# Comparative Study of Different Fusion Techniques in Multimodal Biometric Authentication

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## ABSTRACT
Multimodal biometric authentication resolves no. of issues present in unimodal biometrics. There are number of ways for the fusion of different modalities in multimodal biometrics. Fusion could be either before matching the scores or after matching the score. The presented research paper deals with the comparative study of different techniques which performs fusion of information after matching. The researcher has tried to find the technique best for the fusion.

## General Terms
Multibiometrics, Pattern recognition

## Keyword
Multimodal biometrics, Score level fusion, Rank level fusion, Decision level fusion

## 1. INTRODUCTION
In the present era of information technology, there is a need to implement authentication and authorization techniques for security of resources. There are number of ways to prove authentication and authorization. But the biometric authentication beat all other techniques. Biometric techniques prove the authenticity or authorization of a human being based on his/her physiological or behavioral traits.

Based on the usage of number of traits, they are divided into two categories:

1. Unimodal biometrics – Use of only one trait e.g. face, fingerprint, iris, retinal, gait etc.
2. Multibiometrics – Use of two or more traits or algorithms or samples

Unimodal biometric authentication suffers from the following problems:

1. Noisy sensor data
2. Non-Universality
3. Lack of individuality
4. Lack of invariant representation
5. Susceptibility to circumvention

All these problems can be overcome with the help of multibiometric authentication. Multibiometric authentication can be achieved in different ways like:

1. Multi-algorithm systems – the same biometric data processed with different algorithms
2. Multi-sensor systems – the single biometric trait imaged using multiple sensors
3. Multi-instance systems – use of multiple instances of same biometric trait
4. Multi-sample systems – a single sensor used to get multiple samples of same biometric trait
5. Multi-modal systems – use of the evidences collected from multiple trait

The first four authentications can be achieved with the help of even single modality, while the fifth authentication can be achieved with the help of multiple modalities. Multimodal biometric authentication requires fusing information of different modalities like fingerprint, face, iris, retina, voice etc... The fusion can be achieved in two different ways. The first is information fusion prior to matching and the second method is fusion after matching [1].

### 1.1 Fusion prior to matching
Fusion prior to matching can be achieved in two different ways:

1. Sensor level fusion
2. Feature level fusion

Sensor level fusion is applicable only if the multiple sources represent samples of the single biometric trait obtained either using a single sensor or different compatible sensors.

Feature level fusion is achieved by combining different feature sets extracted from multiple biometric sources. Feature sets could be either homogeneous or heterogeneous. The consolidation of feature set creates problems as the feature sets originate from different algorithm and modalities.

### 1.2 Fusion after matching
Fusion after matching can be achieved in three different ways:

1. Matching score level fusion
2. Rank level fusion
3. Decision level fusion

Matching score level fusion provides richest set of information.

Rank level fusion consolidates the ranks output by the individual subsystems in order to derive a consensus rank of each identity. Rank level fusion provides less information with compare to match score level fusion.

Decision level fusion is carried out at decision level when the decisions output by the individual matcher are available. COTS (**C**ommercial **O**ff **T**he **S**helf) matchers provide only the final decision and those decisions are evaluated with the help of some rules like "AND" or "OR", majority voting, Bayesian decision fusion etc. Here the problem is that we have least information about the features or scores of different modalities.

The researcher has selected fusion after matching because sensor level fusion and feature level fusion sometime don't involve multiple modalities. Also we cannot ignore any data and also the fusion of data set is complex to achieve.

## 2. MATCH SCORE LEVEL FUSION

This fusion technique is also known as measurement level or confidence level fusion. It is comparatively easy to consolidate the scores generated by different biometric matchers. This method is the most commonly used method for fusion.

Here we have to identify the pattern only in two classes: genuine (Truly what something is said to be; authentic) or impostor (A person who pretends to be someone else in order to deceive others, esp. for fraudulent gain). In general there are three different methods to achieve match score level fusion. They are:

1. Density based score fusion
2. Transformation based score fusion
3. Classifier based score fusion

As the match score level fusion use scores from different modalities based on different scaling methods, the scores cannot be combined or used directly. It is required to perform score normalization, thereby converting the scores into common domain or scale.

Score normalization can be carried out with different methods. Here are some methods of normalization worked well with different modalities. Slobodan Ribaric and Ivan Fratric carried out experiments for bimodal biometrics with palmprint and facial features [2]. They adopted match score level fusion for fusion of information. They discovered new normalization technique – piecewise linear normalization. They calculated EER (Equal Error Rate) and minimum TER (Total Error Rate) with different normalization technique. They achieved EER of 2.79 % and min. TER of 5.15 % with this normalization. The chart of comparison is given below:

**Table 1. EER and Min. TER under different normalization techniques**

| Normalization Technique | Piecewise linear | median-MAD | Tanh | Minmax |
|---|---|---|---|---|
| EER | 2.79 | 2.79 | 3.05 | 3.12 |
| Min. TER | 5.15 | 5.42 | 5.74 | 6.39 |

Mingxing He et al. Proposed a new method of normalization for scores in score level fusion, Reduction of High-scores Effect normalization (RHE) [7]. They experimented on four different databases with multi modality of fingerprint, face and fingervein. They revealed that RHE performs better with compare to other techniques of score normalization in score level fusion.

**Table 2. Performance of sum rule-based fusion on NIST-multimodal database [7]**

| FAR (%) | GAR (%) | | | |
|---|---|---|---|---|
| | Minmax | Z-score | Tanh | RHE |
| 0.01 | 97.9 | 98.2 | 97.7 | 99.4 |
| 0.001 | 96.9 | 97.0 | 95.8 | 98.2 |

After performing normalization, the next step is to perform fusion of the scores. Here are some examples of different fusion models for score level fusion. Gian Luca Marcialis and Fabio Roli suggested the following model for score level fusion of fingerprint and face traits [3].

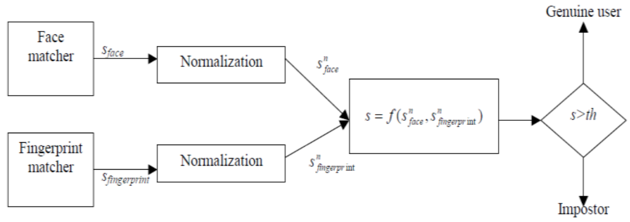


**Fig. 1: Score level fusion suggested by Roli and Marcialis [3].**

They carried out experiments on multimodal data set made up of 100 subjects with two independent face and fingerprint data sets. With the above given scheme, they achieve improvement in the error rate. Their results showed that fusion has improved the reliability of the system by reducing the gap between expected and real performance.

Feifei Cui and Gongping Yang performed biometric fusion with fingerprint and finger vein recognition [4]. They did this with score level fusion. They collected 2880 fingerprint and finger vein images from 80 fingers. With score level fusion they achieved the following performance:

**Table 3. Recognition rate for fingerprint and finger vein fusion.**

| Biometrics method | Recognition rate |
|---|---|
| Fingerprint | 95.3 % |
| Finger vein | 93.72 % |
| Score level fusion | 98.74% |

These results shows that score level fusion works well with compare to unimodal biometric traits.

Fawaz Alsaade experimented score level fusion with face and voice biometrics. He investigated the results under three data conditions and with min-max normalization. He used Adaptive Neuro – Fuzzy Inference System (ANFIS) for decision making [5]. He was able to achieve 0 % EER with ANFIS approach with clean data of both face and voice biometrics.

Table – 4 shows experimental outcomes carried out by Fawaz Alsaade.

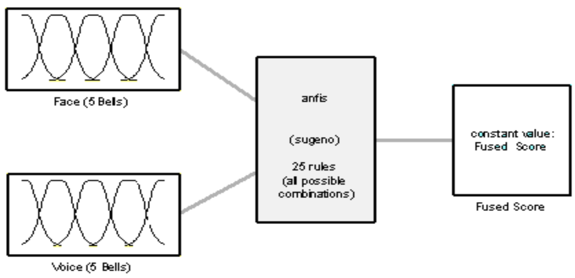


**Fig. 2: The ANFIS structure proposed by Fawaz Alsaade [5]**

**Table 4. Multimodal biometric verification based on clean biometric data [5].**

| Modality | EER% |
|---|---|
| Voice (TIMIT Database) | 2.55 |
| Face (XM2VTS Database) | 3.57 |
| Fused: voice and face by BFS (Brute force search) | 0.05 |
| Fused: voice and face by SVM | 0.68 |
| Fused: voice and face by ANFIS | 0 |

Sarat C. Dass et al. proposed a framework to combine the match score from multiple modalities with the use of likelihood ratio statistic computed using generalized densities which were estimated from genuine and impostor match scores[6]. They conducted experiments on two different databases with different number of users. The details of databases are shown in table -5:

**Table 5 – Details of databases used by Sarat Dass et al. [6].**

| Database | Modalities | No. of Users |
|---|---|---|
| MSU-Multimodal | Fingerprint, Face, Hand-geometry | 100 |
| NIST-Multimodal | Fingerprint (Two Fingers), Face (Two matchers) | 517 |

They proposed two different approaches to combine evidences based on generalized densities:

1. Product rule
2. Copula model

With the above given database and these two score fusion methods, they achieved consistently high performance.

Romaissaa Mazouni and Abdellatif Rahmoun fused face and speech modalities with five different methods of score level fusion: Particle Swarm Optimization (PSO), Adaptive Neuro Fuzzy Interface Systems (ANFIS), Genetic Algorithm (GA), Brute Force Search (BFS), and Support Vector Machine (SVM) [8]. They did their experiments with three kinds of datasets: Clean data, Varied data, Degraded data. They derived the conclusion that Genetic algorithm (GA) and Particle Swarm Optimization performed best among all five method even in worst conditions.

### 3. DECISION LEVEL FUSION

Now a day, if you are using commercial off the shelf tools for biometric verification, then decision level fusion is the only option for fusion, as they don't provide the data about the scores or feature neither they provide details about the ranking of different users after comparison. Decision level fusion is also referred as *abstract* level fusion. They only provide the result of matching in the form of whether the user is genuine or imposter. With decision level fusion, there are different rules that can be used to authenticate the user. Lam and Suen proposed majority voting rule [9].They also proposed behavioral knowledge space method. Xu et al. proposed weighted voting based on Dempster - Shafer theory [10]. Daugman proposed AND/ OR rules for deciding the decision [11].

The general and mostly used approach for decision level fusion is majority voting. Here the input sample is given the identity for which the majority of the matchers are agreed. AND and OR rules are used rarely, because as they combine two different matchers, so sometimes degradation of performance could be there with this method [11]. The main benefit of the majority voting method is that neither you require prior knowledge about the matcher nor the training is required for final decision making [1]. Domingos and Pazzani suggested that naïve Bayesian decision fusion works very well even if the matchers are dependent to each other [12].

## 4. RANK LEVEL FUSION

The rank level fusion is generally adopted for the identification of a person rather than verification. In verification, as we have to compare the template only with one template in the database, here we have to generate rank of identities in sorted order with all modalities. Then after with the help of one method of fusion, we have to fuse the ranking for each person available for different modalities. Then the identity with lowest score is identified as the correct person. This method provide more accuracy with compare to just a identifying best match with one modality. But the only thing is that, it provides less information for fusion purpose. With compare to match score level fusion, here you can easily compare the ranking from different modalities. So the decision making is easy.

Md. Maruf Monwar and Marina L. Gavrilova carried out rank level fusion with face, signature and ear biometric traits [13]. They performed experiments with PCA and fisher's LDA. The rank of individual matchers was combined with highest rank, Borda count, and logistic regression approaches. With this approach, the performance was improved performance even with low quality of data. Table 6 shows performance of the experiment.

**Table 6 – Comparison of different multibiometric systems [13].**

| Systems | Biometric identifiers | Fusion level and approach | EER |
|---|---|---|---|
| Md. Maruf Monwar et al. | Face, Ear, Signature | Rank ; logical regression | 1.12% |
| Garcia – Salicetti et al. | Signature, Voice | Match score; | 1.88% |
| Nandkumar et al. | Fingerprint | Match score | 3.39% |

Ajay kumar and Sumit Shekhar suggested combination of multiple palmprint representations to achieve improvement in the performance with compare to individual performance [14]. They performed various rank level combinations like, Borda Count, Logistic Regression, Highest rank method and Bucklin majority voting approach. With this approach, they performed experiments with NIST BSSR database. The nonlinear fusion approach gave best results for first – rank recognition rates. Average rank one recognition rate was of 99%.

With rank level fusion, three most common approaches are Borda count method, Logistic Regression method and Highest rank method. Out these three methods, Borda count and highest rank method do not use statistical information of the classifier performance. But with Logistic regression method, statistical information is required and weights are assigned to classifiers. These weights depend on the data.

Abaza and Ross performed experiments with two modalities: Fingerprint and Face [15]. They evaluated results with two databases: WVU and NIST. With Modified Highest Rank method, they achieved rank - 1accuracy of ~ 99 % on WVU dataset. They proposed Q-based rank algorithms for rank level fusion. They were able to improve the performance by ~4 %.

## 5. CONCLUSION

In today's environment, commercial biometric systems are more popular. And with these commercial systems, the person cannot get rich information about the biometrics data. But they can provide the information, which is sufficient for either rank level, decision level or score level fusion (fusion after matching). At the same time they are also efficient to give acceptable accuracy for verification and identification. From the above discussion, we can summarize that score level fusion provides more information about the biometric data compare to rank level and decision level fusion. But complexity is more. At the same time, decision level fusion provides very less data i.e. only the results of modalities, so it is very easy to implement. But rank level fusion is better than this approach, as it provides rank to different matches and also we can assign weights to some classifiers. So the researcher has concluded that for better results, one should prefer either rank level or score level fusion.

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