Chapter 4
Multibiometric Systems

This chapter presents the details of design issues in multibiometric systems. The chapter begins with enumerating the advantages of multibiometric systems over biometric system. Various design issues relating to multiple sources of information, acquisition and processing sequences and fusion strategies in multibiometric systems are discussed. This chapter also presents the methodological aspects of the present study.

4.1 Introduction

Certain limitations of biometric systems discussed in the previous chapter can be addressed by designing a system that consolidates multiple sources of biometric information (i.e. evidences). This can be accomplished by integrating multiple traits of an individual or multiple representations and matching algorithms operating on the same biometric. Such system is known as multibiometric system (Ross *et al*., 2006). In multibiometrics, information from multiple sources is integrated in order to achieve better accuracy than unibiometric system. The multiple sources include multiple sensors, algorithms, instances, samples of the same biometric trait or/and multiple biometric traits. Multibiometric system can effectively address the problems of biometric system in the following ways:

(i) *Reduce Non-universality*: Multibiometric systems can minimize non-universality issue. For example, even a person can't be enrolled to the system due to poor quality of his fingerprints; the system may acquire meaningful biometric data by using other biometric traits such as face, iris, voice etc. and enroll the user.

(ii) *Resistance to Spoof Attack*: Multibiometric system can address spoof attacks because it is difficult to spoof multiple biometric traits of a genuine user simultaneously. Moreover, a dynamic acquisition mechanism can be employed that asks user to present the set of traits in a random order. This also ensures the liveliness of the user/biometric traits. Further, the template security can be improved by combining the feature sets from different biometric sources using an appropriate fusion scheme.

(iii) *Handling Noise in Sensed Data*: Multibiometric systems can reduced the problem induced by noisy data effectively. Even the information of one biometric trait is despoiled by noise, information of the other biometric trait(s) can be used and minimize the effect.

(iv) *Minimize Intra-class Variation*: It can act as a fault tolerant system because it can operate even when information from certain biometric sources becomes unreliable and suit for employed as authentication systems involving large number of subject.

(v) *Minimize Inter-class Similarity*: The accuracy of biometric systems can be improved by using proper sources of information and the right fusion methodology. The availability of multiple sources also enhances the feature space reliably and hence, the capacity of enrollment to the system can be increased (Hong *et al*., 1999).

(vi) *Fault Tolerance*: Multibiometric systems is said to be more robust and fault tolerant because the system keeps working even when certain source of information is unreliable or unavailable due to defect of sensor or software malfunction, or suspect for manipulation. This feature is especially useful in large-scale authentication system like a border control system.

However, multibiometric systems also have limitations. These systems require computation effort and storage more than unibiometric systems. Moreover, multibiometric systems take more time for user enrollment and cause more inconvenience to the user. Sometimes, the performance of a multibiometric system may actually be inferior to that of the unibiometric systems if the design is not appropriate. However, due to its attractive features, multibiometric systems are being increasingly deployed in real time security-critical applications e.g., FBI-IAFIS (FBI, 2012), etc.

In designing multibiometric system, the type of information to be used in fusion to make the final decision is one of the fundamental issues. Depending on the type of information used, information can be combined at various levels *viz*. sensor level, feature level, score level, rank level and decision level. In many practical biometric system, information at the sensor level or feature level are either not available (i.e. commercial-off-the-shelf systems) or are incompatible. On the other hand, it is comparatively easy to access and combine the match scores generated by different biometric systems. Therefore, information fusion at the match score level is the most commonly used approach in multibiometric systems and is the focus of the present study.

4.2 Design Issues in Multibiometric Systems

In multibiometric, the biometric evidences (clues of information) from multiple sources are to be acquired and combined. Hence, information acquisition and fusion schemes in the context of biometrics raise several design questions. An appropriately designed human computer interface (HCI) is the primary issue in order to acquire individual's biometric information efficiently (Oviatt, 2003). While designing a multibiometric system, the following major issues are needed to be considered:

(i) *Source of Information*: There are many sources of information including multiple sensors, multiple algorithms, multiple samples, and multiple instances of a trait and multiple traits.

(ii) *Acquisition and Processing Sequence*: The data from multiple information sources (i.e. modalities) can be acquired either in parallel (i.e. simultaneously) or in different time, as need arises, in sequential fashion. Similarly, the information acquired can be processed simultaneously or hierarchically.

(iii) *Type of Information Fuse*: The information acquired from the biometric sources can be processed to obtain one of four different types namely raw biometric data, feature sets, match scores and decision labels. The process of integrating evidence provided by different biometric sources is known as biometric fusion. Depending on the type of information that is fused, the fusion level can be classified as sensor level, feature level, match score level and decision level fusion.

(iv) *Fusion Scheme*: A number of fusion techniques are available for information fusion provided by the multiple sources depending on the type of information to be fused. Many of these fusion schemes may be applicable in an application and performance of each fusion scheme is varied from application to application. Hence, selection of an optimal scheme is a great challenge.

(v) *Cost benefits*: Generally, multibiometric system require higher cost in term of number of sensor, processing/recognition time taken (throughput), storage and computational requirements, and perceived (in)convenience to the user, compared to unibiometric systems. A cost-benefit analysis is required in decision making based on tradeoff between the additional cost and the improvement in performance (reduction in FAR/FRR, increase security etc.) of a multibiometric system.

Details of these design issues are discussed in the following subsections.

4.2.1 Sources of Multiple Evidences

In multibiometric, evidences from multiple sources have to integrated and the possible sources can be discussed under five scenario or systems (Figure 4.1), *viz*. (i) multiple sensors to capture the same biometric trait (e.g., fingerprint captured using optical and solid-state scanners), (ii) multiple algorithms for feature extraction or matching for the same biometric trait (e.g. Phase-based and Zero-crossing representation in iris recognition), (iii) multiple instances of the same biometric trait (e.g., left and right iris or thump impression), (iv) multiple samples of the same biometric trait (e.g., multiple impressions of a person's right palmprint), and (v) multiple biometric traits (e.g., face and fingerprint) (Ross *et al*., 2006). In the first four scenarios, multiple evidences are derived from the same biometric trait. In the fifth scenario, information derived from multiple biometric traits are fused and these systems are known as multimodal biometric systems. Any arbitrary combination of the above five scenarios are possible in biometric fusion and such systems can be known as hybrid multibiometric systems.

A. Multi-sensor Systems

In these systems, image (in the case of fingerprint, face etc.) or track (in the case of vocal) of single trait is taken by using multiple sensors (of different technologies) in order to extract diverse information from (spatially) registered images/track. The availability of multi-sensor data produced from a single modal can improve matching accuracy as well as assist the segmentation and registration procedures (Bendjebbour *et al*. 2001).

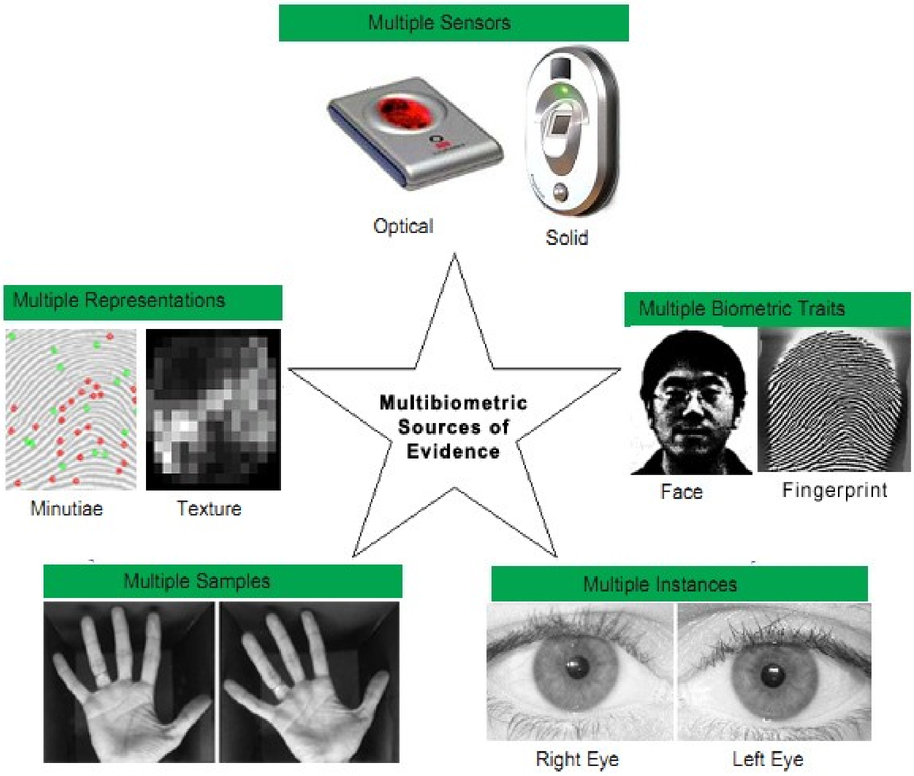


Figure 4.1 Multiple Sources of Information in Multibiometric System

B. Multi-algorithm Systems

In these systems, multiple algorithms are employed to process the same biometric data. For example, Ross *et al*. (2003) used a texture-based algorithm and a minutiae-based algorithm to extract diverse feature sets from the same fingerprint and can improve the performance of the system. This system does not require the new sensors and also enhances user convenience, hence, is cost-effective.

A multi-algorithm system can use multiple feature sets (i.e., multiple representations) extracted from the same biometric data or multiple matching schemes operating on a single feature set. Similarly, Marcialis and Roli (2005) demonstrated the improvement in verification accuracy from combining multiple fingerprint matchers. It can be noted that factors such as the correlation between component algorithms, the disparity in their matching accuracies, and the adopted fusion scheme significantly impact the performance of the multibiometric system.

C. Multi-instance Systems

In these systems, multiple instances of the same body trait are used. For example, the left and right thumb, or the left and right irises of a person can be used to verify an individual's identity. These systems generally do not additional sensors nor new feature extraction and matching algorithms and are, therefore, cost efficient. However, a suitable sensor arrangement might be necessary for human computer interface (i.e. HCI) in order to able the simultaneous capture of the various units/instances with minimum inconvenience to the user (Oviatt, 2003). By using multiple instances, false rejection or failure to enroll will be reduced. Yu *et al*. (2005) have employed both left and right iris in recognition. Multi-instance systems are most necessary in applications where the size of the system database is large.

D. Multi-sample Systems

Multiple samples of the same biometric trait taken by a single sensor can be used as multiple sources in a multibiometric system. Such systems take account for the variations that can occur in the multiple samples, or to obtain a more complete representation of the underlying trait. For example, the frontal profile of a person's face along with the left and right profiles can be used in a face recognition system in order to take account of variations in the facial pose. Similarly, in fingerprint recognition system, combination of multiple impressions of the same finger has been proposed in several literatures. For example, Prabhakar and Jain (2002) combined multiple impressions of a finger in a verification system and report improvement in recognition accuracy. Multiple impressions of a finger can be fused at the image level or at the feature level during enrollment (known as image mosaicking or template consolidation) (Sha *et al.*, 2007).

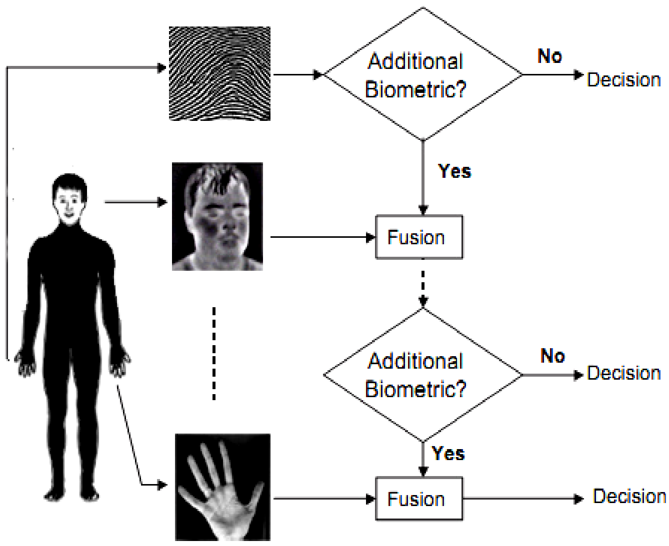
E. Multimodal Systems

These systems collect the information of multiple traits by using multiple sensors and integrate the information to establish identity. In literature, new sensors were proposed as the whole hand sensor (Rowe *et al.*, 2007) in which all five fingerprints, palmprint along with hand geometry are to be captured in a single presentation of a hand. The additional modality information may be used to improve the accuracy in a verification system. With a proper combination scheme, multimodal biometric system can improved the matching speed in an identification system with N enrolled users. For example, one of the traits, say face, can be use first to retrieve the top M matches out of N users ($M << N$) and iris can be used for making the final accurate identification decision.

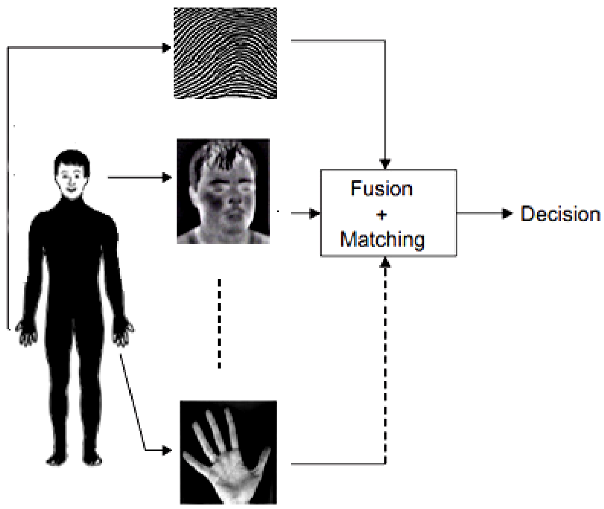
4.2.2 Acquisition and Processing Sequence

The acquisition and procession sequence of the biometric information are significant factors on enrollment as well as authentication time, failure to enroll rate (FTER) and user convenience in designing multibiometric system. The acquisition sequence of biometric data is to be made with concern with the user convenience. Also, the processing sequence of the procured biometric can significantly impact the throughput time in large-scale identification systems (involving millions of enrolled users) since it may be possible to arrive at an identification decision rapidly. Hence, an appropriate human computer interface (HCI) must be employed with which enhances user convenience as well as ensuring that good quality biometric data is obtained from the user and consequently, the enrollment time and the failure to enroll rate (FTER) are to be substantially reduced. Typically, the information acquisition and processing in a multibiometric system can be done in either serial or parallel manner as shown in Figure 4.2. In the serial (also known as cascade or sequential) architecture, the information from the different sources are acquired and processed sequentially and the outcome of one matcher may affect the processing of the subsequent sources. In the parallel design, different sources are processed independently and their results are combined using an appropriate fusion scheme (will be discussed in next section). Both these architectures have own advantages and limitations.

Both serial and parallel acquisition architectures are found in literatures. Generally, physically related biometric traits are conveniently and cost-effectively acquired simultaneously. For example, Frischholz and Dieckmann (2000) used a video camera to acquire face, voice and lip movement simultaneously.



(a)



(b)

Figure 4.2 Architecture of a Multibiometric System: Acquisition and Processing Sequence; (a) Serial (Sequential or Cascade) (b) Parallel (Simultaneous) (Nandakumar, 2008)

In the serial or cascade mode, the biometric information is sequentially processed. This architecture may have advantages such as it can improve user convenience as well as allow fast and efficient searches in large scale identification tasks. In a cascaded multibiometric system, if the identity of the user is found to be sufficiently confidence after processing the first biometric source, the other biometric information of the user may not be required. Hong and Jain (1998b) proposed a cascaded multibiometric system in which the top *m* matching identities is retrieved by using face recognition and a final identification decision is made by verifying these identities by using fingerprint recognition.

4.2.3 Fusion Strategies

The process of integrating information provided by different biometric sources is known as biometric fusion. In biometric system, the amount of biometric information available to the system decreases as it proceeds from the sensor module to the decision module (Figure 4.3). The raw biometric data at sensor module (e.g., fingerprint image in the case of fingerprint recognition) has the highest information content, which gets reduced (to minutiae) by subsequent processing (e.g., after minutiae extraction). In the matching module, matching score contains only a byte and in the decision module (in verification mode), the final decision label contains only a single bit of information (Genuine or Impostor). Depending on types of information available at different levels, the biometric information can be classified into four types, namely, (i) Raw biometric samples, (ii) Feature sets, (iii) Match scores and (iv) Decision labels. The fusion scheme of biometric can be classified according to the type of information to be fussed. They are (i) Sensor level fusion, (ii) Feature level fusion, (iii) Score level fusion and (iv) Decision level fusion (ANSI, 2006) (Figure 4.4). However, the information processing at different stages are expected to reduce the intra-user variability and the noise level of the available information. Further, in many practical multibiometric systems, higher levels of information such as the raw images or feature sets are either not available (e.g., proprietary feature sets used in commercial-off-the-shelf systems) or the information available from different sources is not compatible (e.g., fingerprint minutiae and *Iriscode*). On the other hand, it is relatively easy to access and combine the match scores generated by different biometric matchers. Moreover, Fusion at matching score level needs relatively less work to carry out on testing and evaluating the performance of multibiometric system. Consequently, score level fusion is the most commonly used approach in multimodal biometric systems.

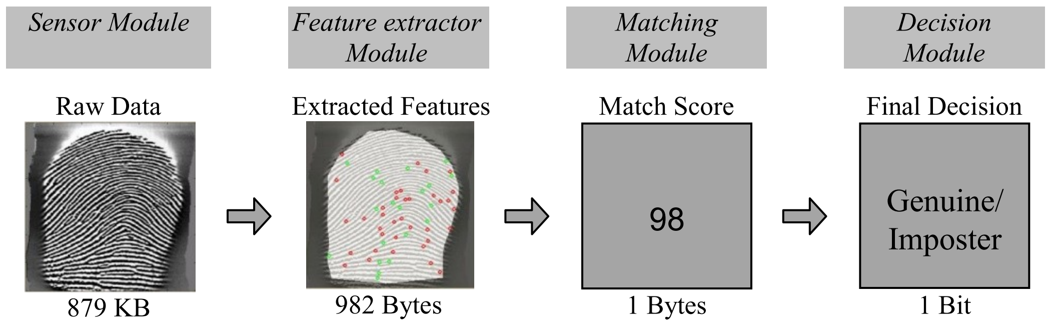


Figure 4.3 Amount of Information Available at Different Modules

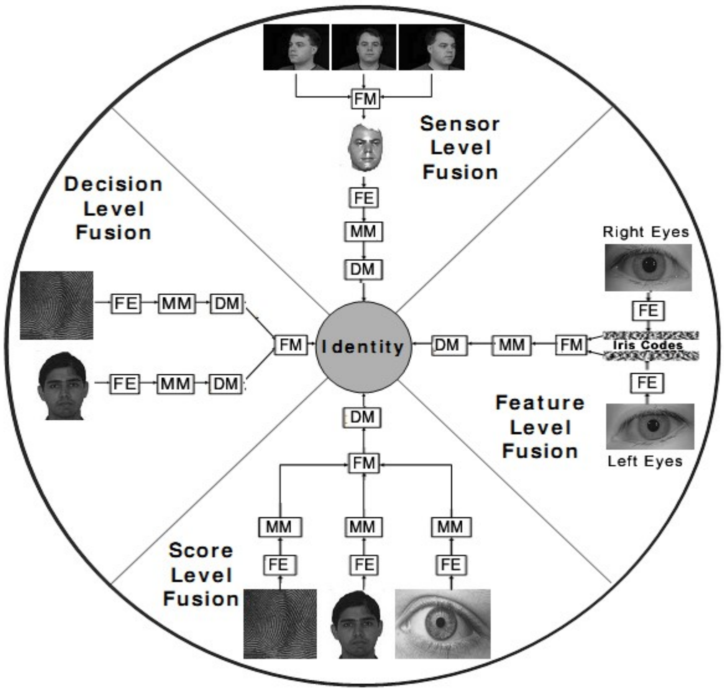


Figure 4.4 Various Levels of Information Fusion in a Multibiometric System. FE: Feature Extraction Module; MM: Matching Module; DM: Decision-making Module; FM: Fusion Module (Ross *et al*. 2006)

Sanderson and Paliwal (2002) have classified the four levels of information fusion in biometric systems into two broad categories: *pre-classification fusion and post-classification fusion* (Figure 4.5). *Pre-classification fusion* (Fusion before matching) refers to combining information prior to the application of any classifier or matching algorithm. In *post-classification fusion* (Fusion after matching), the information is combined after the decisions of the classifiers have been obtained.

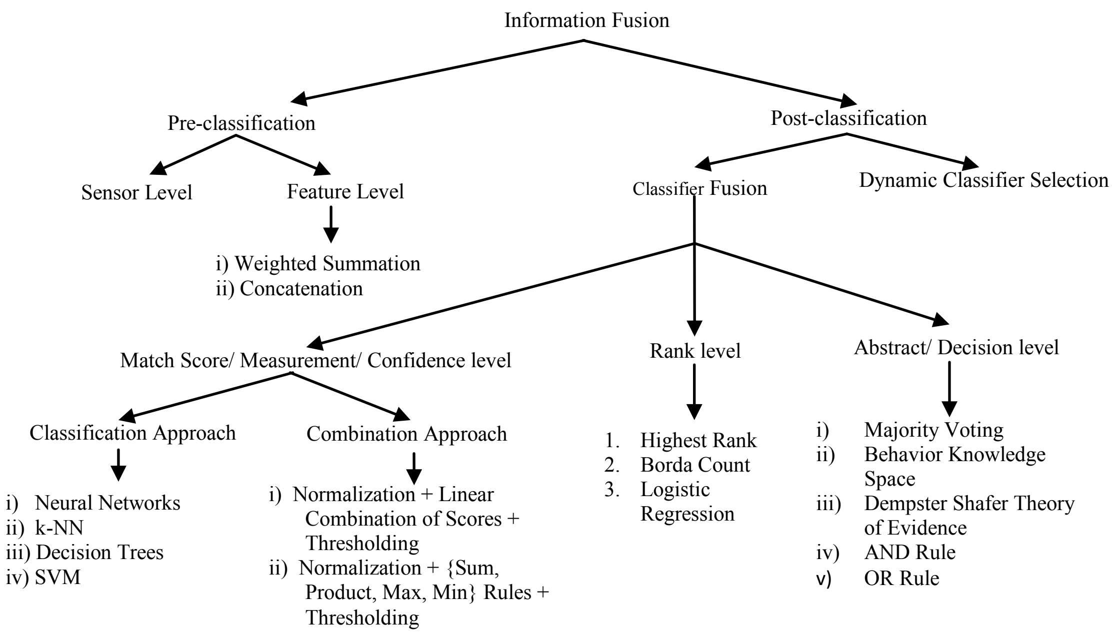


Figure 4.5 Information Fusion Approaches in Biometric System (adopted from Jain *et al.*, 2005)

4.2.3.1 Fusion Prior to Matching

Prior to matching, integration of information from multiple biometric sources can take place either at the sensor level or at the feature level.

4.2.3.1.1 *Sensor Level Fusion*

In sensor level fusion, the information from the different sensors must be compatible and the correspondences between points in the raw data must be either known in advance (e.g., calibrated camera systems) or reliably estimated. So, only few researchers practice fusion at this level for multimodal biometric. Chang *el al.* (2003) concatenated the normalized, masked ear and face images of a subject to form a combined face-plus-ear image and suggest that that the multi-modal biometric offers substantial performance gain.

4.2.3.1.2 *Feature Level Fusion*

In feature level fusion, different feature sets that are extracted from multiple biometric sources are combined before matching. Features can be combined in several ways. In multimodal biometric, the feature sets are generally non-homogeneous (e.g., feature sets of different biometric modalities like face and hand geometry). Feature selection schemes can then be applied to reduce the dimensionality of the resultant feature set.

Concatenation is not possible when the feature sets are incompatible (e.g., fingerprint minutiae and *Iriscode* feature).

Fusion at feature level is difficult to achieve in practice due to the following reasons (Jain *et al.*, 2005):

(i) The relationship between the feature spaces of different biometric sources may not be known. In the case where the relationship is known in advance, care needs to be taken to discard those features that are highly correlated. This requires the application of feature selection algorithms prior to classification.

(ii) The feature sets may be incompatible. For example, the minutiae set of fingerprints and eigen coefficients cannot be directly combined because the former is a variable length feature set whose individual values represent the attributes of a minutia point while the latter is a fixed length feature set whose individual values are scalar entities.

(iii) The 'curse of dimensionality' problem, the most common problem of pattern recognition applications may be occurred while concatenating two feature vectors results in a feature vector with larger dimensionality. It is more severe in biometric applications because of the time, effort and cost involved in collecting large amounts of biometric (training) data.

(iv) A significantly more complex matcher might be required in order to operate on the concatenated feature vector

(v) Most commercial biometric systems do not provide access to the feature sets used in their products due to proprietary reasons.

Due to the constraints mentioned above, most of the attempts at feature level fusion have met with only limited success. Hence, very few researchers have studied integration at the feature level in a multibiometric system and fusion schemes at the match score and decision levels are generally preferred.

4.2.3.2 Fusion after Matching

The schemes for information fusion can be divided into four categories:

4.2.3.2.1 *Dynamic Classifier Selection*

A dynamic classifier selection scheme chooses the biometric source that is most likely to give the correct decision for the specific input pattern (Wood *et al.*, 1997) and has limited for biometric applications.

4.2.3.2.2 *Match Score Level Fusion*

Match score is a measure of the similarity between the input and template biometric feature vectors. In multimodal system, each sub-system provides matching scores indicating the proximity of the feature vector with the template vector. These scores can then be combined to improve the matching performance. When match scores output by different biometric matchers are consolidated in order to arrive at a final recognition decision, fusion is said to be done at the match score level. This is also known as fusion at the *measurement level* or *confidence level*. Details of match score fusion will discussed in the next section.

4.2.3.2.3 *Rank Level Fusion*

When the output of each biometric system is a subset of possible matches (i.e., identities) sorted in decreasing order of confidence, the fusion can be done at the *rank level*. This is relevant in an identification system where a rank may be assigned to the top matching identities. Ho *et al*. (1994) described three methods to combine the ranks assigned by different matchers. In the highest rank method, each possible identity is assigned the best (minimum) of all ranks computed by different systems. Ties are broken randomly to arrive at a strict ranking order and the final decision is made based on the consolidated ranks. The Borda count method uses the sum of the ranks assigned by the individual systems to a particular identity in order to calculate the fused rank. Nandakumar *et al*. (2009) observed that the recognition performance of the simplest rank level fusion scheme, namely, the highest rank method, is comparable to the performance of complex fusion strategies, especially when the goal is not to obtain the best rank-1 accuracy but to just retrieve the top few matches. It can be noted that Rank Level fusion is a method of Decision level fusion.

4.2.3.2.4 *Decision Level Fusion*

In a multimodal biometric system, the decisions output by the individual biometric matchers should be available in order to carry out fusion at the *abstract* or *decision* level. Decision level fusion is only feasible solution when commercial-off-the-shelf (COTS) matchers are used to build a multimodal biometric system because COTS biometric matchers provide access only to the final recognition decision.

4.3 Match Score Level Fusion

In match score level fusion, different biometric matchers provide match scores indicating the degree of matching between the input and query templates. The degree of matching between the input and query templates may be similarity score or distance score. These match scores are consolidated to reach the final recognition decision. After the sensor level and feature level information, match scores contain the richest information about the input biometric sample.

The efficient mechanisms for combination of scores within a multibiometric system are

(i) Each biometric process must produce a score, rather than a hard accept/reject decision, and makes it available to the fusion module.

(ii) In advance of operational use, each biometric process must make available to the fusion module, its technical performance in the appropriate form.

Some common characteristics of the matching scores in a multibiometric system can be summarized as:

(i) The matching score of the individual matchers are not in a common domain.
(ii) The matching scores at the output of the individual matchers may not be homogeneous. For example, one matcher may output a distance (dissimilarity) measure while another may output a proximity (similarity) measure.
(iii) The outputs of the individual matchers need not be on the same numerical scale (range).
(iv) The matching scores at the output of the matchers may follow different statistical distributions.

It must be noted that match scores produced by individual matchers might not be homogenous (i.e. similarity score and dissimilarity score). A higher value of similarity match score indicates better match whereas a smaller value of dissimilarity score indicates better match. In some cases, the match scores produced by different matchers may be in the different range and may have different probability distributions. Because of these reasons, scores are normally normalized prior to fusion. However, density-based fusion schemes do not require normalization. Figure 4.6 depicts a score level fusion framework for processing two biometric sources, taking normalization into account.

Fusion methods at score level can be broadly classified into three categories (Ross *et al.*, 2006): density-based schemes, classifier-based schemes and transformation-based schemes. These schemes are discussed in the following sub-sections.

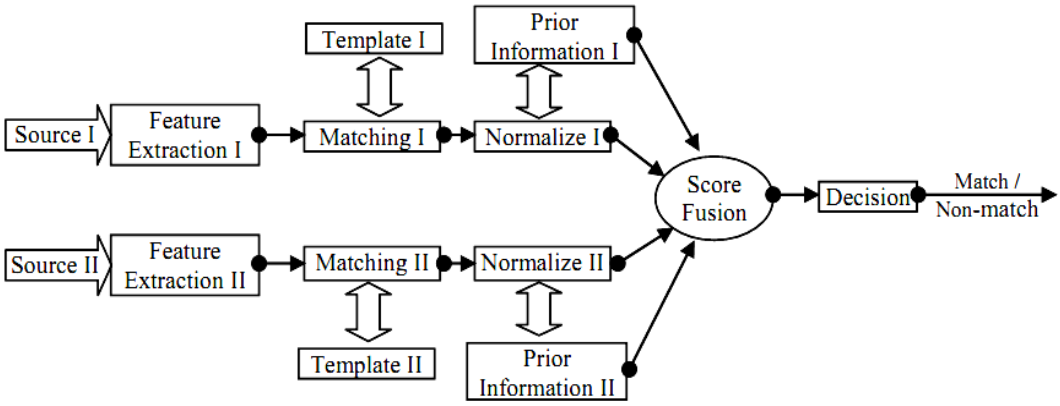


Figure 4.6 Match Score Level Fusion with Score Normalization (ANSI, 2006)

4.3.1 Match Score Fusion Rules

Kittler *et al.* (1998) developed a theoretical framework for combining the evidence produced by multiple classifiers or matchers. There may be two cases: (i) each classifier makes use of a different representation derived from the same input pattern (ii) each classifier uses its own representation of the input pattern. Generalizing both cases, consider a classification problem of an input pattern X into one of M possible classes (w_1, w_2, …, w_m) based on the evidence provided by R different classifiers. Let x_i be the feature vector (derived from the input pattern X) presented to the i^{th} classifier. In the chosen feature space, let $p(x_i|w_k)$ and $P(w_k)$ be probability density function and its prior probability of occurrence for each class w_k. According to the Bayesian theorem, the pattern X should assigned to class w_k that satisfies Equation (4.1).

$$\begin{gathered} assign \quad X \rightarrow w_r \quad if \\ P(w_r \mid x_1,\ x_2,\ \ldots,\ x_R) = \max_k P(w_k \mid x_1,\ x_2,\ \ldots,\ x_R) \end{gathered} \tag{4.1}$$

where, k = 1, 2, ..., M. In pattern recognition, Equation (4.1) is known as the minimum error-rate classification rule. This rule assumes a zero-one loss function which assigns no loss to a correct decision and assigns a unit loss to any misclassification error. The posterior probabilities in Equation 4.1 can be represented by Equation (4.2).

$$P(w_k \mid x_1,\ x_2,\ \ldots,\ x_R) = \frac{p(x_1,\ x_2,\ \ldots,\ x_R \mid w_k)P(w_k)}{p(x_1,\ x_2,\ \ldots,\ x_R)} \tag{4.2}$$

where, $p(x_1, x_2, ..., x_R)$ is the unconditional measurement joint probability density. It can be expressed in term of the conditional measurement distributions defined by Equation (4.3).

$$p\left(x_1,\ x_2,\ \ldots,\ x_R\right) = \sum_{j=1}^{m} p\left(x_1,\ x_2,\ \ldots,\ x_R \mid w_j\right)P\left(w_j\right) \tag{4.3}$$

4.3.1.1 Product Rule

This rule is a direct implication of the assumption of statistical independence between the R feature representations $x_1, x_2, ..., x_R$. The product decision rule can be stated as Equation (4.4)

$$\begin{gathered} assign \quad X \to w_r \quad if \\ P^{-(R-1)}(w_r)\prod_{j=1}^{R} P(w_r \mid x_j) = \max_{k=1,\ldots,M} P^{-(R-1)}(w_k)\prod_{j=1}^{R} P(w_k \mid x_j) \end{gathered} \tag{4.4}$$

4.3.1.2 Sum Rule

It is further assumed that posteriori probabilities computed by the classifiers do not deviate much from the prior probabilities, i.e.

$$P(w_k \mid x_j) = P(w_k)(1+\delta_{j,k}) \tag{4.5}$$

where, $\delta_{j,k}$ is a constant, $0 < \delta_{j,k} << 1$; j = 1, 2, …, R; k=1, 2, …, M. Though this is a strong assumption, it may be readily satisfied when the input is noisy, leading to errors in the estimation of posteriori probabilities. Substituting Equation (4.5) for the posteriori probabilities in Equation (4.4) and with simplification, it can be derived to Equation (4.6)

$$\begin{gathered} assign \quad X \to w_r \quad if \\ (1-R)P(w_r) + \sum_{j=1}^{R} P(w_r \mid x_j) = \max_{k=1}^{M}\left[(1-R)P(w_k) + \sum_{j=1}^{R} P(w_k \mid x_j)\right] \end{gathered} \tag{4.6}$$

4.3.1.3 Max Rule

The max rule approximates the mean of the posteriori probabilities by their maximum value. Equation (4.6) can be derived to Equation (4.7)

$$\begin{gathered} assign \quad X \rightarrow w_r \quad if \\ (1-R)P(w_r) + R\max_{j=1}^{R} P(w_r \mid x_j) = \max_{k=1}^{M}\left[(1-R)P(w_k) + R\max_{j=1}^{R} P(w_k \mid x_j)\right] \end{gathered} \tag{4.7}$$

which under the assumption of equal priors simplifies to Equation (4.8)

$$\begin{gathered} assign \quad X \rightarrow w_r \quad if \\ \max_{j=1}^{R} P(w_r \mid x_j) = \max_{k=1}^{M}\max_{j=1}^{R} P(w_k \mid x_j) \end{gathered} \tag{4.8}$$

4.3.2 Match Score Fusion Schemes

Considering the verification mode of multibiometric system, the goal of the system is to determine whether the input biometric sample *X* belongs to a "genuine" user or an "impostor", the number of classes (*M*) is now reduced to two. The minimum error-rate decision rule in Equation (4.1) is based on the assumption that all types of misclassifying errors are equally costly. However, most practical verification systems assign different costs to FAR and FRR which would require modified Bayesian decision rule. If μ be the ratio of the cost values associated with false accept and false reject errors, the modified Bayesian decision rule becomes Equation (4.9).

$$\begin{gathered} assign \quad X \rightarrow genuine \quad if \\ \frac{P(genuine \mid x_1,\ x_2,\ ...,\ x_R)}{P(imposter \mid x_1,\ x_2,\ ...,\ x_R)} \geq \mu \end{gathered} \tag{4.9}$$

Let s_j represent the match score given by the j^{th} matcher for j=1, 2, …, R. As it is assumed that the feature representations of the R biometric matchers $x_1, x_2, \ldots, x_R$ are not available in score level fusion, the posteriori probabilities $P(genuine| x_1, x_2, \ldots, x_R)$ and $P(imposter| x_1, x_2, \ldots, x_R)$ need to be estimated from *S*. Techniques that have been proposed for estimating these posteriori probabilities can be divided into three broad categories and described in next subsections (Ross *et al.*, 2006).

4.3.2.1 Density-based Score Fusion Scheme

This approach is based on the likelihood ratio test and it requires explicit estimation of genuine and impostor match score densities (Griffin *et al*., 2004; Prabhakar and Jain, 2002). The posteriori probabilities $P(genuine|\ x_1, x_2, \ldots, x_R)$ and $P(imposter|\ x_1, x_2, \ldots, x_R)$ can be approximated by $P(genuine|s\text{=}[s_1, s_2, \ldots, s_R])$ and $P(imposter|s\text{=}[\ s_1, s_2, \ldots, s_R])$ respectively. Conversion of the vector of scores, s, into the probabilities $P(genuine|s)$ and $P(imposter|s)$ requires explicite estimation of the underlying conditional densities $p(genuine|s)$ and $p(imposter|s)$. After estimating the densities, the probabilities $P(genuine|s)$ and $P(imposter|s)$ are computed, and the Bayesian decision rule in Equation (4.9) can be used to make a decision.

4.3.2.2 Classifier based Score Fusion Scheme

In this scheme, a pattern classifier is used to indirectly learn the relationship between the vector of match scores $[S_1, S_2, \ldots, S_R]$ provided by the R biometric matchers and the posteriori probabilities of the genuine and impostor classes, *viz.* $P(genuine|\ x_1, x_2, \ldots, x_R)$ and $P(imposter|\ x_1, x_2, \ldots, x_R)$ (Duda *et al*., 2001). The vector of match scores $[S_1, S_2, \ldots, S_R]$ is treated as a feature vector which is to be classified by using the classifier into one of two classes i.e. "genuine" or "impostor". Based on the training set of match scores from the genuine and impostor classes, the classifier learns a decision boundary between the two classes. Many authors worked on this method (Fierrez-Aguilar *et al*., 2004; Ma *et al*., 2005).

4.3.2.3 Transformation based Score Fusion

Generally, the size of scores vector available for training the fusion module is small due to the time, effort and cost of collecting multibiometric data. In such situation, accurate estimation of the joint conditional densities $p(s\text{=}[s_1, s_2, \ldots, s_R]|\ genuine)$ and $p(s\text{=}[s_1, s_2, \ldots, s_R]|\ imposter)$ is not always possible. In such scenario, it is more appropriate to combine the match scores from different matchers without converting them into posteriori probabilities. However, the match scores are to be made compatible to achieve meaningful combination. Hence, a transformation process known as score normalization is applied to transform the match scores of the different matchers into a common domain. The score fusion rules (discussed in Section 4.3.1) can be applied to obtain the fused match scores from the normalized match scores. Since the normalized match scores do not have any probabilistic interpretation, the score combination rules e.g. the product, sum, max and min rules are the product of scores, sum of scores, max score and min score fusion rules, respectively. The max score and min score fusion rules are also known as order statistics. The weighted sum of scores rule or simply, weighted sum rule is a version of sum of scores fusion rule in which the fused match score are computed as a weighted sum of the match scores of the individual matchers (Ross and Jain, 2003; Wang *et al*., 2003).

4.3.3 Score Normalization

Score normalization refers to the process of changing the location and scale parameters of the match score distributions so that the match scores of different matchers are transformed into a common domain (Jain *et al*., 2005). A scale parameter determines the statistical dispersion of the probability distribution. Larger the scale parameter, more spread out the distribution and smaller scale parameter, more concentrated distribution. The location parameter determines location of the origin and it can be either positive or negative. The location parameter is used to shift a distribution in one direction or another. For a good normalization scheme, the estimates of the location and scale parameters of the match score distribution must be robust and efficient.

4.3.3.1 Min-max Normalization

The min-max normalization is the simplest normalization technique. This technique is best suited for the case where the maximum and minimum values of the scores produced by a matcher are known and the minimum and maximum scores are transformed to 0 and 1, respectively. When the match scores are not bounded, minimum and maximum values can be estimated from the given match scores and then min-max normalization can be applied. Given a set of matching scores $\{s_i\}$, i=1, 2, ..., n, the min-max normalized scores are given by Equation (4.10).

$$s_i^{'} = \frac{s_i - \min}{\max - \min} \tag{4.10}$$

Min–max normalization is highly sensitive to outliers and hence, it is not robust if the minimum and maximum values are estimated from the given set of matching scores. This method retains the original distribution of scores except for a scaling factor and transforms all the scores into a common range [0, 1]. Similarity scores can be transformed into distance scores by subtracting the min–max normalized score from 1 and vice versa.

4.3.3.2 z-score Normalization

The z-score normalization is the most commonly used score normalization technique. It is calculated using the arithmetic mean and standard deviation of the given data. This scheme can be expected to perform well if prior knowledge about the average score and the score variations of the matcher is available. If we do not have any prior knowledge about the nature of the matching algorithm, then we need to estimate the mean and standard deviation of the scores from a given set of matching scores. The normalized scores are given by Equation (4.11)

$$s_i^{'} = \frac{s_i - \mu}{\sigma} \tag{4.11}$$

where, μ is the arithmetic mean and σ is the standard deviation of the given data.

4.3.3.3 Median and Median Absolute Deviation (MAD) Normalization

The median and median absolute deviation (MAD) statistics are less sensitive to the outliers and the points in the extreme tails of the distribution. Therefore, a normalization scheme using median and MAD is robust. The normalized scores using this scheme are given by Equation (4.12)

$$s_i^{'} = \frac{s_i - median}{MAD} \tag{4.12}$$

where, $MAD = median(|s_i\text{-}median|)$.

4.4 Design Methodology

Generally, research methodology is described as a basic guideline to conduct the system's objectives. It is a way to systematically solve the research problem. It is a science of studying how research is done systematically (Kothari, 2004). Defining methodology is important to describe system framework and formulation in order to conduct the present study in an effective way. This section explains the research methodology used in this study.

The general framework of study methodology is depicted as a flow chart in Figure 4.7. Main steps are data collection, image pre-processing, feature extraction, classifiers design, designing of match score fusion and biometric template protection methods.

The reliability of the implemented multibiometric systems and proposed methods depend on the model structure and the input data. To get the reliable results, the input data needs to be trustworthy. Therefore, the standard databases namely, CASIA Iris databases, FVC2004 database and MYCT score databases are employed.

The input iris images are segmented using well-known methods likes Canny edge detection (Liu et al., 2003), Hough transform (Wildes, 1997) and, local histogram intensity and windowing techniques (Merloti, 2004). The iris patterns (or templates) are formed by extracting features from segmented iris images using five extraction methods *viz*. SVD, PCA, AFE, ICA and DWT. These iris patterns are classified using BPNN, SVM with RBF kernel and fkNN. The match scores of these classifiers and the fingerprint and signature match scores from MYCT score database are fused using the proposed IT2 FI along with sum, product, max and fuzzy integral (type-1 FI) match score fusion methods both in multi-classifier and multimodal multibiometric modal.

In cancelable biometric experiments, the cancelable transform based on BioHashing has been applied to the iris and fingerprint patterns in unibiometric and multibiometric models.

The performances of the above models are evaluated in terms of ROC, AUC, EER and correct classification rate, FRR at zero FAR.

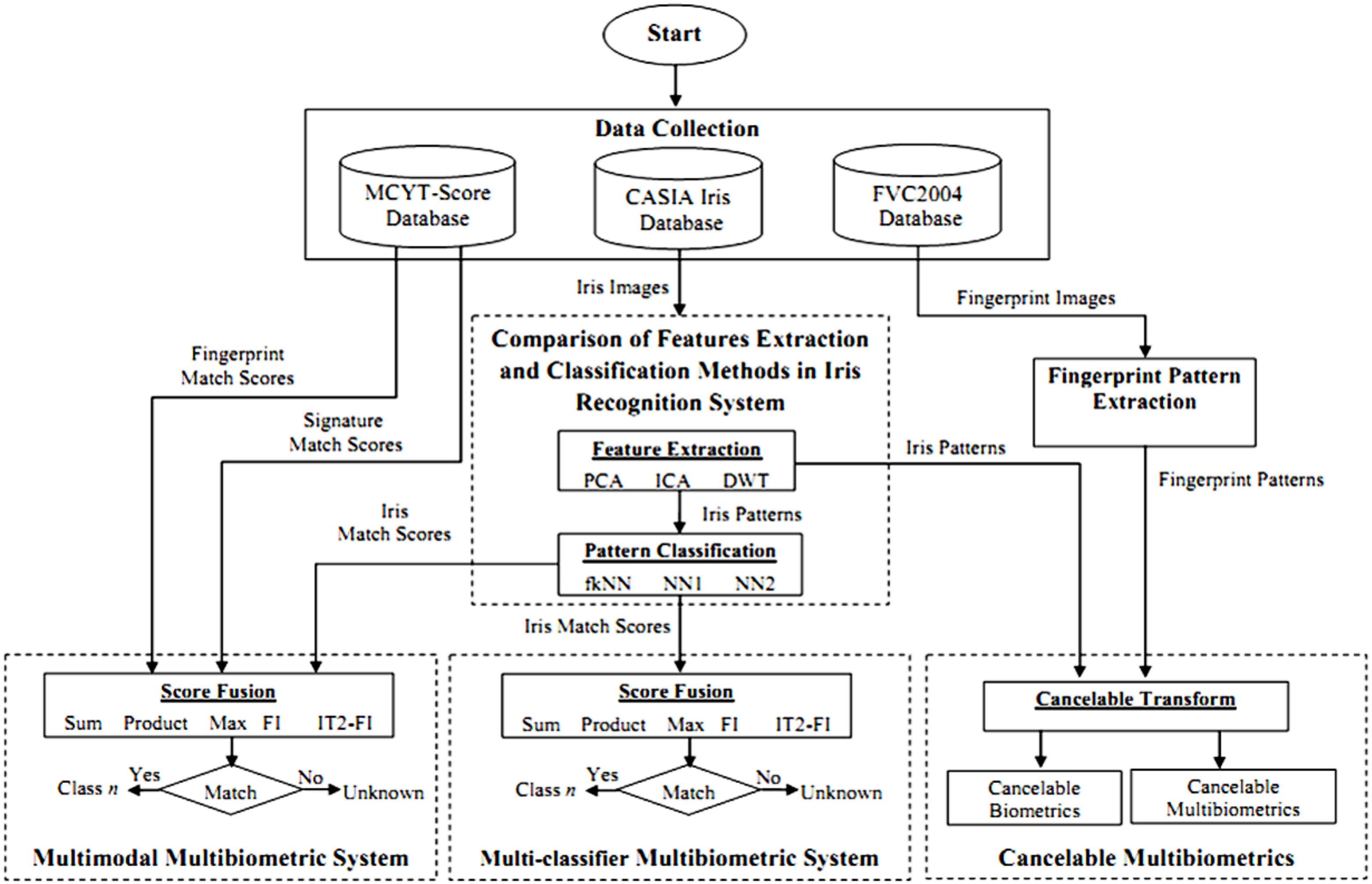


Figure 4.7 Design Methodology

4.5 Chapter Summary

The main focus of this chapter was to highlight the design issues of multibiometric systems with a special emphasis on match score level fusion scheme. The chapter presented details of match score fusion rules and fusion schemes along with score normalization methods. The chapter also presented a design methodology for improving the performance accuracy of multibiometric system.

In the next chapter, to improve the performance of multibiometric systems, a new match score fusion approach based on interval type-2 fuzzy integral is presented.