Research Avenues in Multimodal Biometrics

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ABSTRACT
Growing concern the world over, related to personal and property safety has propelled rapid growth of security and surveillance related technologies. The biometric system is one such that can provide accurate and reliable scheme for person verification. The main aim of biometric based security system is to make sure that rendered service is accessed only by valid user. Biometric systems are of two types: unimodal and multimodal. In these multimodal biometric systems are gaining more popularity as it is capable of addressing some of the challenges involved in designing a biometric systems such as: non-universality, noise in sensed data, large intra-user variations and susceptibility to spoof attacks. In this paper, we give a brief overview of multimodal biometrics and its advantages, challenges, drawbacks and limitations. We also discuss the performance evaluation of multimodal biometrics for two and three modalities for different combinations of algorithms.

General Terms
Image Processing, Biometrics, Security

Keywords
Biometrics, Unimodal, Multimodal biometrics, Fusion, Sum rule.

1. INTRODUCTION
Security plays a very important role in one's life. The accurate identification of the person to access secured application is still challenging due to the limitations imposed by real time applications. Examples of such applications include access to ATM, nuclear facilities, boarding a commercial flight or performing a remote financial transactions etc. The main goal of accurate identification is to prevent the imposter accessing the secured application. There are three ways in which users can be identified such as:

1. Something the user knows:
—Password, PIN
2. Something the user has:
—Key, Cards and Tokens
3. Something the user is:
—Unique Biological properties.

Easily lost, stolen, shared or manipulated and there by undermining the intended security. The third way of identifying the person appears to be more secure, so designing a security system based on biological properties cannot be lost, manipulated or stolen. Biometric system can be defined as a pattern recognition system which is capable of identifying a Person based on their biological properties. These biological properties can be physical characteristics like face, palmprint, iris, handvein etc and/or behavior properties like speech, gait etc. Thus, biometric system offers a natural and reliable solution to recognize the individual using physical or/and behavior characteristics. Figure 1 shows the wide range of physical and behavior characteristics that are quantified as a biometrics.

1.1 Characteristics of Biometrics
Any physical and/or behavior characteristics of a human can be considered as a biometric if it exhibits following characteristics as explained by Jain et al., [1]:

- **Universality:** Each person accessing the biometric application should posses a valid biometric trait.
- **Uniqueness**: The given biometric trait should exhibits distinct features across individuals comprising the population.
- **Permanence:** The biometric characteristics should remain sufficient invariant over a period of time.
- **Measurability:** The biometric characteristics can be quantitatively measured i.e. acquiring and processing of biometric trait should not cause inconvenience to the individual.
- **Performance:** The biometric trait should the required accuracy imposed by the application.
- **Acceptability:** The chosen biometric trait must be accepted by a target population that will utilize the application.
- **Circumvention:** This indicates how easily the chosen biometric trait can fooled using artifacts.

1.2 Types of Biometrics
The biometric system can be classified into two different types:

1. **Unimodal Biometric System:** The unimodal biometric employs single biometric trait (either physical or behavior trait) to identify the user. Example: Biometric system based on Face or Palmprint or Voice or Gait etc.
2. **Multimodal Biometric System**: A biometric system that consolidates the information from multiple sources is known as multimodal biometric system. Example:

   Biometric system based on face and gait or face and speech, etc.

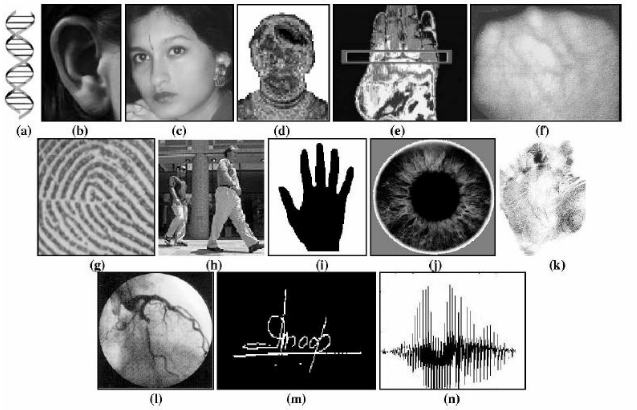

Figure 1: Examples of biometric characteristics [1]

Limitations of unimodal biometric systems Even though the unimodal biometric system offers a reliable solution for secured verification and it is commonly used in numerous commercial system in practice; it suffers from following limitations:

- **Noise in sensed data:** Noise in the sensed data may result from defective or improperly maintained sensor. Ex. fingerprint image with scar, voice sample altered by cold etc.

- **Intra-class variation:** Caused by an individual who is incorrectly interacting with sensor and this will increase False Reject Rate (FRR).

- **Intra-class similarities:** Refers to overlapping of feature spaces corresponding to multiple classes or individuals. This may increase the False Acceptance Rate of the system.

- **Non-universality:** Biometric system may not able to acquire meaningful biometric data from a subset of users.

- **Spoof attacks:** Involves the deliberate manipulation of one's biometric traits in order to avoid recognition. This type of attack is relevant when behavior traits are used.

The performance of a biometric system employing a single trait is constrained by these intrinsic factors.

2. MULTIMODAL BIOMETRIC SYSTEM

Biometric system that perform the identification of person based on the information obtained from multiple biometric traits are known as multimodal biometric system. **Figure 2** shows the block diagram of multimodal biometric system. The multimodal biometric system exhibits number of advantages as compared to that of unimodal biometric system and are listed below:

1. Since multimodal biometric system acquires more than one type of information it offers a substantial improvement in the matching accuracy as compared to that of unimodal system.

2. Multimodal biometric systems are capable of addressing the non universality issue (with respect unimodal biometric system for example: 2% of the population do not have proper fingerprint [1]) by accommodating a large population of users. If user cannot posses a single valid biometric trait still they can be enrolled into a system by using another valid biometric trait. Further certain degree of flexibility can be achieved by enrolling the user by acquiring his multiple traits and perhaps only a subset of acquired traits is requested for verification.

3. Multimodal biometric systems are less sensitive to imposter attacks. It is very difficult to spoof the legitimate user enrolled in multimodal biometric system.

4. Multimodal biometric systems are insensitive to the noise on the sensed data i.e. when information acquired from the single biometric trait is corrupted by noise we can use another trait of the same user to perform the verification.

5. These systems also help in continuous monitoring or tracking the person in situation when a single biometric trait is not enough. For example tracking a person using face and gait simultaneously.

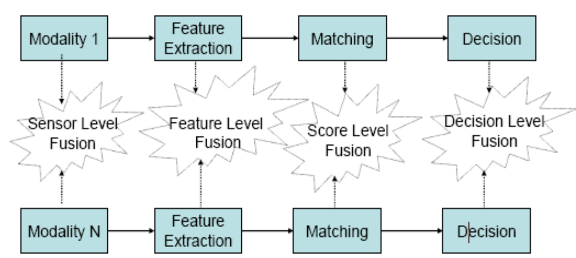

Figure 2: Block diagram of Multimodal Biometric System

2.1 Different Levels of Fusion

As indicated in Figure 2 there are four ways in which information from multiple sources are combined such as sensor level, feature level, match score level and decision level. The amount of the information available for fusion decreases after each level of processing in a biometric system. The raw data represents the richest set of information, while final decision contains just an abstract level of information. Further in many practical multimodal biometric systems, early levels of information such as raw data or feature sets may not be available or even if they are available they may not be compatible for fusion. In such cases information obtained at later levels like match score level or decision level can be employed as it is ease to fuse and all commercial devices provide access to scores and decisions. The brief descriptions of four different levels of fusions are described as follows:

2.1.1 Sensor level fusion
Here raw data obtained from different modalities are fused. The sensor level fusion can be performed only if the sources are either samples of same biometric trait obtained from multiple compatible sensors or multiple instances of same biometric trait obtained using a single sensor [1]. Since sensor level fusion combines the information from different sensors, it requires some preprocessing such as sensor calibration and data registration before performing the fusing.

2.1.2 Feature level fusion
Feature level fusion consolidates the features obtained from different sources. If obtained features are structurally compatible then feature concatenation is carried out to fuse the features obtained from different sources otherwise concatenation is not possible. Moreover combining the features will introduce a curse of dimensionality and hence either feature transformation or feature selection can be applied to reduce the dimensionality of the fused feature set [1].

2.1.3 Match score level fusion
Match score is a measure of the similarity between the input and template biometric feature vector [1]. In match score level fusion, the match score obtained from different matchers are combined. Since scores obtained from different matchers are not homogeneous, score normalization technique is followed to map the scores obtained from different matchers on to a same range [1].

2.1.4 Decision level fusion
Decision level fusion involves the fusion of decision obtained from different modalities. Since decision level fusion holds binary values it is also called as abstract level fusion [1].

3. RECENT WORK
In recent years, multimodal biometrics have received substantial attention from both research communities and the market, but still remains very challenging in real time applications. Since, the heart of multimodal biometric system relies on fusing the information from different biometric traits, all the work reported on multimodal biometric system is confined to four different levels of fusion. As sensor level fusion consolidates the information at very early stage, it is expected to hold more information as compared to any other level of fusion. In literature, very few works are reported on sensor level fusion [2],[3] and [4]. The main interest of the sensor level fusion lies in multi-sample system that captures multiple snapshots of the same biometric. Thus, in literature most of the works reported on sensor level fusion are with the application of fusing visible and thermal face image. Kong et al. [2] proposed a weighted image fusion of visible and thermal face images where weights are assigned empirically on the visible and thermal face images by decomposing them using wavelet transform. Bebis et al. [4] employed a Genetic Algorithm for feature selection and fusion where group of wavelet features from visible and thermal face images are selected and fused to form a single image. Here there is no scope for weighting. Singh et al. [3] proposed a weighted image fusion using 2V-SVM where weights are assigned by finding the activity level of visible and thermal face image. Recently, Kisku et al. [5] proposed a sensor level fusion scheme for face and palmprint. Here, face and palmprint are decomposed using Haar wavelet and then average of wavelet coefficients are carried out to form a fused image of face and palmprint. Finally, inverse wavelet transform is carried out to form a fused image of face and palmprint. Then, feature extraction is carried out on this fused image using Scale Invariant Feature Transform (SIFT) technique to make the decision about accept/reject.

Feature level fusion involves consolidating the evidence presented by two biometric feature sets of the same individual. Thus as compared to match score level or decision level fusion, the feature level exhibits rich set of information. In performing the feature level fusion either we can use same feature extraction algorithm [6],[7],[8] and [9] or different feature extraction algorithm [10], [11] and [12] on different modalities whose features has to be fused. The feature level fusion is challenging because, relationships between features are not known, and structurally incompatible features are common and the curse of dimensionality. Because of these difficulties, only limited work is reported on feature level fusion of multimodal biometric system. The majority of the work reported on feature level fusion is related to multimodal biometric system using face and palmprint. Feng et al. [10] proposed the feature level fusion of face and palmprint in which Principle Component Analysis (PCA) and Independent Component Analysis (ICA) are used for feature extraction. Further, feature concatenation is carried out to obtain the fused features of face and palmprint. Y.Yao et al. [6] also proposed a multimodal biometric system using face and palmprint at feature level. Here, Gabor features of face and palmprints are obtained individually. Extracted Gabor features are then analyzed using linear projection scheme such as PCA to obtain the dominant principal components of face and palmprint separately. Finally, feature level fusion is carried out by concatenating the dominant principal components of face and palmprint to form a fused feature space. X.Y.Jing et al. [7] employed Gabor transform for feature extraction and then Gabor features are concatenated to form fused feature vector. Then, to reduce the dimensionality of fused feature vector, non linear transformation techniques such as Kernel Discriminant Common Vectors are employed. P.Xiuquin [8] proposes a multimodal biometric system using face and ear at feature level. Here, Kernel discriminant analysis is employed as feature extraction method to obtain the features of face and ear independently. This is then concatenated to form a single feature vector. A.Rattani et al. [9] proposed a multimodal biometric system of iris and face in which Scale Invariant Feature Transform (SIFT) features of individual modalities are extracted and concatenated to form the fused feature space. Ross et al. [12] proposed a multimodal biometric system using Face and hand geometry at feature level. Here, face is represented using PCA and LDA while 32 distinct features of hand geometry is extracted and then concatenated to form a fused feature. Then, Sequential Feed Forward Selection (SFFS) is employed to select the most useful features from the fused feature space. Thus from the literatures it is observed that, the feature level fusion is performed by doing feature concatenation.

Match score level fusion consolidates the match scores output by different biometrics. Apart from the raw data and feature vectors, the match scores contain the richest information about the input pattern. Also it is relatively easy to access and combine the scores generated by different biometric matchers [1]. Hence, the majority of the works reported on multimodal biometric are confined to score level fusion. Score level fusion techniques can be divided into three different categories (1) Transformation based methods (2) Classifier Based Methods (3) Density based score fusion. In transformation based method, scores obtained from different modalities are normalized so that, they will lie in the same range. Kittler et al. [13] proposed a theoretical framework for transformation based score level fusion approaches such as sum rule, median rule, min rule, max rule and product rule. In that article [13], experimental results combining the scores from three different modalities such as face (frontal and profile) and speech using indicates the supreme performance of the modalities with sum rule. Snelick et al. [14] proposed a different normalization schemes for transformed based score level fusion and experimental results indicates that Min-Max normalization scheme is more efficient than all other normalization schemes such as Decimal scaling, Median, Double sigmoid and Tanh normalization scheme. Wang et al. [15] proposed weighted sum rule, where weights are calculated depending on the individual performance of the modalities. In classifier based score fusion, a pattern classifier is used to indirectly learn the relationship between the vectors of match scores provided by the 'K' biometric matchers. Hence, the vectors of match scores are treated as a feature vector which is then classified into one of two classes: genuine or imposter.

Based on the training set of match scores from genuine and imposter classes, the classifier learns a decision boundary between two classes. Several classifier have been used to consolidate the match scores of multiple matchers and arrive at a decision. Brunelli et al. [16] uses a Hyper BF network to combine matchers based on voice and face features. Chatzis et al. [17] uses classical K-means clustering, fuzzy clustering and median Radial Basis Function (RBF) for fusion at match score level. Ben-Yacoub et al. [18] evaluate a number of classification schemes for fusion of match scores from multiple modalities, including Support Vector Machine (SVM) with polynomial and Gaussian kernels, C4.5 decision trees, multilayer perceptron, Fishers Linear Discriminant Analysis (FLDA) and Bayesian classifier. Wang et al. [15] employs FLDA and a neural network classifier with RBF to classify the scores from face and iris modalities into genuine and imposter classes. Ross et al. [19] proposed to use decision trees and FLDA for combining the match scores of face, fingerprint and hand geometry modalities. In density based estimation technique, the densities of genuine and imposter scores are estimated either by parametric or non parametric methods. Snealik et al. [14] adapts a parametric approach to estimate the conditional densities of the match scores from different modalities. Here score densities are assumed to follow a Gaussian distribution and finally classification is carried out using Bayes rule. Jain et al. [20] proposed the use of Parzen window based non parametric density estimation method to estimate the conditional density of genuine and imposter scores. Prabhakar et al. [21] proposed to perform score fusion using non parametric approach based on joint multivariate densities. Then, based on the joint densities, the posterior probabilities are computed using Bayes rule. Dass et al. [22] proposed a generalized density estimation scheme which can be used to analyze both continuous and discrete scores. Nanadakumar et al. [23] proposed a density estimation scheme using Likelihood Ratio (LR), where Gaussian Mixture Model (GMM) is used to accurately estimate the underlying density of genuine and imposter scores and finally Neyman-Pearson rule is employed to make the final decision.

In decision level fusion, the decision output by individual modalities is combined. This type of the fusion is preferred when many commercial off-the-self (COTS) biometric matchers provide access only to the final recognition decision. In literature lot of approaches at this level are proposed such as AND and OR rules [24], Majority voting [25], weighted majority rule [26], Bayesian decision [1] and Dempster-Shafer theory of evidence [1]. As decision level fusion include very abstract level of information it is less preferred in fusion of different modalities in designing multimodal biometric systems.

From the survey of literature, it is evident that match score level fusion is widely employed. Since the last 5 years [21], [22], [19] and [23], density based estimation schemes to fuse the information at match score level have achieved better performance as compared with transformation/classifier based fusion schemes. In particular during the previous 2 years [9], [6] and [10], feature level fusion has become the center of attraction for the researchers and earlier results have also demonstrated that feature level fusion has achieved better performance as compared with match score level fusion.

4. PERFORMANCE EVALUATION

The performance evaluation in biometrics can be carried out either using verification or closed identification. Verification refers to 1-to-1 comparison and closed identification is carried out using 1-to-N comparison [1][10]. As compared to closed identification, the verification issue appears to be more challenging and accurate way of evaluating the biometric system. This is because; verification will allow one to evaluate the biometric system when imposters are present which not a case in closed identification. Hence, in this, we have considered the verification. The verification problem can be formulated as a two class problem. Given a test query, the similarity score is obtained by comparing it with all stored templates. Then obtained similarity score is known as genuine score if it is a result of matching two samples of same biometric trait of a user otherwise similarity score is known as an imposter score i.e. if it is a result of matching two biometric samples originating from different users. If imposter scores exceed the threshold it results in a false accept, while genuine scores that falls below the threshold results in a false reject. Then, FAR of a biometric system can be defined as a fraction of scores exceeding the threshold. Similarly, FRR may be defined as a fraction of genuine scores falling below the threshold. Then, we can define GAR as a fraction of genuine scores exceeding the threshold. Hence, in our experiment we calculate the GAR at 0.1% FAR.

Here, we are evaluating the performance of multimodal approach by fusing the data at match score level using sum rule. Palmprint, face and handvein are the three modalities which we use in our experiments due to their universality, acceptability and non-invasive characteristics. We have obtained a sub palmprint and handvein images by selecting Region of Interest (ROI) for feature extraction and to eliminate the variation caused by the rotation and translation. The features are extracted using popular appearance-based algorithms Principal Component Analysis (PCA), Fisher Linear Discriminant (FLD), and Independent Component Analysis (ICA). Subsequently, the different combinations of algorithms and traits are also evaluated in our experiment.

4.1 RESULTS AND DISCUSSION

In this section, the experimental results of multimodal approach for three modalities viz., face palmprint and handvein are discussed in detail. First we evaluated the each modality independently by adopting the well known subspace algorithms PCA, FLD, and ICA results are tabulated in Table-1. Thus, Figure-1 shows the Receiver Operating Characteristic (ROC) curve for performance of PCA, Figure-2 shows ROC curve of FLD and Figure-3 shows ROC curve of ICA for three modalities face, palmprint and handvein.

From the Table-1 we can observe that the ICA algorithm performs well for all individual modalities. The performance of PCA is low compare to FLD and ICA, later we estimated the results for multimodal approach. Table-2 shows the results of face and palmprint combination. Table-3 gives results of face and handvein. Table-4 describes results of palmprint and handvein. And Table-5 shows performance results for combination of three modalities face, palmprint and handvein.

In Table-2 we have evaluated all the different combinations of algorithms for face and palmprint. In that the combination of face with ICA and palmprint with ICA performs better than other combinations, nevertheless the combination of face with PCA and palmprint with PCA algorithms gives comparatively performs little low than other combinations; hence Figure-4 shows the ROC curve of above combination. Table-3 and Figure-5 gives performance results of face and handvein, one can observe that face with ICA and handvein with ICA outperforms and face with PCA and handvein with FLD underperforms. From the Table-4 and Figure-6 again ICA with palmprint and handvein performs better, but FLD with palmprint and FLD with handvein is not up to the mark. Table-4 consist some of combinations of three modalities and three algorithms, face with ICA, palmprint with ICA and handvein with PCA outperforms than any other combination, consequently face with PCA, palmprint with PCA and handvein with PCA underperforms, thus Figure-7 shows the ROC curve. Hence the performance of multimodal system is dependent on modality with appropriate algorithms.

5. CHALLENGES IN DESIGNING MULTIMODAL BIOMETRIC SYSTEM

Since multimodal biometric relies on multiple information, combing the information plays an important role in designing the multimodal biometric system. The following are the challenges involved in designing the multimodal biometric system.

1. Selection of multimodal biometric source is very challenging as it depends upon the application and cost involved in acquiring the same. These also have cultural and gender dimensions under universality.
2. In multimodal biometric system the information acquired from different sources can be processed either in sequence or parallel. Hence it is challenging to decide about the processing architecture to be employed in designing the multimodal biometric system as it depends upon the application and the choice of the source. Processing is generally complex in terms of memory and or computations.
3. Since information obtained from different biometric sources can be combined at four different levels such as: sensor, feature, match score and decision level. Choosing the level of fusion will have direct impact on performance and cost involved in developing a system. Thus, it is challenging to decide the level of fusion to be employed for the given sources and application.

4. Given the biometric source and level of fusion, numbers of techniques are available for fusing the multiple source of information. Hence, it is challenging to find the optimal one for the given application.

6. SUMMARY

In this paper, we have presented a brief overview and challenges involved in designing a multimodal biometric system. In addition to this, we have also presented a brief review of related work in designing a multimodal biometric system. From this study, we can observe that. (1) The selection of modalities strongly depends upon the application and level of security involved and this will also decides the complexity in designing a system. (2) The level of fusion (like sensor, feature, match and decision) plays a crucial role in making a decision, even though the sensor and feature level fusion preserves a rich set of information these may also result in a high computation, in the same way, even though the match score level fusion deals with abstract level of information these may result in less computation. Recent studies [9] [19] have also showed that feature level fusion outperforms the match score level fusion with increased complexity. Thus, choosing the level of fusion is a challenging issue and further depends upon type of sources employed, application and the level of security. Thus, the main aim in designing a multimodal biometric system is to address the drawbacks in designing a unimodal biometric based security system such as non universality, less sensitive to spoof attacks and noise.

Even though there exist a wide range of multimodal biometric system in real time there are still open questions to address:

i. What are the best combinations (modalities)?

ii. How will we identify good combination?

iii. How to decide the number of modalities (source) in designing a multimodal biometric system.

iv. Whether multimodal biometric system will outperform multi-algorithm approaches.

v. How the modality depends on feature extraction and matching algorithms.

vi. Whether multimodal biometric system will outperform n-modal biometric system.

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Table 1. Performance in GAR at 0.1% of FAR

Method	PCA	FLD	ICA
Face	22.18	42.83	46.89
Palmprint	39.41	61.14	62.17
Handvein	12.23	23.11	44.61

Table 2. Face and Palmprint at 0.1% of FAR

Method	GRA
Face-PCA + Palm-PCA	61.18
Face-FLD + Palm-FLD	75.91
Face-ICA + Palm-ICA	78.81
Face-PCA + Palm-FLD	65.03
Face-FLD + Palm-ICA	72.55
Face-PCA + Palm-ICA	76.09

Table 3. Face and Handvein at 0.1% of FAR

Method	GRA
Face-PCA + Handvein-PCA	40.76
Face-FLD + Handvein-FLD	48.52
Face-ICA + Handvein-ICA	75.25
Face-PCA + Handvein-FLD	27.38
Face-FLD + Handvein-ICA	49.97
Face-PCA + Handvein-ICA	52.67

Table 4. Palmprint and Handvein at 0.1% of FAR

Method	GRA
Palm-PCA + Handvein-PCA	69.88
Palm-FLD + Handvein-FLD	66.12
Palm-ICA + Handvein-ICA	87.23
Palm-PCA + Handvein-FLD	43.41
Palm-FLD + Handvein-ICA	75.89
Palm-PCA + Handvein-ICA	77.09

Table 5. Face, Palmprint and Handvein at 0.1% of FAR

Method	GRA
Face-PCA + Palm-PCA + Handvein-PCA	64.23
Face-FLD + Palm-FLD + Handvein-FLD	79.87
Face-ICA + Palm-ICA + Handvein-ICA	77.63
Face-PCA + Palm-PCA + Handvein-ICA	79.92
Face-ICA + Palm-ICA + Handvein-PCA	90.00
Face-ICA + Palm-PCA + Handvein-FLD	72.31
Face-FLD + Palm-FLD + Handvein-ICA	86.17

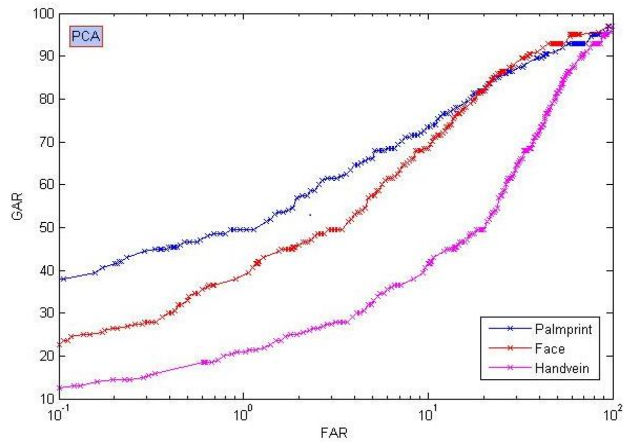

Figure 1: ROC curve for PCA

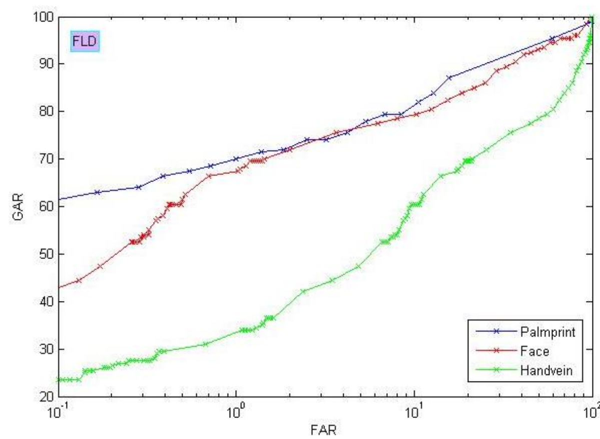

Figure-2: ROC curve for FLD

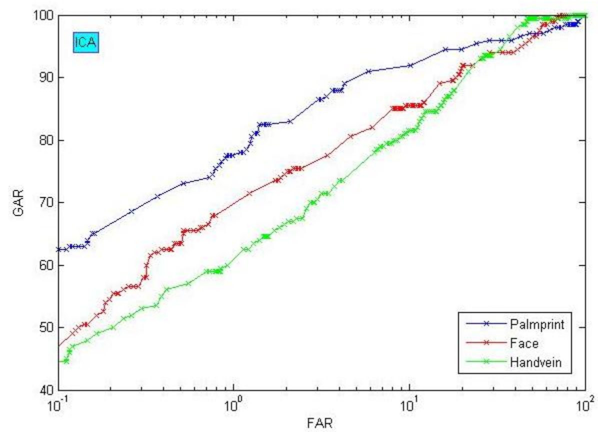

Figure-3: ROC curve for ICA

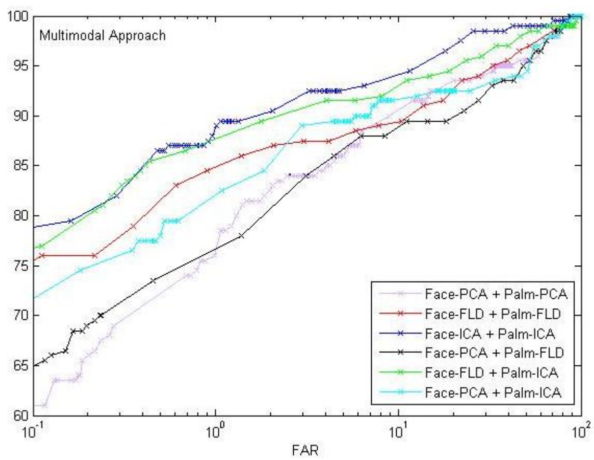

Figure-4: ROC curve for fusion of Face and Palmprint

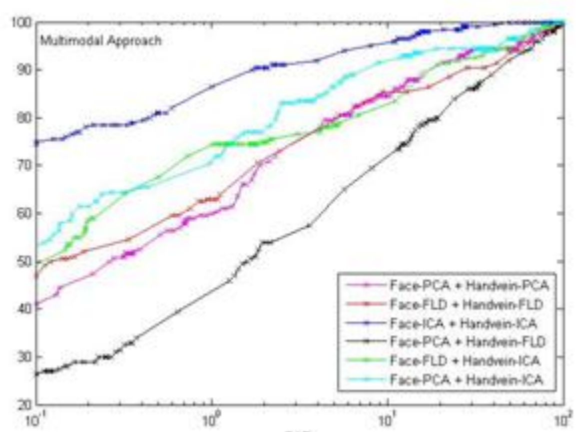

Figure-5: ROC curve for fusion of Face and Handvein

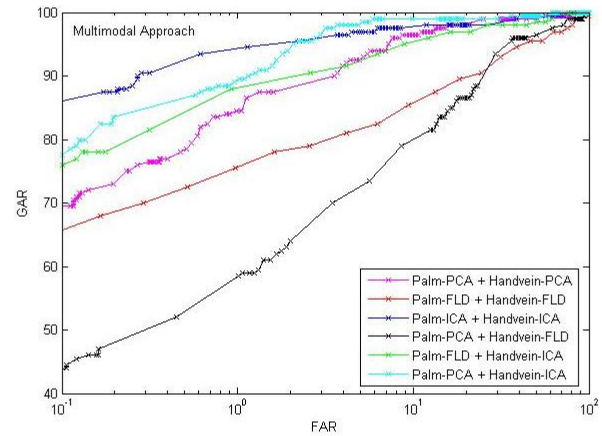

Figure-6: ROC curve for fusion of Palmprint and Handvein

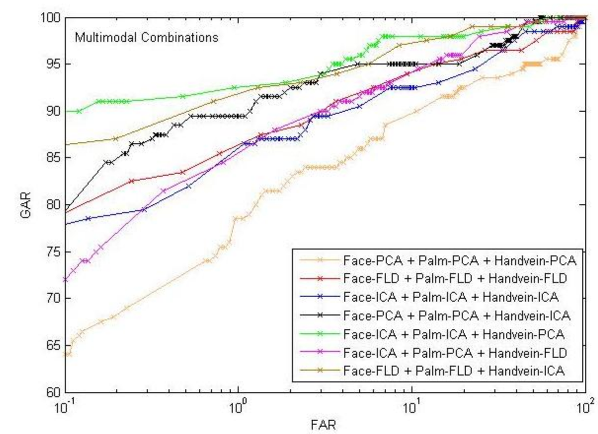

Figure-7: ROC curve for fusion of Face, Palmprint and Handvein

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