6. Multimodal Biometrics

Multimodal biometrics is based on combination of more than one type of biometric modalities or traits. The most compelling reason to combine different modalities is to improve the recognition rate & reliability. This can be done when biometric features of different biometrics are statistically independent. There are other reasons to combine two or more biometrics. One is that the different biometric modalities might be more appropriate for the different applications. Another reason is simply customer preference.

6.1 Multimodal Biometrics-Definition & Types

Multimodal biometrics refers to the use of a combination of two or more biometric modalities in a verification / identification system for improvement of performance over the individual systems. Identification based on multiple biometrics represents an emerging trend. The International Committee for Information Technology Standards (INCITS) and researchers have described methods for performing multi-biometric fusion [24]. In general, the use of the terms multimodal or multi-biometric indicates the presence and use of more than one biometric aspect (modality, sensor, instance and/or algorithm) in some form of combined use for making a specific biometric verification/identification decision [24]. As discussed earlier the goal of multi-biometrics is to reduce one or more of the following:

- False Accept Rate (FAR).
- False Reject Rate (FRR).
- Failure to Enroll Rate (FTE).
- Susceptibility to artifacts or mimics.

To further the understanding of the distinction among the multi-biometric categories [24], [26] they are briefly summarized as follows.

Multimodal biometric systems take input from single or multiple sensors measuring two or more different modalities of biometric characteristics. For example, a system combining face and iris characteristics for biometric recognition would be considered a multimodal system regardless of whether face and iris images were captured by different or same imaging devices. It is not required that the various measures be mathematically combined in anyway. For example, a system with fingerprint and face recognition would be considered ‘multimodal’ even if the ‘OR’ rule was being applied, allowing users to be verified using either of the modalities [21].

Multi-algorithmic biometric systems take a single sample from a single sensor and process that sample with two or more different algorithms. The technique could be applied to any modality. Algorithms can be designed to optimize performance under different circumstances [21], [24].

Multi-instance biometric systems [21] use one sensor (or possibly multiple sensors) to capture samples of two or more different instances of the same biometric characteristics. For example, systems capturing images from multiple fingers are considered to be multi-instance rather than multimodal. However, systems capturing, for example, sequential frames of facial or iris images are considered to be multi-presentation rather than multi-instance. This is whether or not the repeated captured images are combined at the image (feature) level, some other level of combination or a single image is selected as the one best used for pattern matching.

Multi-sensorial biometric systems [21] sample the same instance of a biometric trait with two or more distinctly different sensors. Processing of the multiple samples can be done with one algorithm or some combination of multiple algorithms. For example, a face recognition application could use both a visible light camera and an infrared camera coupled with specific frequency (or several frequencies) of infrared illumination.

For a specific application in an operational environment, there are numerous system design considerations, and trade-offs that must be made among factors such as improved performance (e.g. verification or identification accuracy, system speed and throughput, robustness, and resource requirements), acceptability, circumvention, ease of use, operational cost, environment flexibility and population flexibility. Especially for a large-scale identification system, there are additional system design considerations such as operation and maintenance, reliability, system acquisition cost, life cycle cost and planned system response to identified susceptible means of attacks, all of which will affect the overall deployability of the system.

6.2 Fusion in Multimodal Biometric Systems [27]

In multimodal biometrics we use more than one biometric modality; we have more than one decision channels. *We need to design a mechanism that can combine the classification results from each biometric channel; this is called as biometric fusion*. Multimodal biometric fusion combines measurements from different biometric traits to enhance the strengths and diminish the weaknesses of the individual measurements. Fusion at matching score, rank and decision levels have been extensively studied in the literature [27], [28]. Multimodal Biometrics systems with various levels of fusions are possible, such as sensor level, feature level, matching score level and decision level. This is shown in Fig. 6.1.

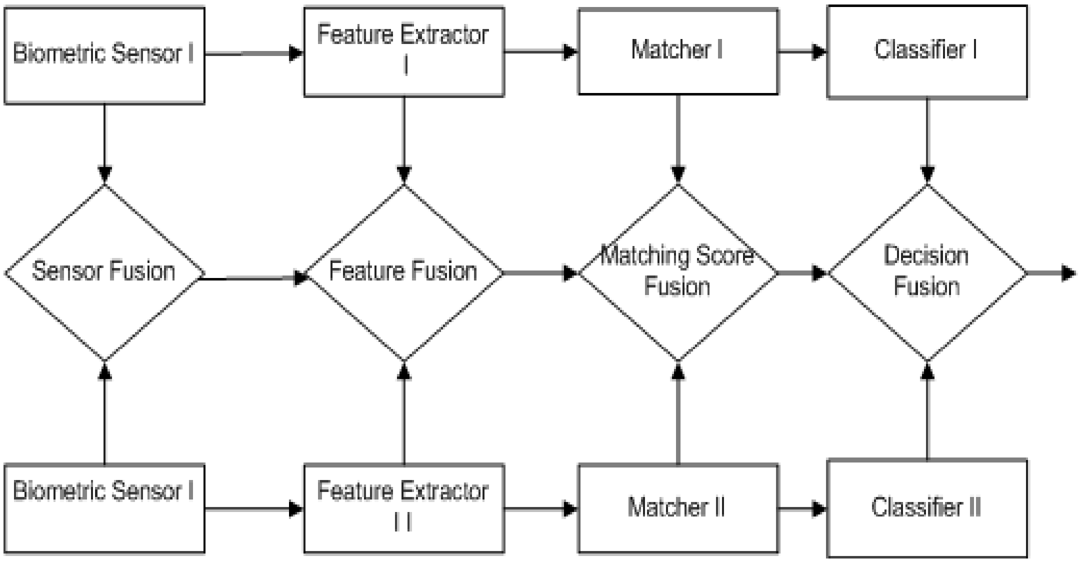


Fig. 6.1. Fusion levels in Multimodal Biometric Systems

A. **Sensor level Fusion**: In sensor Fusion we combine the biometric traits coming from sensors like thumbprint scanner, video camera, iris scanner etc., to form a composite biometric trait and process.
B. **Feature Level Fusion**: In feature level fusion signal coming from different biometric channels are first preprocessed, and feature vectors are extracted separately, using specific fusion algorithm we combine these feature vectors to form a composite feature vector. This composite feature vector is then used for classification process.
C. **Matching Score Level**: Here, rather than combining the feature vector, we process them separately and individual matching score is found, then depending on the accuracy of each biometric channel we can weight & fuse the matching

level to find composite matching score which will be used for classification.

D. **Decision level Fusion**: Each modality is first pre-classified independently. The final classification is based on the fusion of the outputs of the different modalities

Multimodal biometric system can implement any of these fusion strategies or combination of them to improve the performance of the system. We have implemented fusion of modalities which are discussed in previous chapters. Mainly feature level fusion, matcher & decision level fusion are implemented as they are simple and cheaper. Sensor level fusion is complex and needs multiple sensors; this increases cost of implementation. The fusion strategy and results will be discussed in coming section.

Multi-algorithmic biometric systems using fingerprint & iris are discussed previously. Fusion of feature vectors extracted using partitioned complex plane in transform domain is performed for both fingerprint as well as iris in chapter 3 & chapter 4. In chapter 4 we have discussed multi-instance iris recognition for VQ, Kekre's wavelets, DCT & Walsh transforms based feature vectors. Fusion for left & right iris feature vector is performed and results are presented. In this chapter we discuss mainly multimodal implementation. Multimodal systems using combination of face & iris, face & keystroke dynamics are explored here.

6.3 Fusion of Face & Iris

Face recognition systems are becoming ubiquitous and inevitable in today's world. Being less intrusive and universal face recognition systems serve as good option for access control and surveillance. Iris recognition enjoys universality, high degree of uniqueness and moderate user co-operation. This makes Iris recognition systems unavoidable in emerging security & authentication mechanisms.

In chapter 4, various unimodal face & iris based biometric authentication are discussed, besides this multi-instance and multi-algorithmic iris recognition is discussed in section 4.2. & section 4.3. In this section a multimodal system which is a combination of a unimodal face recognition and multi-algorithmic iris recognition is proposed, the proposed system is combination of unimodal face and multi-algorithmic iris recognition system hence it is referred as hybrid multimodal biometric system. Proposed system has more accuracy as compared to unimodal biometric systems, but this system is more complex.

Face features are extracted using multilevel decomposition of face image using Kekre's wavelet and the iris features are extracted using 1D transform of row & column mean, Kekre's wavelet based texture features and Kekre's Fast Codebook Generation (KFCG) & Kekre's Median Codebook Generation (KMCG) algorithms based VQ codebooks. The architecture of proposed system is shown in Fig. 6.2.

6.3.1 Face Recognition

In section 4.1.2 a face recognition technique based on a new family of wavelets called Kekre's wavelets for multiresolutoin analysis of face images is discussed. Different variants of feature vectors are generated and their performance for face recognition has been analyzed. The Correct Classification Rate (CCR) is 87.53%. Various variants of the feature vector are tested and distance measures such as Euclidian distance and Relative Energy Entropy (REE) are used. The Kekre's wavelets based feature vector normalized by level-wise energy (RKEEF - Section 4.1.2.2) is used to construct proposed multimodal system; this is shown in Fig. 6.2.

6.3.2 Multi-algorithmic Iris Recognition

In section 4.2 & 4.3 use of DCT and Vector Quantization with clustering using Linde-Buzo-Gray (LBG) Algorithm, Kekre's Median Codebook Generation Algorithm (KMCG) & Kekre's Fast Codebook Generation Algorithm (KFCG) is explored. In another variation Row & Column mean and its 1D transform is used for Iris feature vector generation in section 4.2.3.3. In the proposed system above mention feature vector extraction methods are combined to implement a multi-algorithmic iris recognition system. Phoenix iris database [231] is used for iris recognition; we are using iris localization method based on circular Hough transform. Iris preprocessing improves the performance of the system. The extracted region of interest (ROI) is then used for feature extraction. Three different algorithms are used for texture feature extraction.

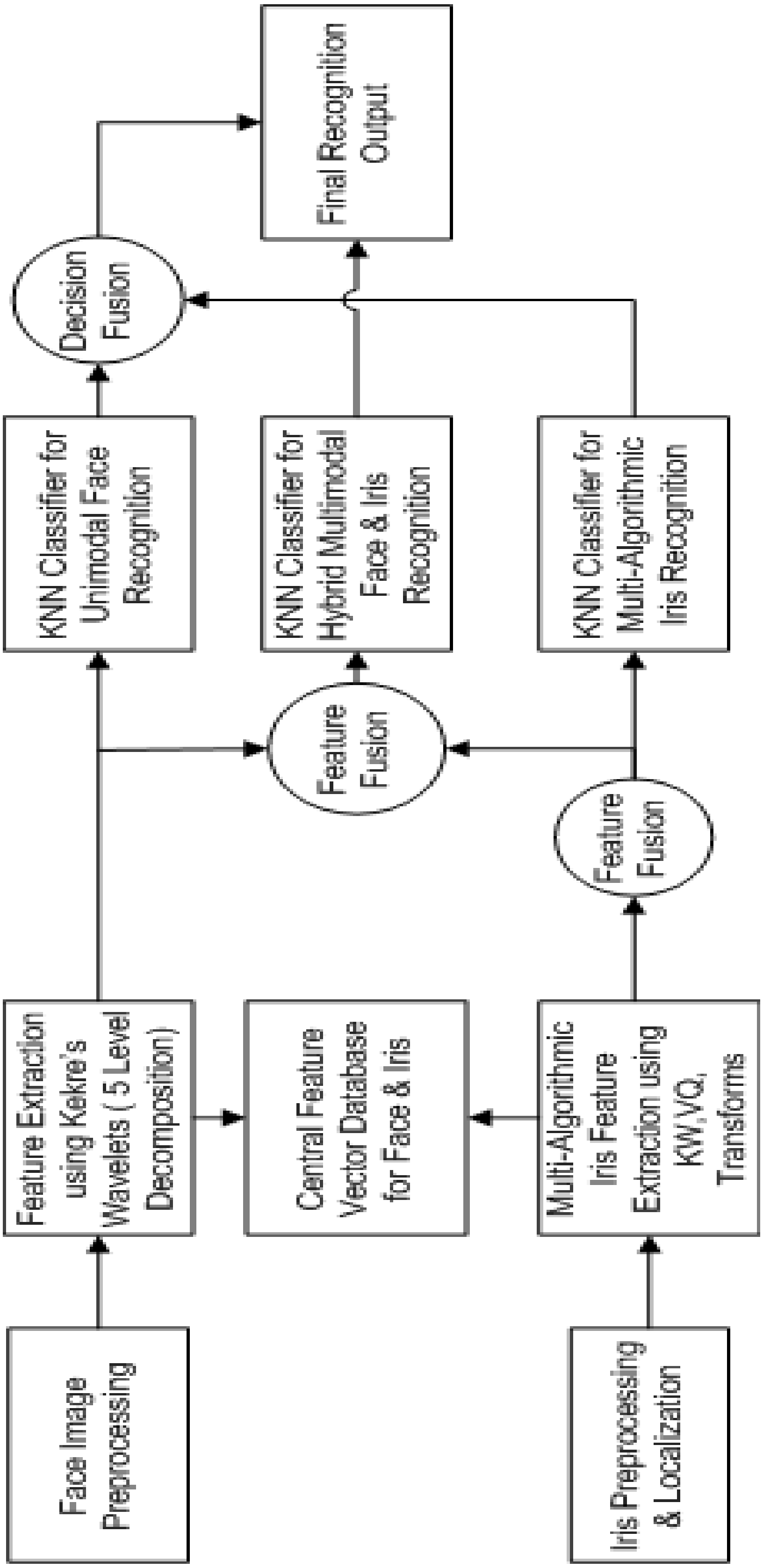


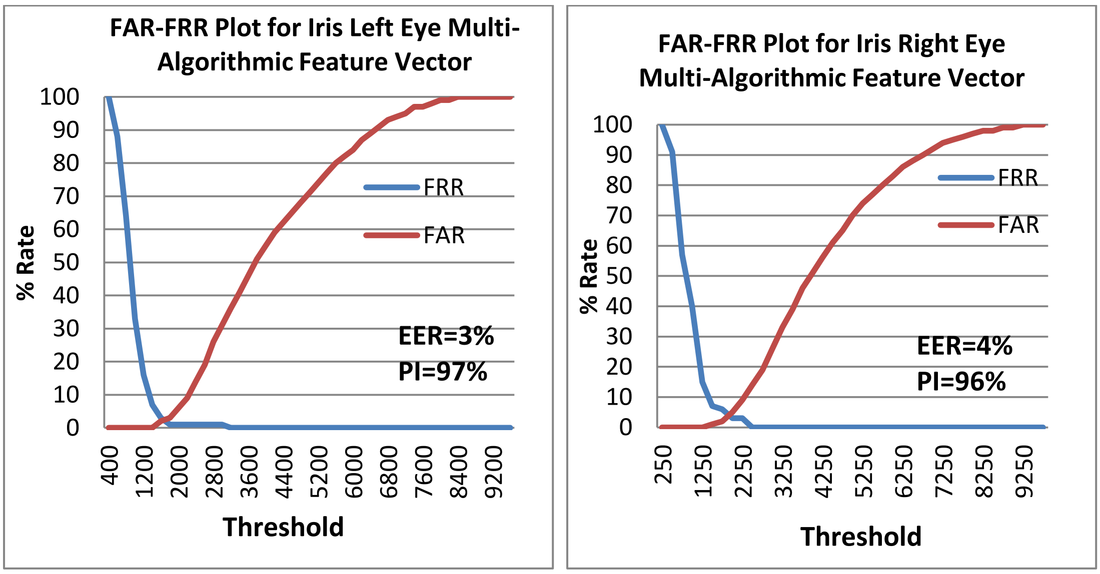
Fig. 6.2. Multimodal Biometric System using Face & Iris Fusion [275]
This is an example of a unimodal face recognition system being combined with a Multi-algorithmic Iris recognition system.

The feature vectors of iris generated by above mentioned three algorithms (VQ, Kekre's Wavelets, 1D Walsh & DCT) are fused together to form a composite feature vector, this is called feature fusion. This is an example of multi-algorithmic iris recognition system. As left as well as right eye iris images are considered for recognition purpose the system is also an example of multi-instance biometric system.

6.3.3 Hybrid Multimodal System

Kekre's wavelet based unimodal feature vector of face is fused with the multi-algorithmic & multi-instance iris recognition system to form a fused feature vector of Face+ Iris. (The feature vector size is 2156 Bytes of face + 81408 Bytes of Iris Composite features = 83564 Bytes total). This is a novel feature fusion scheme having combination of Unimodal + Multi-algorithmic + Multi-instance biometric modalities hence it is called as **Hybrid Multimodal biometric System**. Though the system is complex the accuracy is higher than individual modalities.

Each feature vector is given to respective K- Nearest Neighborhood Classifier, total three K-NN classifiers are implemented. One each for face & Iris feature vector and one for final hybrid feature vector. Besides this the decisions from face & iris classifiers are also fused to implement decision fusion based multimodal system.



(a) **(b)**

Fig. 6.3. FAR-FRR Plot for Multi-algorithmic Iris Recognition (a) Only Left Eye Testing (b) Only Right Eye Testing

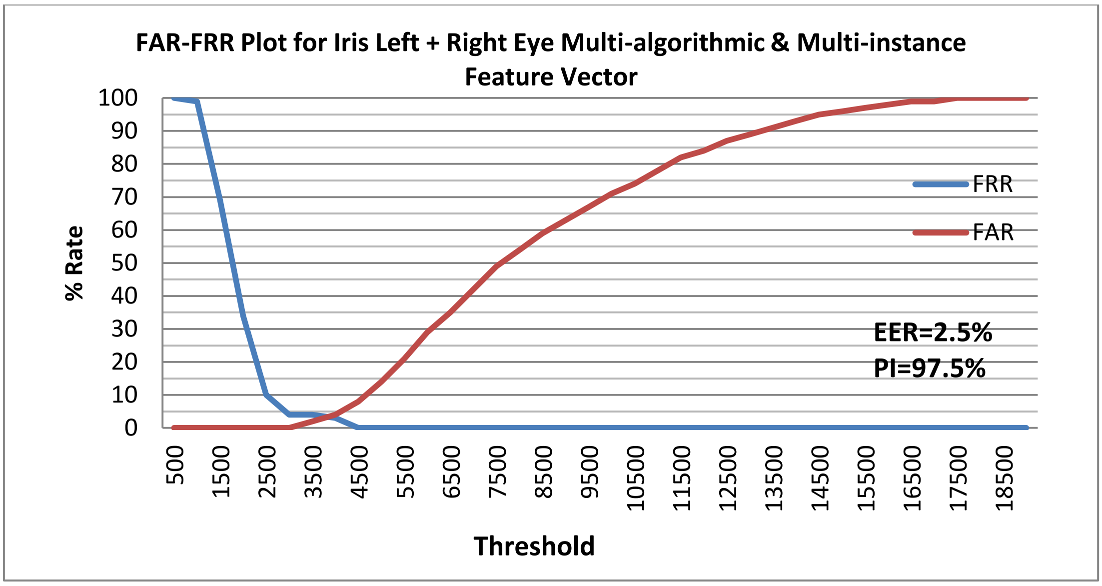


Fig. 6.4. FAR-FRR Plot for Multi-algorithmic & Multi-instance fusion of Iris Recognition with Left + Right Eye Testing

6.3.4 Results for Face & Iris Fusion

The proposed system is programmed into Visual C# 2.5 (MS Visual Studio 2005). The system is tested on PC with AMD Athlon FX 64 processor running at 1851MHz, 1.5 GB RAM with Windows XP SP3 – 32 bit Operating System. For testing Phoenix iris database [231] and Computer Vision Research Projects Face Database-Faces94 [242] are used. Each user from Phoenix database is associated with one user from Face database to implement multimodal system. Three left iris and three right iris images are taken for training and six face images are taken for training. System is tested in both Authentication as well as Recognition (Identification) mode.

Total 101 face users and 64 iris users were enrolled. The hybrid system consists of 64 individuals with total 768 biometric samples and 384 hybrid feature vectors. On this test bed total 4041 genuine as well as forgery tests are performed. Iris testing is performed on left & right eye samples individually as well as in combination. In case of iris only (without fusion with face biometrics) three different test set are analyzed. In case of Left eye iris only the PI is 97% & CCR is 95.44%. In case of right eye only the PI is 96% & CCR is 94.98%. When both the feature vectors are combined in a multi-instance iris recognition system the PI & CCR has marginally increased to 97.5% & 96.21% respectively. The FAR-FRR analysis plots are shown in Fig. 6.3 (a) & (b). As discussed in the previous section this feature vector is fused with face feature vector to form the composite Hybrid Feature Vector. When this fusion is performed the final system gives PI of 98 % as shown in Fig. 6.4.

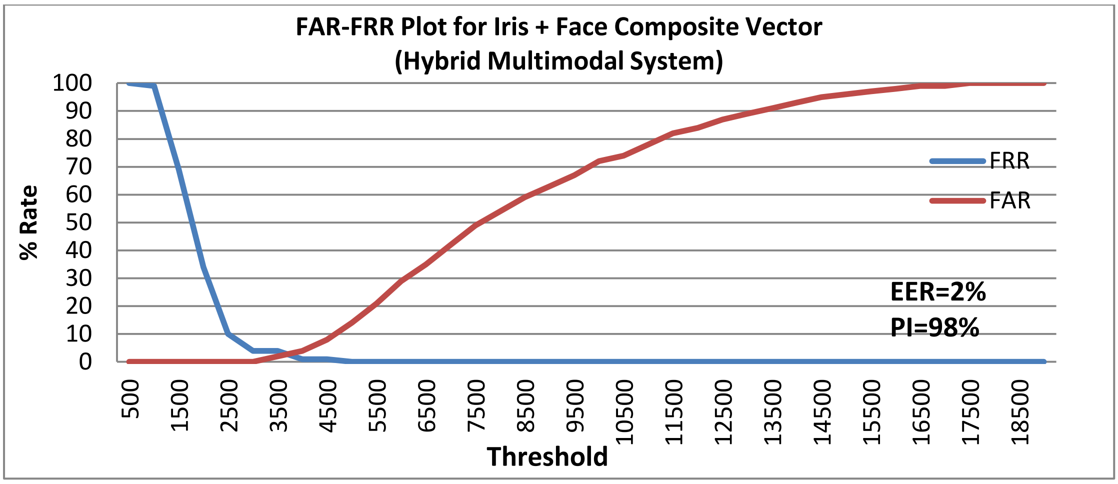
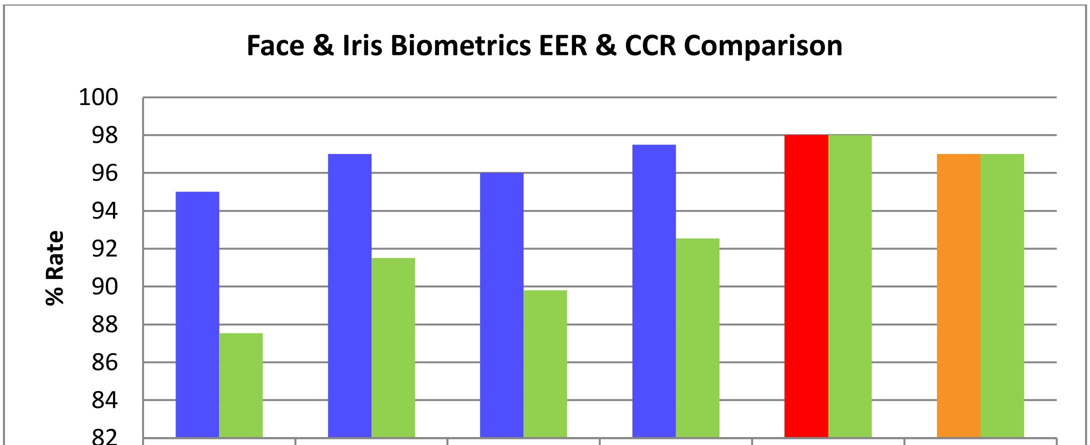


Fig. 6.5. FAR-FRR Plot for Final Hybrid Multimodal System with Fusion of Face & Iris



	Face	Iris (Left)	Iris (Right)	Iris (Left + Right)	Face + Iris Feature Fusion	Face + Iris Decision Fusion
PI	95	97	96	97.5	98	97
CCR	87.53	91.51	89.8	92.54	98	97

Fig. 6.6. Performance Index (PI) & CCR comparison for Final Hybrid Multimodal System with Face & Iris Recognition Systems
(For Iris Recognition Maximum Performance is considered for Comparison)
(Red bar Shows PI of Feature Fusion & Orange Bar Shows PI of Decision Fusion, Feature Fusion has Higher EER and CCR)

Face Recognition system has PI of 95 % (RKEEF feature Vector-Section 4.1.2.2) and corresponding Correct Classification Rate (CCR) is 85 %. **But the final system has CCR of 98% in case of Feature Fusion and 97% in case of Decision Fusion**. The proposed hybrid system gives highest CCR as compared to the individual systems. The performance of face, iris and final hybrid multimodal systems is compared in Fig.6.6. The PI and the final Correct Classification Rates (CCR) of individual as well as multimodal systems are compared. It is clearly seen that proposed hybrid multimodal system (Represented by Face + Iris Fusion) gives maximum PI and CCR. This proves the superiority of multimodal biometrics systems.

6.4 Fusion of Face & Keystroke Dynamics

In another implementation of multimodal biometrics face & keystroke dynamics are combined. In previous section face recognition using Kekre's wavelets is discussed, this system is based on a physiological biometric trait. This physiological biometric is combined with a behavior based biometric to form a multimodal biometric system.

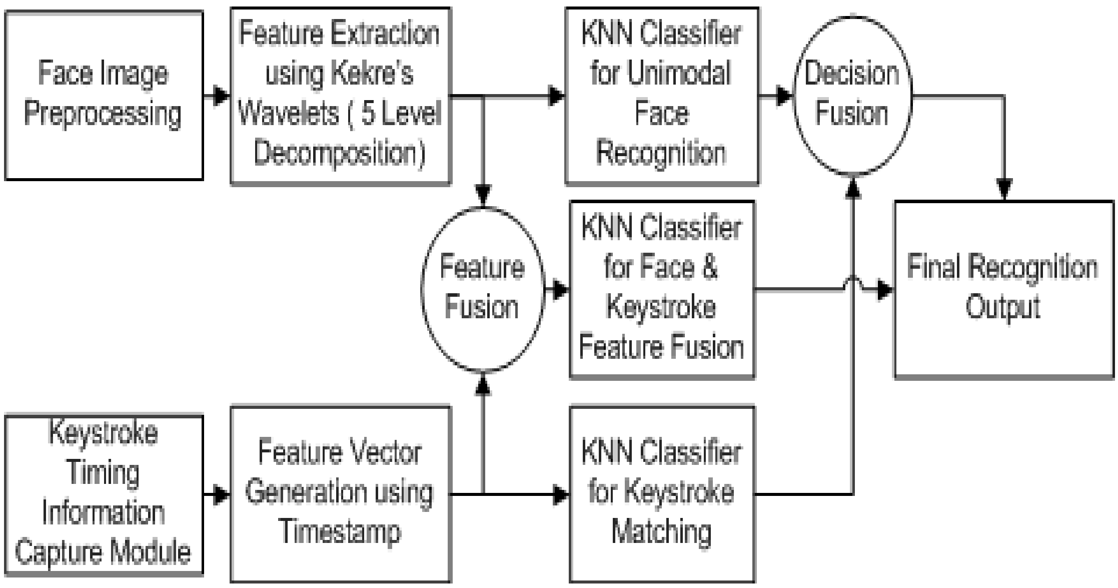
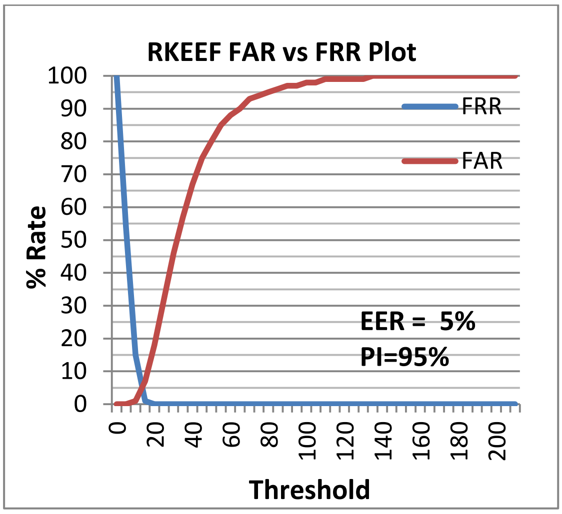


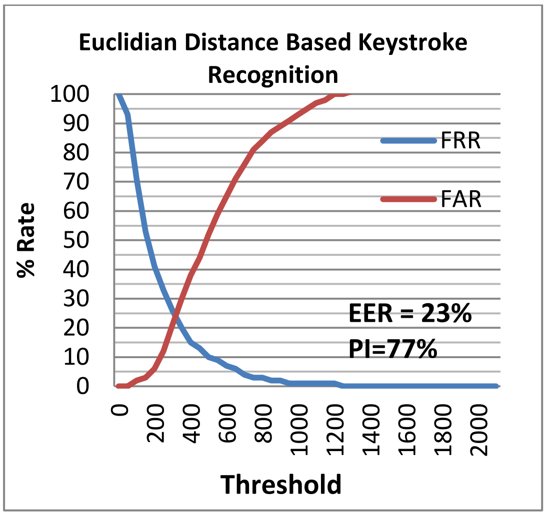
Fig. 6.7. Architecture of Multimodal Biometric System using Face & Keystroke Dynamics Fusion

In section 5.5 Keystroke Dynamics is discussed. The keystrokes are captured and the timing information along with the key pressed is used for matching the dynamic keystroke information. Relative Energy Entropy (REE) and Euclidian Distance (ED) based metrics were used for finding distance between keystroke timing sequences. In the current multimodal system the keystroke information is classified using Euclidian Distance based classifier as it has higher PI.

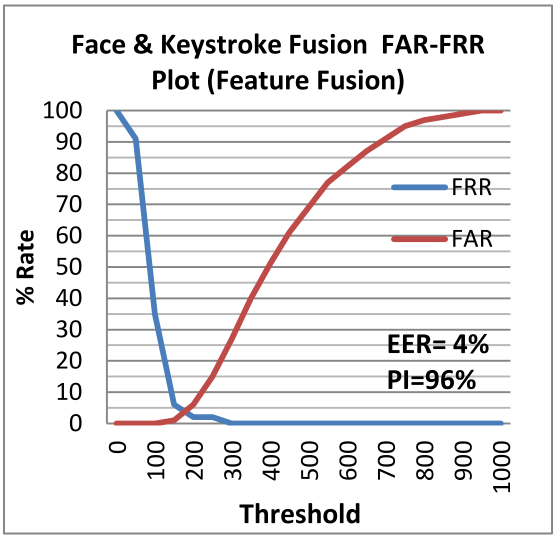
These two systems are combined together to implement a multimodal biometric system as shown in Fig. 6.7. The system has both the feature fusion and decision fusion implemented. The proposed architecture consists of three K-NN classifiers. One for each face & keystroke (Unimodal Feature Vector classification) and one for the fused feature vector classification.



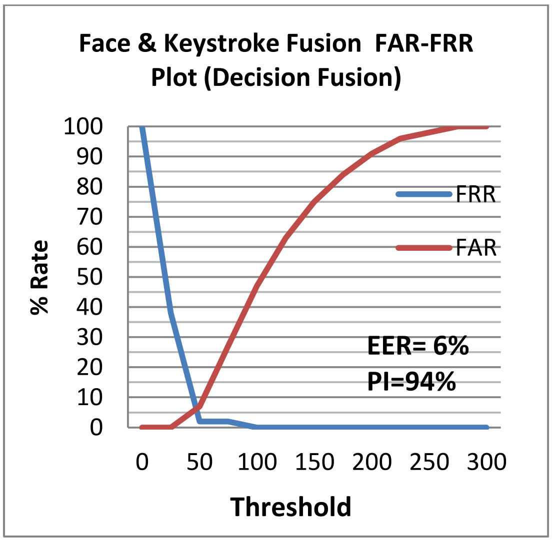
(a)



(b)



(c)



(d)

Fig. 6.8. FAR-FRR Plots for Multimodal Biometric System using Face & Keystroke

(a) FAR-FRR Plot for Face Biometrics (RKEEF Feature Vector)
(b) Keystroke Dynamics Euclidian Distance FAR-FRR Plot
(c) FAR-FRR Plot for Face + Keystroke Feature Fusion
(d) FAR-FRR Plot for Face + Keystroke Decision Fusion

The FAR-FRR analysis for the fusion of face & keystroke dynamics is shown in Fig. 6.8. From previous section it is seen that the Kekre's wavelets based face recognition using relative wavelet energy entropy based feature vector gives 5% EER and Euclidian distance based keystroke matching has 23% EER, this is shown in

Fig. 6.8 (a) & (b). The Feature fusion gives 4% EER & the decision fusion gives 6% EER. The EER is degraded as the EER of keystroke dynamics based biometrics is comparatively high (23%). The system is tested for 101 different users, for enrollment 6 face images and 10 dynamic passwords are stored for each user. Total 2572 different tests are performed.

The comparison for PI & Accuracy i.e. Correct Classification Ratio (CCR) is given in Fig. 6.9. The individual CCR for Face and Keystroke Dynamics based systems is low; 87.53 & 75% respectively. The Multimodal biometric system has higher PI & accuracy as compared to the unimodal systems; feature fusion gives 96% PI & 90% CCR and that of decision fusion is 94% PI & 88% CCR. There is 2.83% improvement over accuracy of face recognition system and 17% improvement over the keystroke dynamics based systems. This shows that the fusion of face and keystroke dynamics yields performance improvement.

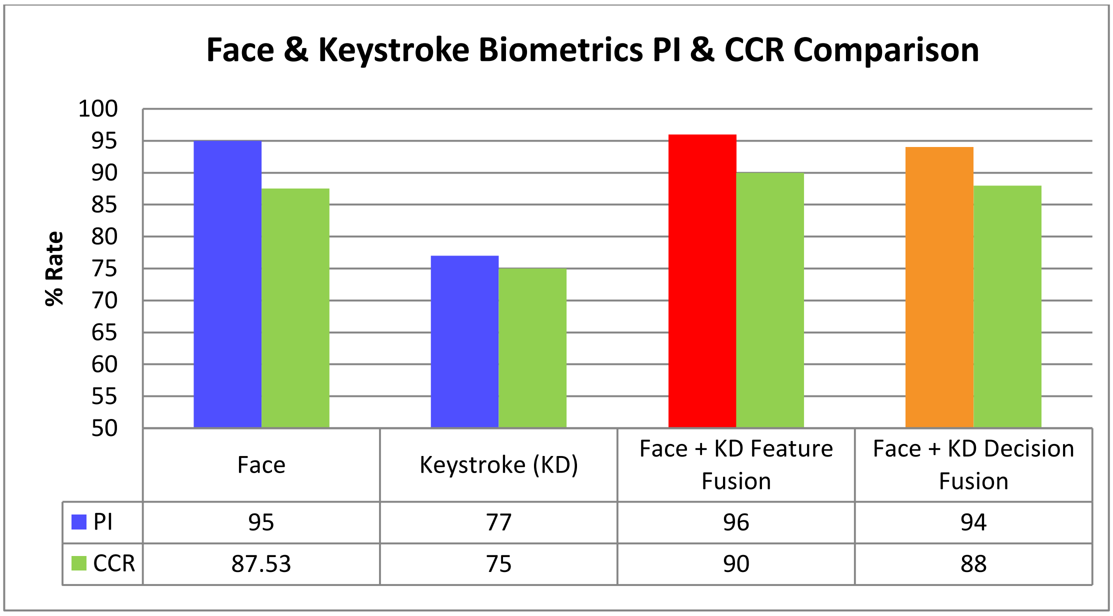


Fig. 6.9. PI & CCR comparison for Multimodal System with Face & Keystroke Dynamics
(Red bar Shows PI of Feature Fusion & Orange Bar Shows PI of Decision Fusion, Feature Fusion has Higher PI and CCR)

6.5 Summary

This chapter is focused on multimodal biometric systems, their types and the performance improvement achieved. The definition and types of multimodal biometric systems, different feature fusion mechanisms are elaborated in section 6.1 & 6.2.

Different multimodal combinations are discussed here. Face & iris based multimodal system is discussed in section 6.3. This system is implemented by combining a unimodal face recognition system and a combination of multi-algorithmic & multi-instance biometric system; this system is called as hybrid multimodal system. Though the system is complex the achieved CCR is 98% (face-87.53% & iris- 97.5%). The fusion of face & iris is an example of fusion of two physiological biometric traits.

In section 6.4, face & dynamic keystroke information based biometric systems are combined to implement multimodal biometric system. This is an example of physiological & behavioral biometric fusion. The results clearly show the improvement in the performance, the CCR of final multimodal system is 90% is greater than the individual biometric systems (face-87.53%, keystroke-75%). Both the feature fusion and decision fusion of feature vector is implemented in the face & keystroke dynamics fusion. In the next chapter we present conclusion & future research directions.