of identity. For example,

in a face and voice based multimodal biometric system, due to ambient noise, if the individual's voice signals cannot be accurately measured, the facial characteristics may be used for authentication.

2.3.2 Fewer Enrolment Problems

Multimodal biometric systems address the problem of non-universality or the insufficient population coverage, where a portion of a population has a biometric characteristic that is missing or not suitable for recognition and thus reduce the failure to enroll rate significantly [FriD00]. Depending on the system design, many multimodal biometric systems can perform matching even in the absence of one of the biometric samples. For example, in a fingerprint and face based multimodal system, a person (who is a carpenter) cannot enrol his fingerprint information to the system due to the scars in his fingerprint. In this case, the multimodal system can still perform authentication using the facial characteristics of that person.

2.3.3 Enhanced Security

Multimodal biometric systems make life difficult for any impostor to spoof multiple biometric traits of a legitimately enrolled individual. "A spoof attack is where a person pretends to be another person by using falsified information" [DunY09]. For example, Japanese researchers have demonstrated how to create fake fingerprints that has some success at fooling commercial fingerprint recognition systems [MMYH02]. The advantage of multimodal systems is that the impostor would have to be able to spoof more than one biometric trait simultaneously, which would be significantly more

challenging. Further, some multimodal biometric system employs challenge-response [RoNJ06] mechanism to fight against spoof attacks by asking the user to present a random subset of traits at the point of acquisition. Multimodal biometric systems can also serve as a fault tolerant system [RoNJ06]. If any single trait is unavailable in a multimodal biometric system, the system can still work with other available traits.

2.4 Information Sources for Multimodal Biometric Systems

Multimodal biometric systems rely on the evidence presented by multiple sources of biometric information [HonJ98]. There are several design issues that are associated with the multimodal biometric system development process including source of information, choice of biometric traits, information fusion, cost benefit, processing sequences, level of robustness and so on. Among all of these factors, sources of information and information fusion are considered the two main factors [RoNJ06]. Thus, these two factors are discussed in this thesis.

The sources of biometric information differ from systems to systems depending on the application requirements. The term multimodal biometric system refers specifically to those biometric systems where multiple biometric modalities are used [RoNJ06]. The term multibiometric is more generic and includes multimodal systems and some other configurations using only one biometric modality with different samples instances or algorithms [NCDJ09].

Based on the sources of information, the following six categories of multibiometric systems are proposed by [RoNJ06]. They are [RoNJ06]:

Multiple sensors - one biometric trait: In these systems, different sensors are used for capturing different representations of the same biometric modality to extract different information. For example, a biometric system may use 2D, 3D or X-ray images for authentication. As these systems consider only one biometric trait, so, if the biometric system is not appropriate, one can't get any benefit from the multiple acquisition of the biometric trait.

Multiple instances - one biometric trait: In these systems, multiple instances of the same biometric trait are used for authentication. For example, the image of left and right eye of a subject may be used for retina recognition system. These systems are cost efficient, as the same sensors or the same feature extraction and matching algorithm can be used.

Multiple algorithms - one biometric trait: These systems use one biometric trait but use different matching algorithms. For example, a system may use eigenface and Voronoi diagram as matching algorithms for the same set of face images and later combine the results. These systems also suffer with the poor quality of input.

Multiple samples with single sensor - one biometric trait: These systems use single sensor but multiple samples of the same biometric trait. For example, a single sensor may be used to capture different facial expression images of a subject and latter a mosaicing scheme may be used to build a composite face image from all the available face images of that subject.

Multiple biometric traits: These systems use more than one biometric traits and hence are referred to as multimodal systems. For example, a biometric system may use face and voice for person authentication. The cost of deploying these systems is substantially more due to the requirements of new sensors and for the development of the new user interface [SoDG00]. Usually the identification accuracy of these systems are proportional to the number of traits.

Hybrid systems: These systems use more than one scenarios discussed above for robust authentication [RoNJ06]. For example, a biometric system may use two iris matching algorithms and three face matching algorithms in one face and iris based multimodal biometric system.

Figure 2.2 illustrates the biometric sources.

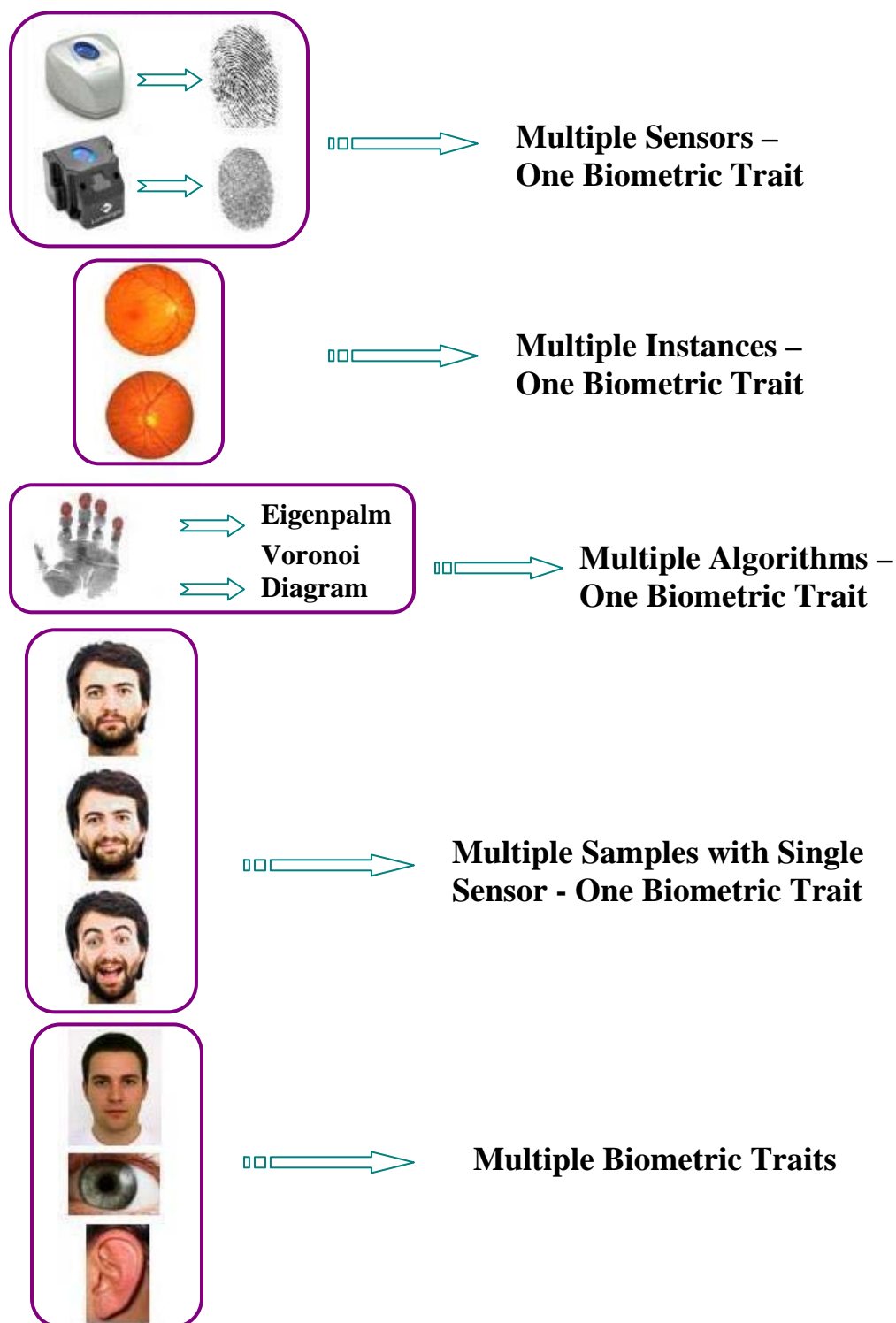


Fig. 2.2: Possible information sources of multibiometric systems (adopted from [RoNJ06]). (source: Google Image [ImaG])

2.5 Information Fusion in Multimodal Biometric Systems

According to [LBRS04], “Information fusion can be defined as an information process that associates, correlates and combines data and information from single or multiple sensors or sources to achieve refined estimates of parameters, characteristics, events and behaviors”. A good information fusion method allows minimizing the influence of unreliable sources compared to reliable ones [KlBM08]. Number of disparate research areas including robotics, image processing, pattern recognition, information retrieval etc. utilize and describe information fusion in their context of theory. Thus information fusion establishes itself as an independent research area over the last decade. Since, multimodal biometric systems rely on the evidence presented by multiple sources of biometric information, information fusion is essential for analysis, indexing and retrieval of such information. There are numbers of fusion techniques for any particular information. Choosing appropriate fusion techniques for any specific information depends on the necessity of the application and the performance of the fusion techniques proven by previous research. In their research, Sanderson and Paliwal [SanP01] categorized the fusion methods into two broad categories - fusion before matching and fusion after matching, considering the possible fusion elements (type of biometric information). Fusion before matching category contains sensor level fusion and feature level fusion, while fusion after matching contains match score level fusion, rank level fusion and decision level fusion. Figure 2.3 shows the biometric fusion classification and Figure 2.4 shows the possible fusion before matching and fusion after matching levels. In figure 2.4, fuzzy fusion is not shown as this fusion method can be employed in any levels.

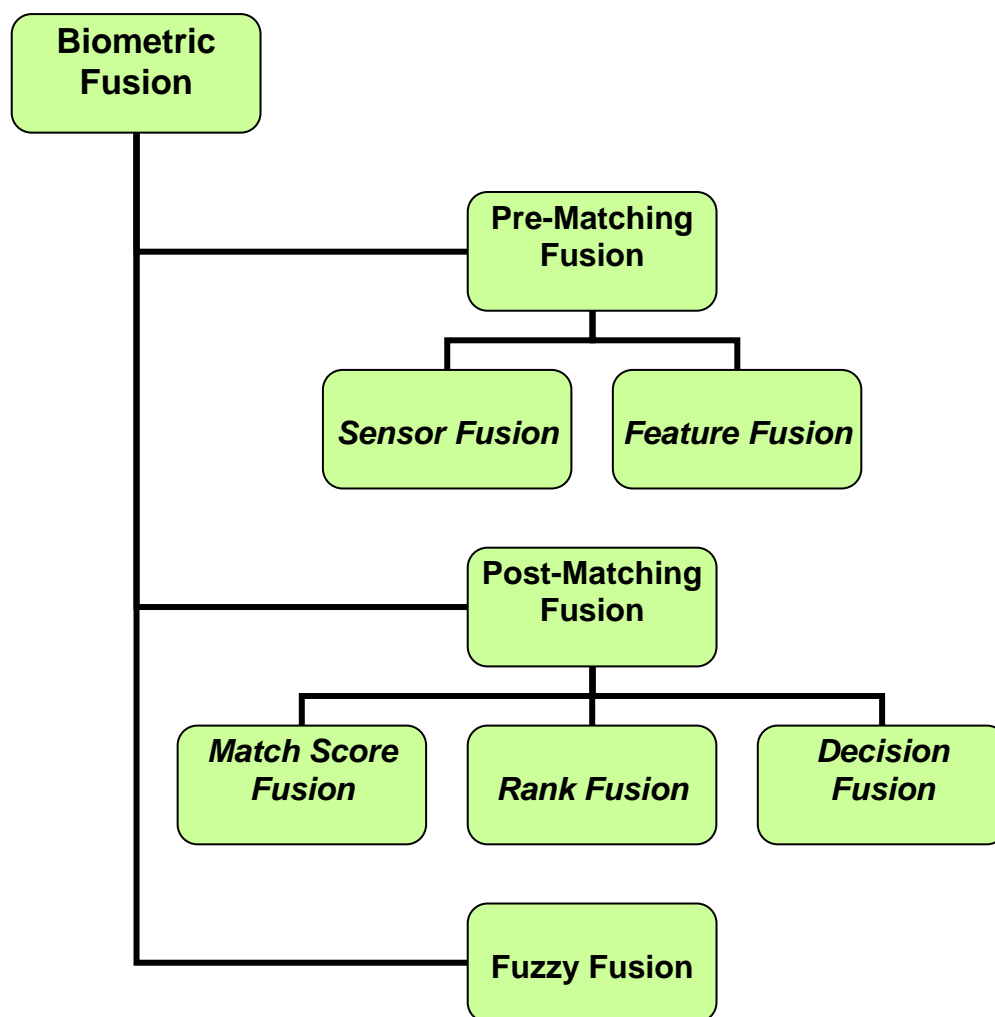


Fig. 2.3: Biometric fusion classification.

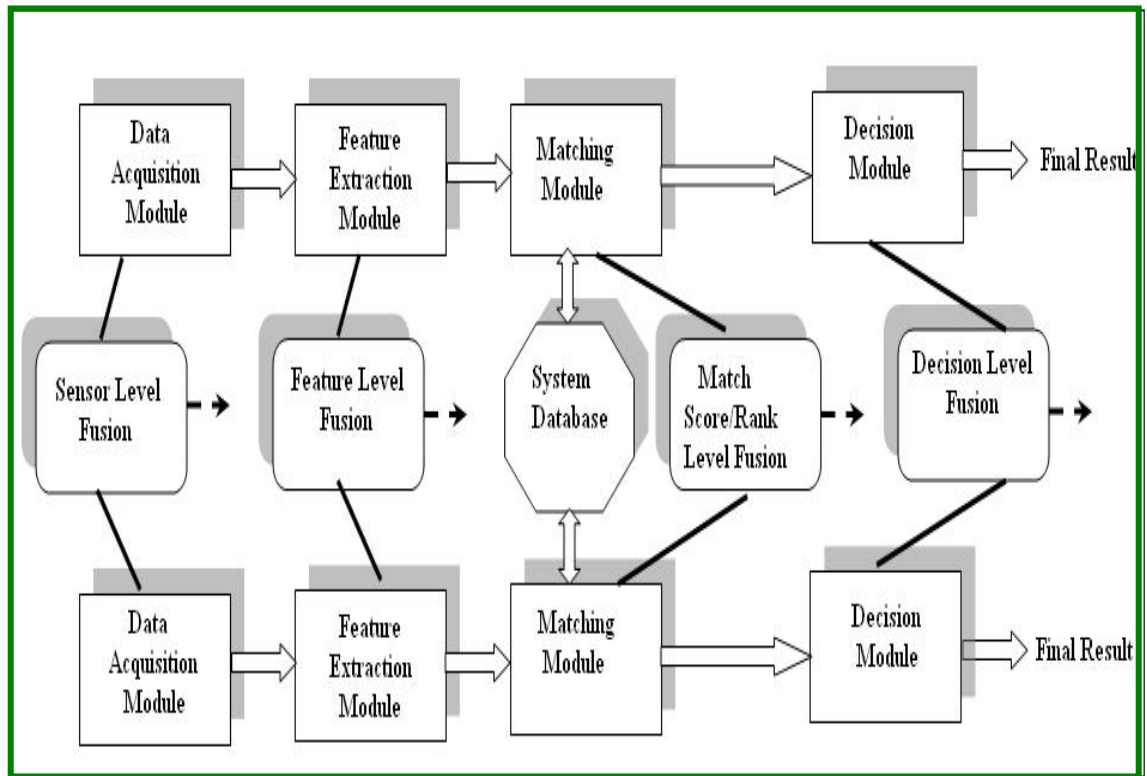


Fig. 2.4: Possible fusion before matching and fusion after matching levels [GavM09].

2.5.1 Fusion before Matching

Fusion in this category integrates evidences before matching or comparison occurs. According to Kokar et al., “By combining low level features it is possible to achieve a more abstract or a more precise representation of the world” [KoWT04]. Thus, biometric sources at the earlier stage are believed to be contained with much rich information (Figure 2.5). For this reason, fusion methods in this category are popular to some researchers. The possible drawback of this category is additional cost or time due to the development of new matching algorithms for new biometric feature sets. Sensor and feature level fusion fall under this category.

2.5.1.1 Sensor Level Fusion

Sensor level fusion is defined as “the consolidation of evidence presented by multiple sources of raw data before they are subjected to feature extraction” [RoNJ06]. For example, in the case of face biometrics, both 2D texture information and 3D depth (range) information (obtained using two different sensors) may be fused to generate a 3D texture image of a face to be utilized for feature extraction and matching [Hsu02]. In another research [LiuC03], authors combined multiple instances of faces captured using a single camera by mosaicking method to obtain better recognition performance.

2.5.1.2 Feature Level Fusion

Feature level fusion consolidates more than one feature sets extracted from multiple data sources to create a new feature set to represent the individual. The geometric features of the hand, for example, may be augmented with the eigen-

coefficients of the face in order to construct a new high-dimension feature vector [RosG05].

This fusion method is expected to produce comparatively better results than other fusion methods as more raw information is available for fusion which may be unavailable for after matching fusion methods [RoNJ06]. But there are some difficulties if the feature sets originate from multiple biometric traits. Firstly, the feature sets from different modalities may be obtained from different algorithms. Therefore, finding relationship between these feature sets is difficult. Secondly, this fusion can create ‘curse of dimensionality’ problem which is known as problems associated with high dimensional features space. Thirdly, a feature normalization technique is necessary if the feature sets exhibit significant differences in their range as well as distribution. Feature normalization refers to changing the location and scale parameters of the feature distributions at the outputs of the individual feature extraction methods [RoNJ06]. Fourthly, in most commercial biometric systems, feature sets are unavailable. On the other hand, if the feature sets originate from single biometric identifier, template update or template improvement [MYCC04] algorithms can be used for feature level fusion.

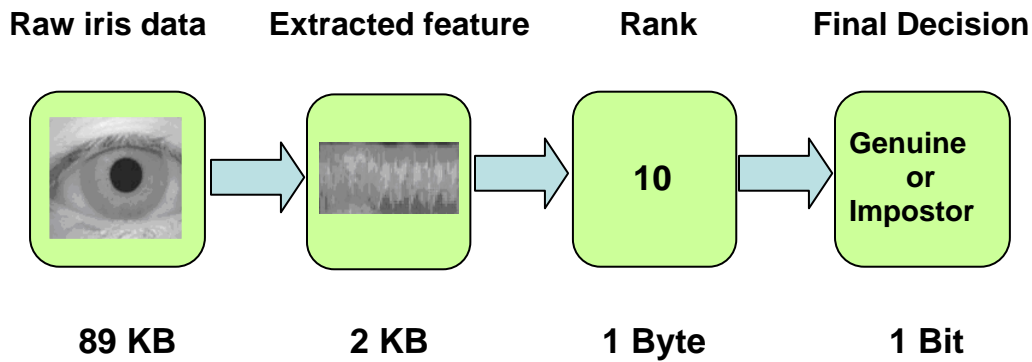


Fig. 2.5: Example of how information available for fusion decreases in every level of a biometric system (adopted from [RoNJ06]).

2.5.2 Fusion after Matching

This category of fusion combines comparison scores or other information or decisions obtained after comparison is done. Most multimodal biometric systems have been developed using these fusion methods as the information needed for fusion is easily available compared to fusion before matching methods. The matching scores, the ranking list (sorted order) based on matching scores or the individual biometric decision can be used for fusion in this category.

2.5.2.1 Match Score Level Fusion

Match score level fusion method consolidates matching scores generated from different classifiers and can be applied to most of the multibiometric scenarios. For example, this fusion method can consolidate matching scores obtained from two different algorithms for two instances of retina, as well as this fusion method can be used to

consolidate matching scores obtained from a face matcher and an fingerprint matcher [HonJ98].

For obtaining a single matching score this fusion method applies arithmetic operations, such as addition, subtraction, maximum, minimum, and median on to different matching scores. As an example, the match scores generated by three different matchers for the face, fingerprint and hand modalities of a user may be combined via the simple sum rule in order to obtain a new match score which is then used to make the final decision [RosJ03]. As different matching scores from different algorithms may not share the same underlying properties or the score range, score normalization is necessary in match score level fusion methods. Min-max, decimal scaling, z-score, median, median absolute deviation, double sigmoid, tanh-estimator are some examples of score normalization technique. Normalization process is costly in terms of time and choosing inappropriate normalization can lead to very poor recognition accuracy.

2.5.2.2 Decision Level Fusion

Decision level fusion method consolidates the final decision of single biometric matchers to form a consolidated decision. When each matcher outputs its own class label (i.e., accept or reject in a verification system, or the identity of a user in an identification system), a single class label can be obtained by employing techniques, such as, “AND”/“OR”, majority voting, weighted majority voting, decision table, Bayesian decision and Dempster-Shafer theory of evidence [RoNJ06]. Many biometric systems can only output the final decision, thus decision level fusion is very appropriate for those

biometric systems. The available information for this fusion method is binary (yes/no in most cases), which allows very simple operations for fusion.

2.5.2.3 Rank Level Fusion

Rank level fusion consolidates multiple ranking lists obtained from several biometric matchers to form a final ranking list which would aid in establishing the final decision [RoNJ06]. Sometimes, only the final ranked outputs from a biometric system are available. Furthermore, in some biometric systems, the matching scores from the matchers are not suitable for fusion. Thus rank level fusion is a feasible solution in such systems [KumS10]. This type of fusion is relevant in identification systems where each classifier associates a rank with every enrolled identity. Techniques such as Borda count [Bord1781] may be used to make the final decision [Blac63]. Methods for rank level fusion are discussed in details in chapter 5.

Among the available fusion methods, pre-matching fusion approaches, such as sensor level fusion and feature level fusion methods have not been used extensively due to limited access to the information. Match score level fusion methods are very popular with developers and also has been extensively investigated by biometric researchers as some of the earlier methods. But match score fusion approach needs normalization of the outcomes of unimodal matchers which is computationally extensive. Moreover inappropriate choice of normalization technique can degrade the system performances. Decision level fusion approaches are too abstract and used primarily in the commercial biometric system where only the final outcomes are available for processing. Rank level fusion method, however is a relatively new approach compared to others and still remains

understudied. Very limited research has been conducted on fusion at this level which has the potential of efficiently consolidating rank information in multimodal biometric identification system. Thus in this doctoral thesis, I choose rank level fusion for consolidation of multimodal biometric (face, ear and iris) information.

Fuzzy logic based fusion is another impressive information fusion approach which has been successfully applied in many different applications for the past years, such as automatic target recognition, biomedical image fusion and segmentation, gas turbine power plants fusion, weather forecasting, aerial image retrieval and classification, vehicle detection and classification and path planning. Thus, I decided to utilize the fuzzy fusion method for biometric information fusion aiming at the issue of improvement of authentication speed. Further, with the fuzzy logic based fusion, I can obtain the level of confidence for the final recognition outcome which can be very important in some security critical biometric applications. My contribution to this research is unique in the area of rank information fusion utilizing the Markov chain method for the first time for biometric rank consolidation and in the area of fuzzy logic based fusion. The next subsection presents a brief discussion on fuzzy fusion.

2.5.3 Fuzzy Fusion

The fuzzy fusion method can be employed in both before matching or after matching stages. When this fusion method is applied in before matching stage, usually it is to reduce the size of the dataset for comparison or matching. This fusion can also be employed in after matching stage to increase the recognition performance and to obtain the level of confidence of the final outcomes.

The method is based on fuzzy logic [Zade65], which is the classic and most widely applied technology in computational intelligence [Wang09]. The fuzzy logic approach enables imprecise information is processed in a way that resembles human thinking, e.g. big versus small, high versus low. It allows intermediate values to be defined between a normalized range of $[0, 1]$ by a partial membership for a fuzzy set.

2.6 Chapter Summary

Biometric is the automated method of recognizing a person based on a physiological or behavioral characteristic. Biometric technologies are becoming the foundation of an extensive array of highly secure identification and personal verification solutions [Newm09]. But biometric system based solely on a single biometric suffers from noisy sensor data, intra-class and inter-class variations over time, continuous threats of spoof attacks, unacceptable error rates etc., and hence may not always meet the necessary security requirements. To meet the rigorous security requirements, multimodal biometric system is emerging as a trend from the last decade which utilizes or is capable of utilizing, more than one physiological or behavioral characteristic for enrolment, verification, or identification. In this chapter, I have discussed advantages of multimodal systems compared to single biometric systems, as well as the two main factors involved in multimodal biometric system development, which are sources of information and information fusion for multimodal biometric system. Further, the functionalities and performance metrics of biometric systems are also discussed in this chapter.

CHAPTER THREE: PREVIOUS RESEARCH ON BIOMETRIC AND INFORMATION FUSION

Automatic person authentication by machine utilizing biometric traits has been a subject of study since 1970s. However, recognizing person utilizing multiple biometric traits was introduced very recently [BFOG05] and has significant advantages, including better recognition accuracy and higher resistance to sub-system failures [FOGB04]. Among these advantages, increasing the recognition performance is the main focus of the majority of research conducted in the field.

Information fusion is necessary to properly utilize multiple biometrics for decision making in a single system. The first application (combining neural networks) of information fusion has been reported in 1965 [TumG99]. Later this method has been used in various areas, such as econometrics, machine learning, pattern recognition, information retrieval etc. [WuMc06].

In this doctoral research, I concentrate on rank information fusion in the context of multimodal biometric system. I utilize the Markov chain based and fuzzy logic based fusion methods as tools for biometric rank fusion.

This chapter discusses some of the previous research done on different biometric and multimodal biometric systems as well as research on information fusion methods for combining multimodal information with the main concentration is given to rank information fusion. Further, some of the previous research on Markov chain method has also been discussed in this chapter.

3.1 Multimodal Information Fusion Research

Due to some problems associated with the unimodal biometric data, such as small variation over the population, large intra-variability over time, not present in all the population etc., the use of multimodal biometrics is a first choice solution [RosJ04]. The main objective of a multimodal biometric system is to improve the recognition performance of the system and to make the system robust over the limitations associated with unimodal biometric systems. Over the years, several approaches have been proposed and developed for multimodal biometric authentication system with different biometric traits and with different fusion mechanisms. The following sub-sections discussed some of the research utilizing different fusion methods for multimodal biometric systems.

3.1.1 Research on Sensor Fusion

A multisensory multimodal biometric system fuses information presented by multiple sources of raw data (image, video, sound, text, symbols etc.) at sensor level [RoNJ06] and is expected to produce more accurate results than the system that integrate information at later stages due to the availability of more information.

In 2003, Liu and Chen [LiuC03] propose a face mosaicking technique. This is a method for combining two or more images of the same face. The authors used a 3D ellipsoidal model to approximate human head images. Later, using geometric mapping, authors projected 2D face images onto the ellipsoidal model and utilized CMU PIE database [SiBB03] and a patch based probabilistic model for classification.

Another key contribution in this area is the research reported in [RaRK10]. The authors proposed an approach to combine information obtained from face and palmprint

image using particle swarm optimization (PSO). The Kernel Direct Discriminant Analysis (KDDA) and the nearest neighbor method are used for feature extraction and classification. Using FRGC face database [PFSB05] and polyU palmprint database (JYYL07), the authors tested the recognition performance with match score level fusion and with genetic algorithm applied on the same set of databases.

3.1.2 Research on Feature Fusion

Feature level fusion consolidates information from multiple biometric feature sets of the same individual. As the most information (features) regarding the identity of a person is available at this level, so feature level fusion is expected to perform better than match score level or decision level fusion methods [RosG05]. However, there are some inherent drawbacks associated with this fusion method. The feature spaces of different biometric traits may not be compatible and the feature level fusion may lead to the ‘curse of dimensionality’ problem by concatenating several features as one [RoNJ06]. Due to these drawbacks, the study on feature level fusion is seldom reported.

In 2004, Feng et al. [FDHZ04] developed a system for face and palmprint using feature level fusion technique. The authors used ORL face database and polyU palmprint database [JYYL07] and employed concatenation method for feature fusion. Two feature extraction approaches – PCA and ICA to see which results in a better recognition performance were also investigated. As noted by authors, ICA performed better than PCA in both monomodal and multimodal validation framework.

In another attempt to develop a multimodal biometric system, Rattani et al. [RKBT10] proposed a multimodal biometric system combining face and fingerprint

information at the feature level. In their research, authors extracted feature sets from face and fingerprint images and then concatenated (after necessary normalization) them to obtain combined feature set for their system. The authors also employed dimensionality reduction method to handle the problem of ‘curse of dimensionality’ and implemented several feature reduction techniques for the proposed system. The authors conducted experiments on BANCA face database [BBBH03] and a local fingerprint database to evaluate the recognition accuracy with match score level fusion for the same set of database.

While in limited experiment settings, both sensor level fusion and feature level fusion outperform match score level fusion, in practice this is not the case.

3.1.3 Research on Match Score Fusion

Matching score fusion consolidates matching scores generated from different classifiers and can be applied to most of the multibiometric scenarios because of its content of adequate information to make genuine and impostor case distinguishable and because of the easy availability of the scores [HHFR09]. But to utilize different matching scores from different classifiers, normalization of these scores is required which can be a bottleneck of this system for the time requirements. Also choosing inappropriate normalization technique can produce very low recognition accuracy.

In 1998, a bimodal approach was proposed for a Principal Component Analysis (PCA) based face and minutiae-based fingerprint identification system with a fusion method at the match score level (integrating the matching scores of different classifiers and making a decision based on the consensus matching scores) [HonJ98]. The MSU

fingerprint database [JaHB97] and a public domain face database results showed that the system achieved higher recognition accuracy using match score level fusion than when using any single biometric trait.

In 2005, Jain et al. proposed a multimodal approach for face, fingerprint and hand geometry, with fusion at the score level [JaNR05]. The authors examined simple-sum-rule, max-rule and min-rule method of match score fusion with seven normalization techniques. The final outcomes showed that all fusion approaches (except for the median-MAD normalization technique) exhibit better recognition performance than monomodal approaches [JaNR05].

3.1.4 Research on Decision Fusion

Decision level fusion method integrates the final decisions of single biometric matchers to form a consolidated decision. The consolidated decision can be obtained by employing various techniques including “AND”/“OR”, majority voting, weighted majority voting, decision table, Bayesian decision and Dempster-Shafer theory of evidence. Decision level fusion is too rigid and comparatively less sophisticated than other fusion methods as it operates only on binary information [RoNJ06].

In 2000, Frischholz and Dieckmann developed a commercial multimodal approach, BioID, for a model-based face classifier, a vector quantization (VQ)-based voice classifier and an optical-flow-based lip movement classifier for verifying persons [FriD00]. Weighted sum rule and majority voting approaches of decision level fusion method were used for fusion. Their experiments on 150 persons for three months demonstrated that the system can reduce the FAR significantly.

In another attempt in 2009, the research of Yu et al. [YXZL09] presented a multibiometric approach which combines palmprint, fingerprint and finger geometry collected by a digital camera at decision fusion level. Three decision fusion rules, including “AND” rule, “OR” rule and majority voting, are employed to perform the fusion. Experimental results conducted on a database of 86 hands (10 impressions per hand) showed that the proposed decision fusion methods are effective. Among the three decision fusion methods, majority voting was more accurate than the other two decision methods.

3.1.5 Research on Rank Fusion

Rank level fusion or in other words biometric rank aggregation is a process of combining the individual ranking preferences of several biometric matchers, into a single ranking list of the alternatives, which represents the consensus and which would aid in establishing the final authentication decision [RoNJ06]. In most commercial biometric systems, match score or feature level fusion is not possible due to the unavailability of such information [KumS10]. A few of such systems output ranked identities instead of the final (yes/no) decision, thus rank level fusion is a feasible option for those systems. This can often be the case to protect the proprietary biometric algorithms. Further, in some biometric systems, the matching scores from the matchers are not in suitable format for combination [RoNJ06].

The rank information aggregation problem has been addressed in various fields such as - i) in social choice theory which studies voting algorithms which specify winners of elections or winners of competitions in tournaments, ii) in statistics when studying

correlation between rankings, iii) in distributed databases when results from different databases must be combined, iv) in collaborative filtering, and v) in bioinformatics when gene expression similarity search, meta-analysis of microarray data is needed [Truc98] [Fagi99][PeHG00][PiDD08]. The criterion for success is the position of the true class in the consensus ranking, as compared to its position in the rankings before fusion.

One of the contributions of rank aggregation research is the work reported in [FarV08] in which rankings of documents are combined in order to produce a consensus ranking. Their proposed method was based on decision rules and showed better performance over other positional data fusion methods.

Another important contribution in this area is the work reported in [Ailo10] where the author discussed about rank aggregation from partial ranking lists. According to the research, one of the main drawbacks of considering full rankings is that obtaining full ranking information from all sources is not always possible. The author described some scenarios where only partial ranking list is available, such as – in web page searching, in sports tournaments, in election etc.. The main outcomes of the research were two approximation algorithms for aggregating partial rankings. The first was a 2-approximation, generalizing a well-known [AiCN05] 2-approximation for full rank aggregation. The second approximation algorithm was a $3/2$ -approximation algorithm, generalizing a recent algorithm [AiCN05] for full rank aggregation to the problem of partial rank aggregation.

In the area of bioinformatics, one important rank information fusion research is the work of Pihur et al. from University of Louisville, KY, USA [PiDD08]. In the research, the authors used a weighted rank aggregation method based on the Cross-

entropy Monte Carlo algorithm to find cancer genes through meta-analysis of microarray experiments. The research included a two steps experiment approach which demonstrated the efficacy of rank level fusion to find out cancer genes.

Very recently, some pattern recognition researchers have started to investigate rank level fusion in the context of multimodal biometrics. In 2009, a reported research suggested several modifications to enhance the performance of a quality based rank-level fusion scheme in the presence of weak classifiers or low quality input images [AbaR09]. Their experimental outcomes have demonstrated a significant performance gain, including image quality, when the fusion scheme is utilized.

In another attempt reported in 2010 [KumS10], the authors investigated a new approach for person recognition using rank level combination of multiple palmprint representations. The authors used Borda count, weighted Borda count, maximum rank and nonlinear weighted ranking method on two palmprint image databases. Among all of the fusion approaches they investigated, the usage of nonlinearities in conjunction with the weights resulted in the highest performance improvement.

3.1.6 Research on Fuzzy Logic Based Fusion

Fuzzy logic based fusion, often called fuzzy fusion, uses fuzzy logic [Zade65]. Fuzzy fusion method has been widely used in many applications, including automatic target recognition, biomedical image fusion and segmentation, gas turbine power plants fusion, weather forecasting, aerial image retrieval and classification, vehicle detection and classification, and path planning.

In 1999, Solaiman et al. [SoPU99] proposed a fuzzy-based multisensor data fusion classifier which was applied to land cover classification. The authors used a Fuzzy Membership Map (FMM) to combine information gathered from multiple sensors. Due to the use of fuzzy concepts, their proposed classifier was ideally suited for integrating multisensor and a priori information and also results in confidence maps.

In another study, authors developed a new vehicle classification algorithm using fuzzy logic [KKLC01]. In the algorithm, authors used vehicles' weight and speed to classify different vehicles using fuzzy rules. With their experimental results, they showed that the proposed classification algorithm using the fuzzy logic significantly reduces the errors in vehicle classification.

Another key contribution to the fuzzy fusion domain of literature is the work of Wang et al. [WDLL07] where authors used fuzzy fusion for multimodal medical image application. To overcome the problem of blurriness of the most medical images, the authors proposed a new method of medical image fusion using fuzzy radial basis function neural networks (Fuzzy-RBFNN), which is functionally equivalent to T-S fuzzy model [Hunt96]. Genetic algorithm was used to train the networks. The research outcome demonstrated good performance when compared to other methods for blurry images.

A 2010 paper [DSWL10] proposed a data fusion method based on fuzzy set theory and Dempster-Shafer evidence theory [Shaf76] for automatic target recognition. The authors represented both the individual attribute of target in the model database and the sensor observation as fuzzy membership function and constructed a likelihood function to deal with fuzzy data collected with each sensor. At the end, sensor data from different sources was fused based on the Dempster combination rule [Demp67].

In another research on applying fuzzy fusion in the medical imaging research domain, Chaabane and Abdelouahab in 2011 [ChaA11] proposed a system of fuzzy information fusion framework for the automatic segmentation of human brain tissues. Their method consisted of the computation of fuzzy tissue maps in both images by using Fuzzy C-means algorithm. Reported results from experiments were encouraging and underlined the potential of the data fusion in the medical imaging field.

From the above discussion, it can be concluded that many multimodal biometric systems with various methods and strategies have been proposed over the last decade to achieve higher accuracy rate and to increase robustness against spoof attacks and external conditions [MonG09] (some of the systems are summarized in Table 3.1). A general rule in theory assumes that the integration at an early stage of processing leads to systems which might be more accurate than those where the integration is introduced at later stages [RoNJ06]. Unfortunately, in practice fusion at sensor level is hard to achieve, due to the different natures of the biometric traits, which might be hardly compatible (e.g., fingerprint and face). Moreover, most commercial biometric systems do not provide access to the feature sets which minimizes the feasibility of a fusion at feature level. Fusion at matching level or at decision level does not require the creation of new databases or matching modules (the ones which constitute the monomodal subsystems are employed). In general, fusion at matching level [RosJ03] is preferable, but robust and efficient normalization techniques are necessary in the decision module.

Table 3.1: Some multimodal biometric systems.

Year	Modalities Used for Fusion	Authors	Fusion	Fusion Approach
1998	Face and fingerprint	Hong and Jain [Hon98]	Match score	Product rule
2000	Face, voice and leap movement	Frischholz and Dieckmann [FriD00]	Decision	Weighted sum rule, Majority voting
2003	Face, fingerprint and hand geometry	Ross and Jain [RosJ03]	Match Score	Sum-rule, decision tree and linear discriminant function
2003	2D and 3D faces	Liu and Chen [LiuC03]	Sensor	Face mosaic
2004	Face and palmprint	Feng et al. [FDHZ04]	Feature	Feature concatenation
2005	Face, fingerprint and hand geometry	Jain et al. [JaNR05]	Match score	Simple-sum-rule, max-rule and min-rule
2009	Fingerprint, face and hand geometry	Nandakumar et al. [NCDJ09]	Match score	Likelihood ratio
2009	Hand biometrics (palmprint, fingerprint, finger geometry)	Yu et al. [YXZL09]	Decision	AND rule, OR rule, majority voting
2010	Fingerprint and face	Rattani et al. [RKBT10]	Feature	Delaunay triangulation
2010	Face and palmprint	Raghavendra et al. [RaRK10]	Sensor	Particle swarm optimization
2010	Two palmprint images	Kumar and Shekhar [KumS10]	Rank	Borda count, weighted Borda count, maximum rank, nonlinear weighted rank

Normalization technique can be time consuming and selecting inappropriate normalization technique can lead to very poor recognition performance. Fusion at the decision level is poor given the limited availability of information which is restricted to the Boolean outputs of the subsystems' decision modules, and, in some cases, to the quality scores of the samples. But it is the only possibility of integration at hand if the match scores of the subsystems are not available. Thus fusion at the rank level is a

feasible approach compared to others which consolidates outputs of different classifiers in which no actual matching scores but only the relative positions of the user/identifier are needed [KumS10]. Very limited research has been conducted on fusion at this level which has the potential of efficiently consolidating rank information in any multimodal biometric identification system.

Fuzzy logic based fusion is another impressive information fusion approach which has been applied in many different applications for the past years. This fusion method uses fuzzy logic and thus can provide the level of confidence of the final output.

Thus in this doctoral research, I am motivated to work on rank level fusion and on fuzzy fusion for multimodal biometric security system. My contribution to this research is investigating different rank level fusion approaches such as highest rank, Borda count and logistic regression. I also make a unique contribution in the area of rank information fusion utilizing the Markov chain method for the first time for biometric rank consolidation and in the area of fuzzy logic based fusion utilizing biometric rank and match score information. The next subsection discusses some previous research conducted on Markov chain method.

3.1.7 Research on Markov Chain

Markov chain is named for the Russian mathematician Andre Andreyevich Markov. It is a mathematical model consists of a number of states [Mark'06]. The transitions from one state to another are dependent only upon the starting state of any transition, rather than upon how that state was reached. That means the transition in a Markov chain depends only on the immediately previous state not all the past states.

Markov chains have found a wide range of applications. Many researchers used Markov chain in different applications of physics, chemistry, statistics, internet applications, economics, finance, signal processing, pattern recognition, social sciences, biology games, music and sports [GriS97].

In an attempt to select consensus biomarkers from high throughput experimental data, in 2007, Dutkowski and Gambin [DutG07] used the Markov chain method. The authors presented solutions for consensus biomarker feature selection utilizing the Markov chain and the principal component analysis methods.

Markov chain method has also been investigated by some researchers for ranking web pages [DKNS01]. In their research, authors proposed a Markov chain based rank aggregation method to reduce search engine spams.

In this doctoral research, for the first time, Markov chain has been utilized for multimodal biometric information fusion. This approach brought a new dimension to the current ways of biometric rank aggregation and can be effectively used by the homeland and border security forces and by other intelligence services.

3.2 Biometric Research

In this subsection, I present history of individual biometrics and the rationale for choosing face, iris and ear in this multimodal biometric system. Biometrics (derived from the Greek words *bios* = "life" and *metron* = "measure") is the science of identifying humans using biological characteristics [MMJP09]. One of the earliest uses of biometrics was recorded by explorer Joao de Barros (one of the first great Portuguese historians, most famous for his 'Decades of Asia', a history of the Portuguese in India and Asia [Wiki])

[McMa05]. According to J. Barros's report, body parts have been used to identify people in ancient China since the 14th century and later in Europe [Wern08]. Today, the technology of biometrics has grown from fingerprint to many more biometric identifiers, such as: face, voice, hand-geometry, iris, retina, palmprint, gait, keystroke dynamics, signature etc.. However, the first modern biometric device, Identimat, was introduced in 1970s, as part of a time clock at Shearson Hamill, a Wall Street investment firm [Mill94]. The device measured the shape of the hand and the lengths of the fingers for uniquely identification of different persons. At the same time, fingerprint-based automatic checking systems were widely used in law enforcement by the FBI (Federal Bureau of Investigation) and by the US government departments [Zhan04]. Advances in hardware, such as faster processing power and greater memory capacity made biometrics more viable. After fingerprint, other biometric characteristics such as iris, retina, face, voice, palmprint, ear, signature etc. emerged during last century as means of identifying or verifying people [Zhan00]. Today, it is becoming more common to see biometric devices in many places including computer rooms, vaults, research labs, airports, day care centers, blood banks, ATMs, theme parks and military installations.

Researchers investigated different biometric identifiers based on several factors including application scenario, associated cost and availability of the identifiers. Each biometric trait has its advantages and limitations, and no single trait is expected to effectively meet all the above mentioned requirements imposed by all applications. Therefore, there is no universally best biometric trait and the choice of biometric depends on the nature and requirements of the application [Jain05]. In this doctoral research, I have used face, ear and iris biometric identifiers.

Face is the most natural and primary way for recognizing people [BCPR04]. Among all the biometric traits, face is the most common and heavily used biometric for person identification. Face recognition is friendly and non-invasive [FDHZ04]. Further, face can be captured by commonly available sensors and can be easily verified [Wils10].

Ear is not a frequently used biometric trait, but researchers in [BurB98] showed that identification by ear biometrics is promising because it is non-invasive like face recognition. Further, ear images can be acquired in a similar manner to face images (i.e., the camera which is used for acquiring face can also be used for acquiring ear images) and can be efficiently used in surveillance scenarios.

Iris pattern recognition is generally considered to be the most accurate among all the biometric traits available today [Wild97]. Iris recognition has a lot of advantages such as, flexibility for use in identification or verification, platform independency, higher recognition performance, permanency over time etc., which made iris recognition suited for various security critical applications [IrTD03].

The next three sub-sections discuss some of the previous research done on individual biometric system based on face, ear and iris.

3.2.1 Research on Face Recognition

Around 1950's, Bruner and Tagiori started to analyse faces to distinguish them in order to conduct psychological research [BruT54]. But research on automatic machine recognition of faces started in the 1970s by Prof. Takeo Kanade of Carnegie Mellon University [Kana73][ZCPR03]. Over the past decades, extensive research has been

conducted by psychologists, neuroscientists, and engineers on various aspects of face recognition by humans and machines.

The early face recognition was mainly based on measured facial attributes such as eyes, eyebrows, nose, lips, chin shape etc. [ChWS95]. In [HonJ98], the authors mentioned the lack of appropriate resources, particularly proper algorithms, as the barrier to achieve satisfactory performance from a face-based biometric system. Modern face recognition algorithms can be divided into three categories: holistic methods, which use the whole face image for recognition; feature-based methods, which use local regions such as eyes or mouth; and hybrid methods, which use both local regions and the whole face [ZCPR03].

Many holistic face recognition methods, as well as image analysis methods, are based on PCA (Principal Component Analysis) [KirS90], LDA (Linear Discriminant Analysis) [BeHK97] and ICA (Independent Component Analysis) [BaLS98]. In 1991, Turk and Pentland [TurP91] provided first use of PCA for face recognition using eigenspace decomposition. In their work, faces were compared using a Euclidean distance measure by projecting them into eigenface components and results were provided for a 16-users database of 2500 images in various conditions. This technique has been the subject of many improvements. In [BeHK97], Belhumeur et al. provide a face recognition algorithm, known as fisherface, using both PCA and FLDA (Fisher's Linear Discriminant Analysis) methods to overcome the problem of illumination and pose variations in.

A successful feature-based method is elastic bunch graph matching [WFKM97], which tolerated deformations of the faces. It used local features (chin, eyes, nose, etc.) represented by wavelets and computed from different face images of the same subject.

Example of a hybrid face recognition system is the system developed by Huang et al. in 2003 [HuHB03], where a combination of component-based recognition and 3D morphable models had been used for pose and illumination invariant face recognition.

For my system, a customized fisherface method, introduced in [BeHK97], which utilizes both PCA and FLDA, has been used for face recognition.

3.2.2 Research on Ear Recognition

Ear is a relatively new class of biometrics used for person authentication. Ear was first used for recognition of human being by Iannarelli [Iann89] who used manual techniques to identify ear images. Samples of over 10,000 ears were studied to prove the distinctiveness of ears. But the potential for using the ear's appearance as a means of personal identification was recognized and advocated as early as 1890 by the French criminologist Alphonse Bertillon.

After Iannarelli's classification, Victor et al. [ViBS02] used PCA and FERET evaluation protocol for ear identification. Burge and Burger [BurB98] introduced geometric algorithm utilizing Voronoi diagram of ears' curve segments for automated ear recognition.

In 2003, Chang, Bower and Barnabas [ChBB03] developed an ear recognition system using eigenear method and compare with eigenface method. They also combined eigenface and eigenear techniques to evaluate the performance of the system.

Bhanu and Chen presented a 3D ear recognition method using a new local surface descriptor [BhaC03]. The similarity of two ears was determined by three factors - the number of similar local surface descriptors in ears, geometric constraint, and the match quality.

3.2.3 Research on Iris Recognition

Human iris, which has a very complex layered structure unique to an individual, is an extremely valuable source of biometric information [DRCD06]. The general structure of the iris is genetically determined, but the particular characteristics are “critically dependent on circumstances (e.g. the initial conditions in the embryonic precursor to the iris)” and stable with age: iris recognition is thus considered as a promising biometric approach [Wild97].

Several iris recognition systems have been developed, which exploit the complexity and stability over time of iris patterns and claim to be highly accurate. The most well-known algorithm, on which the principle state-of-the-art iris recognition systems are based, is the algorithms developed by Daugman [Daug93]. That approach was comprised of the four steps - position localization of the iris, normalization, features extraction and matching. The author used 2D Gabor Wavelets [Daug88] to perform feature extraction from iris and Hamming distance [Hamm50] for comparing those features for classification.

Some other approaches of iris recognition were also introduced. In [Wild97], a histogram based model fitting method was used to localize the iris. For representation and matching, author registered a captured image to a stored model, filtered with isotropic 2D

band-pass decomposition (Pyramid Laplacian), and followed by a correlation matching based on Fisher's Linear Discriminant [Fish36]. Some recent approaches used Support Vector Machines as classifiers for iris recognition [RoyB06][WanH04].

A lot of research has also been conducted in the last two decades on other biometric traits including fingerprint, voice, signature, palm-print, gesture, DNA, hand-print, and typing patterns. Among those, fingerprint based unimodal biometric systems are widely used. As those traits are beyond the scope of this research work, so they are not discussed here.

3.3 Chapter Summary

Information fusion is the process of integration information to obtain comparatively better results [Wiki]. One of the potential applications of information fusion is the multibiometric information fusion where information from more than one biometric sources or classifiers is consolidated to obtain a better authentication decision. Over the past years, researchers investigated multimodal information fusion utilizing different combination of biometric traits with different fusion mechanisms. In this chapter, I have presented a brief description of research conducted on different fusion schemes for multimodal biometric information consolidation. Since I have used rank level fusion and fuzzy logic based fusion, more concentration is given to previous research on these two types of fusion. Also prior research on Markov chain method has been discussed as I introduce this method for biometric rank aggregation in this research. As individual biometric identifiers, I have used face, iris and ear. Therefore, previous

research conducted on face, iris and ear biometric identifiers are also discussed in this chapter.

CHAPTER FOUR: METHODOLOGY FOR MULTIMODAL BIOMETRIC SYSTEM

In this chapter, I present the methodology for the proposed multimodal biometric system based on rank level fusion and fuzzy logic based fusion utilizing face, iris and ear biometric information. I start with the overview of the proposed rank level fusion based multimodal biometric system with proper illustration and later describe the underlying algorithms for the three unimodal matchers for face, iris and ear biometrics. At the end, I give an overview of the proposed fuzzy fusion based multimodal biometric system with proper illustration.

For a multimodal biometric system, selecting the proper biometric traits is one of the main tasks. There is no single biometric trait that is the best. The appropriate biometric type for a given application depends on many factors including the type of biometric system operation (identification or verification), perceived risks, types of users, and various need for security [Wils10]. Each biometric trait has associated advantages and limitations. It is often the case that a single biometric trait is not capable of satisfying above mentioned requirements needed by different applications.

In the proposed system, the main goal is to evaluate the performance of the multimodal biometric system based on rank level fusion using Markov chain approach and the new fuzzy fusion approaches over the unimodal biometric system and other multimodal systems. So, I decided to use face, ear and iris biometric traits for this purpose. All of these biometric traits are from the similar region of the human body, i.e. from the facial region, which could be helpful to faster data collection and processing.

As previously stated, the main purpose of this research is to evaluate the performance of rank level fusion and fuzzy logic based fusion approaches over other fusion methods. Thus, for this system, those biometric traits should be chosen which are best suited for identification (as rank level fusion is applicable only in the identification mode). Following this argument, utilizing face, ear and iris biometrics are feasible for the proposed multimodal biometric system. I select those biometric traits since for all of those there are effective indexing techniques and effective and cheap comparison methods [HONJ98].

For efficient consolidation of biometric information, I examine various rank level fusion methods. Although rank fusion has been heavily investigated in other research areas, only limited research utilized rank information for biometric authentication. This type of fusion is relevant in identification systems where each classifier associates a rank with every enrolled identity. As my system is designed to identify person and to output ranked identities, rank level fusion is the feasible fusion approach for this system.

I introduce the Markov chain method in biometric rank aggregation process. Markov chains are applied in a number of ways to many different fields – physics, chemistry, statistics, internet applications, economics, finance, information sciences, social sciences, mathematical biology, games, music, and sports. I demonstrate that Markov chain approach for biometric rank aggregation has several advantages. This method handles the partial ranking list very well and provides a more holistic viewpoint of comparing all candidates against each other [DKNS01]. Further, Markov chain method can handle uneven comparison and can be viewed as the natural extensions of some other heuristics (such as Borda's method [Bord1781] or Copeland method [Cope51]).

Considering these advantages, I introduce this method as a tool for biometric rank information consolidation.

Further I introduce fuzzy fusion method for biometric rank aggregation. Utilizing fuzzy logic, this fusion method has been efficiently employed in many application areas including medical imaging, object recognition, weather forecasting and robotics. Based on the previous successful application of fuzzy fusion in other areas, I decided to use this fusion approach in the proposed multimodal biometric system.

4.1 System Overview for Rank Level Fusion

After individually comparing face, ear and iris matching, I implement two fusion modules - one for rank fusion and another for fuzzy fusion. A detailed diagram of the multimodal biometric system based on rank fusion is shown in figure 4.1. In the enrolment phase, face, ear and iris images are acquired first and then processed according to the training and classification algorithms. As our face and ear database contains, images with illumination change (also some ear images have the problem of occlusion), I use fisherimage method for the identification of these two traits. Fisherimage method for recognition has the ability to handle different image conditions, such as background noise, image shift, occlusion of objects, scaling of the image, and illumination change [BeHK97]. For this, two projection matrices are created, one for the face and one for the

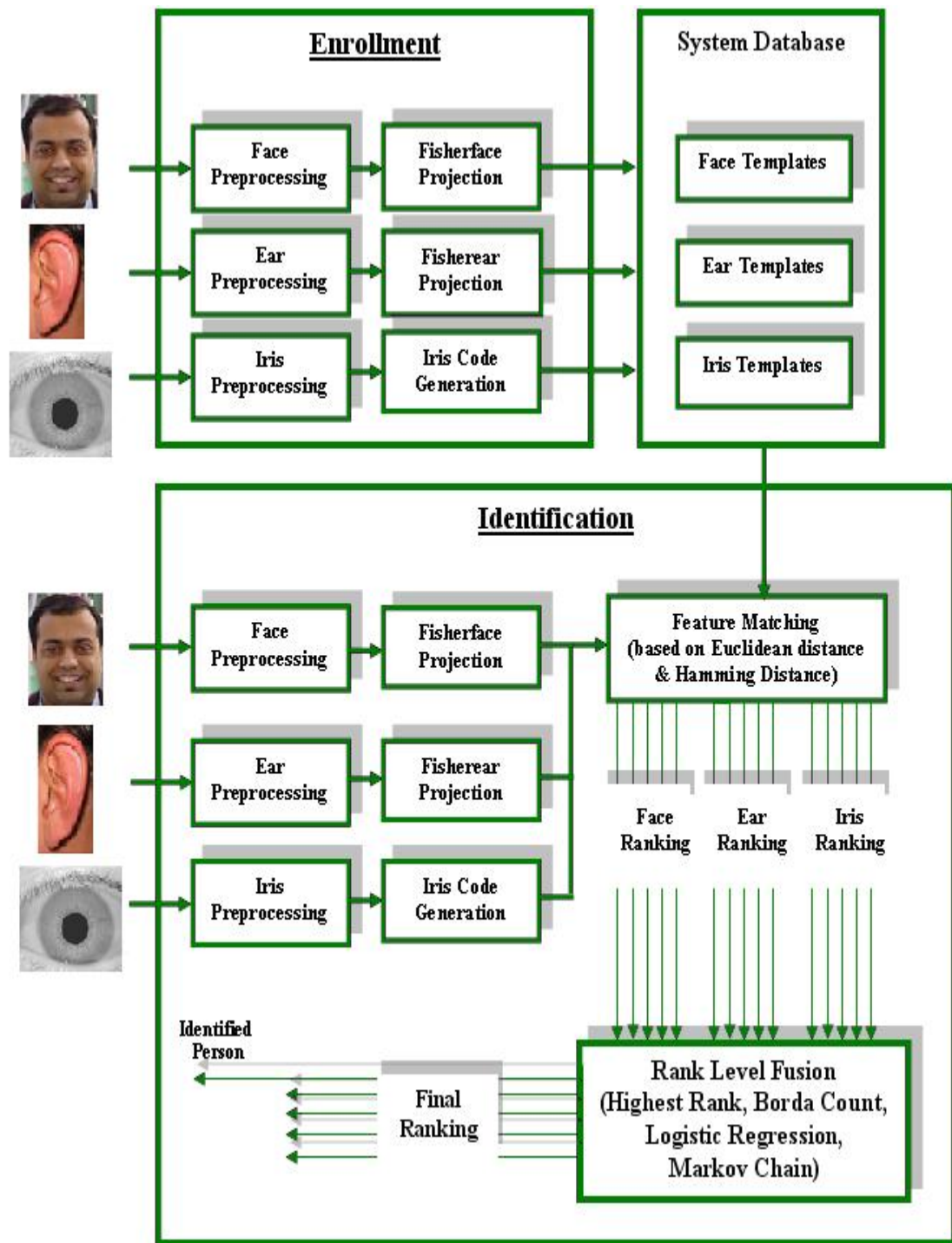


Fig. 4.1: The proposed multimodal biometric system based on rank level fusion.

ear, whose components can be viewed as images, referred to as fisherimages. These two projection matrices are the face templates and the ear templates, called fisherfaces and fisherears respectively.

For iris recognition, irises were detected from the eye images and then a binary iris code is generated from each iris using 2D Gabor filter [Gabo46]. These iris codes are the iris templates.

In the Identification phase, face and ear images are recognized measuring the Euclidian distance between the test image and the images in the fisherfaces and fisherears. For iris, the Hamming distance [Hamm50] (the number of positions at which the corresponding symbols of two equal length strings are different) is calculated between the codes generated from the test iris with the iris codes in the database. This method is chosen because of its simplicity and successful use in previous iris recognition research [Daug04].

In each of the three cases, top- n identities are obtained as outputs that are ranked according to their distances. The identities of these three ranking list then are combined using the rank level fusion approach to find out a consensus rank of the identities and the identity at the top of the consensus ranking list will be identified as the desired identity. For rank level fusion, along with the Markov chain method, three other rank fusion methods - highest rank, Borda count and logistic regression are also investigated to find out the consensus ranking from the three ranking lists. Details of these rank fusion methods including the Markov chain method are described in section 5.1 of Chapter 5.

4.2 Unimodal Matchers

One of the main issues which control the performance of the multimodal biometric system is the evidences presented by multiple sources of biometric information. In my multimodal biometric system, all the biometric traits used are images. As the main purpose of this research is to evaluate the performances of rank fusion and fuzzy fusion, introduced into this multimodal biometric system, and due to the inherent cost associated, I used a virtual multimodal database (data collected from different subjects) comprised of three different image databases – one each for face, ear and iris. The next subsections provide a detailed description of the unimodal face, ear and iris recognition processes.

4.2.1 Face Matcher

The face matcher of my system is used for face recognition, which finds recognizable facial characteristics from images, reduce the key features to digital codes, and match them against known facial templates. The inputs to this matcher are face images from a facial image database and the output is a ranking list with the top- n matches, i.e. first n recognized match faces.

In order to recognize faces, I first extract and select features from the faces to represent the face images in the most effective way to separate individuals in the feature space. Many approaches to selecting and extracting effective features have been suggested in the pattern recognition literatures. Among various approaches to this problem, the most successful are the appearance based approaches, which generally operate directly on images or appearances of objects and process the images as two-dimensional (2-D) holistic patterns. Principal Component Analysis (PCA) and Linear

Discriminant Analysis (LDA) are two powerful tools used for data reduction and feature extraction in the appearance-based approaches. Two state-of-the-art face recognition methods, Eigenfaces [TurP91] and Fisherfaces [BeHK97], built on these two techniques, respectively, have been proved to be very successful.

Between the two methods, I chose Fisherimage, which is a combination of PCA and LDA [BeHK97] for face and ear recognition in my multimodal biometric system (as my face and ear datasets contains face and ear images with certain illumination change). This method produces a subspace projection matrix, similar to that used in eigenimage method [MonG09]. However, eigenimage method attempts to maximise the scatter matrix of the training images in image space, while fisherimage method attempts to maximise the between class scatter matrix, also called extra-personal, while minimising the within class scatter, also called intra-personal (Figure 4.2). In fisherimage method, images of the same face class move closer together, while images of difference faces move further apart. Further, fisherimage method has several other advantages. This method is robust against noise and occlusion; against illumination, scaling and orientation; and against facial expressions, glasses, facial hair and makeup.

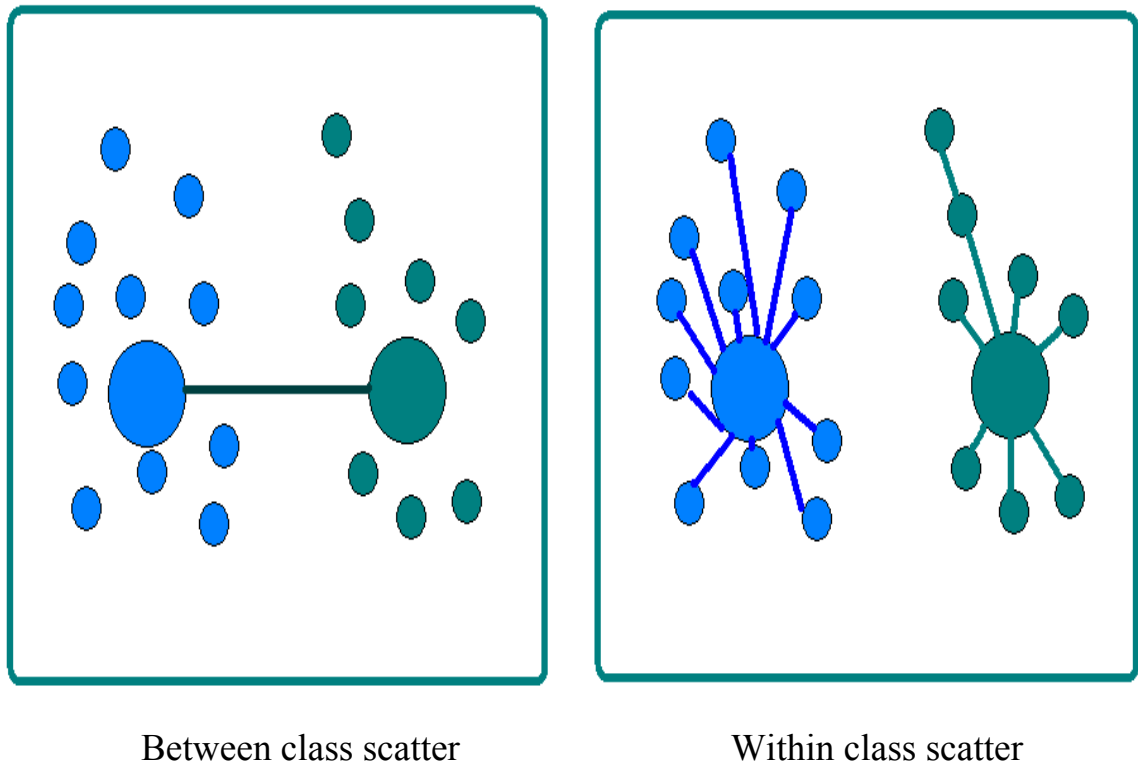


Fig. 4.2: Examples of between class and within class matrices (adopted from [YeJi02]).

Also Fisherimage method can handle high resolution or low resolution images efficiently, and can provide faster recognition with low computational cost. The calculation for this method is done using standard method [BeHK97] [TurP91] and is summarized below.

I first initialized our system with a set of training set of face image vectors containing multiple images of each subject as,

$$\text{Training set} = \left\{ \underbrace{\Gamma_1 \Gamma_2 \Gamma_3 \Gamma_4 \Gamma_5}_{X_1} \underbrace{\Gamma_6 \Gamma_7 \Gamma_8 \Gamma_9 \Gamma_{10}}_{X_2} \underbrace{\Gamma_{16} \Gamma_{17} \dots}_{X_4} \dots \underbrace{\Gamma_N}_{X_c} \right\} \quad (4.1)$$

where Γ_i is a face image vector, N is the total number of images and each image belongs to one of c classes $\{X_1, X_2, \dots, X_C\}$ where C is the number of subject in the database. The face image vector Γ is obtained by reconstructing the original face image by adding each column one after another. Thus, a face image represented by $(N_x \times N_y)$ pixels can be reconstructed into an image vector Γ of size $(P \times I)$, where P is equal to $(N_x * N_y)$.

Then I define the between class scatter matrix (S_B) and the within class scatter matrix (S_W) with the following two equations:

$$S_B = \sum_{i=1}^C |X_i| (\Psi_i - \Psi)(\Psi_i - \Psi)^T \quad (4.2)$$

$$S_W = \sum_{i=1}^C S_i \quad (4.3)$$

where, $\Psi = \frac{1}{N} \sum_{i=1}^N \Gamma_i$ is the arithmetic average of all the training image vectors in the

database at each pixel points and its size is $(P \times I)$. $\Psi_i = \frac{1}{|X_i|} \sum_{\Gamma_i \in X_i} \Gamma_i$ is the average

image of class X_i at each pixel points and $|X_i|$ is the number of samples in class X_i and its size is $(P \times I)$. The mean or average face images of each class are necessary for the calculation of each face class's inner variation. S_i is the scatter of class i which I define as,

$$S_i = \sum_{\Gamma_i \in X_i} (\Gamma_i - \Psi_i)(\Gamma_i - \Psi_i)^T \quad , \quad (4.4)$$

The size of the between class scatter matrix (S_B) and the within class scatter matrix (S_W) are both $(P \times P)$. The between class scatter matrix (S_B) represents the scatter of each class mean around the overall mean vector. The within class scatter matrix (S_W) represents the average scatter of the image vectors of different individuals around their respective class means.

After defining between class scatter matrix (S_B) and the within class scatter matrix (S_W), I define the total scatter matrix S_T of the training set as,

$$S_T = \sum_{i=1}^N (\Gamma_i - \Psi)(\Gamma_i - \Psi)^T \quad (4.5)$$

The objective of using Fisher's Linear Discriminant is to classify the face image vectors. A commonly used method to do so is to maximize the ratio of the between class scatter matrix of the projected data to the within-class scatter matrix of the projected data.

Thus, an optimal projection W which maximizes between-class scatter and minimizes within-class scatter can be found by the following equation:

$$W = \max(J(T)) \quad (4.6)$$

Where $J(T)$ is the discriminant power and can be obtained by the following equation:

$$J_T = \left| \frac{T^T \cdot S_B \cdot T}{T^T \cdot S_W \cdot T} \right| \quad (4.7)$$

Where, S_B and S_W are the between class scatter matrix and within class scatter matrix respectively.

Hence the optimal projection matrix W can be re-written as:

$$W = \max(J(T)) = \max \left| \frac{T^T \cdot S_B \cdot T}{T^T \cdot S_W \cdot T} \right|_{T=W} \quad (4.8)$$

and can be obtained by solving the generalized eigenvalue problem:

$$S_B W = S_W W \lambda_W \quad (4.9)$$

Where, λ is the eigenvalue of the corresponding eigenvector.

From the generalized eigenvalue equation, only $c-1$ or less of the eigenvalues come out to be nonzero. This is due to the fact that SW is the sum of c matrices of rank one or less, and because at most $c-1$ of these are linearly independent. As a result, no more than $c-1$ of the eigenvalues are nonzero, and only the eigenvectors coming out with these nonzero eigenvalues can be used in forming the W matrix and the size of the W matrix is $(P \times (c-1))$.

Once I construct the W matrix, it is used as the projection matrix. The training image vectors are projected to the classification space by the dot product of the optimum projection W and the image vector as follows;

$$\text{Classification space projection, } g(\Phi_i) = W^T \cdot \Phi_i \quad (4.10)$$

where Φ_i is the mean subtracted image and can be obtained by the following equation:

$$\Phi_i = \Gamma_i - \Psi_i \quad (4.11)$$

This projection matrix is of the size $((c-1) \times 1)$ and its components can be viewed as images, referred to as fisherimages.

After enrolling the face images, I need a recognition output which lists first n recognition results as for rank level fusion, the proposed multimodal system needs a

ranking output from all unimodal matchers. To achieve this, I perform the following tasks:

1) I project the test face image into the fisherspace, and measure the distance between the unknown face image's position in the fisherspace and all the known face image's positions in the fisherspace.

The projection of the test image vector to the classification space is done by the same manner:

$$\text{Classification space projection, } g(\Phi_T) = W^T \cdot \Phi_T \quad (4.11)$$

which is of the size $((c-1) \times 1)$.

The distance between the projections is calculated by the Euclidean distance between the training and test classification space projections;

$$\begin{aligned} \text{Euclidean distance, } d_{Ti} &= \|g(\Phi_T) - g(\Phi_i)\| \\ &= \sqrt{\sum_{k=1}^c (g_k(\Phi_T) - g_k(\Phi_i))^2} \end{aligned} \quad (4.12)$$

2) Then I select the image closest to the unknown image in the fisherspace.

3) I repeat step two (without considering the match image obtained through step 2) until I obtain n match images.

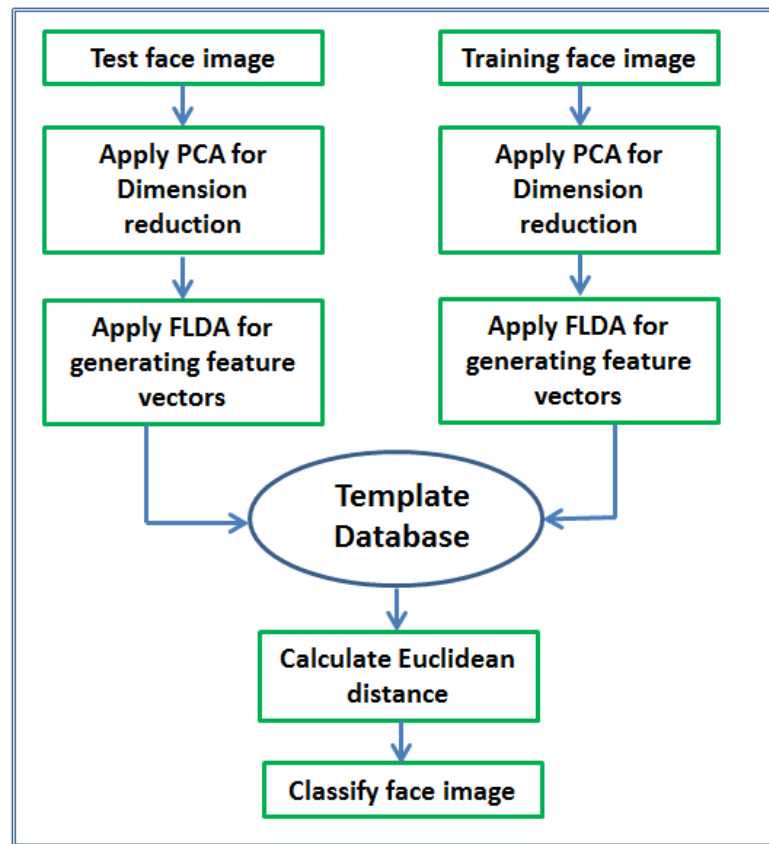


Fig. 4.3: General flowchart for fisherface generation process.



Fig. 4.4: Sample fisherfaces generated in this proposed multimodal system.

Figure 4.3 presents general flowchart for fisherface generation process and figure 4.4 presents sample fisherface generated in my multimodal biometric system.

4.2.2 Ear Matcher

Figure 4.5 shows the anatomy of the external ear. Ear biometrics is often compared with face biometrics [HurA07]. Chang used standard PCA algorithm for ear recognition, and gets the conclusion that ear and face does not have much difference on recognition rate [ChBB03]. In my multimodal system, I use two ear databases. One is USTB ear database [USTB] and the other is a public domain ear database [Perp95]. The database contains ear images with illumination and orientation variation. Thus, in this research, I develop my own method which utilize fisherimage algorithm for ear recognition.

The steps for generating fisherears are the same as fisherface generation process. First, I define the between class scatter matrix and the within class scatter matrix for ear after defining the ear training set. Then, I define the total scatter matrix for ear. Using this total scatter matrix, finally I obtain the optimum projection matrix. Similar to face, the components of this projection matrix can be viewed as images, referred to as fisherears. For ear recognition in my system, I first project a test ear image into fisherspace. A threshold is then applied for the final decision based on the distance between the test ear and the recognized ear from the ear template. Similar to face recognition, this threshold is chosen based on numerous trials and can be modified during execution time.

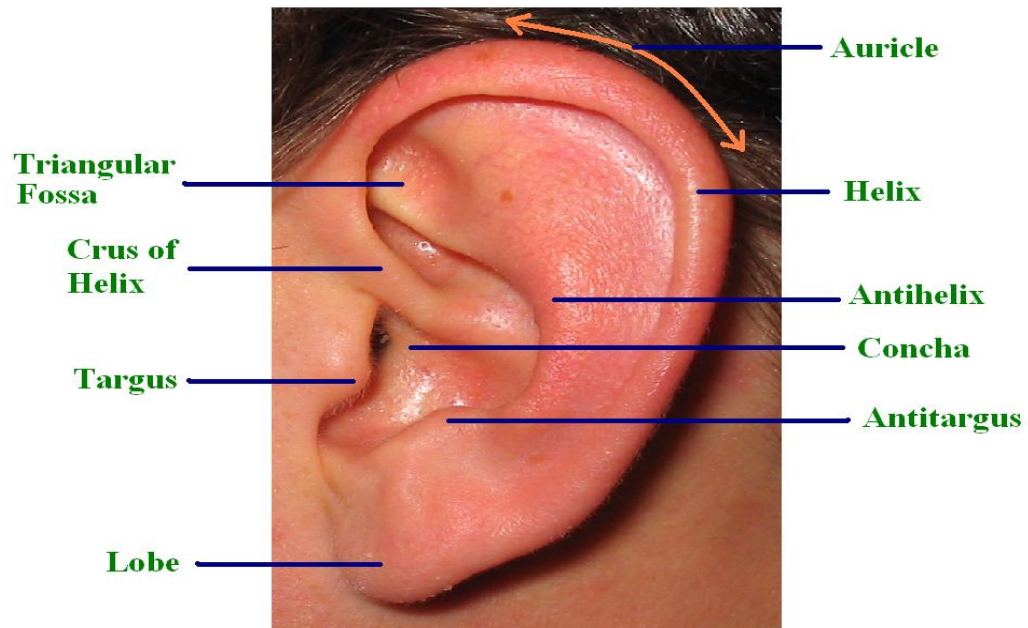


Fig. 4.5: Anatomy of an external ear (source: Google Image [ImaG])

In order to apply rank level fusion method, I create a ranking list by listing the ear recognition outputs based on their distance scores in the feature space. In the proposed system, the first n matches are used for rank level fusion.

Figure 4.6 shows sample ear images taken from USTB ear database and Figure 4.7 shows sample fisherears (from USTB database) generated after constructing the ear matcher.



Fig. 4.6: Sample ear image sets taken from USTB database.

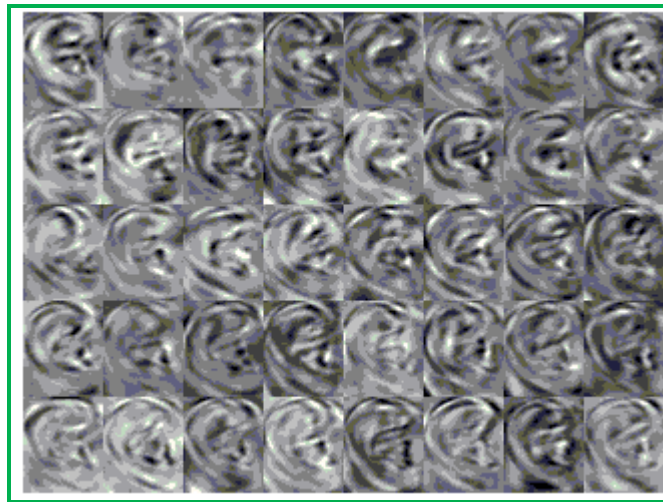


Fig. 4.7: Sample fisherears generated from USTB ear database.

4.2.3 Iris Matcher

The iris is a plainly visible ring that surrounds the pupil of one's eye. It is a muscular structure that controls the amount of light entering an eye, with intricate details that can be measured, such as, striations, pita, and furrows [Vacc07]. Iris recognition system first creates the measurable features of the iris. These features are then stores and later compared with new algorithms of irises presented to a capturing device for either identification or verification purpose.

For iris recognition in my system, I choose to use Hamming distance method [Hamm50] for recognition after the iris image pre-processing and encoding with Hough transform [Houg62] and 2-D Gabor wavelet [Gabo46]. At first, I localize the iris part of the eye image (from inside the limbus (outer boundary) and outside the pupil (inner boundary)) using an automatic segmentation algorithm based on Hough transform. The Hough transform method is a general technique for identifying the locations and orientations of certain types of features in a digital image and has several advantages. This method is conceptually simple, easy to implement, handles missing and occluded data very gracefully, and can be adapted to many types of forms, not just lines. As iris has edges with a known shape as circle, using Hough transform is feasible for detecting and linking edges to form closed iris areas.

In the segmentation process, I utilized Hough transform [Houg62] method. For iris region extraction from eye images, a circular Hough transform method is employed in which circular iris edge points are extracted through a voting mechanism in the Hough space [Wild97]. Two edge detected images of the original eye images – one with the horizontal gradients and the other with the vertical gradients, are generated for efficient

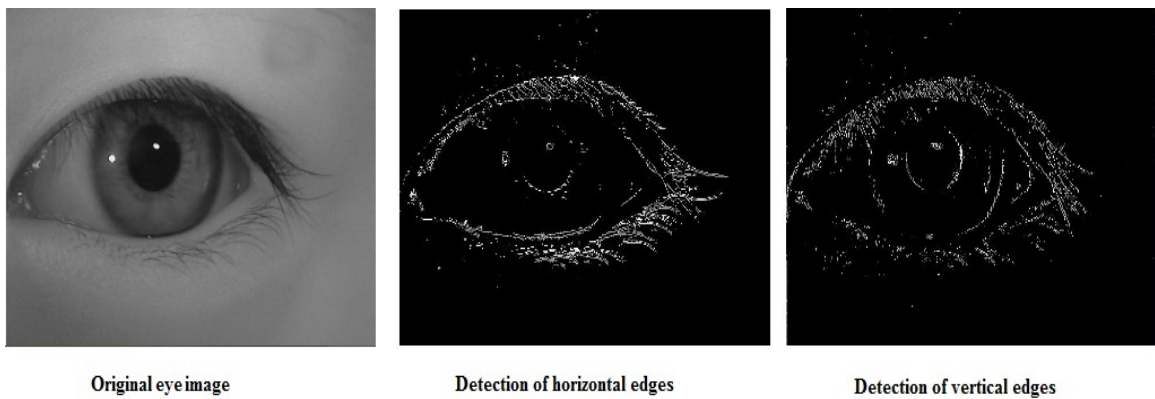


Fig. 4.8: An eye image from CASIA database and corresponding horizontal and vertical edge maps.

isolation of the iris boundary. Figure 4.8 illustrates this process.

After localizing the pupil and iris in the eye image, I store the radius and the x and y centre coordinates for both circles (pupil and iris). Then I isolate the eyelids by fitting a line to the upper and lower eyelid using the linear Hough transform. A second horizontal line is then drawn, which intersects with the first line at the iris edge that is closest to the pupil and thus allows maximum isolation of eyelid regions. If the maximum in Hough space is lower than a set of thresholds, then no line is fitted, since this corresponds to non-occluding eyelids.

The iris region is then transformed into polar coordinates system to facilitate the feature extraction process. For this, first I exclude the portion of the pupil from the conversion process because it has no biological characteristics. The transformation process produces iris regions which have the same constant dimensions so that two

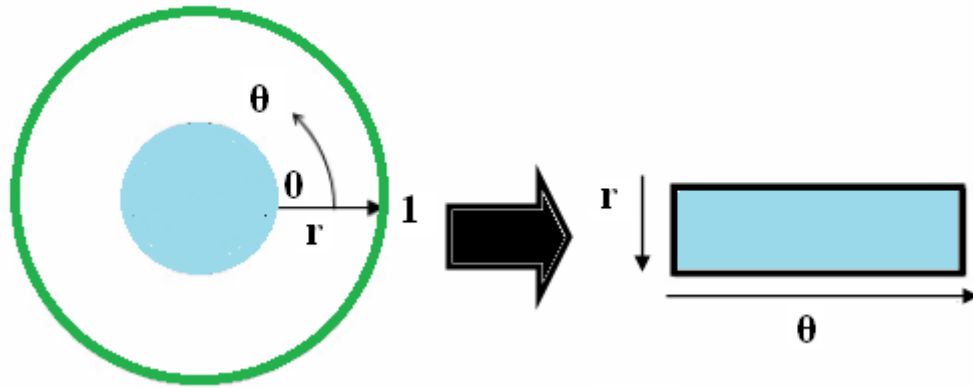


Fig. 4.9: The rubber sheet model (adopted from [Daug93]).

images of the same iris under different conditions have characteristic features at the same spatial location. I use the rubber sheet model (illustrated in Figure 4.9) to remap each point within the iris region to a pair of polar coordinates $((r, \theta))$, where r lies in the interval $[0, 1]$ and θ is the angular variable, cyclic over $[0, 2\pi]$. This remapping of the iris region can be modeled as,

$$I(x(r, \theta), y(r, \theta)) \longrightarrow I(r, \theta) \quad (4.13)$$

with $x(r, \theta) = (1-r) x_p(\theta) + r x_i(\theta)$

$$y(r, \theta) = (1-r) y_p(\theta) + r y_i(\theta) \quad (4.14)$$

where $I(x,y)$ is the iris region image, (x,y) are the original Cartesian coordinates, (r,θ) are the corresponding normalized polar coordinates, and (x_p, y_p) and (x_i, y_i) are the coordinates of the pupil and iris boundaries along the θ direction. The transformed pattern produces a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution.

Then I encode the normalized iris pattern into an iris code through a process of demodulation (introduced in [Daug93]) that extracts phase sequences using a 2-D Gabor wavelets,

$$h_{\{\text{Re}, \text{Im}\}} = \text{sgn}_{\{\text{Re}, \text{Im}\}} \int_{\rho} \int_{\phi} I(\rho, \phi) e^{-i\omega(r_0 - \rho)^2 / \alpha^2} \times e^{-(\theta_0 - \phi)} e^{-(\theta_0 - \phi)^2 / \beta^2} \rho d\rho d\phi \quad (4.15)$$

where $h_{\{\text{Re}, \text{Im}\}}$ is a complex-valued bit whose real and imaginary parts are either 1 or 0 (sign) depending on the sign of the 2-D integral; $I(\rho, \phi)$ is the raw iris image, α and β are the multi scale 2-D wavelet size parameters, ω is wavelet frequency and (r_0, θ_0) represent the coordinates of each region of iris for which the phasor bits $h_{\{\text{Re}, \text{Im}\}}$ are computed. The total iris code generation process is illustrated in Figure 4.10.

The next step is comparing two code-words to find out if they represent the same person or not. I use Hamming distance method for this purpose. The method is based on the idea that the greater the Hamming distance between two iris feature vectors, the

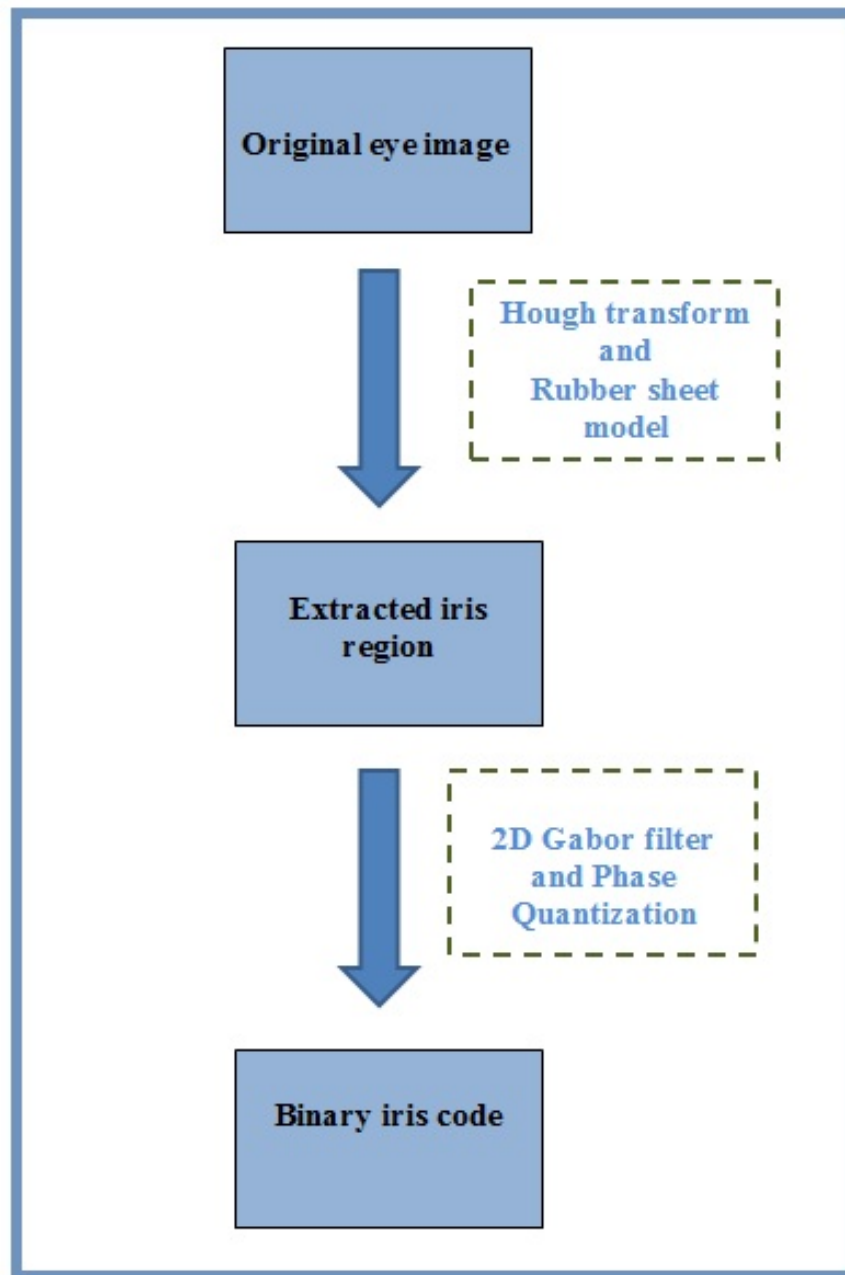


Fig. 4.10: Iris code generation process.

greater the difference between them. The Hamming distance (HD) between two Boolean iris vectors is defined as follows:

$$HD = \frac{\|C_A \otimes C_B \cap M_A \cap M_B\|}{\|M_A \cap M_B\|} \quad (4.16)$$

where, C_A and C_B are the coefficients of two iris images and M_A and M_B are the mask image of two iris images. The \otimes is the XOR operator which shows difference between a corresponding pair of bits, and \cap is the AND operator which shows that the compared bits are both have not been impacted noise [Daug93]. In equation 4.16, the denominator is used to reduce the effect of the unwanted portion of the iris due to eyelashes or eyelids. In an ideal scenario, the Hamming distance of two irises should be 0. But as this is not usually the case in real life scenario (due to noise in the iris images), therefore, I utilized a threshold- based Hamming distance method in my system.

For the proposed system, only the top- n matches are considered for fusion, that is, the templates will be sorted according to the Hamming distance in the ascending order and the top- n templates are used for the rank level fusion.

4.3 System Overview for Fuzzy Fusion

I developed a fuzzy fusion method after individually comparing face, ear and iris biometric samples similar to rank level fusion method. This method uses fuzzy logic and

rank information for multimodal biometric information fusion. Although, fuzzy fusion method has been widely used in many applications, such as object recognition, biomedical imaging, pattern recognition, bioinformatics and robotics, according to the best of our knowledge, this is first time this fusion method is being used for biometric rank information consolidation. Figure 4.11 shows the system block diagram of the proposed multimodal biometric system for fuzzy fusion method.

Similar to rank fusion process in this proposed system, fuzzy fusion method also works at the after matching stage. Face, iris and ear recognition have been done first. In each of the three cases, top- n identities are obtained as outputs that are ranked according to their distances. But unlike rank fusion, where only the ranked identities (ranking list) are needed, fuzzy fusion method utilizes ranked identity as well as the associated matching scores of those identities.

In the enrolment phase, the average matching scores (calculated from face, ear and iris match scores) for an identity are calculated and stored in the database as a fuzzy template for that identity. One of my motivations of using the fuzzy fusion method in this multimodal biometric system is to obtain the confidence level of the final output. Recognition outcomes with confidence level can be very important in some security critical biometric applications. To obtain the level of confidence for the final outcome, I employ some fuzzy rules elaborated on the basis of individual biometric matching performances and on the robustness of the biometric traits.

In the identification phase, after calculating the individual face, ear and iris matching scores for the test subject, a combined score is calculated in the similar way as

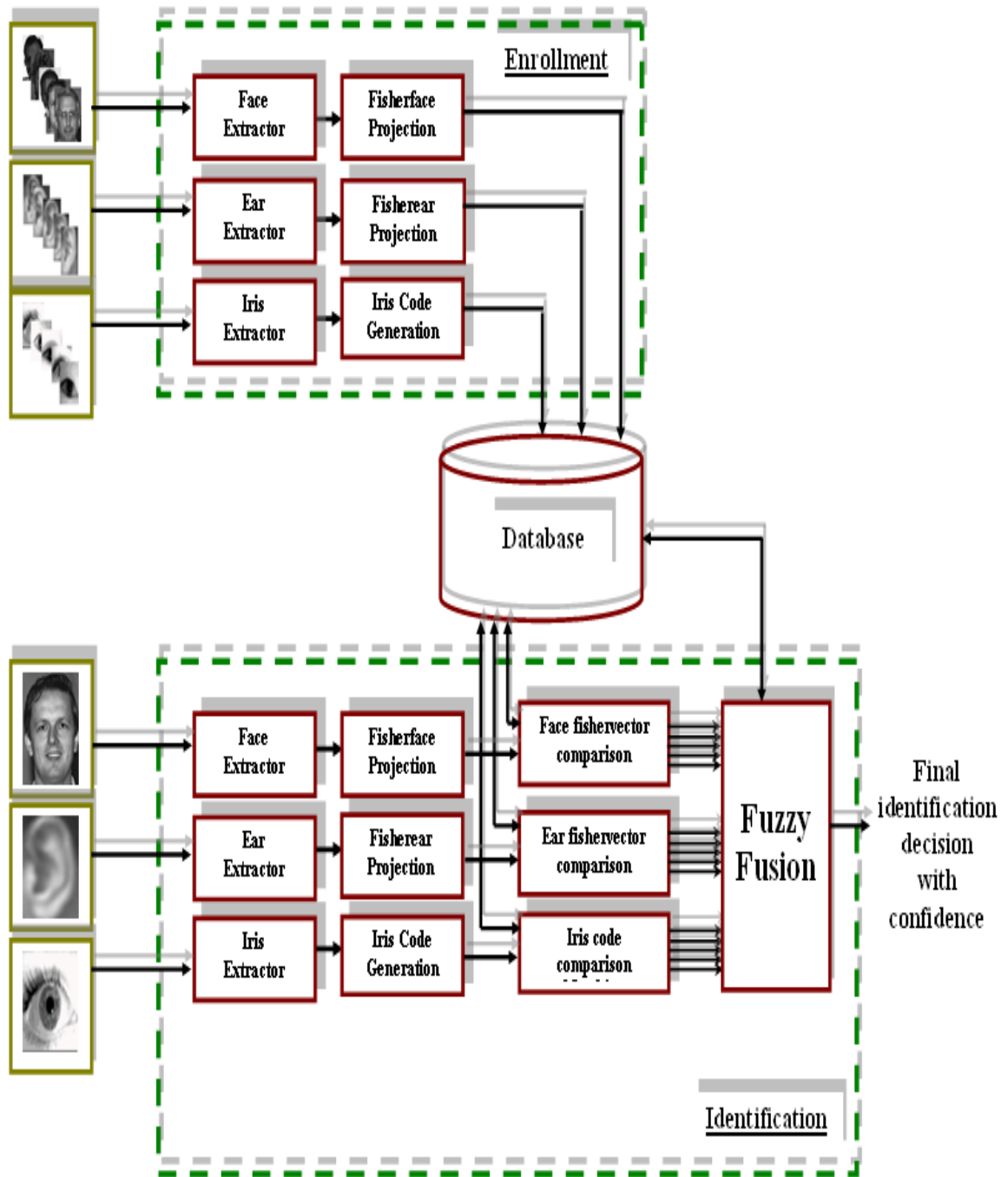


Fig. 4.11: System diagram with fuzzy level fusion.

in the enrolment phase. This score is then compared with the previously stored fuzzy templates in the database according to the specified fuzzy rules. Thus the final identification decision is obtained through this fuzzy fusion method with the associated level of confidence. Section 5.2 of chapter 5 describes the fuzzy fusion method in details.

4.4 Chapter Summary

In this chapter, I provide the methodology for the proposed multimodal biometric system. Starting with the rational for choosing face, iris and ear as three biometric traits for this system, I then describe the three unimodal matchers for these biometric traits in details. Fisherimage method is used in this system for face and ear recognition. Iris recognition process uses Hough transform for iris localization, Gabor filter for iris coding and Hamming distance for iris comparison. All of these methods have been discussed with their potential advantages and with necessary diagrams. The overall system workflows for rank level fusion and fuzzy fusion are also discussed with proper system diagrams. Further, I briefly discuss my selected publications resulted from this research and utilizing the above methodology.

In [MonG09], I presented a multimodal biometric system based on face, signature and ear biometric identifiers. All of the unimodal matchers employed fisherimage method for recognition. The outcomes of unimodal matchers were combined through different rank fusion methods, such as highest rank method, Borda count method and Logistic regression method. Based on the experimental results, I concluded that fusing individual modalities improve the overall performance of the biometric system even in the presence of low quality data.

In [MonG11], I presented a multimodal biometric system based on face, ear and iris. I described the Markov chain based rank level fusion and also obtained significant improvement in recognition accuracy over other fusion methods.

In [MoGW11], a fuzzy fusion based multimodal biometric system has been presented. I employed fuzzy logic based fusion to evaluate the recognition performance and the overall response time of the system. Further, the confidence levels of the recognition outcomes are obtained.

CHAPTER FIVE: RANK AND FUZZY FUSION FOR MULTIMODAL BIOMETRIC SYSTEMS

The most important part in a multimodal biometric system development is information fusion. I discussed the pros and cons of different multimodal biometric fusion methods in chapter two and three; and in this doctoral research, I decided to employ rank level fusion and proposed Markov chain based rank fusion in my multimodal biometric system development process. Further, I introduced fuzzy fusion for multimodal biometric information in this system. My results show that both rank level fusion and fuzzy fusion methods have the potential of efficiently consolidating biometric information and produce faster and reliable outcomes in any multimodal biometric identification system [MoGW11][MonG09].

Rank level fusion consolidates rank information produced from face, iris and ear biometric matchers. I investigate highest rank method, Borda count method and logistic regression method and introduced the Markov chain method for consolidation of rank information. Utilizing fuzzy logic, the fuzzy fusion method consolidates rank and matching score obtained from three unimodal matchers. The next two subsections describe rank fusion and fuzzy fusion methods in details for the proposed multimodal biometric system.

5.1 Rank Fusion for Biometric Information

The rank level fusion approach is used in biometric identification systems when the individual matcher's output is a ranking of the "candidates" in the template database

sorted in a decreasing order of match scores (or, an increasing order of distance score in appropriate cases). The system is expected to assign a higher rank to a template that is more similar to the query.

In this research, I have applied fisherimage method for face and ear recognition, and Hough transform, Gabor wavelet and Hamming distance method for iris recognition. From all of these matchers, a list of enrolled identities sorted according to their similarity/distance scores are easily obtained, which makes possible for me to use rank level fusion for this multimodal biometric system.

I first implemented three methods for rank fusion, such as highest rank, Borda count and logistic regression, in my multimodal biometric system for finding out the final recognition decision. Later I proposed Markov chain method for biometric rank consolidation and compared to these three methods. All of these methods are discussed in the following sections.

5.1.1 Highest Rank Fusion

The highest rank method is good for combining a small number of specialized matchers and hence can be effectively used for a multimodal biometric system where the individual matchers perform well [RoNJ06]. In this method, the consensus ranking is obtained by sorting the identities according to their highest rank. The following steps show the procedure of employing highest rank fusion method:

Step 1: Get three ranking lists from three biometric classifiers.

Step 2: For all ranking lists -

Step 2a: For all identities in the three ranking lists -

Step 2a(i): Find out the consensus rank of each identity

utilizing the following equation -

$$\text{Consensus rank, } R_c = \min_{i=1}^n R_i \quad (5.1)$$

Where, n is the number (in this case, three) of

ranking lists, i.e., number of biometrics used.

Step 3: Sort R_c in ascending order and replace with corresponding identity.

The advantage of this method is the ability to utilize the strength of each matcher. [RoNJ06]. Three classifiers are used in this work and hence the maximum number of identities sharing the same consensus rank will be three which is planned to break randomly.

5.1.2 Borda Count Rank Fusion

The rank-level combination using Borda count approach is based on the generalization of majority vote and is the most commonly used method for rank-level fusion [KumS10]. This method [BorD1781] selects the class decision that is highly ranked by multiple classifiers. In this fusion method, the score of the highest ranked decision is $(n-1)$ when the number of classes is n and the second highest ranked class gets the score of $(n-2)$, etc. The following steps show the Borda score calculation process in this work.

Step 1: Get three ranking lists from three biometric classifiers.

Step 2: For all ranking lists -

Step 2a: For all identities in the three ranking list -

Step 2a(i): Find out the total Borda score of each identity

utilizing the following equation –

$$\text{Total Borda score, } B_c = \sum_{i=1}^n B_i \quad (5.2)$$

Where, n is the number of ranking list, i.e., number of algorithms used in this work and B_i is the Borda score in the i -th ranking list. For a ranking list with m identities, the Borda score of j -th identity will be $B = m - j$.

Step 3: Sort B_c in descending order and replace with corresponding identity.

The Borda score method assumes that the ranks assigned to the users by the individual classifiers are statistically independent and the performances of all three algorithms are equal. The advantage of this method is that it is easy to implement and requires no training. The disadvantage of this method is that it does not take into account

the differences in the individual algorithm's capabilities and assumes that all the matchers perform equally well, which is usually not the case in most real biometric systems [RoNJ06].

5.1.3 Logistic Regression Rank Fusion

The logistic regression method, which is a variation of the Borda count method, calculates the weighted sum of the individual ranks [HoHS94]. In this method, the final consensus rank is obtained by sorting the identities according to the summation of their rankings obtained from individual matchers multiplied by the assigned weight.

Step 1: Get the ranking lists from different biometric classifiers.

Step 2: Assign different weights to all ranking lists.

Step 3: For all ranking lists –

Step 3a: For all identities in the three ranking list -

Step 3a(i): Find out the total Rank score of each identity
utilizing the following equation –

$$\text{Total Rank score, } R_c = \sum_{i=1}^m W_i R_i \quad (5.3)$$

Where, n is the number of ranking list, R_i is the Borda score in the i -th ranking list and W_i is the weight assigned to the i -th classifier.

Step 4: Sort R_c in descending order and replace with corresponding identity.

The weight to be assigned to the different matchers is determined by the recognition performances obtained through numerous trial executions of the system and through applying common knowledge. This method is very useful when the different matchers have significant differences in their accuracies but requires a training phase to determine the weights. Also, one of the key factors that has direct effect on the performance of a biometric system is the quality of the biometric samples. Hence, the single matchers' performance can vary with different sample sets which make the weights allocating process more challenging and inappropriate weight allocation can eventually reduce the recognition performance of this multimodal biometric system (using logistic regression) compared to unimodal matchers. So, in some cases, logistic regression method cannot be employed for rank aggregation.

Figure 5.1 illustrates the highest rank, the Borda count and the logistic regression rank fusion approaches. In this figure, the less the value of the rank, the more accurate the result is. Here, the rank for 'Person 1' is 1, 2 and 2 respectively from the face, ear and signature matchers. For the Highest rank method, the fused score is 1 for person 1.

Similarly, for person 2, person 3, person 4 and person 5, the fused ranks are 1, 3, 2 and 3 respectively. There is a tie between person 1 and person 2 and 'Person 3' and 'Person 5'. These ties are broken arbitrarily. So, in the final reordered ranking, 'Person 1' gets the top position in the reordered rank list whereas, 'Person 2' is in the second position.

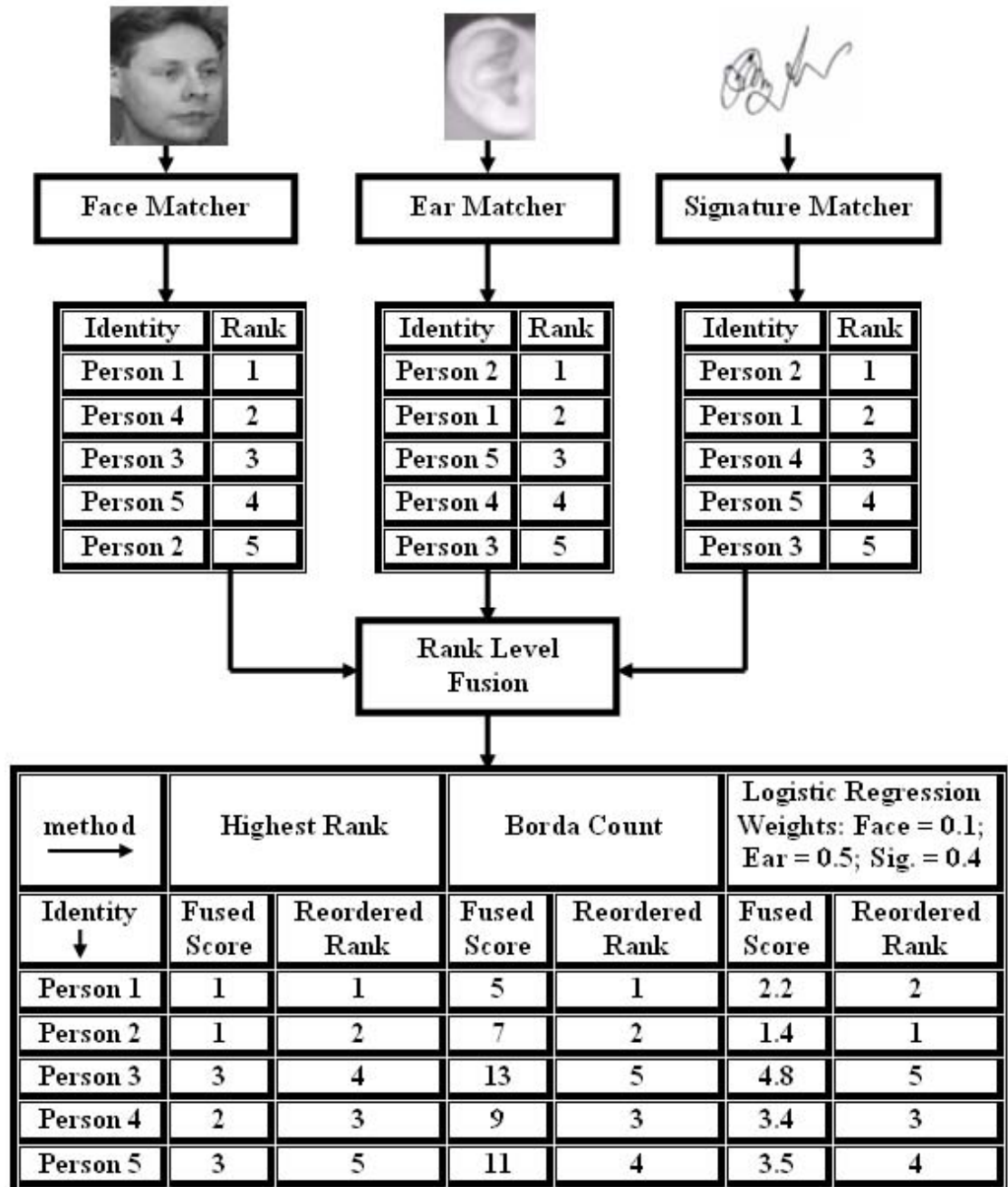


Fig. 5.1: Example of rank level fusion using highest rank, Borda count and logistic regression method (adopted from [GavM11]).

For the Borda count method, the initial ranks are first added. Thus, 5, 7, 13, 9, and 11 can be found as the fused score for 'Person 1' to 'Person 5' respectively. So, 'Person 1' gets the top position in the reordered list due to his/her lowest fused score, 'Person 2' gets the second position and so on.

For the logistic regression method, the matchers need to be assigned weights which are determined by the recognition performance of the matchers. For this system, suppose face matcher is assigned a weight of 0.1, ear matcher is assigned a weight of 0.5 and signature matcher is assigned a weight of 0.4. This weight assignment can be done by evaluating the performance of the three matchers with a number of experiments and by researching the previous investigations of these matchers. For this system, it is assumed the matcher with the minimum weight works better than the other matchers. So, face matcher works better than the ear matcher or signature matcher. The fused scores for different identities are calculated by multiplying their positions in the initial rank lists with the appropriate weight assigned to each matcher. Thus, 2.2, 1.4, 4.8, 3.4 and 3.5 fused scores are found for 'Person 1' to 'Person 5' respectively. So, 'Person 2' is on top position in the reordered ranking list.

I developed a multimodal biometric system based on rank level fusion method using the above three approaches. Among the three approaches, logistic regression method showed the best performance as shown in the experiment results in chapter 6. But this approach has some drawbacks. As the single matcher's recognition performance varies with different databases, so allocating appropriate weights to these matchers requires appropriate learning technique, which is time consuming and inappropriate weight allocation can result in wrong recognition results. The size of the multimodal

biometric database is usually huge and thus only the top few results are considered for the final reordered ranking. Hence, a very common scenario of a rank based multimodal biometric system is that some results may rank at top by a few classifiers and the rest of the classifiers do not even output the result. In this situation, the logistic regression approach cannot produce a good recognition performance.

Further, I considered the biometric rank aggregation similar to a voting mechanism. In a voting method evaluation, the most important thing is to ensure the fairness of the voting system. Among the fairness criteria, the two most important criteria are Condorcet Winner Criterion and the Condorcet Loser Criterion [Cond1785].

Condorcet Winner Criterion - If there exists an alternative a , which would win in pairwise votes against each other alternative, then a should be declared the winner of the election. Note that there is not necessarily such an alternative a . This alternative is called the Condorcet winner [Cond1785].

Condorcet Loser Criterion - If there exists an alternative a , which would lose in pairwise votes against each other alternative, then a should not be declared the winner of the election [Cond1785].

None of the rank fusion approaches described above ensures the election of Condorcet Winner. For example, in Figure 5.2, Condorcet criteria are violated in the highest rank method and Borda count method. This has been motivated me to propose Markov chain approach for biometric rank fusion in my multimodal biometric system

Face Matcher	Ear Matcher	Iris Matcher
Identity X	Identity Y	Identity M
Identity Y	Identity Z	Identity X
Identity N	Identity N	Identity Y
Identity Z	Identity X	Identity N
Identity M	Identity M	Identity Z

Highest Rank	Borda Count
Identity M	Identity Y
Identity Y	Identity X
Identity X	Identity N
Identity Z	Identity M
Identity N	Identity Z

Fig. 5.2: Highest rank and Borda count rank fusion methods (in both fusion methods, Condorcet criteria are violated).

(which satisfies Condorcet criteria) which is one of my main contributions in this doctoral thesis. Section 5.1.4 describes Markov chain rank fusion method in details.

5.1.4 Markov Chain Rank Fusion

Markov chain is a random process or set of states in which the probability that a certain future state will occur depends only on the present or immediately preceding state of the system, and not on the events leading up to the present state [GriS97].

In the Markov chain biometric rank information fusion method, it is assumed that there exists a Markov chain on the enrolled identities and the order relations between those identities in the ranking lists (obtained from different biometric matchers) represent the transitions in the Markov chain. The stationary distribution of the Markov chain is

then utilized to rank the entities [MonG11][DKNS01]. The construction of the proposed consensus ranking list from the Markov chain is done through necessary customization by common methods [Scul07] and is summarized in Figure 5.3.

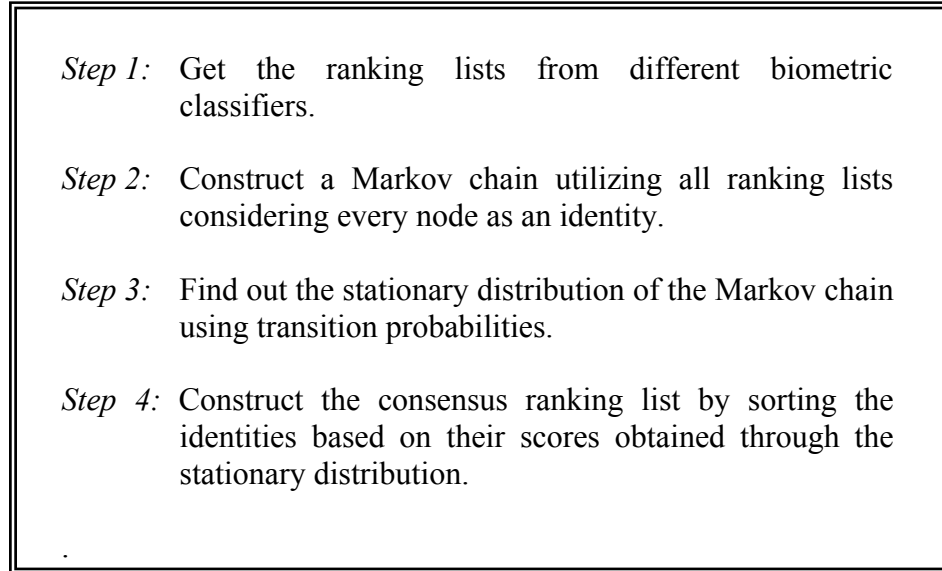


Fig. 5.3: Construction steps for the Markov chain biometric rank fusion method.

This Markov chain approach for biometric rank aggregation exhibits several advantages similar to web ranking research demonstrated in [DKNS01]. In case of partial ranking list, this method works very well utilizing comparisons between all candidates against each other. This method also handles the situation when the results of the initial ranking lists are very different. Further Markov chain model can be obtained through natural extensions of some heuristics [DKNS01].

There are four types of Markov chains introduced in [DKNS01]. Among those four methods, the last method ensures the selection of the Condorcet winner. This method

also follows the Copeland's method [DKNS01]. Thus, in this work, the last of the four methods has been adapted to biometric system.

The transition of this Markov chain can be obtained through Copeland's method [Cope51], in which the consensus ranking list is obtained via arranging the identities by subtracted the pairwise losses from the number of pairwise wins. Copeland's method also satisfies the extended Condorcet condition [DKNS01].

Figure 5.4 shows a Markov chain with its transition matrix build on the transition method described above. For this example, let us assume that four persons are to be classified by three classifiers/matchers. But each classifier outputs only the first three results of their ranking list (i.e., each classifier outputs a partial list). From these partial lists, a full list has been created. The missing items in the list can be inserted randomly or by examining the partial lists. In this example, in the first list among the four subjects, only one is missing. So, that subject (person) can easily be putted at the end of the list without other consideration. As, the list of the first matcher already contains subject *a*, subject *b* and subject *c*, so the fourth subject is obviously subject *d*. Similarly, the already enlisted subjects in the list of second matcher are subject *b*, subject *c* and subject *d*. Hence the fourth entry in this list is subject *a*. According to the same method, the fourth entry in the list of the third matcher is subject *c* as subject *a*, subject *b* and subject *d* are already in the list.

In the case of more than one unlisted entries (subjects), two methods can be applied. The first method is the random method in which the subjects which are not listed in the partial list obtained from a matcher are positioned in the list by a random algorithm. The second method uses the relative positions of the unlisted subjects in the

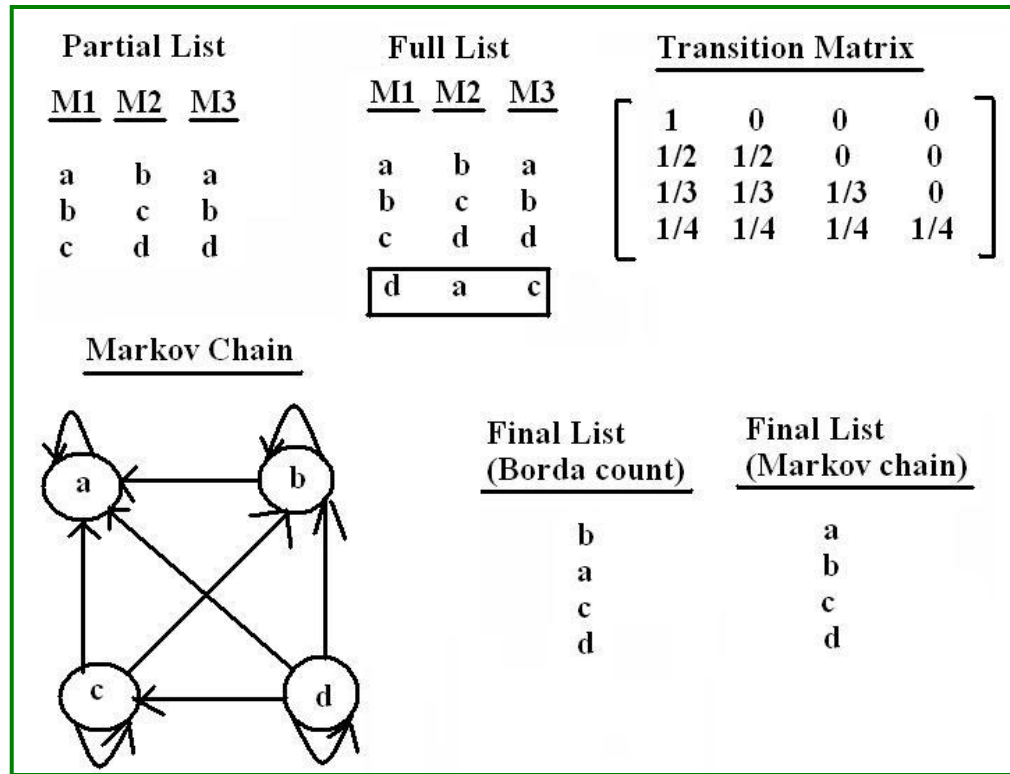


Fig. 5.4: Markov chain and the transition matrix constructed from three ranking lists.

partial lists to place those (unlisted subjects) in the full ranking list. If the relative positions are not available, then a random algorithm is used (similar to first method) to place the subjects in the final list.

Based on these full lists, a transition matrix is created. As there are four subjects considered in the example, so the transition matrix has four rows and four columns. The first row belongs to subject *a*, and similarly the second row, the third row and the fourth row belong to subject *b*, subject *c* and subject *d* respectively. In the same way, the first,

second, third and fourth columns belong to subject a , subject b , subject c and subject d respectively. An entry '1' in the (1,1) position mean the only possible state to transition from state a is a . An entry ' $1/2$ ' in position (2,1) means there is 50% probability of a transition to state a from state b . Similarly, there is 50% probability to transition from state b from state b . In other words, from state b , only transition to state a and state b (itself) is possible. Further, from the fourth row of the transition matrix, it is clear that from the state d , transition to all other states is possible.

A Markov chain is constructed from the transition matrix. Transition from one state to another state is shown using normal arrow. The final ranking list (which satisfies the Condorcet criterion) can be obtained by applying the Copeland method, i.e., by sorting the nodes in the majority graph (Markov chain) by out-degree minus in-degree. The figure also shows that if I apply the Borda count method to the lists, I obtain a final list which does not satisfy the Condorcet criteria. This may also be the case for highest rank fusion as there is a tie between identity a and identity b . If this tie is broken randomly, there is 50% chances to select identity b as the winner, which is the violation of Condorcet criteria. Experimental results in section 6.1 and 6.2 confirm that Markov chain rank fusion method is better than the other rank fusion methods, such as highest rank, Borda count and logistic regression method.

Hence, this method can be a good solution to person identification problem for security critical multimodal biometric system, especially, where the match score or feature sets are not available and the single biometric matchers can only output the ranking list of identities.

5.2 Fuzzy Fusion for Biometric Information

Fuzzy fusion method is recently emerged as information consolidation tool. Most fuzzy fusion methods reported in the literature are developed for areas such as automatic target recognition, biomedical image fusion and segmentation, gas turbine power plants fusion, weather forecasting, aerial image retrieval and classification, vehicle detection and classification and path planning. The advantage of fuzzy fusion method is that it utilizes both match score and rank information from unimodal biometrics. Also, the level of confidence of recognition outcomes of the proposed multimodal system can be obtained using this fusion method.

The next two sub-sections describe the basic concepts of fuzzy logic and the fuzzy fusion mechanism for the new multimodal biometric system.

5.2.1 Fuzzy Logic

Fuzzy logic refers to all of the theories and technologies that employ fuzzy sets, which are classes with un-sharp boundaries [PedG98]. The idea of fuzzy sets was introduced in 1965 by Professor Lotfi A. Zadeh from the Department of Electrical Engineering and Computer Science at the University of California, Berkeley [Zade65]. The core technique of fuzzy logic is based on following four basic concepts:

1) *Fuzzy sets* - A fuzzy set [Zade75] is a set in which the members of the set can have partial membership, meaning they can have a membership value of any number between 0 and 1 unlike the ‘crisp’ set where the members can have only two membership value, i.e. 0 and 1.

2) *Linguistic variable* - A linguistic variable is a novel concept in fuzzy logic where a variable can have values in linguistic terms of words or sentences rather than numbers, which allows reasoning be done at the fuzzy level rather than that of crisp numeric variables [Zade75].

3) *Possibility Distribution* - During an assignment of a fuzzy set to a linguistic variable, the fuzzy sets put constraints on the value of the variable. This process is called possibility distribution [Zade81].

4) *Fuzzy rules* - Fuzzy rule is the most widely used technique developed using fuzzy sets and has been applied to many disciplines. Some of the applications of fuzzy rules include control (robotics, automation, tracking, consumer electronics), information systems (DBMS, information retrieval), pattern recognition (image processing, machine vision), decision support (HMI, sensor fusion).

The development of fuzzy rule-based inference consists of three basic steps – fuzzification, inference and defuzzification. In the fuzzification step, fuzzy variables and their membership functions are defined, i.e., the degree to which the input data match the condition of the fuzzy rules have been calculated. In the inference step, fuzzy rules have been developed and those rules' conclusion based on their matching degree has been calculated. In the last step, the fuzzy conclusion is converted into a discrete one if necessary. This process is called defuzzification.

5.2.2 Fuzzy Fusion Method

Figure 5.5 shows a data flow chart for the proposed fuzzy fusion module, which is a fuzzy rule-based inference system. The initial input to this fuzzy fusion module is the individual similarity scores and the average similarity score for a person. The output of this module is the identification decision of the multimodal biometric system.

The fuzzy inference mechanism is the centre of the fuzzy fusion module. As discussed in the previous section, the first step for fuzzy inference is fuzzification where the input is modelled as fuzzy variables.

Score normalization is necessary for applying the fuzzy fusion technology in the similarity scores. I used min-max normalization technique for score normalization to obtain all match score values in the range of 0 to 1.

For this multimodal system, suppose, s_j^i denote the i -th match score output by the

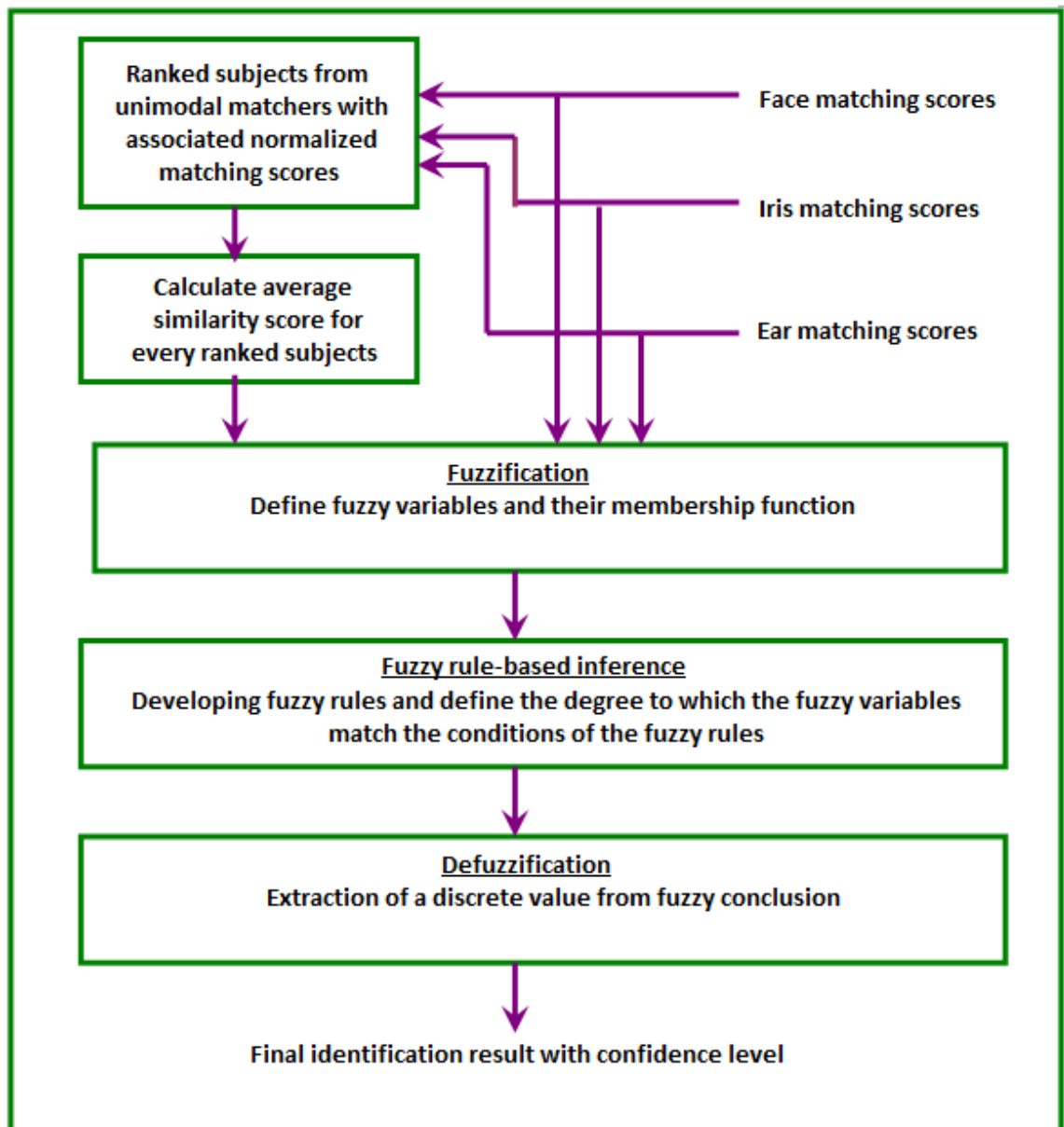


Fig. 5.5: Fuzzy fusion module flowchart of the proposed multimodal biometric system.

j -th matcher, $i = 1, 2, \dots, N$, where N is the number of subjects enrolled in the system, and $j = 1, 2, 3$. In [RoNJ06], the min-max normalized score ns_j^t for the test score s_j^t is obtained as follows:

$$ns_j^t = \frac{s_j^t - \min_{i=1}^n s_j^i}{\max_{i=1}^n s_j^i - \min_{i=1}^n s_j^i} \quad (5.4)$$

In this research, I used the same equation to perform the Min-max normalization of the matching scores obtained from different classifiers.

Assume there are N subjects enrolled in the database and among them, K users appeared in the ranking lists of three matchers, i.e. $K \leq N$ AND $n \leq K \leq 3n$ as only top- n ranked subjects produced by each matcher. Let the number of biometric traits and hence matchers be M , i.e. $M = 3$. Also let $s_{k,m}$ is the match score generated for subject k by m matcher, $s_{k,m} \geq 0$ and $s_{k,m} \leq 1$ after normalization. Thus I obtain the average similarity score for a particular subject s_k by the following equation:

$$s_k = \frac{1}{M} \sum_{m=1}^M s_{k,m} \quad (5.5)$$

There are only top- n ranked matches produced by each matcher, but I may get the average match scores for more than n subjects, since some identifiers may not be included in all of the rank lists (maximum $3n$; i.e. when all three matchers output ranking list based on the match score where no identifiers). In this case, I put a provision for the fusion module to collect the absent matching scores from the matching modules. For this purpose, initially the fusion module compares the identity presents in all three ranking lists and brings necessary matching scores from the matching module for comparison. Later I use the resultant average similarity score and the three match scores of three classifiers as inputs to the proposed fuzzy inference system.

After obtaining these fuzzy variables, I define the fuzzy membership function, which is the degree to which the input data match the condition of the fuzzy rules. As my multimodal database is a virtual multimodal database based on three different datasets collected from three different sources, I consider .95 (out of maximum 1) similarity score as very good matching score. Thus, I define the fuzzy linguistic variables, high (H), medium (M), and low (L) as follows:

$$\begin{aligned}
 &H, \text{ when } s \geq 0.95 \\
 &M, \text{ when } 0.80 \leq s \leq 0.94 \\
 &L, \text{ when } s \leq 0.79
 \end{aligned} \tag{5.6}$$

1. If AS = 'H', FS = 'H', IS = 'H' and ES = 'H', then 'SI'	26. If AS = 'M', FS = 'L', IS = 'H' and ES = 'M', then 'WI'
2. If AS = 'H', FS = 'H', IS = 'H' and ES = 'M', then 'SI'	27. If AS = 'M', FS = 'L', IS = 'H' and ES = 'L', then 'WI'
3. If AS = 'H', FS = 'H', IS = 'M' and ES = 'H', then 'SI'	28. If AS = 'M', FS = 'L', IS = 'M' and ES = 'H', then 'WI'
4. If AS = 'H', FS = 'H', IS = 'M' and ES = 'M', then 'SI'	29. If AS = 'M', FS = 'L', IS = 'M' and ES = 'M', then 'WI'
5. If AS = 'H', FS = 'M', IS = 'H' and ES = 'H', then 'SI'	30. If AS = 'M', FS = 'L', IS = 'M' and ES = 'L', then 'WI'
6. If AS = 'H', FS = 'M', IS = 'H' and ES = 'M', then 'SI'	31. If AS = 'M', FS = 'L', IS = 'L' and ES = 'H', then 'NI'
7. If AS = 'H', FS = 'M', IS = 'M' and ES = 'H', then 'WI'	32. If AS = 'M', FS = 'L', IS = 'L' and ES = 'M', then 'NI'
8. If AS = 'M', FS = 'H', IS = 'H' and ES = 'M', then 'WI'	33. If AS = 'L', FS = 'H', IS = 'H' and ES = 'L', then 'WI'
9. If AS = 'M', FS = 'H', IS = 'H' and ES = 'L', then 'WI'	34. If AS = 'L', FS = 'H', IS = 'M' and ES = 'L', then 'NI'
10. If AS = 'M', FS = 'H', IS = 'M' and ES = 'H', then 'WI'	35. If AS = 'L', FS = 'H', IS = 'L' and ES = 'H', then 'NI'
11. If AS = 'M', FS = 'H', IS = 'M' and ES = 'M', then 'WI'	36. If AS = 'L', FS = 'H', IS = 'L' and ES = 'M', then 'NI'
12. If AS = 'M', FS = 'H', IS = 'M' and ES = 'L', then 'WI'	37. If AS = 'L', FS = 'H', IS = 'L' and ES = 'L', then 'NI'
13. If AS = 'M', FS = 'H', IS = 'L' and ES = 'H', then 'WI'	38. If AS = 'L', FS = 'M', IS = 'H' and ES = 'L', then 'WI'
14. If AS = 'M', FS = 'H', IS = 'L' and ES = 'M', then 'WI'	39. If AS = 'L', FS = 'M', IS = 'M' and ES = 'L', then 'NI'
15. If AS = 'M', FS = 'H', IS = 'L' and ES = 'L', then 'WI'	40. If AS = 'L', FS = 'M', IS = 'L' and ES = 'H', then 'NI'
16. If AS = 'M', FS = 'M', IS = 'H' and ES = 'H', then 'WI'	41. If AS = 'L', FS = 'M', IS = 'L' and ES = 'M', then 'NI'
17. If AS = 'M', FS = 'M', IS = 'H' and ES = 'M', then 'WI'	42. If AS = 'L', FS = 'M', IS = 'L' and ES = 'L', then 'NI'
18. If AS = 'M', FS = 'M', IS = 'H' and ES = 'L', then 'WI'	43. If AS = 'L', FS = 'L', IS = 'H' and ES = 'H', then 'WI'
19. If AS = 'M', FS = 'M', IS = 'M' and ES = 'H', then 'WI'	44. If AS = 'L', FS = 'L', IS = 'H' and ES = 'M', then 'NI'
20. If AS = 'M', FS = 'M', IS = 'M' and ES = 'M', then 'WI'	45. If AS = 'L', FS = 'L', IS = 'H' and ES = 'L', then 'NI'
21. If AS = 'M', FS = 'M', IS = 'M' and ES = 'L', then 'WI'	46. If AS = 'L', FS = 'L', IS = 'M' and ES = 'H', then 'NI'
22. If AS = 'M', FS = 'M', IS = 'L' and ES = 'H', then 'WI'	47. If AS = 'L', FS = 'L', IS = 'M' and ES = 'M', then 'NI'
23. If AS = 'M', FS = 'M', IS = 'L' and ES = 'M', then 'NI'	48. If AS = 'L', FS = 'L', IS = 'M' and ES = 'L', then 'NI'
24. If AS = 'M', FS = 'M', IS = 'L' and ES = 'L', then 'NI'	49. If AS = 'L', FS = 'L', IS = 'L' and ES = 'H', then 'NI'
25. If AS = 'M', FS = 'L', IS = 'H' and ES = 'H', then 'WI'	50. If AS = 'L', FS = 'L', IS = 'L' and ES = 'M', then 'NI'
	51. If AS = 'L', FS = 'L', IS = 'L' and ES = 'L', then 'NI'

AS = Average score; FS = Face matcher's score; IS = iris matcher's score; ES = Ear matcher's score
SI = Strongly identified; WI = Weakly identified; NI = Not identified.

Fig. 5.5: Fuzzy rules for the proposed fuzzy fusion method.

Once the fuzzy variables are adequately mapped into the membership functions, the fuzzy fusion is to develop the fuzzy rules, which are elaborated on the basis of individual biometric matching performances and on the robustness of the biometric traits. This step is necessary to obtain the confidence of the final recognition outcome from the system, which is one of my motivations to utilize this fusion method. For this fuzzy inference system, I considered 51 rules explained in Figure 5.5. For these rules, I considered the average match score as well as the performances of individual matchers. The reason to use the individual match scores is that the databases used in this system are obtained from different sources and hence are of different quality. Further, different matching algorithms are used for this system – the fisherimage technique for face and ear biometrics, and Hough transform Gabor wavelet and Hamming distance techniques for iris biometric. Thus, I obtain different results from three different matchers which allow me to put different confidences on matching results. Among the four inputs to the fuzzy inference system (average match score and three individual match scores), I assign the highest confidence on the average match score in the fuzzy rules. Based on the previous biometric performance results [MonG11] [MonG09], among the three individual match scores, I put the highest confidence on the score obtained from the iris matcher and the lowest confidence on the score obtained from the ear matcher.

With the four parameters, i.e. the average score and the three unimodal matcher's scores, there are 81 alternatives. Among these 81 alternatives, only the 51 possibilities are possible, as according to the definition of the fuzzy linguistic variables, the alternatives such as -

If AS = 'L', FS = 'M', IS = 'H' and ES = 'M' and

If AS = 'M', FS = 'H', IS = 'H' and ES = 'H'

(AS = Average score; FS = Face matcher's score; IS = iris matcher's score; ES = Ear matcher's score)

are not possible.

At the final stage of this fuzzy inference system, I obtain a single scalar output suitable for the final classification by combining the results produced by all fuzzy rules. Figure 5.6 shows the steps for this fuzzy fusion method.

I also tested the system performance of fuzzy fusion utilizing soft biometric information. In this case, the fuzzy inference engine is a two input one output system, unlike the first case, where the fuzzy inference engine is a four input one output system. The average similarity score is obtained by a different formula which is shown below:

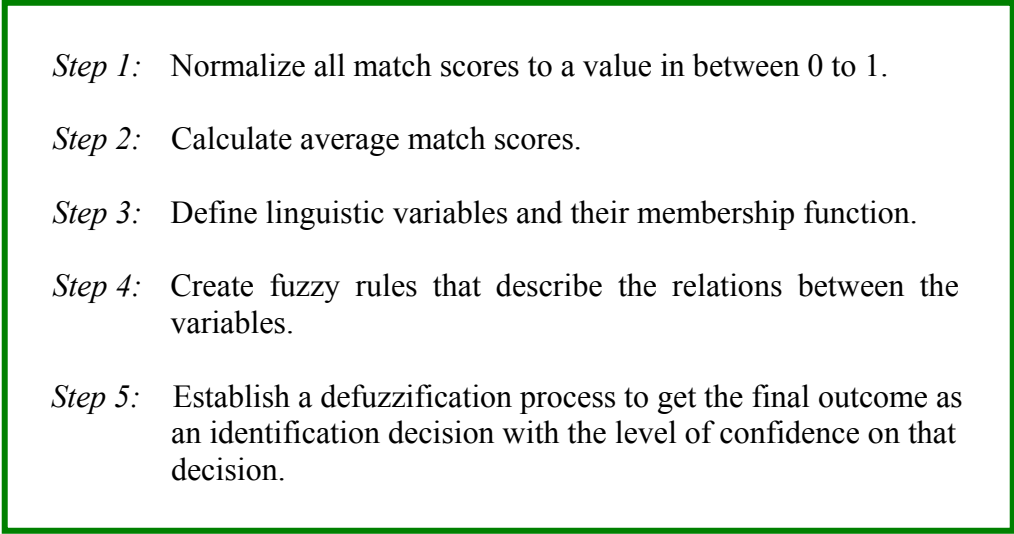
- 
- Step 1:* Normalize all match scores to a value in between 0 to 1.
 - Step 2:* Calculate average match scores.
 - Step 3:* Define linguistic variables and their membership function.
 - Step 4:* Create fuzzy rules that describe the relations between the variables.
 - Step 5:* Establish a defuzzification process to get the final outcome as an identification decision with the level of confidence on that decision.

Fig. 5.6: Steps for fuzzy fusion method.

$$S_k = \frac{1}{M} \sum_{m=1}^M w_m S_{k,m} \quad (5.6)$$

where w_m is a weight for the m -th matcher and $\sum_{m=1}^3 w_m = 1.0$.

Weights on different matching scores are applied based on the same consideration, i. e., based on the numerous trial and researching preliminary results reported in [MoGW11] and [MonG09]. I assigned the following weights for the three match scores:

$$\begin{cases} w_m = 0.45, & \text{for iris match score} \\ w_m = 0.30, & \text{for face match score} \\ w_m = 0.25, & \text{for ear match score} \end{cases} \quad (5.7)$$

The second input to the fuzzy inference system is the average soft biometric score. The same procedure is applied to the latter as the average primary biometrics match score.

I obtained three soft biometrics values – gender, ethnicity and eye color from the face database. Suppose, the number of soft biometric used in this system is S and $soft_{k,i}$ be the value of k -th user for i -th soft biometric, where $i > 0$ and $i \leq S$. I used only the

Boolean value for soft biometrics, i.e., either $soft_{k,i} = 0$ or $soft_{k,i} = 1$, and assigned the following weights for this soft biometrics:

$$\begin{cases} w_i = 0.50, \text{ for gender} \\ w_i = 0.30, \text{ for ethnicity} \\ w_i = 0.20, \text{ for eye color} \end{cases} \quad (5.8)$$

The average soft biometric score for a particular subject $soft_{k,i}$ can then be obtained by the following equation:

$$soft_k = \sum_{i=1}^S w_i soft_{k,i} \quad (5.9)$$

where w_i is the weight for the i -th soft biometric $\sum_{i=1}^3 w_i = 1.0$.

Once the average weighted match score and average weighted soft biometric score are obtained, I used them as input to the fuzzy inference engine. In this case, I put less confidence on soft biometric score as soft biometrics information are not fully reliable and can be altered easily by impostor. For the two inputs one output fuzzy inference system, I considered the rules shown in Figure 5.7. Experimental results in chapter 6 indicate that the inclusion of the soft biometric information does not improve the recognition performance by a significant amount. Also, privacy problem arises when

soft biometrics information is used. For this reason, using soft biometrics in multimodal biometric security systems is not recommended in many security systems.

1. If AS = 'H' and SS = 'H', then 'SI'
2. If AS = 'H' and SS = 'M', then 'SI'
3. If AS = 'H' and SS = 'L', then 'WI'
4. If AS = 'M' and SS = 'H', then 'WI'
5. If AS = 'M' and SS = 'M', then 'WI'
6. If AS = 'M' and SS = 'L', then 'WI'
7. If AS = 'L' and SS = 'H', then 'WI'
8. If AS = 'L' and SS = 'M', then 'NI'
9. If AS = 'L' and SS = 'L', then 'NI'

AS = Average scores; SS = Soft biometrics score
SI = Strongly identified; WI = Weakly identified; NI = Not identified.

Fig. 5.7: Fuzzy rules for the fuzzy fusion method utilizing soft biometric information.

5.3 Chapter Summary

In this chapter, I present the methodology for the rank fusion method and the fuzzy fusion method for the proposed multimodal biometric system. For rank level fusion I define and discuss advantages and disadvantages of highest rank method, Borda count method and logistic regression method. Then, I introduce Markov chain method for biometric rank aggregation. I discuss advantages of this method and show how this method satisfies one of the main fairness criteria in rank aggregation. Fuzzy fusion method is then discussed with a step by step flow diagram. Further I discuss fuzzy fusion method utilizing soft biometrics information.

CHAPTER SIX: EXPERIMENTATIONS AND RESULTS

This chapter discusses the implementation procedures, databases used for testing, and the outcomes of the proposed multimodal biometric system research. Two multimodal biometric databases were used to evaluate the performance of the proposed system. To compare with other fusion methods, the outcomes of rank fusion methods and fuzzy fusion have been tested against the performance of match score and decision fusion methods implemented on the same databases.

6.1 Implementation Overview

I have implemented proposed multimodal biometric system in MATLAB 7.0 on a PENTIUM-IV windows XP workstation. The system is Graphical User Interface (GUI)-based and menu driven. The necessary image pre-processing is done by selecting the image directory. The thresholds for recognizing face, ear and iris can be changed in run time to allow users more flexibility. For rank level fusion approaches, after the initial unimodal matching, the system outputs only the top- n matches of individual biometrics. Then, after selecting the appropriate rank fusion approach, the system outputs the final identification result. In case of logistic regression rank fusion approach, the system can automatically assigns weights for face, ear and iris based on the FARs and FRRs obtained through numerous trial execution of the system. For the fuzzy fusion method, the top- n ranked match images and the top ten similarity scores are produced for single and for multimodal biometric recognition after fusion. Also for the soft biometric experiment in the fuzzy fusion method, soft biometric information is integrated with the primary

biometric information (face, ear and iris) for every user. The weights for face, ear and iris (and for soft biometric identifiers), in both logistic regression rank fusion and fuzzy fusion were pre-assigned. This weight assignment is done after carefully analysing the performances of other similar systems' and of the proposed system through numerous trial executions. There is also a menu driven option for the user in the system to change weights during execution.

For convenient use of the system, the database consisting of different subdirectories of training faces, ears and irises, is automatically linked to the identification system. The multiple biometrics of a single person can be chosen by selecting the directory containing face, ear and iris images of that person. For adapting to other external databases, either one needs to copy the images to the current directory or needs to assign the current directory to the external database. Once the program is trained for the first time, there is no need for further training if the same datasets are used. To make the system robust, initial thresholds are chosen in such a way that the system can differentiate between a face and a non-face image. Further, there is a menu driven provision in the system to change the threshold during run time. For efficient use, the system has an action-button-driven option to free the used memory and clear all the selected images.

The 'Appendix' section at the end of the thesis includes the implementation steps and the snapshots of the program written for rank level fusion and fuzzy fusion methods.

6.2 Experimental Data

Due to the inherent cost and effort associated with constructing a multimodal database, most of the multimodal biometric systems employ a virtual database, which contains records created by consistent pairing a user from one unimodal database (e.g., face) with a user from another database (e.g., iris) [RNJ06]. The creation of virtual users is based on the assumption that different biometric traits of the same person are independent [GavM09]. In this work, I made the same assumption and used a virtual database which contains data from three different unimodal databases for iris, ear and face.

For iris, I have used the CASIA Iris Image Database (ver 1.0) maintained by the Chinese Academy of Science [CASIA] (with proper permission). Iris images of this version of CASIA database were captured with a homemade iris camera. This iris database includes 756 black and white iris images from 108 eyes (hence 108 classes). For each eye, 7 images are captured in two sessions, where three samples are collected in the first session and four in the second session. The pupil regions of all iris images in CASIA-IrisV1 were automatically detected and replaced with a circular region of constant intensity to mask out the specular reflections. This replacement process made the whole CASIA database less realistic, but I continued with this database as eventually the iris data includes only the information obtained from the region between the pupil and the sclera.

The ear images are from the USTB database [USTB] (with proper permission). The database contains ear images with illumination and orientation variation and individuals were invited to be seated 2m from the camera and change his/her face

orientation. The images are 300 x 400 pixels in size. Due to the different orientation and image pattern, the ear images of this database need normalization. Normalization technique, similar to one used in [YuM07] for extracting the required portion of ear images is employed in this system.

For face, the popular Facial Recognition Technology (FERET) database [PhMR98] is used (with proper permission), which documentation lists 24 facial image categories. FERET face database was collected at George mason University and the US Army Research Laboratory facilities and was recorded in 15 sessions between 1993 and 1996. All face images were recorded under different illumination environment with a 35 mm camera and at last converted to 8-bit grey scale images. There are 14,051 images of 1199 person that are 256 x 384 in size and are in varying expression and pose.

To build the virtual multimodal database for the proposed system, all the classes (subjects) of each datasets have been numbered. Then I have randomly selected same classes from each three datasets. The images within the same class of three datasets are then paired to form a single class of our virtual multimodal database. Half of the classes are chosen for training purpose and the rest are used for testing purpose. Figure 6.1 shows a small portion of the virtual multimodal database created from CASIA iris dataset, FERET face dataset and USTB ear dataset.

To fully test the proposed multimodal biometric system performance, a second virtual multimodal database has been created. A sample of this database is shown in Figure 6.2. In this database, a public domain ear database [Perp95] which contains 102 gray scale images (6 images for 17 subjects) has been used. The images were captured with a grey scale CCD camera Kappa CF 4 (focal 16 mm, objective 25.5 mm, f-number

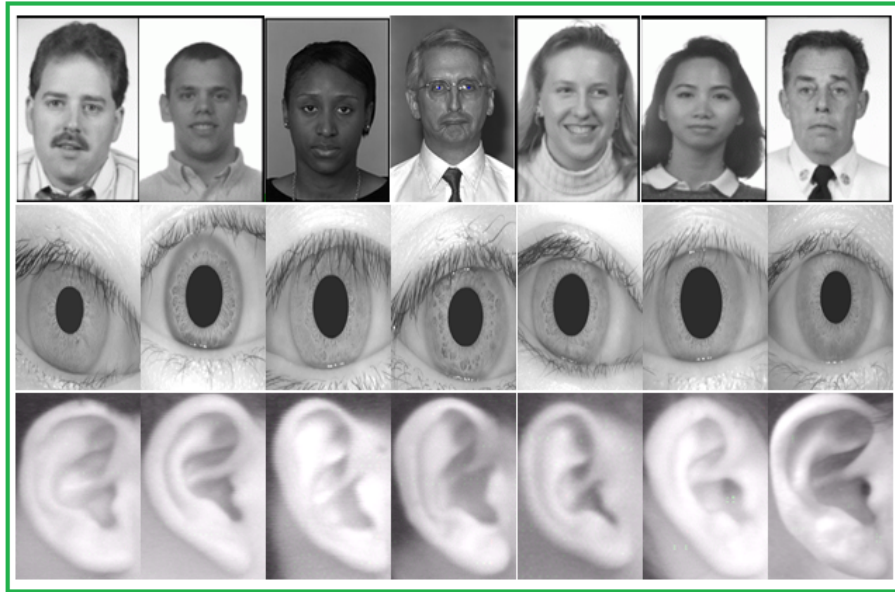


Fig 6.1: A small portion of the virtual multimodal database [FERET][CASIA] [USTB].

1.4-16) using the program Vitec Multimedia Imager for VIDEO NT v1.52. Each raw image has a resolution of 384 x 288 pixels and 256-bit grey scales. The camera was at around 1.5 m from the subject. Six views of the left profile from each subject were taken under uniform, diffuse lighting. Slight changes in the head position were encouraged from image to image. The total number of subjects in that database is 17.

The face data in our second virtual multimodal database is from the University of Essex, UK Computer Vision Science Research Project [FACE08]. There are 395 subjects in this face dataset with each having 20 face images and almost all of them are undergraduate students (age range is 18-20). Each image has a resolution of 180 x 200 pixels. The subjects are both male and female and the background of the image is plain green. The lighting and expression variations in the image are very minimal.

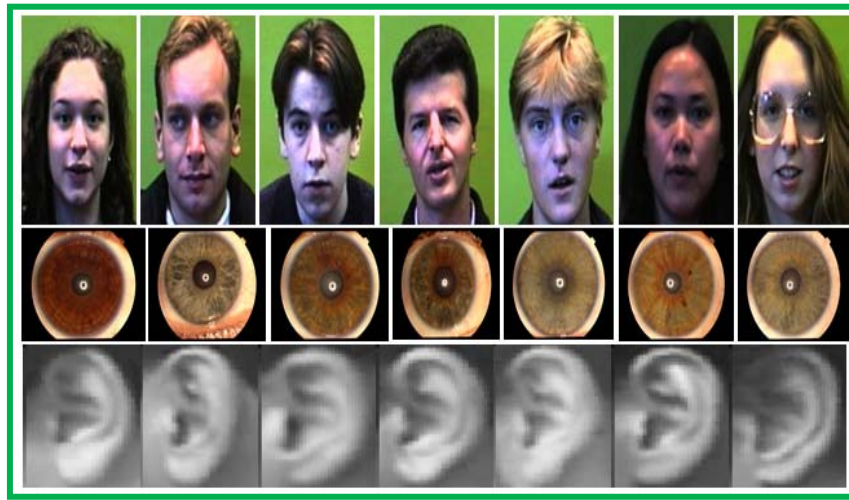


Fig 6.2: A small portion of the second virtual multimodal database [FACE08] [DMSD06][Perp95].

The iris dataset in the second database is from the Department of Computer Science at Palacký University in Olomouc, Czech Republic [DMSD06]. This iris database contains 3 iris images of left eye and 3 iris images of right eye of 64 subjects. Each image in the database are of 24 bit RGB with a resolution of 576 x 768 pixels.

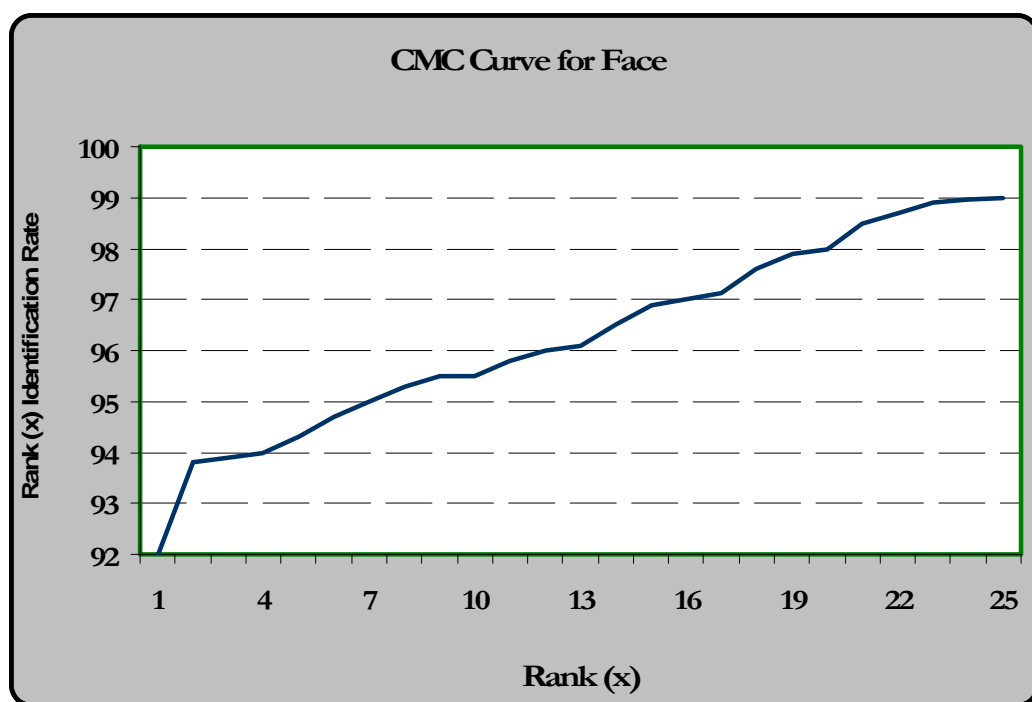
6.3 Experimental Results

The goal of this experimentation was to establish the superiority of the proposed Markov chain based rank level fusion method with other methods and to compare it with the new fuzzy logic based fusion method. After experimentation, the results have been analyzed by plotting the recognition values on different biometric system performance curves. For the proposed rank level fusion, a Cumulative Match Characteristic (CMC) curve [MooP01] is used to summarize the identification rate at different rank values. As

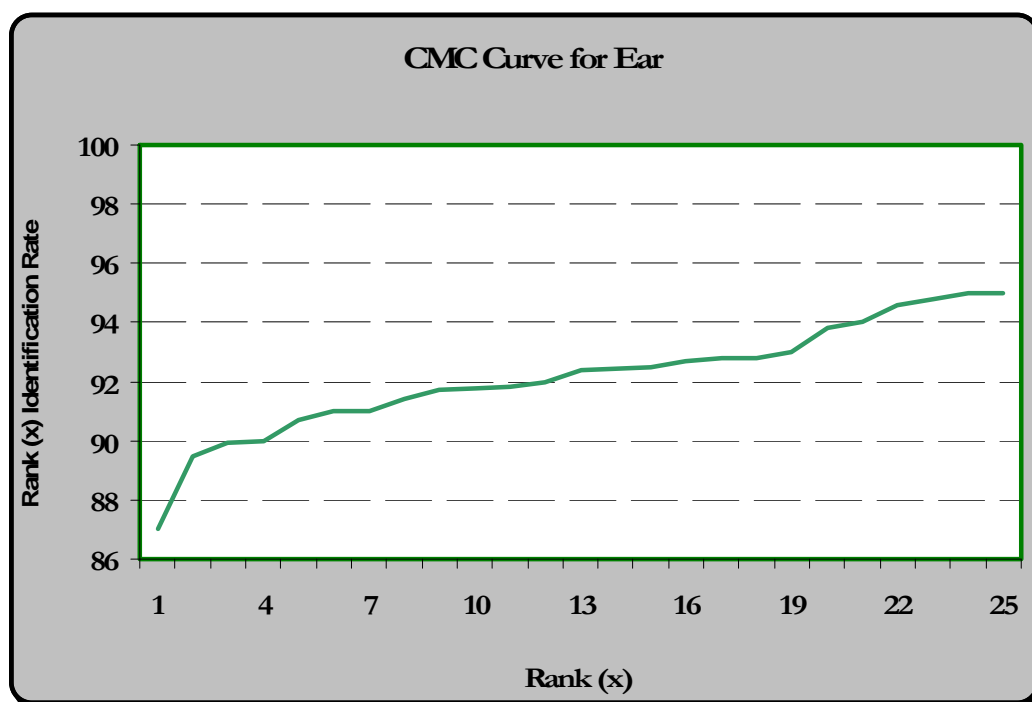
rank level fusion method can only be used for identification, the identification rate has been used which is the proportion of times the identity determined by the system is the true identity of the user providing the query biometric sample. If the biometric system outputs the identities of the top x matches, the rank- x identification rate is defined as the proportion of times the true identity of the user is contained in the top- n matching identities.

Figures 6.3 (a), 6.3 (b), and 6.3 (c) show CMC curves for our three unimodal matchers utilizing the first virtual multimodal database. Among the three unimodal matchers, iris matchers produce the best results with the 93.21% rank-1 identification rate. Rank-1 identification rates for face and ear are 92.03% and 87.16% respectively.

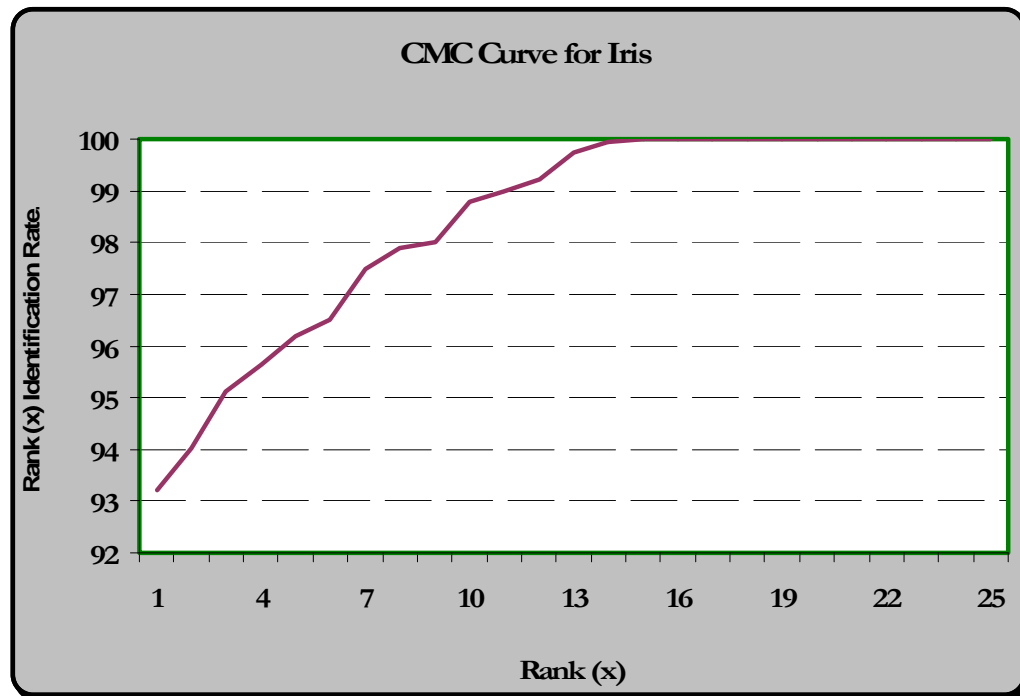
Figure 6.4 shows the CMC curves for four rank level fusion approaches applied on the first virtual multimodal database. Highest rank, Borda count, logistic regression and Markov chain approaches to rank level fusion have been applied in this experiment and the best rank-1 identification rates through Markov chain approach (97.96%) has been obtained. Among the other three, logistic regression approach is the best (almost 95.93%). The results can be explained as follows. As the performances of our individual



(a)



(b)



(c)

Fig. 6.3: CMC curves for unimodal biometrics – (a) for face, (b) for ear and (c) for iris.

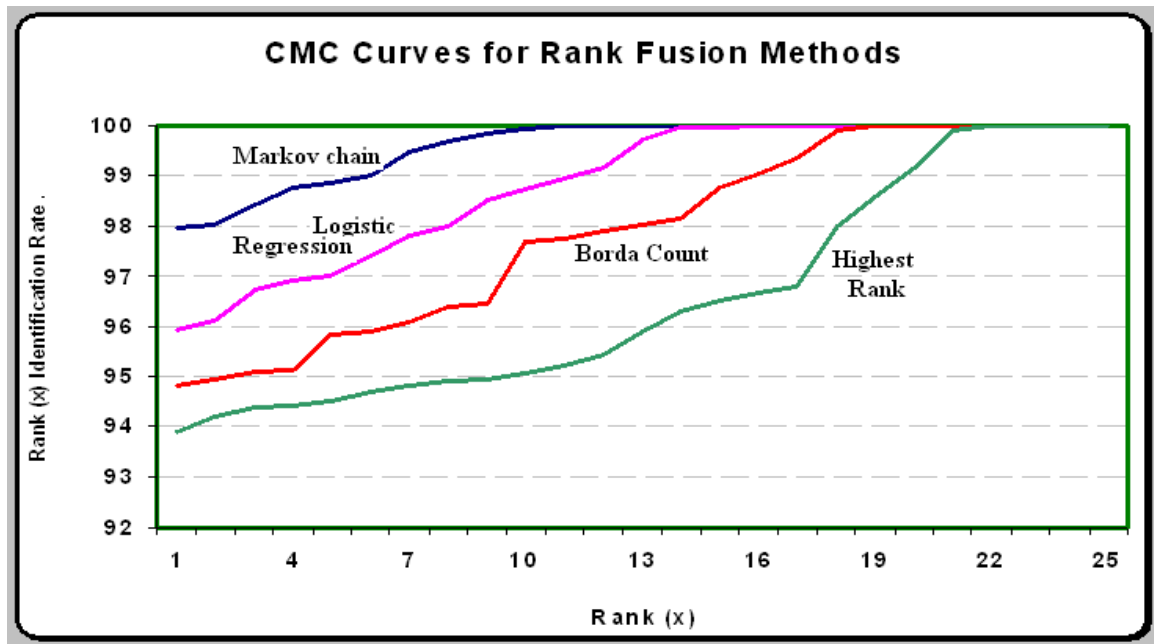


Fig. 6.4: CMC curves for four rank fusion approaches applied on the virtual multimodal database.

matchers are not equal, hence the highest rank and Borda count approaches have not produced satisfactory classification results. Borda count rank fusion approach produced 94.81% rank-1 identification rate whereas, the highest rank fusion approach produced 93.89% rank-1 identification rate.

To properly evaluate the proposed face, ear and iris based multimodal biometric system, performance of the system has been tested the system on the second virtual multimodal database. Figure 6.5 shows the CMC curves for face, ear and iris matchers. Among the three unimodal matchers, for the second virtual multimodal database, face matcher produced the best result with a 91.84% rank-1 identification rate. For iris and ear, the rank-1 identification rate is 87.13% and 81.67% respectively. These results differ from the results obtained from the first virtual multimodal database as the three individual datasets differ a lot in quality. In the second virtual multimodal database, the face images are very clear with very limited illumination and pose changes. On the other hand, the quality of the ear dataset is not good and the inter-class variations among the ear images are very limited. Thus, this ear dataset produced lower rank-1 identification rate. Similarly, the identification rates of the iris images are lower. These factors have influenced the outcomes of the unimodal matchers.

Figure 6.6 shows the CMC curves for four rank level fusion approaches along with the best unimodal matcher – face applied to the second virtual multimodal database. Similar to the previous experimentation, highest rank, Borda count, logistic regression and Markov chain approaches for rank fusion have been applied. Among all of these, Markov chain approach outperforms other with a 96.45% rank-1 identification rate.

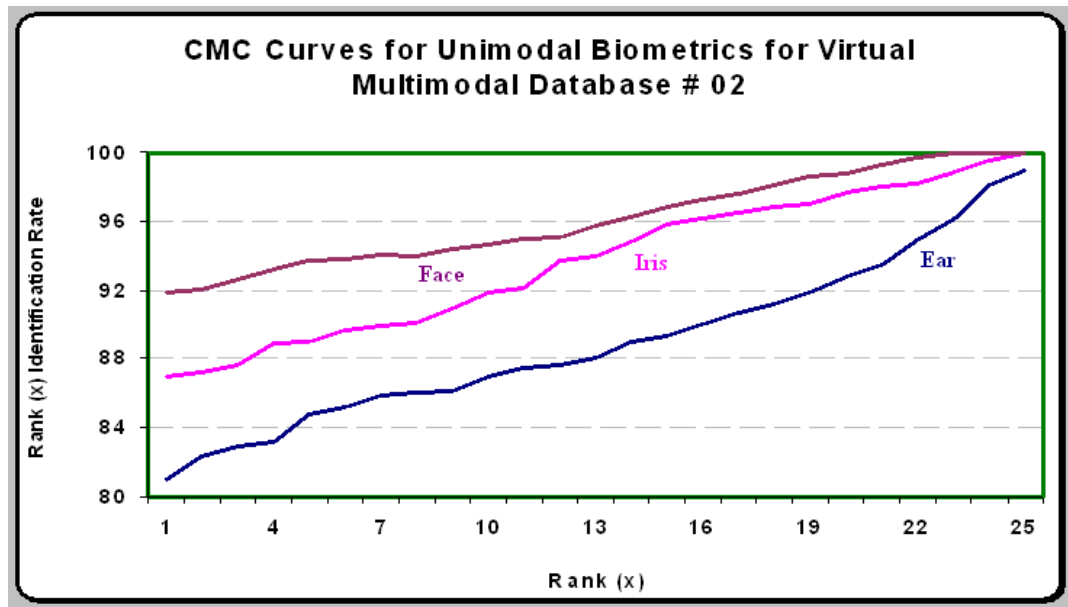


Fig. 6.5: CMC curves for unimodal matchers applied on the second virtual multimodal database.

Rank-1 identification rates for logistic regression, Borda count and highest rank approaches are 94.41%, 93.89% and 92.03% respectively. As the quality of the ear and iris images in the respective datasets are comparatively poor, the highest rank and Borda count rank fusion approaches have produced non-satisfactory results compared to the first virtual multimodal database.

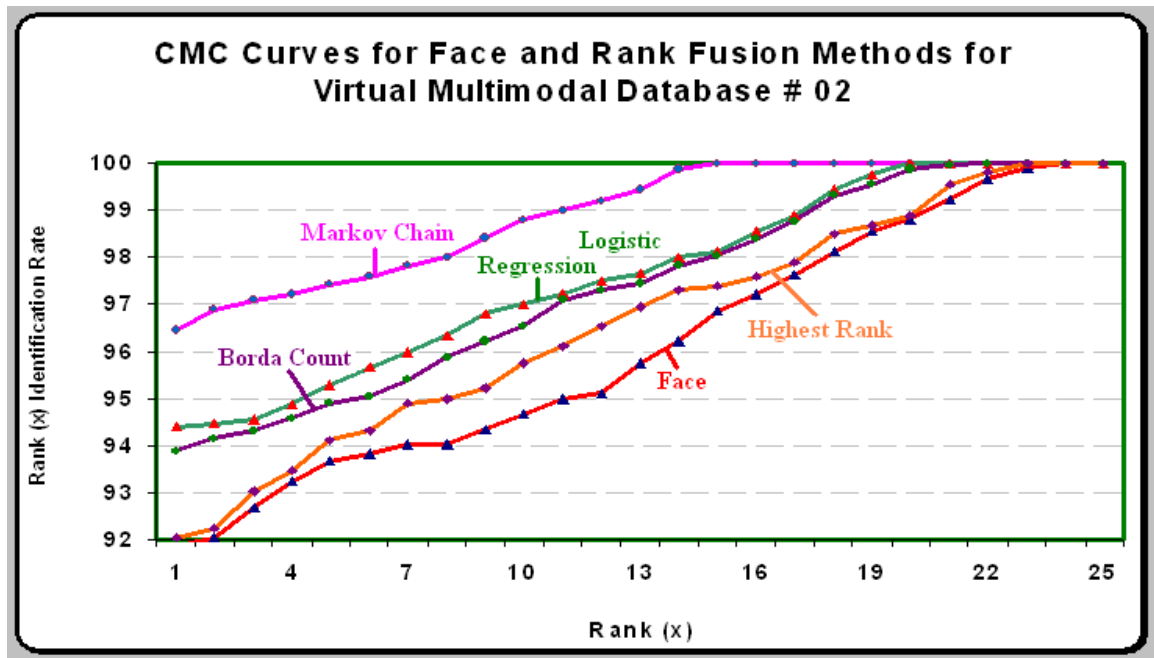


Fig. 6.6: CMC curves for four rank fusion approaches and face unimodal matcher applied on the second virtual multimodal database.

I also introduced fuzzy logic based fusion in this multimodal biometric system.

Figure 6.7 shows the ROC curves [Egan75] for the unimodal matchers and for the fuzzy fusion approach which are obtained through the experimentation with my first virtual multimodal database. For a FAR of 0.1%, I got 95.82% GAR (Genuine Accept Rate), which is equivalent to $(1 - FRR)$ [RoNJ06]. For the unimodal matchers, for the same FAR, i.e., 0.1%, the GARs for face, ear and iris are 84.03%, 80.56% and 91.56% respectively.

I have also compared fuzzy fusion approach with the rank fusion approaches which is shown in the figure 6.8. For the first virtual multimodal database, fuzzy fusion outperformed highest rank, Borda count and logistic regression methods. For a FAR of

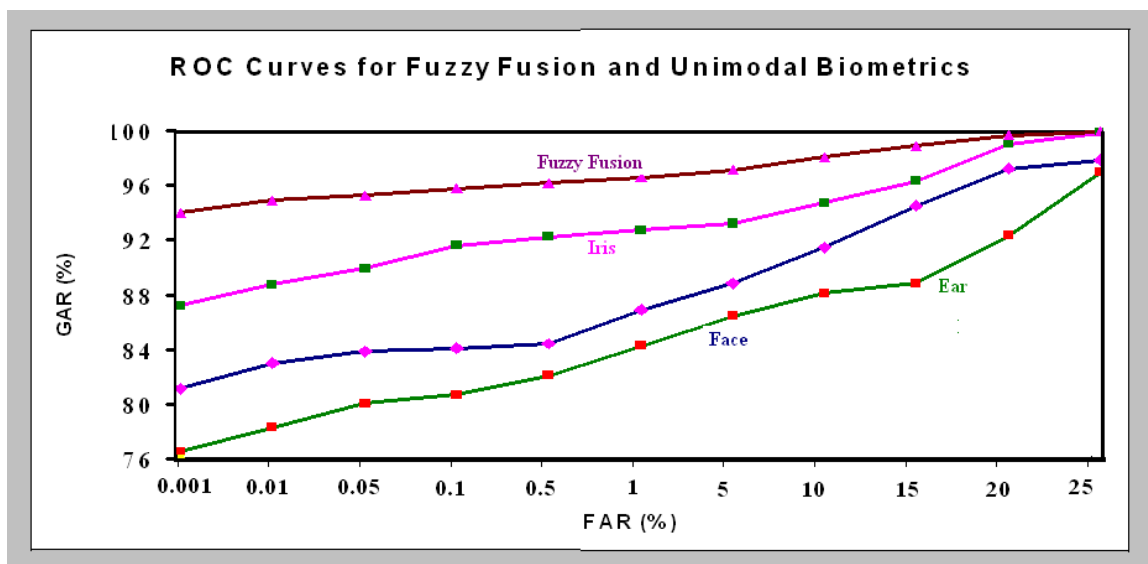


Fig. 6.7: ROC curves for unimodal biometrics and for fuzzy fusion.

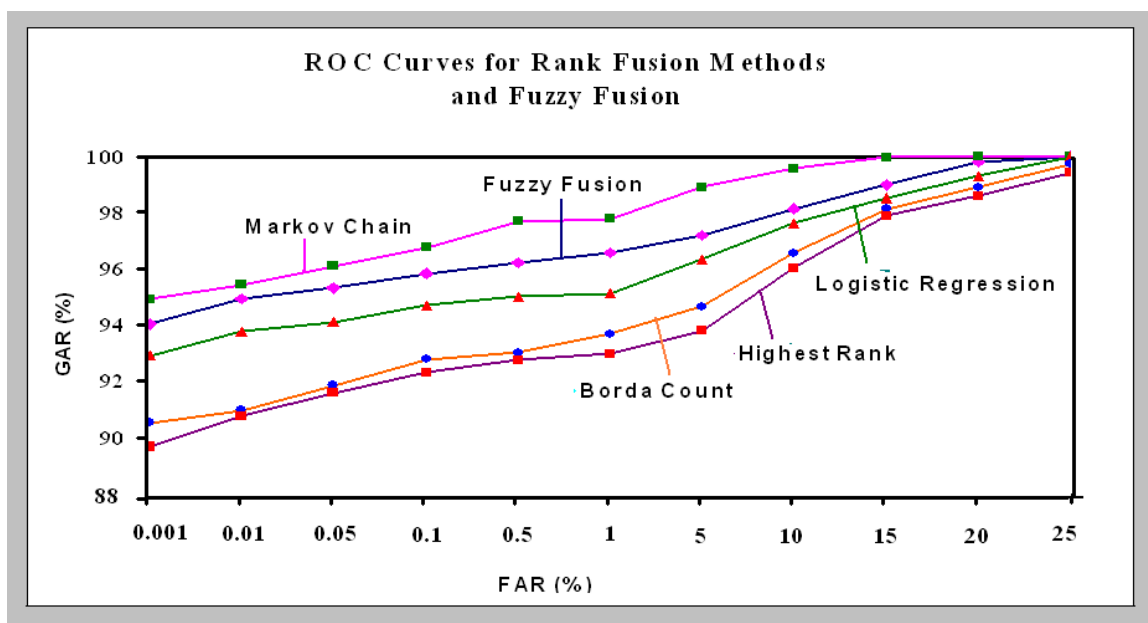


Fig. 6.8: ROC curves for fuzzy fusion and different rank fusion approaches.

0.1%, the GAR of highest rank fusion method is 92.31%, the GAR of Borda count method is 92.79% and the GAR of logistic regression method is 94.71%. Among all of these fusion approaches, Markov chain method gave us the best GAR of 96.75% for the same FAR. Although the recognition performance of the new fuzzy fusion method is not as good as Markov chain based rank fusion method, this method gives us the level of confidence on the recognition outcomes which is important in some application areas. Also, the fuzzy rules of this fusion method can be extended to make decisions on “Strictly Not Identified” subjects for some application areas, such as access to a very restricted area.

In order to efficiently evaluate the proposed system and to compare with other well-known fusion approaches, I did experiment with match score level fusion and decision level fusion. As one of the best match score level fusion methods, ‘sum rule’ and ‘product rule’ with ‘min-max’ normalization technique [RoNJ06] have been applied. For decision level fusion approaches, ‘AND’ rule [Daug00], ‘OR’ rule [Daug00], ‘majority voting’ [LamS97] and ‘weighted majority voting’ [Kunc04] approaches have been applied. For the ‘weighted majority voting’ approaches, the highest weights have been assigned for irises and the lowest weights have been assigned for ears in the first virtual multimodal database. Figure 6.9 and Figure 6.10 show the outcomes of these experimentations.

From Figure 6.9 and Figure 6.10, it is clear that Markov chain based rank level fusion outperforms both match score level fusion and decision level fusion for the first virtual multimodal database. Among the match score level fusion methods, ‘product rule’ based method performs better than ‘sum rule’ based method. Among the decision level

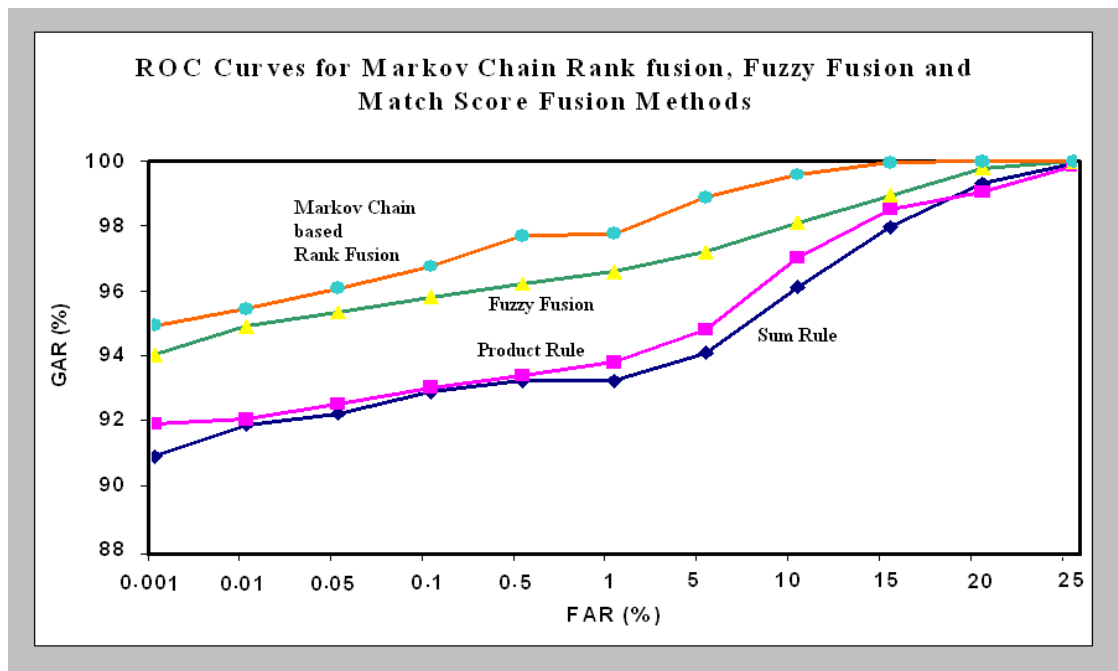


Fig. 6.9: Comparison between Markov chain based rank fusion, fuzzy fusion and match score fusion approaches.

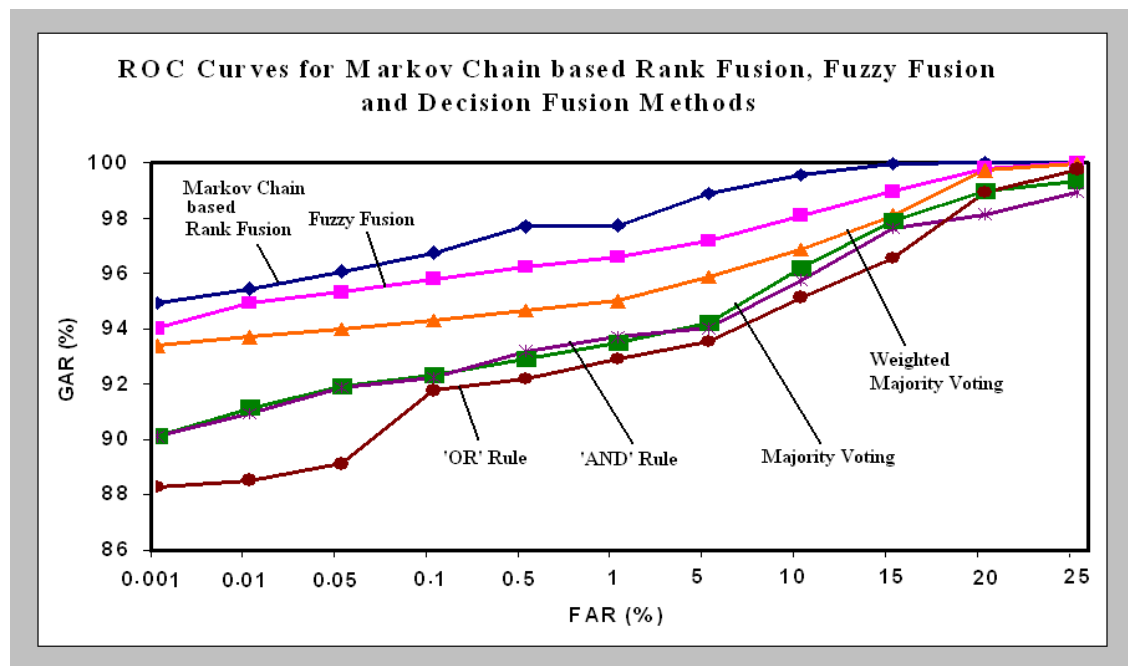


Fig. 6.10: Comparison between Markov chain based rank fusion, fuzzy fusion and decision fusion approaches.

fusion approaches, ‘weighted majority voting’ method performs the best and the performance of ‘OR’ rule based method is the minimum. Also in both experiments, fuzzy fusion method performs better than match score fusion and decision fusion approaches.

In order to evaluate the performance of the fuzzy fusion method when soft biometrics are used as additional information, I utilized three soft biometrics (gender, ethnicity and eye color) in my fuzzy fusion method. Figure 6.11 and Figure 6.12 show the performances of these experimentations for the two databases of my system.

From Figure 6.11, it is clear that the inclusion of soft biometric information in fuzzy method does not have much influence on the final authentication outcome. Sometimes, the inclusion of soft biometric information can make the system faster, especially, when these biometrics are used at first to divide the database (divide the operating spaces, i.e. the system operates only on those data where these soft biometrics are present). This is not the case in this experiment, as these soft biometric identifiers are used at after matching stage. Similar kind of performance variation is obtained with experiment utilizing the second database as shown in Figure 6.12.

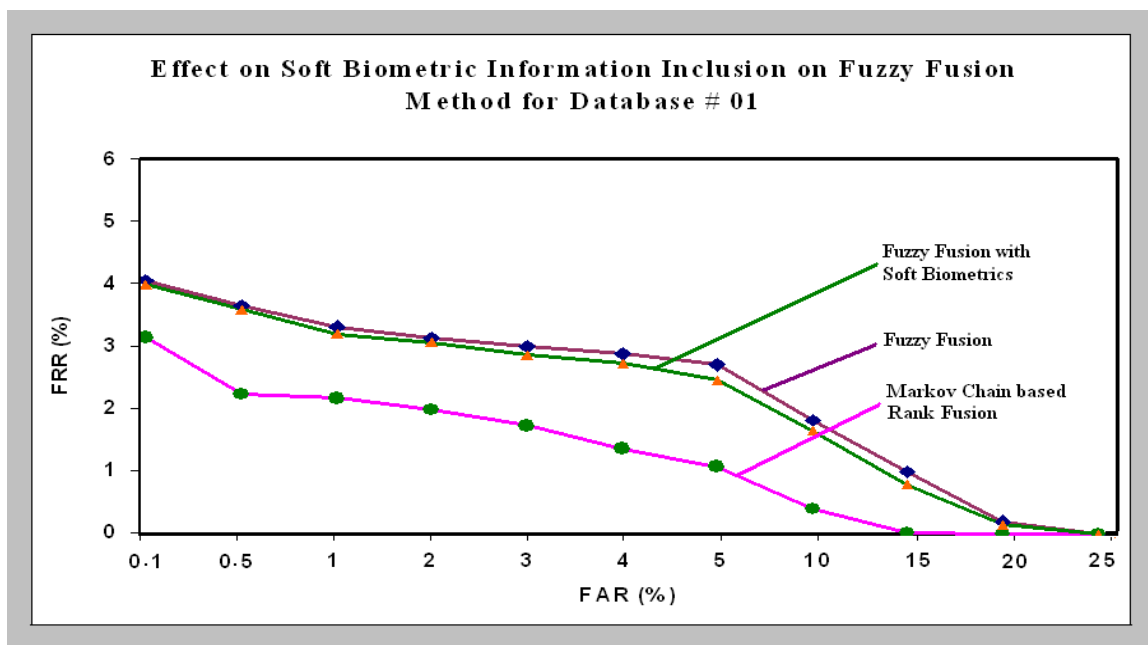


Fig. 6.11: Fuzzy fusion performance with the inclusion of soft biometric information tested with the first database.

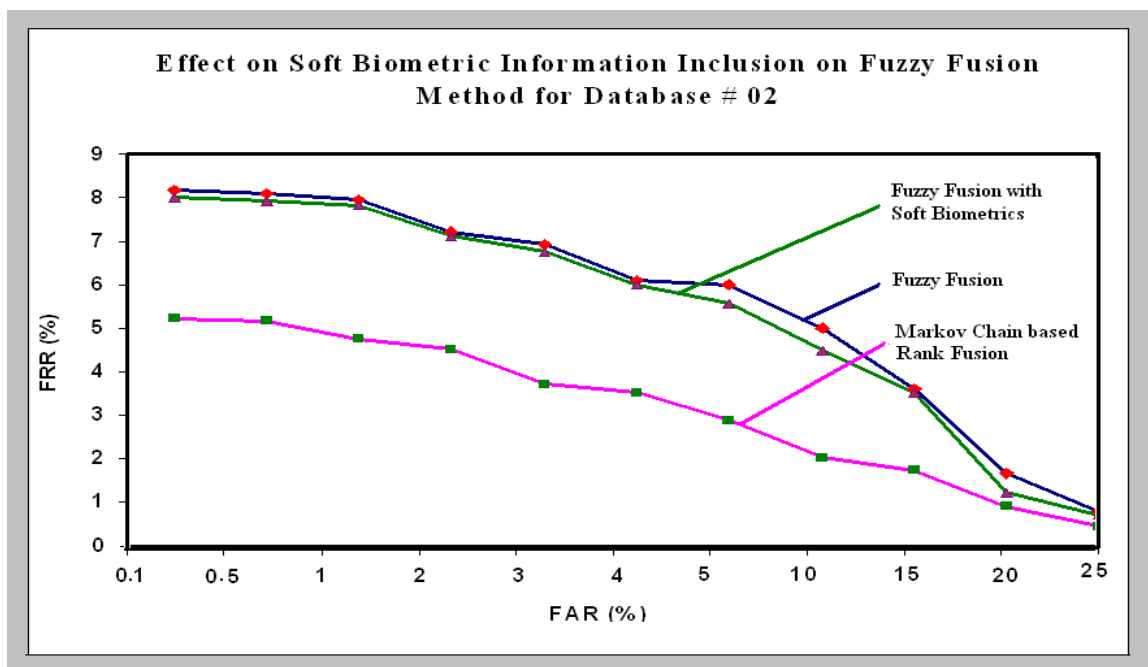


Fig. 6.12: Fuzzy fusion performance with the inclusion of soft biometric information tested with the second database.

I have also compared the Equal Error Rates (EER) of various approaches, which is the point in a ROC curve where the FAR equals the FRR (1-GRR), with the two sets of virtual multimodal databases. Figure 6.13 shows the EERs comparison for the first virtual multimodal database. For this graph, ROC curve for iris has been used as a representative for unimodal matchers, ROC curve for Markov chain method as a rank fusion approach, ROC curve for product rule as a match score level fusion approach and ROC curve for weighted majority voting method for decision fusion approach as these are the best performing methods in their respective categories. From the curves, the best EER has been obtained for Markov chain method which is 2.03%. Fuzzy fusion method gives us an EER of 3.08%. For match score level fusion and decision fusion approaches, the EERs are 5.15% and 4.73% respectively.

The same experimentations have been conducted on the second virtual multimodal database and the results are shown in Figure 6.14. As the qualities of these individual databases were not very good, the EERs obtained were not as high as EERs obtained with the first virtual multimodal database. In this experiment, Markov chain rank fusion method outperformed other approaches once again with an EER of 3.64%.

From all of these experiments, it is clear that the performances of individual matchers influence the performance of rank fusion or fuzzy fusion. As one of the performance factors of individual matchers is the quality of the database (others factors are matching algorithm, processing power of the computer etc.), so utilizing high quality database can enhance performances of both the Markov chain based rank fusion and fuzzy fusion methods.

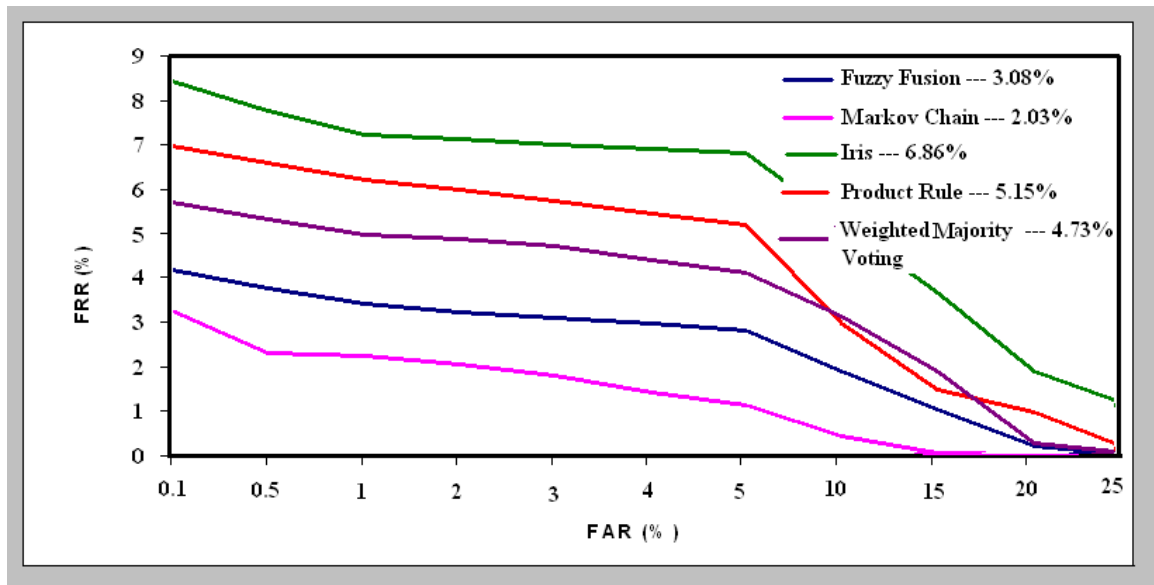


Fig. 6.13: Comparison between EERs of different fusion approaches with the first datasets.

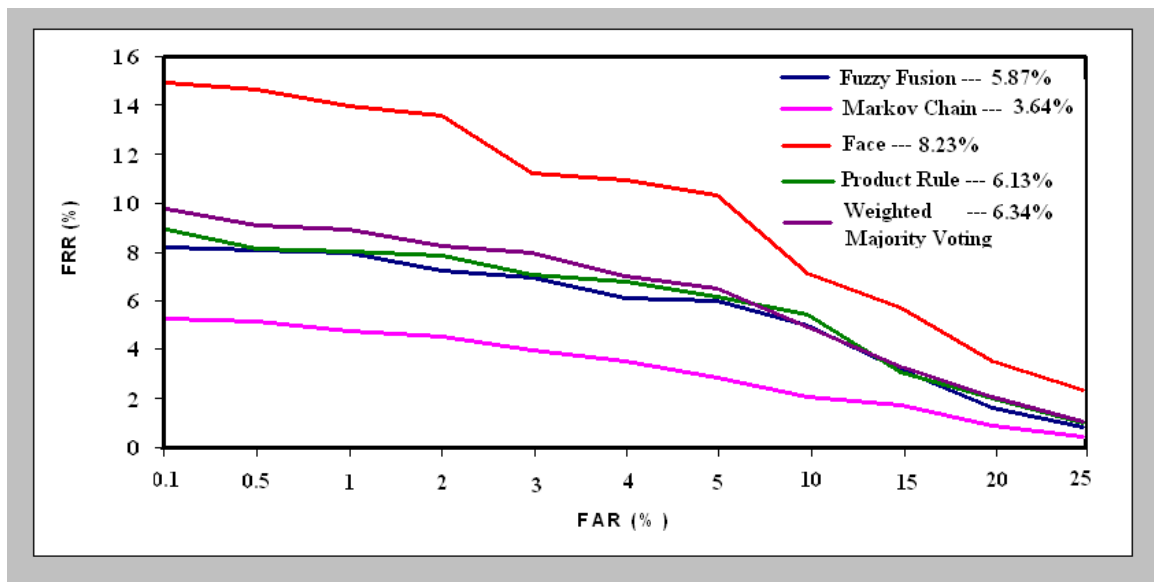


Fig. 6.14: Comparison between EERs of different fusion approaches with the second datasets.

Training and authentication response times are other important measures of any multimodal biometric system. For most security critical applications or in a crowded place, faster performance (enrolment and identification/verification times) of a biometric system is essential. These response times depend on a variety of factors, such as the size and the quality of the databases, algorithm used and on the speed of the computer. To evaluate the performance of the proposed multimodal biometric security system, the enrolment and final authentication times for Markov chain based rank fusion method and fuzzy fusion methods have been compared as only these two approaches have been considered as these are the best performing ones. Table 6.1 shows the comparison.

From table 6.1, it can be seen that fuzzy fusion method responses faster than Markov chain rank fusion method. Although Markov chain based rank level fusion method gives us better authentication results, fuzzy fusion method can be effectively used in some appropriate areas where faster security system is needed.

Table 6.1: Training and response time comparison.

Approaches	Training Time (min)	Authentication Time (min)
Face/Ear	1.03 ± 0.15	0.51 ± 0.22
Iris	$.83 \pm 0.11$	0.42 ± 0.16
Fuzzy fusion	2.59 ± 0.29	1.17 ± 0.08
Markov Chain	2.59 ± 0.29	1.89 ± 0.63

6.4 Chapter Summary

The proposed face, ear and iris based multimodal system has been developed and its performance has been evaluated and compared with other well-known after matching fusion approaches. Two virtual multimodal databases of different quality have been constructed for this purpose. The first virtual multimodal database consists of FERET face, CASIA iris, and USTB ear databases. The second virtual multimodal database consists of University of Essex FACE database, a public domain ear database, and Palacký University in Olomouc, Czech Republic iris database. The quality of the second database is not as good as the first database as the between class variation of the ear images are very limited and the iris images are already extracted and are not in good representation. From numerous trial experimentations with the same set of databases and testing with different thresholds, the best authentication performance has been obtained by Markov chain rank level fusion with the first set of virtual multimodal databases. Among other fusion approaches, the recognition performance of the fuzzy fusion method is slightly lower than the performance of Markov chain rank fusion method, but better than other fusion approaches tested in these experimentations. Further, fuzzy fusion method with the inclusion of three soft biometric identifiers has been tested. The recognition performance in this case is almost equal for the both multimodal databases. Different results obtained through various experimentations using both databases have been illustrated. Performances of rank level fusion approaches compared to unimodal biometrics have been illustrated using CMC curves. Similarly performances of fuzzy fusion compared to unimodal biometrics have been shown for both virtual databases. Further, to summarize performances of the proposed Markov chain based rank fusion and

fuzzy fusion methods on the two virtual multimodal databases, equal error rates (EER), which is the point in a ROC curve where the false accept rate and false reject rate are equal, for different unimodal matchers and for different fusion approaches have been generated. Training and response times have also been monitored and calculated which show that, fuzzy fusion method responses faster than Markov chain based rank fusion method, although the latter is better in terms of authentication accuracy. Also, fuzzy fusion provides more detailed information to the user about the level of confidence for recognition outcomes.

CHAPTER SEVEN: SUMMARY, CONCLUSION AND FUTURE WORK

This chapter provides the thesis summary, presents contributions achieved through this doctoral research, makes conclusions and suggests possible future direction of the research on multimodal biometric fusion.

7.1 Summary of the Thesis

The thesis starts by introducing biometric and its importance in the current world. Biometric systems and challenges for these systems are also presented in chapter 1. Then the focus and scope of my research are defined with the thesis contributions. A very brief methodology for the proposed multimodal biometric system is also presented in this chapter.

Next, multimodal biometric system has been thoroughly discussed to build the foundation for the rest of the thesis. Pros and cons of multimodal biometric systems along with various development issues have been discussed. The thesis develops a multimodal biometric system using face, ear and iris biometric traits with the novel rank level fusion method based on Markov chain and the new fuzzy fusion method. For the two virtual multimodal databases used in this system, the proposed methods outperform other traditional rank fusion and other approaches.

In chapter 3, previous related works in the areas of face, ear and iris recognition and on different fusion approaches are reviewed. Due to the challenges with unimodal biometric systems and to meet the demanding security requirements, several approaches have been proposed and developed in literatures for multimodal biometric authentication

system with different biometric traits and with different fusion mechanisms. Among the available fusion methods, pre-matching fusion approaches, such as sensor level fusion and feature level fusion methods have not been used extensively due to limited access to the information. Match score level fusion methods are very popular with developers and also has been extensively investigated by biometric researchers as some of the earlier methods. But match score fusion approach needs normalization of the outcomes of unimodal matchers which is computationally extensive. Moreover inappropriate choice of normalization technique can degrade the system performances. Decision level fusion approaches are too abstract and used primarily in the commercial biometric system where only the final outcomes are available for processing. Thus in this doctoral research, I have used rank level fusion which is relatively new approach compared to others and still remains understudied. I have also introduced the new fuzzy fusion for faster processing and more detailed outcomes on biometric identification confidence.

The development procedures for the proposed multimodal system have been illustrated in the chapter 4. Fisherimage technique has been used for face and ear recognition. For iris recognition, Hough transform is used for iris localization, and Hamming distance method is used for iris comparison.

Proposed new rank fusion approach and fuzzy fusion have been introduced in chapter 5 along with necessary theoretical overview and methodology. For rank level fusion, highest rank, Borda count, logistic regression methods have been investigated. A new rank fusion method based on Markov chain has been introduced in this thesis. A

novel fuzzy fusion approach is also employed in the system to investigate the performance of fusion strategy of multimodal biometric system.

Outcomes of the rigorous experimentations have been presented and discussed in chapter 6. Two sets of virtual multimodal database (database constructed with randomly combine different biometric traits from different database for a single subject) have been used. For performance evaluation, CMC and ROC curves have been used and finally EERs of different unimodal and multimodal systems have been generated. Further, enrolment and response times which are very essential in time critical security systems have been calculated for different scenarios.

7.2 Summary of Contributions

This section highlights the contributions of this research to multimodal system development for security critical applications utilizing rank level fusion and fuzzy fusion.

- In this doctoral thesis, I have fully developed and implemented a multimodal biometric system. This multimodal biometric system can overcome drawbacks associated with unimodal biometric systems.

- Several multimodal biometric systems have been developed with different biometric traits and fusion approaches. I have utilized face, ear and iris biometric traits, all from the face region. Using these traits allows efficient and convenient capturing of the real time biometric data.

- For fusion, I have introduced new rank level fusion and fuzzy fusion approaches. Both of these fusion approaches have been investigated in different application areas and have potential to be efficiently utilized in the multimodal biometric systems.

- I investigated different rank fusion approaches, such as highest rank method, Borda count method and logistic regression method against the introduced Markov chain based rank fusion algorithm. This Markov chain rank fusion method significantly increases the recognition performance of the multimodal biometric system as well as satisfies the Condorcet criteria, which is essential for fair ranking process.

- To increase processing time and to provide more information about the final outcome to the user, I have developed a fuzzy fusion algorithm which utilizes fuzzy logic along with rank and match score information. Based on the experiments, this fusion method works faster than Markov chain method.

- I have developed a complete automatic multimodal biometric system framework (tested using different multimodal databases) that has a very high potential for to be employed in various government and consumer security critical applications as well as for commercialization.

The synthesis of methods and models from multiple fusion scenarios, such as the Markov chain based rank fusion and fuzzy fusion are the main thesis contributions which also provide to a practiced solution for multimodal biometric security system.

7.3 Conclusions

In this doctoral thesis, I have presented a multimodal biometric system using face, ear and iris biometric identifiers (all from facial region). To combine the information from these three biometric identifiers, I introduced new rank level fusion and fuzzy fusion approaches. After investigating different rank level fusion approaches, I proposed Markov chain based rank fusion which satisfies the Condorcet criteria essential for any fair rank aggregation process. This Markov chain based rank fusion approach significantly enhances recognition performance of the multimodal biometric system. I also introduced fuzzy fusion which improves the response time and provides more confidence information of the outcomes for the developed multimodal biometric system. Further, to evaluate the performance of fuzzy fusion, I incorporated soft biometric information in the fuzzy fusion method. The extensive experimentations with two virtual multimodal databases indicate that the proposed multimodal system outperforms other commonly used methods and can help government or public/private sectors to protect valuable property or information, as well as can ensure the overall security of the region or country.

7.4 Future Research Direction

The outcomes of this research have been published and presented through important venues, such as IEEE Transactions on Systems, Man and Cybernetics; Signal, Image and Video Processing, Springer; International Journal of Biometrics, Inderscience; IEEE ICCI*CC; IEEE Symposium on Computational Intelligence etc. and have benefitted both academic and enterprise applications. There are some issues and open questions left for future research.

A true multimodal database is very useful for developing a reliable and efficient security application. Due to the type of collected sample data, the changes in the background and illumination are varied. True multimodal database with the identical conditions can be employed for further performance analysis.

In most cases, biometric based security systems need to operate in real-time mode. The proposed system can be extended to operate in the real-time enrolment and authentication environment. Proper instruments (for capturing real-time data) and peripheral communications are needed for this purpose. Special concentration is needed to automatically acquire soft biometric information in real-time setup.

More research can be conducted to find the optimum matching algorithms for unimodal biometrics to enhance the overall performance of the multimodal system.

Dual or tri-level fusion scenarios (different fusion in different levels of the system) can be investigated to make the system faster and significantly reduce the error rate.

These represent possible future direction of research in this exciting and rich field.

REFERENCES

- [AbaR09] Abaza, A., and Ross, A. (2009). Quality based rank-level fusion in multibiometric systems. In *proc. of 3rd IEEE International Conference on Biometrics: Theory, Applications and Systems*, pp. 1-6, Washington DC, USA.
- [AiCN05] Ailon, N., Charikar, M., and Newman, A. (2005). Aggregating inconsistent information: ranking and clustering. In *proc. of 37th Annual ACM Symposium on Theory of Computing (STOC)*, pp. 684–693, Baltimore, MD, USA.
- [Ailo10] Ailon, N. (2007) Aggregation of partial rankings, p-ratings and top-m lists. *Algorithmica*, vol. 57(2), pp. 284-300.
- [BaLS98] Bartlett, M. S., Lades, H. M., and Sejnowski, T. (1998). Independent component representation for face recognition. In *proc. of SPIE Symposium on Electronic Imaging: Science and Technology*, vol. 3299, pp. 528–539.
- [BBBH03] Bailly-Baillire, E., Bengio, S., Bimbot, F., Hamouz, M., Kittler, J., Marithoz, J., Matas, J., Messer, K., Popovici, V., Pore, F., Ruiz, B., and Thiran, J. P. (2003). The BANCA database and evaluation protocol. In *proc. of International Conference on Audio- and Video-Based Biometric Person Authentication (AVBPA)*, pp. 625-638, Guildford, UK.
- [BCPR04] Bolle, R. M., Connell, J. H., Pankanti, S., Ratha, N. K., and Senior, A. W. (2004). *Guide to biometrics*. New York: Springer-Verlag.
- [BeHK97] Belhumeur, P., Hespanha, J., and Kriegman, D. (1997). Eigenfaces vs. fisherfaces: Recognition using class specific linear projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Special Issue on Face Recognition, vol. 19(7), pp. 711-20.

- [BFOG05] Bigun, J., Fierrez-Aguilar, J., Ortega-Garcia, J., and Gonzalez-Rodriguez, J. (2005). Combining biometric evidence for person authentication. In M.Tistarelli, J.Bigun, and E.Grosso (Eds.): Biometrics School 2003, LNCS 3161, pp. 1–18.
- [BhaC03] Bhanu, B., and Chen, H. (2003). Human ear recognition in 3D. In proc. of Workshop on Multimodal User Authentication (MMUA), pp. 91–98, Santa Barbara, CA, USA.
- [Blac63] Black, D. (1963). The Theory of Committees and Elections (2nd ed.) Cambridge: Cambridge University Press.
- [Borda1781] Borda, J. C. [1781]. M’emoire sur les ´elections au scrutin. Histoire de l’Acad’emie Royale des Sciences.
- [BruT54] Bruner, I. S., and Tagiuri, R. (1954). The perception of people. In Handbook of Social Psychology, G. Lindzey (Ed.), vol. 2, Reading, MA: Addison-Wesley, pp. 634–654.
- [Bube03] Bubeck, U. M. (2003). Multibiometric authentication: An overview of recent developments. Term project, San Diego State University, California, USA. Available at: <http://www.ub-net.de/cms/fileadmin/uwe/doc/bubeck-multibiometrics.pdf>.
- [BurB98] Burge, M., and Burger, W. (1998). Ear biometrics. In Biometrics: Personal Identification in Networked Society, A. K. Jain, R. Bolle, and S. Pankanti (Eds.). Norwell, MA, USA: Kluwer Academic Publishers, chapter 13, pp. 273-286.
- [CASIA] CASIA: Casia iris image database (2004) Retrieved on May 23, 2008. Available at: www.sinobiometrics.com

- [ChaA11] Chaabane, L., and Abdelouahab, M. (2011). Improvement of brain tissue segmentation using information fusion approach. *International Journal of Advanced Computer Science and Applications*, vol. 2(6), pp. 84-90.
- [ChBB03] Chang, K., Bowyer, K., and Barnabas, V. (2003). Comparison and combination of ear and face images in appearance-based biometrics. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, pp. 1160–1165.
- [ChDJ05] Chen, Y., Dass, S. C., and Jain, A. K. (2005). Fingerprint quality indices for predicting authentication performance. In *proc. of Fifth International Conference on Audio and Video-Based Biometric Person Authentication (AVBPA)*, pp. 373-381, Rye Brook, USA.
- [ChWS95] Chellappa, R., Wilson, C., and Sirohey, A. (1995). Human and machine recognition of faces: A survey. In *proc. of IEEE*, vol. 83(5), pp. 705–740.
- [Cond1785] M.-J. Condorcet. *Essai sur l'application de l'analyse _a la probabilit_e des d_ecisions rendues _a la pluralit_e des voix*.
- [Cope51] Copeland, A. H. (1951). *A reasonable social welfare function*. Mimeo, University of Michigan.
- [Daug00] Daugman, J. (2000). Combining multiple biometrics. Available at: <http://www.cl.cam.ac.uk/users/jgd1000/combine/combine.html>.
- [Daug04] Daugman, G. (2004). How iris recognition works. *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14(1), pp. 21–30.

- [Daug88] Daugman, J. G. (1988). Complete discrete 2-D Gabor transforms by neural networks for image analysis and compression. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 36(7), pp. 1169–1179.
- [Daug93] Daugman, J. G. (1993). High confidence visual recognition of persons by a test of statistical independence. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, pp. 1148-1161.
- [Demp67] Dempster, A. P. (1976). Upper and lower probabilities induced by a multivalued mapping. *Annals of Mathematical Statistics*, vol. 38(2), pp. 325–339.
- [DKNS01] Dwork, C., Kumar, R. Naor, M., and Sivakumar, D. (2001). Rank aggregation methods for the web. In *proc. of Tenth International Conference on the World Wide Web (WWW)*, pp. 613-622, Hong Kong, China.
- [DMSD06] Dobeš, M., Martinek, J., Skoupil, D., Dobešová, Z., and Pospíšil, J. (2006). Human eye localization using the modified Hough transform. *Optik*, vol. 117(10), pp. 468-473.
- [DRCD06] Dessimoz, D., Richiardi, J., Champod, C., and Drygajlo, A. (2006). MBiIoD – Multimodal biometrics for identity documents: State-of-the-art. *Research Report*. Universite de Lausanne, Switzerland.
- [DSWL10] Deng, Y., Su, X., Wang, D., and Li, Q. (2010). Target recognition based on fuzzy Dempster data fusion method. *Defence Science Journal*, vol. 60(5), pp. 525-530.
- [DunY09] Dunstone, T., and Yager, N. (2006). *Biometric system and data analysis: Design, evaluation, and data mining*. New York: Springer.

- [DutG07] Dutkowski, J., and Gambin, A. (2007). On consensus biomarker selection. *BioMed central (BMC) Bioinformatics*, vol. 24(8), S5.
- [Egan75] Egan, J. (1975). *Signal detection theory and ROC analysis*. New York: Academic Press.
- [EMGG06] English, A., Means, C., Gordon, K., and Goetz, K. (2006). *Biometrics: A technology assessment*. Ball State University, Muncie, IN, USA.
- [FACE] Face database, Computer Vision Science Research Project, University of Essex, UK, 2008. Available at: <http://cswww.essex.ac.uk/mv/allfaces/index.html>.
- [Fagi99] Fagin, R. (1999). Combining fuzzy information from multiple systems. *Journal of Computer and System Sciences*, vol. 58(1), pp. 83–99.
- [FarV08] Farah, M., and Vanderpooten, D. (2008). An outranking approach for information retrieval. *Information Retrieval*, vol. 11(4), pp. 315-334.
- [FDHZ04] Feng, G., Dong, K., Hu, D., and Zhang, D. (2004). When faces are combined with palmprint: A novel biometric fusion strategy. In *proc. of First International Conference on Biometric Authentication (ICBA)*, pp. 701-707, Hong Kong, China.
- [Fish36] Fisher, R. A. (1936). The use of multiple measurements in taxonomic problems. *Ann. Eug.*, vol. 7(2), pp. 179-188.
- [FOGB04] Fierrez-Aguilar, J., Ortega-Garcia, J., Gonzalez-Rodriguez, J., and Bigun, J. (2004). Kernel-based multimodal biometric verification using quality signals. In *Proceedings of SPIE*, vol. 5404, pp. 544-554.
- [FriD00] Frischholz, R., and Dieckmann, U. (2000). BioID: A multimodal biometric identification system. *IEEE Computer*, vol. 33(2), pp. 64-68.

- [Gabo46] Gabor, D. Theory of communication. Journal of the Institute of Electrical Engineering, vol. 93, pp. 429-457.
- [GavM11] Gavrilova, M., and Monwar, M. M. (2011). Current trends in multimodal system development: Rank level fusion. Chapter in Patrick Wang (Ed.), Pattern Recognition, Machine Intelligence and Biometrics (PRMIB), High Education Press (HEP) and Springer, p. 657-673.
- [GavM09] Gavrilova, M., and Monwar, M.M. (2009). Fusing multiple matchers' outputs for secure human identification. International Journal of Biometrics (IJBM), vol. 1(3), pp. 329-348.
- [GoMM97] Golfarelli, M., Maio, D., and Maltoni, D. (1997). On the error-reject tradeoff in biometric verification systems. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19(7), pp. 786-796.
- [GriS97] Grinstead, C. M., and Snell, J. L. (1997). Introduction to probability (2nd ed.). Providence, RI, USA: American Mathematical Society.
- [Hamm50] Hamming, R. W. (1950). Error detecting and error correcting codes. Bell System Technical Journal, vol. 29(2), pp. 147-160.
- [HHFR09] M. He, et al. (2010). Performance evaluation of score level fusion in multimodal biometric systems. Pattern Recognition. vol. 43(5), pp. 1789-1800.
- [HoHS94] Ho, T. K., Hull, J. J., and Srihari, S. N. (1994). Decision combination in multiple classifier systems. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 16(1), pp. 66-75.

- [HonJ98] Hong, L., and Jain, A. K. (1998). Integrating faces and fingerprints for personal identification. *IEEE Transaction on Pattern Analysis and Machine Intelligence*, vol. 20(12), pp. 1295–1307.
- [Houg62] Hough, P. V. C. (1962). Method and means for recognizing complex patterns. US Patent 3069654.
- [Hsu02] Hsu, R.-L. (2002). Face detection and modeling for recognition. PhD thesis. Department of Computer Science and Engineering, Michigan State University, East Lansing, USA.
- [HuHB03] Huang, J., Heisele, B., and Blanz, V. (2003). Component-based face recognition with 3D morphable models. In *proc. of International Conference on Audio- and Video-Based Person Authentication (AVBPA)*, pp. 27-34, Guildford, UK.
- [Hunt96] Hunt, K. J. (1996). Extending the functional equivalence of radial basis function networks and fuzzy inference system. *IEEE Transactions on Neural Network*, vol. 13, pp. 776-778.
- [HurA07] Hurley, D. J., Arbab-Zavar, B. (2007). The ear as a biometric. In *Handbook of Biometrics*, A. K. Jain, P. Flynn, A. Ross (Eds.), New York: Springer, pp. 131-150.
- [Iann89] Iannarelli, A. (1989). *Ear Identification*. Forensic Identification Series. Fremont, CA, USA: Paramount Publishing Company.
- [ImaG] Google images. www.google.com/imghp. Retrieved on December, 2010.
- [IrTD03] Iris recognition (2003). Iris Technology Division, LG Electronics USA, 7 Clarke Drive, Cranbury, NJ 08512, USA.

- [JaFR07] Jain, A. K., Flynn, P., and Ross, A. (2007). Handbook of biometrics. New York: Springer.
- [JaHB97] Jain, A. K., Hong, L., and Bolle, R. (1997). On-line fingerprint verification. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19(4), pp. 302-314.
- [Jain05] Jain, A. K. (2005). Biometric recognition: How do I know who you are? In proc. of International Conference on Image Analysis and Processing, Springer LNCS, vol. 3617/2005, pp. 19-26.
- [JaNR05] Jain, A. K., Nandakumar, K., and Ross, A. (2005). Score normalization in multimodal biometric systems. Pattern Recognition, vol. 38, pp. 2270-2285.
- [JaRN11] Jain, A. K., Ross, A., and Nandakumar, K. (2011). Introduction to biometrics. New York: Springer-Verlag.
- [JaRP04] Jain, A. K., Ross, A., and Prabhakar, S. (2004). An introduction to biometric recognition. IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, no. 1, pp. 4-20.
- [JYYL07] Jing, X. Y., Yao, Y. F., Yang, J. Y., Li, M., and Zhang, D. (2007). Face and palmprint pixel level fusion and kernel DCV-RBF classifier for small sample biometric recognition. Pattern Recognition, vol. 40, pp. 3209–3224.
- [Kana73] Kanade, T. (1973). Picture processing system by computer complex and recognition of human faces. PhD thesis, Kyoto University, Japan.
- [KCKC06] Kim, J., Cho, S., Kim, D., and Chung, S.-T. (2006). Iris recognition using a low level of details, Springer Lecture Notes in Computer Science, vol. 4292, pp. 196-204.

- [KirS90] Kirby, M., and Sirovich, L. Application of the karhunen-loeve procedure for the characterization of human faces. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 12(1), pp. 103-108.
- [KKLC01] Kim, S.-W., Kim, K., Lee, J.-H., and Cho, D. (2001). Application of fuzzy logic to vehicle classification algorithm in Loop/Piezo-sensor fusion systems. *Asian Journal of Control*, vol. 3(1), pp. 64–68.
- [KIBM08] Kludas, J., Brunio, E., and Marchand-Maillet, S. (). Information fusion in multimedia information retrieval. In *proc. of 5th International Workshop on daptive Multimedia Retrieval: Retrieval, User, and Semantics*, pp. 147-159, Paris, France.
- [KoWT04] Kokar, M. M., Weyman, J., and Tomasik, J. A. (2004). Formalizing classes of information fusion systems. *Information Fusion*, vol. 5, pp.189–202.
- [KumS10] Kumar, A., and Shekhar, S. (2010). Palmprint recognition using rank level fusion. In *proc. of IEEE International Conference on Image Processing (ICIP)*, pp. 3121-3124, Hong Kong, China.
- [Kunc04] Kuncheva, L. I. (2004). *Combining pattern classifiers: Methods and algorithms*. Wiley.
- [LamS97] Lam, L., and Suen, C. Y. (1997). Application of majority voting to pattern recognition: An analysis of its behavior and performance. *IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans*, vol. 27 (5), pp. 553-568.

- [LBRS04] Linas, J., Bowman, C ., Rogova, G ., Steinberg, A., Waltz, E ., and White, F. (2004). Revisiting the JDL data fusion model II. In proc. of 7th International Conference on Information Fusion, Stockholm, Sweden.
- [LiJa04] Li, S. Z., Jain, A. K. (Eds.) (2004). Handbook of face recognition. New York, USA :Springer.
- [LiuC03] Liu, X., and Chen, T. (2003). Geometry-assisted statistical modeling for face mosaicing. In proc. of IEEE International Conference on image Processing (ICIP), vol. 2, pp. 883-886, Barcelona, Spain.
- [Mark'06] Markov, A. A. (1906). Extension of the limit theorems of probability theory to a sum of variables connected in a chain. Reprinted in Appendix B of: R. Howard. Dynamic Probabilistic Systems, volume 1: Markov Chains. John Wiley and Sons.
- [MaWT02] Ma, L., Wang, Y., and Tan, T. (2002). Iris recognition based on multichannel Gabor filtering. In proc. of 5th Asian Conference on Computer Vision (ACCV), pp. 279-283, Melbourne, Australia.
- [McMa05] McMahon, Z. (2005). Biometrics: History. Computer Science Department, Indiana University. Retrieved online on March 2010, from <http://cs.indiana.edu/~zmcmahon/biometrics-history.htm>
- [Mill94] Miller, B. (1994). Vital signs of identity. IEEE Spectrum, vol. 31(2), pp. 22-30.
- [MitP05] Mitra, S., and Pal, S. K. (2005). Fuzzy sets in pattern recognition and machine intelligence. Fuzzy Sets and Systems, vol. 156, pp. 381-386.
- [MMJP09] Maltoni, D., Maio, D., Jain, A. K., and Prabhakar, S. (2009). Handbook of fingerprint recognition (2nd ed.). New York: Springer-Verlag.

- [MMYH02] Matsumoto, T., Matsumoto, H., Yamada, K, and Hoshino, S. (2002). Impact of artificial ‘gummy’ fingers on fingerprint systems. In proc. of SPIE Optical Security and Counterfeit Deterrence Techniques IV, vol. 4677, pp. 275–289.
- [MoGW11] Monwar, M. M., Gavrilova, M., and Wang, Y. (2011). A novel fuzzy multimodal information fusion technology for human biometric traits identification. In proc. of the 10th IEEE International Conference on Cognitive Informatics & Cognitive Computing, August 18-20, 2011, Banff, Alberta, Canada. (Accepted on April 28, 2011; submission ID: 17)
- [MonG09] Monwar, M. M., and Gavrilova, M. (2009). A multimodal biometric system using rank level fusion approach. IEEE Transactions on Systems, Man, and Cybernetics - Part B: Cybernetics (special issue on Cognitive Informatics and Cybernetics), vol. 39(4), pp. 867-878.
- [MonG11] Monwar, M. M., and Gavrilova, M. (2011). Markov chain model for multimodal biometric rank fusion. Signal, Image and Video Processing, Springer-Verlag London Limited, DOI: 10.1007/s11760-011-0226-8, pp. 1-13.
- [MooP01] Moon, H., and Phillips, P. J. (2001). Computational and performance aspects of PCA-based face recognition algorithms. Perception, 30(5): 303-321.
- [MoSV99] Moreno, B., Sanchez, A., Velez, J. F. (1999). On the use of outer ear images for personal identification in security applications. In proc. of IEEE 33rd Annual International Carnahan Conference on Security Technology, pp. 469-476.
- [MuYX04] Mu, Z., Yuan, L., and Xu, Z. (2004). Shape and structural feature based ear recognition. In proc. of International conference on Advances in Biometric Person Authentication, pp. 663-670, Guangzhou, China.

- [MYCC04] Moon, Y. S., Yeung, H. W., Chan, K. C., and Chan, S. O. (2004). Template synthesis and image mosaicking for fingerprint registration: An experimental study. In *proc. of IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, vol. 5, pp. 409-412, Montreal, Canada.
- [NCDJ09] Nandakumar, K., Chen, Y., Dass, S. C., and Jain, A. K. (2009). Likelihood ratio-based biometric score fusion. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 30(2), pp. 342-347.
- [Newm09] Newman, R. (2009). *Security and access control using biometric technologies*. Boston : Course Technology.
- [NguW97] Nguyen, H. T., and Walker, E. A. (1997). *A first course in fuzzy logic*. Boca Raton, FL, USA: CRC Press.
- [PedG98] Pedrycz, W., and Gomide, F. A. C. (1998). *An introduction to fuzzy sets: Analysis and design complex adaptive systems*, Cambridge, MA, USA: MIT Press.
- [PeHG99] Pennock, D. M., and Horvitz, E. (2000). Social choice theory and recommender systems: Analysis of the axiomatic foundations of collaborative filtering. In *proc. of Seventeenth National Conference on Artificial Intelligence and Twelfth Conference on Innovative Applications of Artificial Intelligence (AAAI/IAAI)*, pp. 729-734, Austin, TX, USA.
- [Perp95] Perpignan, C. (1995). *Compression neural networks for feature extraction: Application to human recognition from ear images*. M.Sc. Thesis, Faculty of Informatics, Technical University of Madrid, Spain.

- [PFSB05] Phillips, P. J., Flynn, P. J., Scruggs, T., Bowyer, K. W., Chang, J., Hoffman, K., Marques, J., Min, J., and Worek, W. (2005). Overview of the face recognition grand challenge. In *proc. of IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, pp.947–954, San Diego, CA, USA.
- [PhMR98] Phillips, P. J., Moon, H., and Rauss, P. (1998). The FERET database and evaluation procedure for face recognition algorithms. *Image Vision Computing* vol. 16(5), pp. 295-306.
- [PiDD08] Pihur, V., Datta, S., and Datta, S. (2008). Finding cancer genes through meta-analysis of microarray experiments: Rank aggregation via the cross entropy algorithm. *Genomics*, vol. 92, pp. 400-403.
- [RaRK10] Raghavendra, R., Rao, A., and Kumar, G. H. (2010). Multisensor biometric evidence fusion of face and palmprint for person authentication using Particle Swarm Optimization (PSO). *International Journal of Biometrics*, vol. 2(1), pp. 19-33.
- [Rene04] Renesse, R. L. V. (2002). Implications of applying biometrics to travel documents. In *proc. of SPIE*, vol. 4677, pp. 290–298.
- [Ritt99] Ritter, N. (1999). Location of the pupil-iris border in slit-lamp images of the cornea. In *proc. of International Conference on Image Analysis and Processing*, pp. 740-745.
- [RKBT10] Rattani, A., Kisku, D. R., Bicego, M., and Tistarelli, M. (2010). Feature level fusion of face and fingerprint biometrics. In *proc. of 1st IEEE International Conference on Biometrics: Theory, Applications and Systems*, pp. 1-6, Washington DC, USA.

- [RoNJ06] Ross, A., Nandakumar, K., and Jain, A. K. (2006). Handbook of multibiometrics. New York: Springer-Verlag.
- [RosG05] Ross, A. and Govindarajan, R. (2005). Feature level fusion using hand and face biometrics, in proc. of SPIE Conf. on Biometric Tech. for Human Identification II, Orlando, USA, 2005, pp. 196-204.
- [RosJ03] Ross, A., and Jain, A. K. (2003). Information fusion in biometrics. Pattern Recognition Letters, vol. 24, pp. 2115–2125.
- [RosJ04] Ross, A., and Jain, A. K. Multimodal biometrics: An overview. In proc. of 12th European Signal Processing Conference (EUSIPCO), pp. 1221–1224, Vienna, Austria.
- [RoyB06] Roy, K., and Bhattacharya, P. (2006), Iris recognition with support vector machines, Springer Lecture Notes in Computer Science ICB 2006, Zhang, D., and Jain, A. K. (Eds.), vol. 3832, pp. 486-492.
- [SanP01] Sanderson, C., and Paliwal, K. K. (2001). Information fusion for robust speaker verification. In proc. of Seventh European Conference on Speech Communication and Technology, pp. 755-758, Aalborg, Denmark.
- [Scho] www.scholarpedia.org. Retrieved on September, 2011.
- [Scul07] Sculley, D. (2007). Rank aggregation for similar items. In proc. of the SIAM Conference on Data Mining, Minneapolis, Minnesota, USA, pp. 587-592.
- [Shaf76] Shafer, G. (1976). A mathematical theory of evidence. New Jersey, USA: Princeton University Press.

- [SiBB03] Sim, T., baker, S., and Bsat, M. (2003). The CMU pose, illumination, and expression database. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25(12), pp. 1615-1618.
- [SoDG00] Soltane, M., Doghmane, N., and Guersi, N. (2010). Face and speech based multi-modal biometric authentication. *International Journal of Advanced Science and Technology*, vol. 21, pp. 41-56.
- [SoPU99] Solaiman, B., Pierce, L. E., and Ulaby, F. T. (1999). Multisensor data fusion using fuzzy concepts: Application to land-cover classification using ERS-1/JERS-1 SAR composites. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, pp. 1316-1326.
- [Truc98] Truchon, M. (1998). An extension of the Condorcet criterion and Kemeny orders. Cahier 9813, Centre for Research in Applied Economics and Finance, University of Rennes, France.
- [TumG99] Tumer, K., and Ghosh, J. (1999). Linear and order statistics combiners for pattern classification. In *Combining artificial neural nets: Ensemble and modular multi-net systems*, A.J.C. Sharkey (Ed.). London: Springer-Verlag, pp. 127-161.
- [TurP91] Turk, M., and Pentland, A. (1991). Eigenfaces for recognition. *Journal of Cognitive Neuroscience*, vol. 3(1), pp. 71-86.
- [UIRJ04] Uludag, U., Ross, A., and Jain, A. K. (2004). Biometric template selection and update: A case study in fingerprints. *Pattern recognition*, vol. 37(7), pp. 1533-1542.
- [USTB] USTB ear database, China. Retrieved on May 11, 2008. <http://www.ustb.edu.cn/resb/>

- [Vacc07] Vacca, J. R. (2007). Biometric technologies and verification systems. Butterworth-Heinemann, Elsevier, Burlington, MA, USA.
- [ViBS02] Victor, B., Bowyer, K., and Sarkar, S. (2002). An evaluation of face and ear biometrica. IEEE International Conference on Pattern Recognition (ICPR), pp. 429-432, Quebec, Canada.
- [WAGH96] Wildes, R. P., Asmuth, J. C., Green, G. L., Hsu, S. H., Kolczynski, R. J., Matey, J. R., and McBride, S. E. (1996). A machine-vision system for iris recognition. Machine Vision and Applications, vol. 9, pp. 1-8.
- [Wang09] Wang, Y. (2009). Fuzzy inferences methodologies for cognitive informatics and computational intelligence. In proc. of 8th IEEE International Conference on Cognitive Informatics (ICCI), pp. 241-248, Hong Kong, China.
- [Wang09] Wang, Y. (2009). Toward a formal knowledge system theory and its cognitive informatics foundations. Transactions of Computational Science, Springer, vol. 5, pp. 1-19.
- [WanH04] Wang, Y, and Han, J. (2004). Iris recognition using support vector machines. Springer Lecture Notes in Computer Science ISSN 2004, vol. 3173, pp. 622-628.
- [WDLL07] Wang, Y.-P., Dang, J.-W., Li, Q., and Li, S. (2007). Multimodal medical image fusion using fuzzy radial basis function neural networks. In proc. of International Conference on Wavelet Analysis and Pattern Recognition (ICWAPR), vol. 2, pp. 778-782, Beijing, China.
- [Wern08] Werner, C. (2008). Biometrics: Trading privacy for security. Available at: http://media.wiley.com/product_data/excerpt/26/07645250/0764525026.pdf.

- [WFKM97] Wiskott, L., Fellous, J.-M., Kuiger, N., and Malsburg, C. v.-d. (1997) Face recognition by elastic bunch graph matching. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19(7), pp. 775–779.
- [Wiki] www.wikipedia.org. Retrieved on December, 2010.
- [Wild97] Wildes, R. (1997). Iris recognition: An emerging biometric technology. In *proc. of IEEE*, vol. 85(9), pp. 1348-1363.
- [Wils10] Wilson, C. (2010). *Vein Pattern recognition: A privacy-enhancing biometric*. Boca Raton, FL, USA: CRC Press.
- [WJMM05] Wayman, J. L., Jain, A. K., Maltoni, D., and Maio, D. (2005). An introduction to biometric authentication systems. In *Biometric systems: Technology, design and performance evaluation*, J. L. Wayman, A. K. Jain, D. Maltoni, and D. Maio (Eds.). London: Springer-Verlag, chapter 1, pp. 1-20.
- [WuMc06] Wu, S., and McClean, S. (2006). Performance prediction of data fusion for information retrieval. *Information Processing and Management*, vol. 42, pp. 899-915.
- [YeJi02] Ye, J. (2002). Principal component analysis and linear discriminant analysis for feature reduction. Available at: <http://www.public.asu.edu/~jye02>.
- [YXZL09] Yu, P., Xu, D., Zhou, H., and Li, H. (2009). Decision fusion for hand biometric authentication. In *proc. of IEEE International Conference on Intelligent Computing and Intelligent Systems (ICIS)*, vol. 4, pp. 486 – 490, Shanghai, China.
- [Zade65] Zadeh, L. A. (1965). Fuzzy sets. *Information and Control*, vol. 8, pp. 338–353.

- [Zade75] Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning – I. *Information Sciences*, vol. 8, pp. 199-249.
- [Zade81] Zadeh, L. A. (1965). Possibility theory and soft data analysis. In Cobb, L. and R. M. Thrall (ed.). *Mathematical Frontiers of the Social and Policy Sciences*. Boulder, Colorado: Westview Press, pp. 69-129.
- [ZCPR03] Zhao, W., Chellappa, R., Phillips, P. J., and Rosenfeld, A. (2003). Face recognition: A literature survey. *ACM Computing Surveys*, vol. 35(4), pp. 399-458.
- [Zhan00] Zhang, D. (2000). *Automated biometrics: Technologies and systems*. Boston, MA, USA: Kluwer Academic Publishers.
- [Zhan04] Zhang, D. (2004). *Palmprint authentication*. Boston, MA, USA: Kluwer Academic Publishers.

APPENDIX

The program execution or the software running process is shown below in step-by-step.

Step 1: Open the program through MATLAB software. MATLAB 7.0 or later version is required to get the fully functional multimodal biometric fusion software. Open the Graphical User Interface (GUI) written for the program. Two GUIs have been developed for this purpose – one for rank level fusion (Figure 6.15) and one for fuzzy fusion (Figure 6.16).

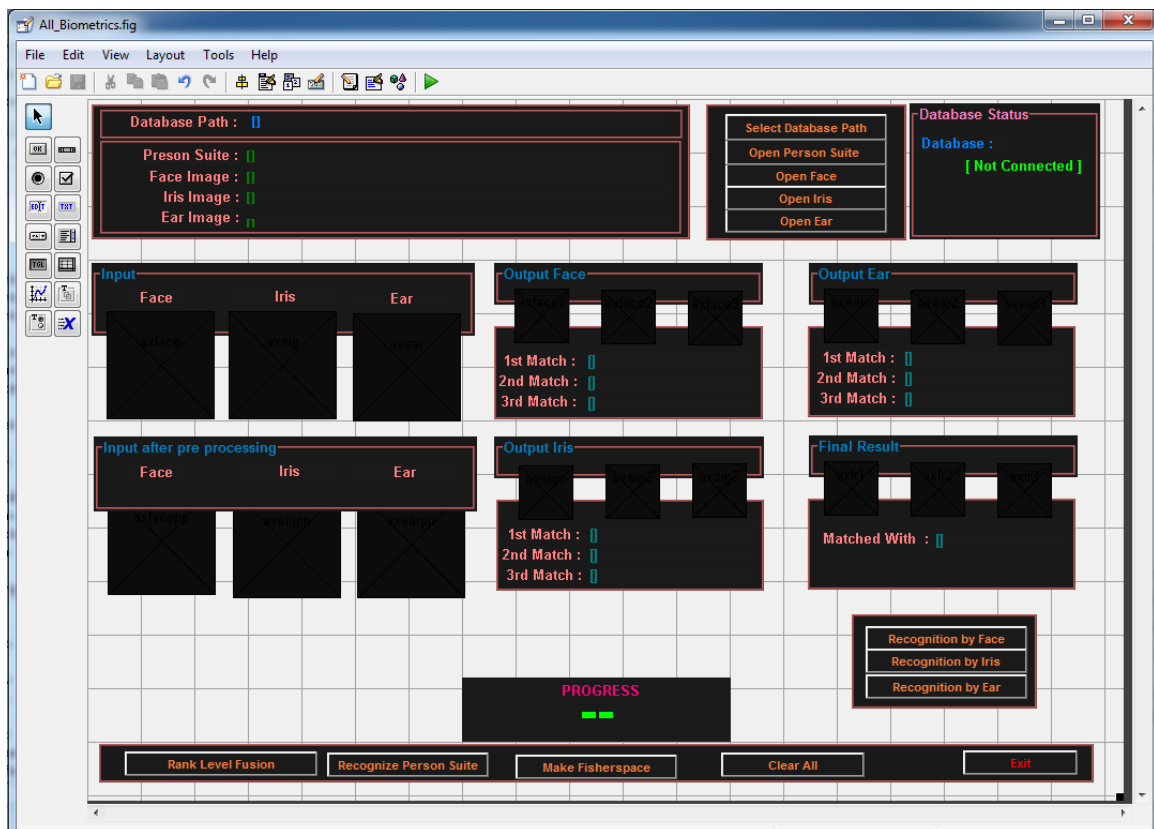


Fig. 6.15: Snapshot of the rank fusion system before execution.

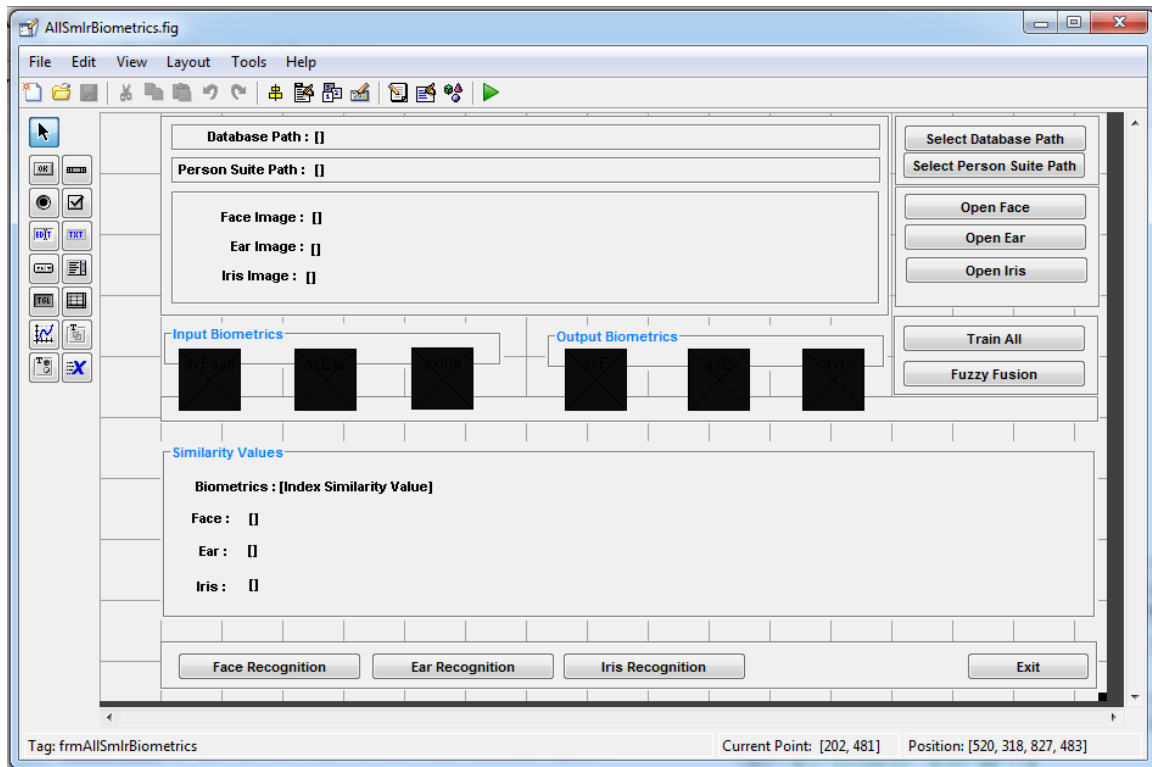


Fig. 6.16: Snapshot of the fuzzy fusion system before execution.

Step 2: Run or execute the program. Figure 6.17 and Figure 6.18 show the snapshots of the programs for rank level fusion and fuzzy fusion respectively.

Step 3: Select proper database path through the executed software (Figure 6.19).

Step 4: Open 'Person Suite' to input the multimodal biometric information of the test subject into the system. The individual face, ear or iris biometric information can also be selected through individual options in the software (Figure 6.20).

Step 5: Train the system with the existing databases. This option can be chosen from a submenu captioned 'Training Image Generator' under the 'Tools' menu or by

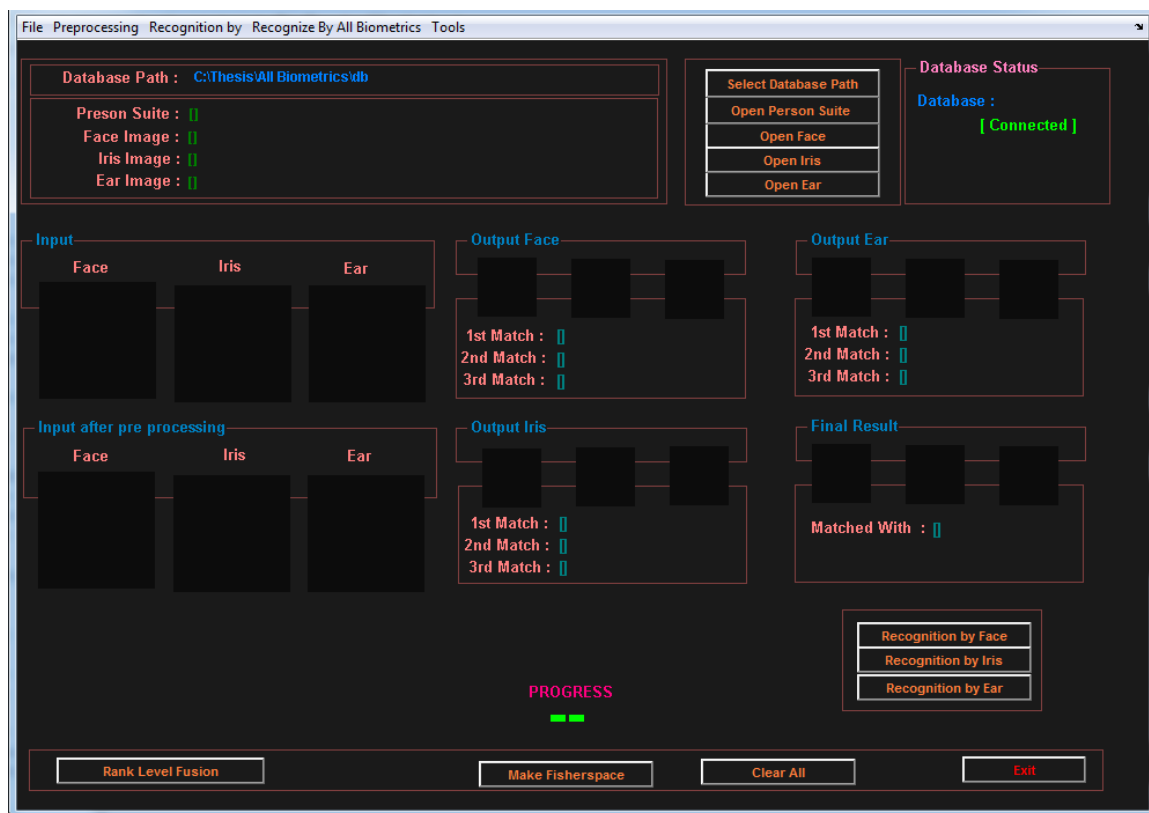


Fig. 6.17: Snapshot of the fuzzy rank fusion system after execution.

clicking the appropriate button (Figure 6.21).

Step 6: Change thresholds and other optional parameters if necessary through appropriate menu selection (Figure 6.22).

Step 7: Recognize the input person through rank level fusion method or fuzzy fusion method (Figure 6.24 and Figure 6.25). In the software for rank level fusion, there is an option for choosing different rank level fusion methods (Figure 6.23).

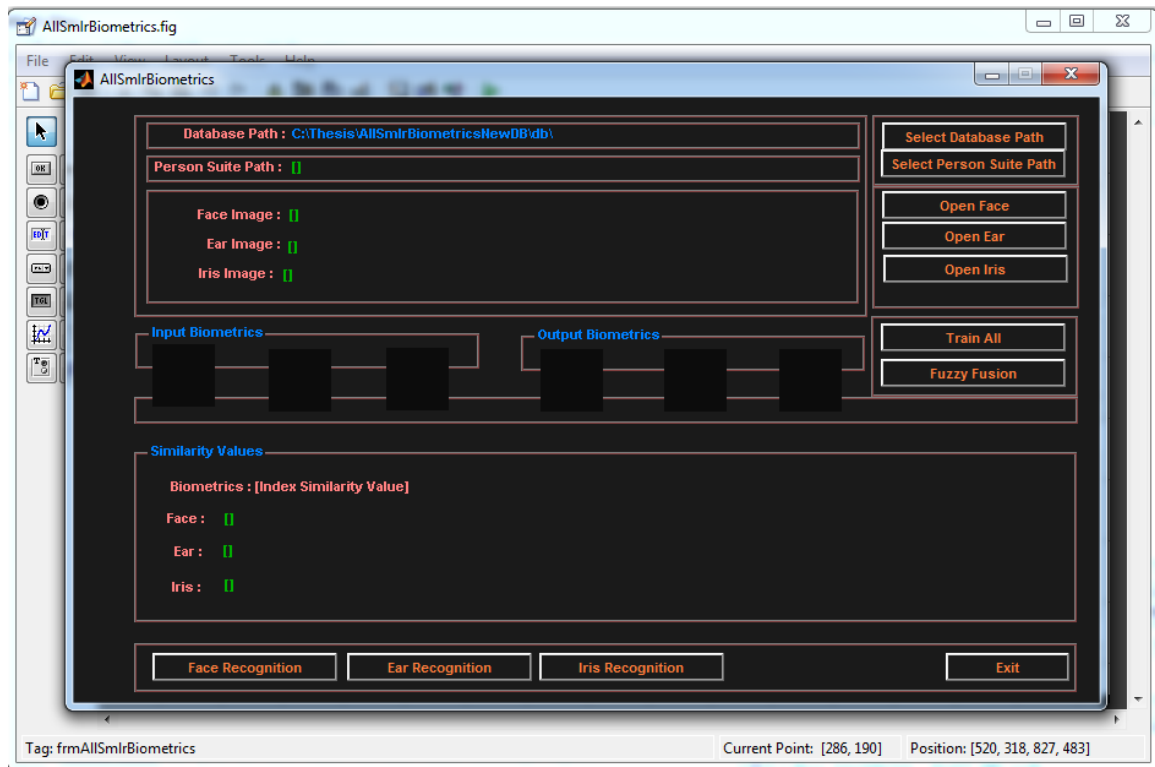


Fig. 6.18: Snapshot of the fuzzy fusion system after execution.

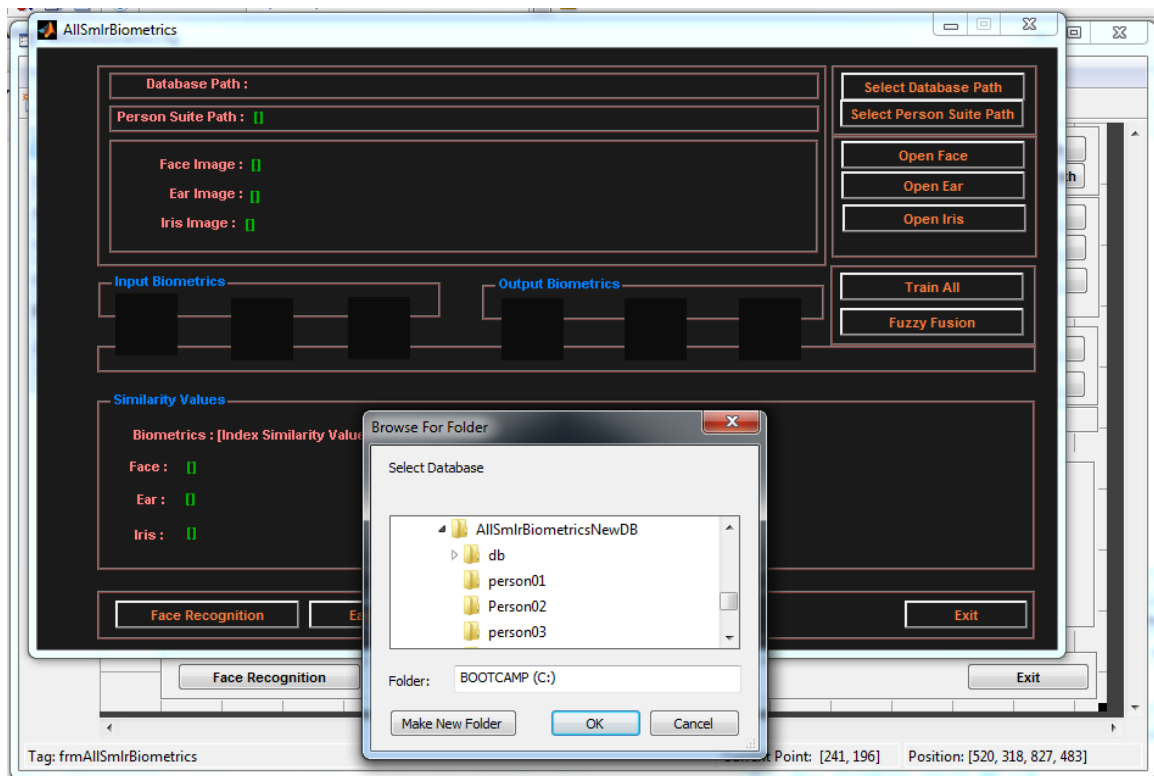


Fig. 6.19: Snapshot of the fuzzy fusion system during database path selection.

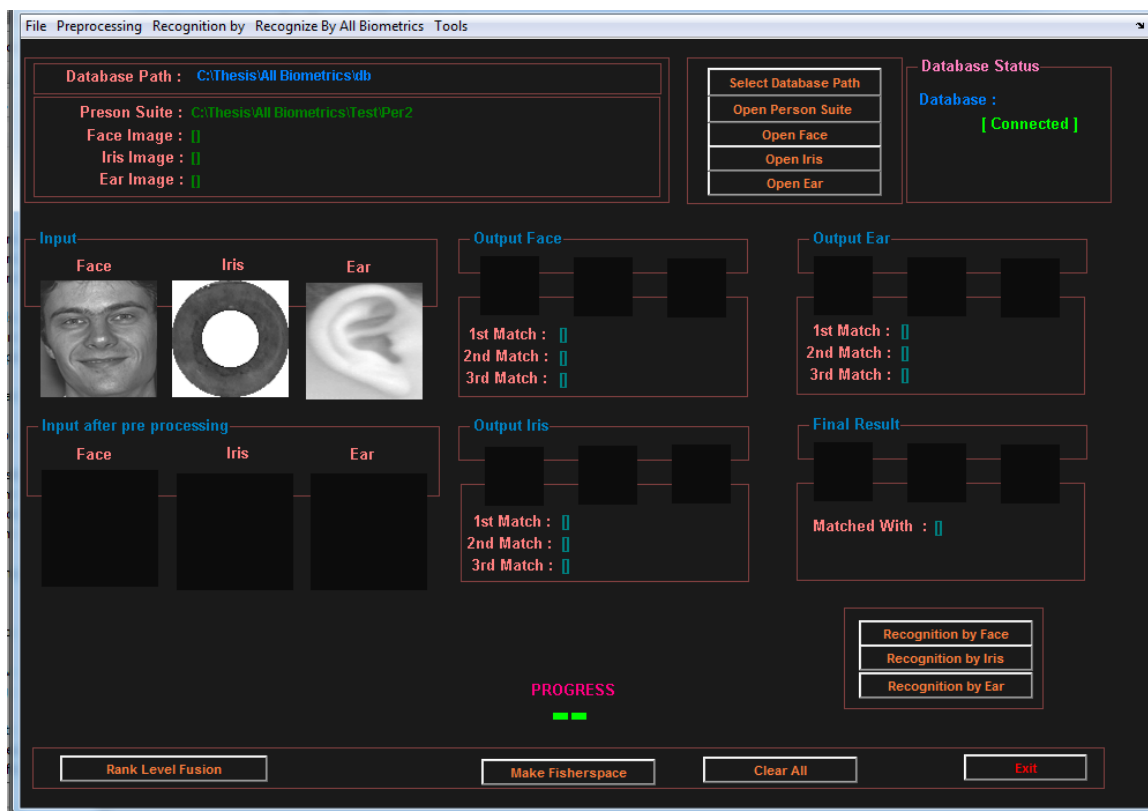


Fig. 6.20: Snapshot of the rank fusion system during opening all the multimodal information of the test subject.

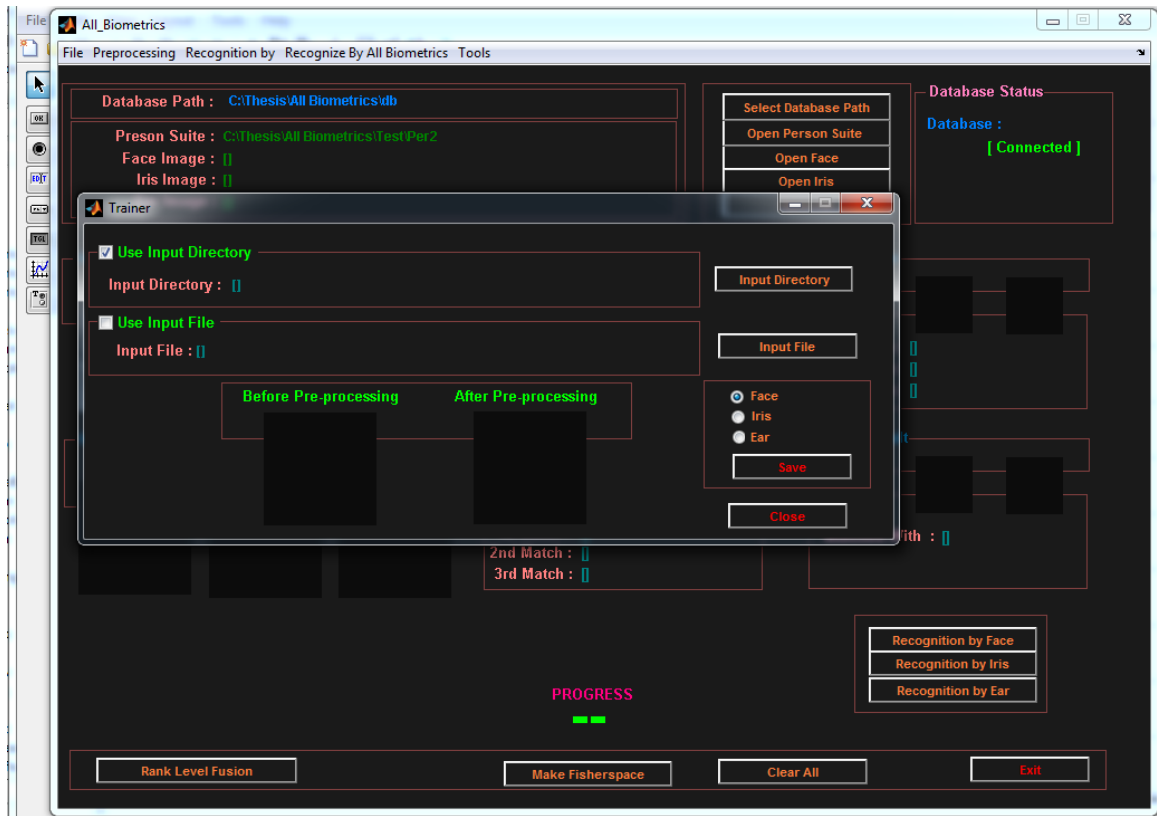


Fig. 6.21: Snapshot of the rank fusion system during selecting training options in the system with pre-selected databases.

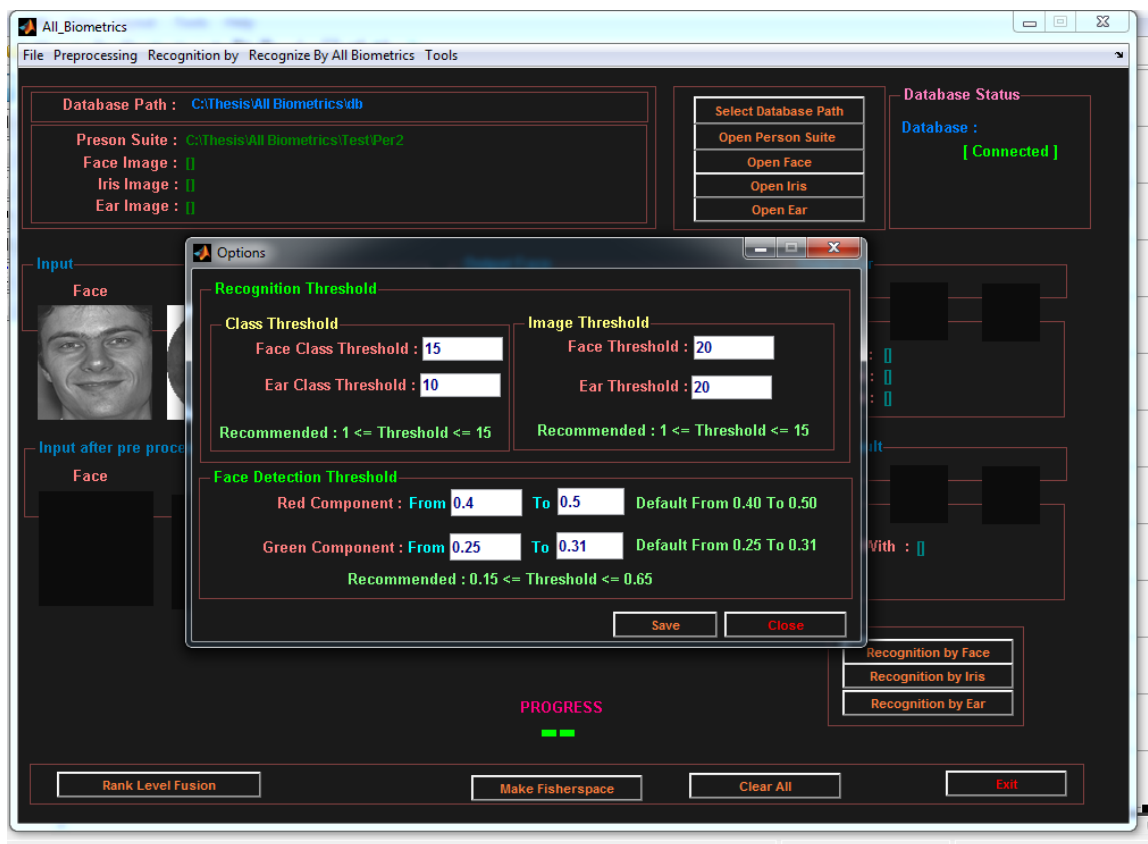


Fig. 6.22: Snapshot of the rank fusion system during changing threshold options for better recognition.

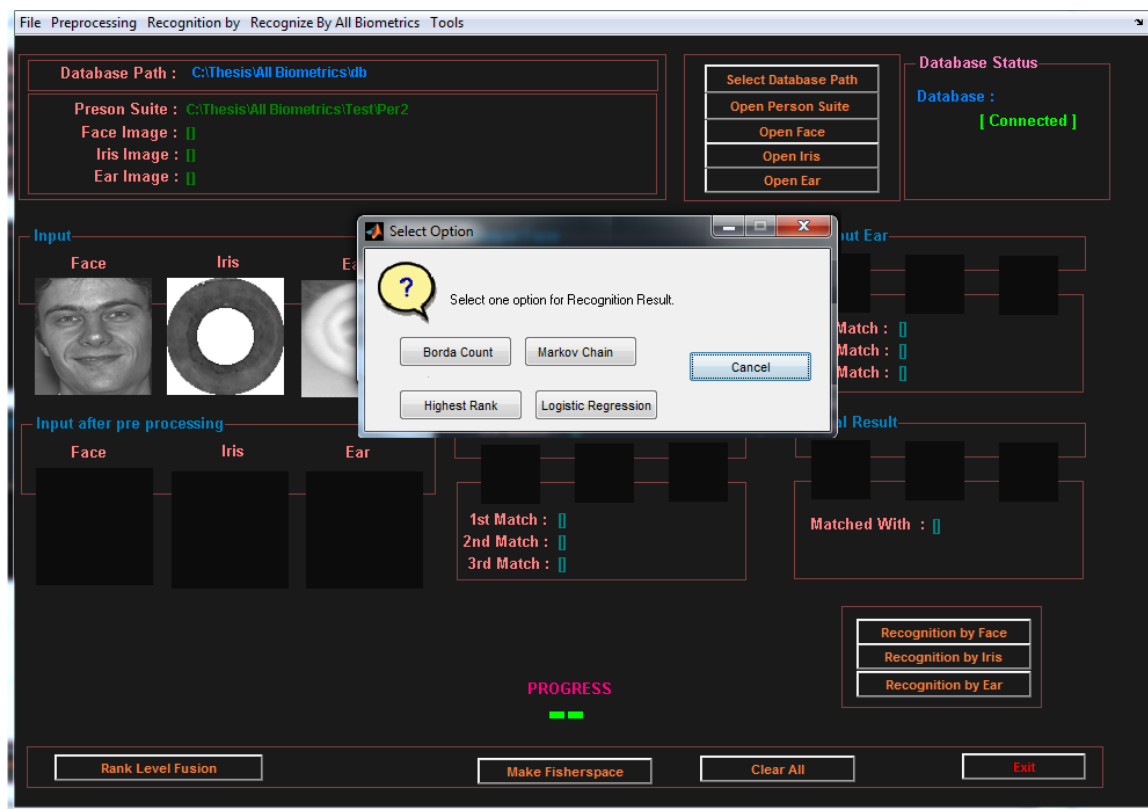


Fig. 6.23: Snapshot of the rank fusion program during selecting different rank level fusion options.

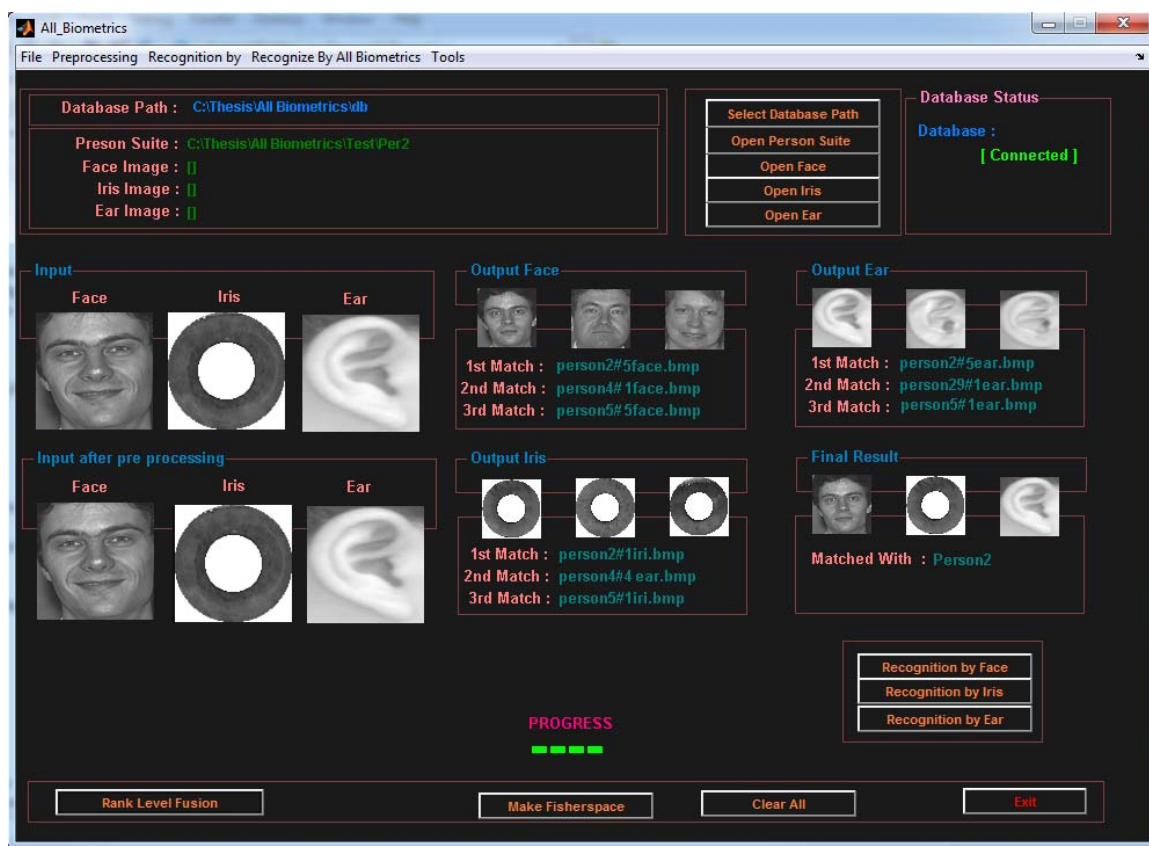


Fig. 6.24: Snapshot of the rank fusion system with the final recognition outcome of the test subject/person.

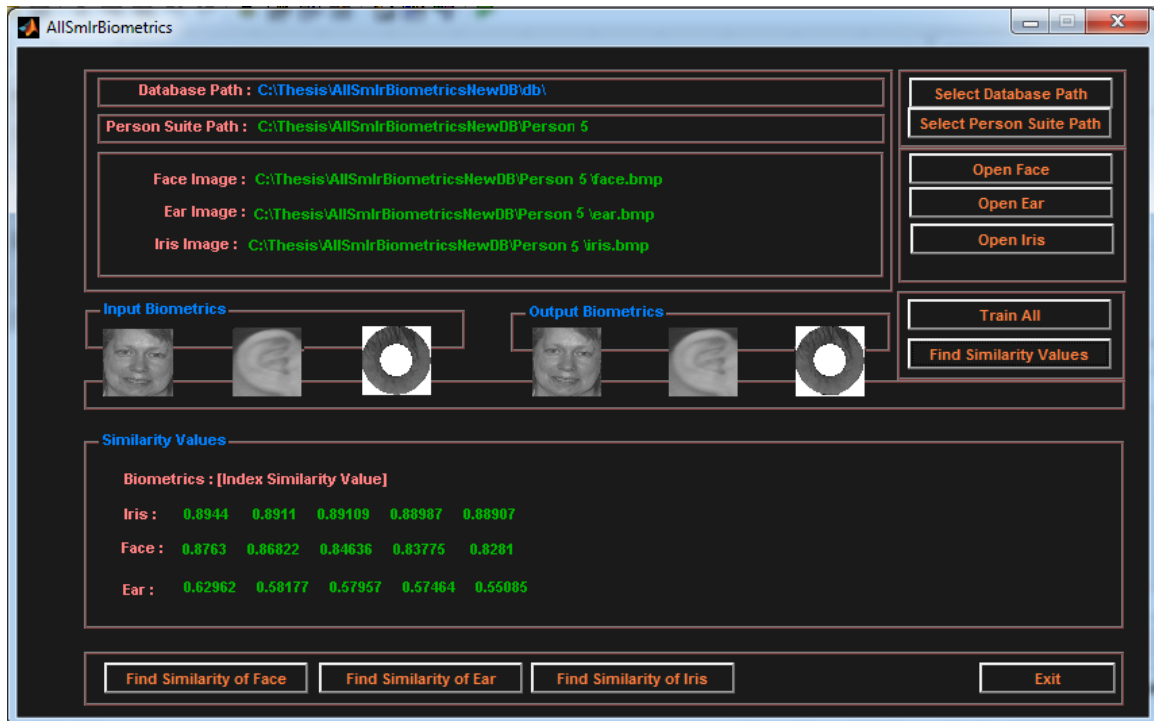


Fig. 6.25: Snapshot of the fuzzy fusion system with the final recognition outcome of the test subject/person.