Fusion of Dependent and Independent Biometric Information Sources

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Project Manager: S. Dahel 613-993-9949

Contract Number: W7714-4-0-9130

Contract Scientific Authority: Q. Xiao 613-998-1245

Defence R&D Canada - Ottawa

Contract Report

DRDC Ottawa CR 2005-052

March 2005

Abstract

In this report, an overview of information fusion techniques for dependent and independent sources, specifically for biometric applications, is provided. The information fusion architecture is presented for both dependent and independent sources addressing in detail the various fusion techniques at four different levels namely: raw data or signal level, feature level, decision level and multi-level integrated fusion. Furthermore, the report addresses the question of whether independent biometric sources can be fused to provide multi-modal biometric system with enhanced performance. The report shows that even when the sources are independent, the performance of a multi-modal biometric system can be better than that of a biometric system based on single source. The performance is measured in terms of total false accept rate (FAR) and false rejection rate (FRR). The conditions for achieving an improved performance for the decision level fusion using AND, OR and majority voting are derived theoretically and confirmed through computer simulations.

Keywords: information fusion, biometrics, dependent, independent, signal fusion, feature fusion, decision fusion.

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Executive summary

Information fusion utilizes a combination of different sources of information, either to generate one representational format, or to reach a decision. Information can be from both dependent and independent sources. In this report, a literature review of information fusion techniques, in particular for biometric information fusion, is given. We classify fusion into two main categories: fusion of dependent sources and fusion of independent sources. Both categories of fusion can be carried out in four different levels: raw data level, feature level, decision level and multi-level integrated fusion. For the dependent sources, raw data level fusion is widely applied particularly in target-tracking, remote sensing image fusion, navigation, etc. However, it is not suitable for independent biometric sources since the biometric traits contain different signal formats. Feature level fusion is applicable to both independent and dependent sources. Developed methods include: nonparametric techniques (nearest-neighbor rule, Parzen window and metric classifier), soft computing techniques (MLP, RBF, SVM, GA, and fuzzy logic), unsupervised learning and clustering techniques and stochastic techniques (Bayesian classifier, HMM and EM ML). Since features from different sources are concatenated resulting in a vector with large dimensions, the problem of high dimensionality must be addressed. Features can also be used in an individual classifier, which outputs matching scores. In this scheme, rule based methods (majority voting, aggregation rules, Borda count) are in the mainstream while others such as statistical decision (Bayesian decision, DM), information based (expert system, fuzzy sets), and learning based (SVM, MLP, RBF) methods have also been proposed. Since in the case of decision level fusion, individual classifiers output a hard decision it is favorable to the independent sources while some literature exist that formulates decision level fusion for dependent sources as well. The techniques here include rule-based (majority voting, AND/OR, PROD/SUM, etc), machine learning and NN, linear classifier, statistical decision theory (ML, Bayesian, DM), fuzzy k-means, logistic regression etc. Among them, the SVM is reported to have a better performance while the rule-based algorithms are the simplest and easiest to analyze.

Preliminary theoretical analysis is developed here using decision level fusion to determine whether fusion of independent biometric sources could improve the overall identification performance. The performance is evaluated by two common indices: false acceptance rate (FAR) and false rejection rate (FRR) as well as the total error. When two independent biometric traits are used, the performance of the integrated system based on the AND/OR fusion rules is proved to give better performance in terms of total error than that of an individual biometrics under certain condition. FAR and FRR decreases with number of biometric sources. However, the FAR and FRR cannot be simultaneously reduced. To this extent, we also investigate the choice of majority voting rule for three independent source fusions in this report. Fusion of independent sources is found to produce improved performance than those of AND/OR and individual sources under certain conditions. Computer experiments are carried out to confirm the theoretical derivation and to illustrate that that fusion of independent sources is indeed possible and results in a better overall performance for biometric identification.

Li, W., Huang, D., Leung, H. 2005. Fusion of Dependent and Independent Biometric Information Sources. DRDC Ottawa CR 2005-052. University of Calgary.

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1. Introduction

Information fusion is usually considered to be combining various sources of information, either to generate one representational format, or to reach a decision. The motivations for using information fusion include: (1) Utilizing multi-sensor fusion to increase the estimation accuracy of target-tracking [1-4]; (2) Utilizing complementary information to reduce the measurement errors [5-7]; (3) Utilizing multiple classifier fusion to increase the correct classification rates [5-16]; (4) Reducing the cost of implementation possibly by using several cheap sensors rather than one expensive sensor.

For the purpose of this study, we divide information fusion into two categories: dependent and independent source fusion. Fusion under both categories can be carried out at four different levels: raw data-level fusion [22-28], feature-level fusion [29-57], decision-level fusion [58-73], and multi-level integrated fusion [74-77]. Information fusion has a wide range of applications including (1) in defense systems for target detection, identification, surveillance, tracking, and threat assessment; (2) in geoscience and Geomatics for vehicle localization and navigation, segmentation and classification of remote sensing images; (3) in robotics and intelligent vehicles that require identification of environments and navigation; (4) in medicine where information fusion is used for diagnosis and modeling of the human body, classification of different tissues, and 3D imaging; (5) in industrial engineering.

Multi-modal biometric system is a relatively new application of information fusion while individual biometrics has been used for a fairly long time. For example, fingerprint has been widely used by police for person verification and identification. To increase the reliability, biometric fusion especially multi-modal biometric fusion has drawn a lot of attention recently. Common biometrics include fingerprint [17], face [18], hand geometry, finger geometry, iris, retina, signature, voice, gait, smell, keystroke, ECG, etc [20, 21]. While unimodal biometrics uses the fusion of multiple measurements, it can be considered as the fusion of dependent sources. In the case of multi-modal biometric fusion such as fingerprint and face, the information fusion is performed over independent sources since the two sources hardly have any correlation in the statistical sense. Although many unimodal and multi-modal biometric fusion techniques have been proposed in the literature, theoretical analysis of these fusion methods has not been addressed yet. In particular, very few published papers are found that have rigorous results on multi-modal biometrics [81-83].

There are two main objectives of this report. First, an overview of information fusion techniques for dependent and independent sources, especially for the biometrics applications will be given. Various fusion techniques for dependent and independent sources are reviewed and briefly explained in the report. Second, we will address the question of whether independent biometric sources can be fused to provide a multi-modal biometric system with enhanced performance. The rest of this report is organized as follows. Section 2 introduces the architecture of information fusion. Dependent and independent sources based information fusion techniques are overviewed in Section 3 and Section 4 respectively. Section 5 presents the theoretical analysis of decision-level fusion. Simulation results are presented in Section 6. Finally, conclusions are drawn in Section 7.

2. The Structure of Information Fusion

2.1 Comparison of fusion, integration, and classification

Before discussing the structure of information fusion, we first compare the concepts of fusion, integration, and classification. Fusion and classification are compared in Figure 1. There are many kinds of information fusion applications such as multi-sensor fusion based target-tracking, navigation, image fusion, and classifier fusion. Classification can be divided into two categories: non-fusion based classifier and fusion based classifier. For classification problems, there is a common part for fusion and classification, i. e, classifier fusion. Classifier fusion is also called classifier combination by some researchers.

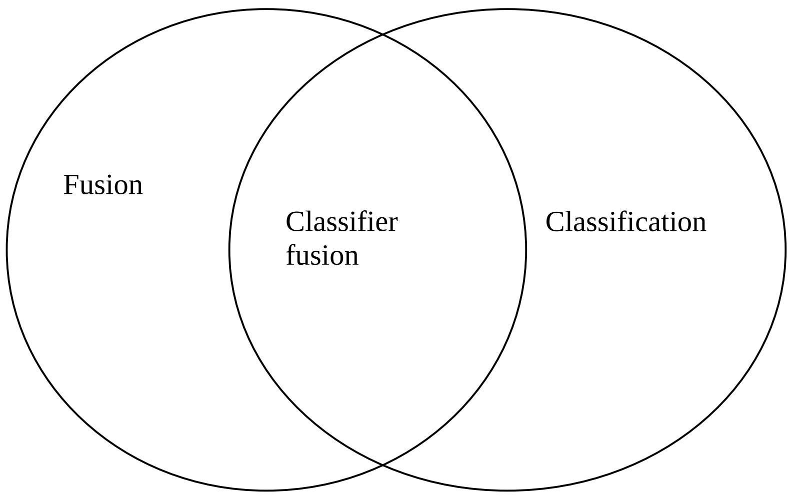


Figure 1. *Relationship between fusion and classification problems*

There is no consistent definition for multi-sensor integration in the literature. One definition is given in [4]. Multi-sensor fusion is one component of multi-sensor integration. Besides multi-sensor fusion, multi-sensor integration also includes sensor registration, sensor modeling, and other functional components.

2.2 Classification of information fusion techniques

According to the relationship of the sources to be fused, information fusion can be divided into two categories: dependent sources based and independent sources based. Each category can be further divided into four subcategories: raw sensor measurement level (sensor-level), feature-level, decision-level, and multi-level integrated fusion as shown in Figures 2.

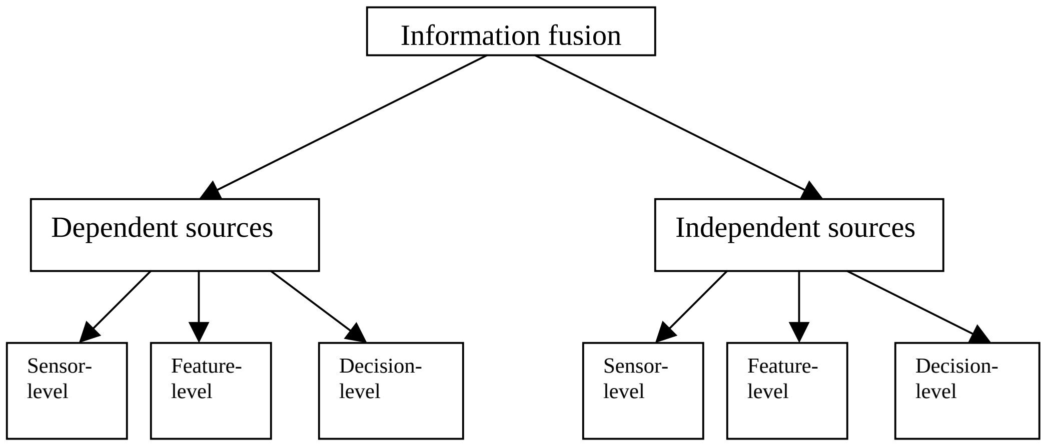


Figure 2. *Classification of information fusion techniques*

The structure of information fusion is shown in Figure 3. In the raw data-level fusion, the raw data from multiple sensors are combined directly. For example, multiple remote sensing images are fused together to produce one single image by averaging the intensities of multiple images. Random measurement noise of fingerprint images can be reduced by combining the raw images. After raw data fusion, feature is then extracted from the fused data by feature extraction module (FEM), and finally processed by the matching module (MM) and decision module (DM).

The second type is feature-based. There are two kinds of feature-based information fusion approaches. The first is feature concatenation. The feature vectors from multiple sensors are concatenated to form a new feature vector with a larger dimension. The concatenated feature vector is then input into the matching module and decision module. The second is called score-level fusion or classifier fusion by some researchers. The individual feature vectors from each sensor are first input into their own feature matching modules (FMM). Each FMM provides a matching score indicating the proximity of the feature vector with the template vector. These scores are finally combined to assert the veracity of the claimed identity.

The third type is decision-based. For each sensor, there is a decision making module that classifies its own extracted feature vector into two classes – accept or reject. The decision results (accept/reject) from multiple sensors can be fused finally by some methods such as the majority voting scheme.

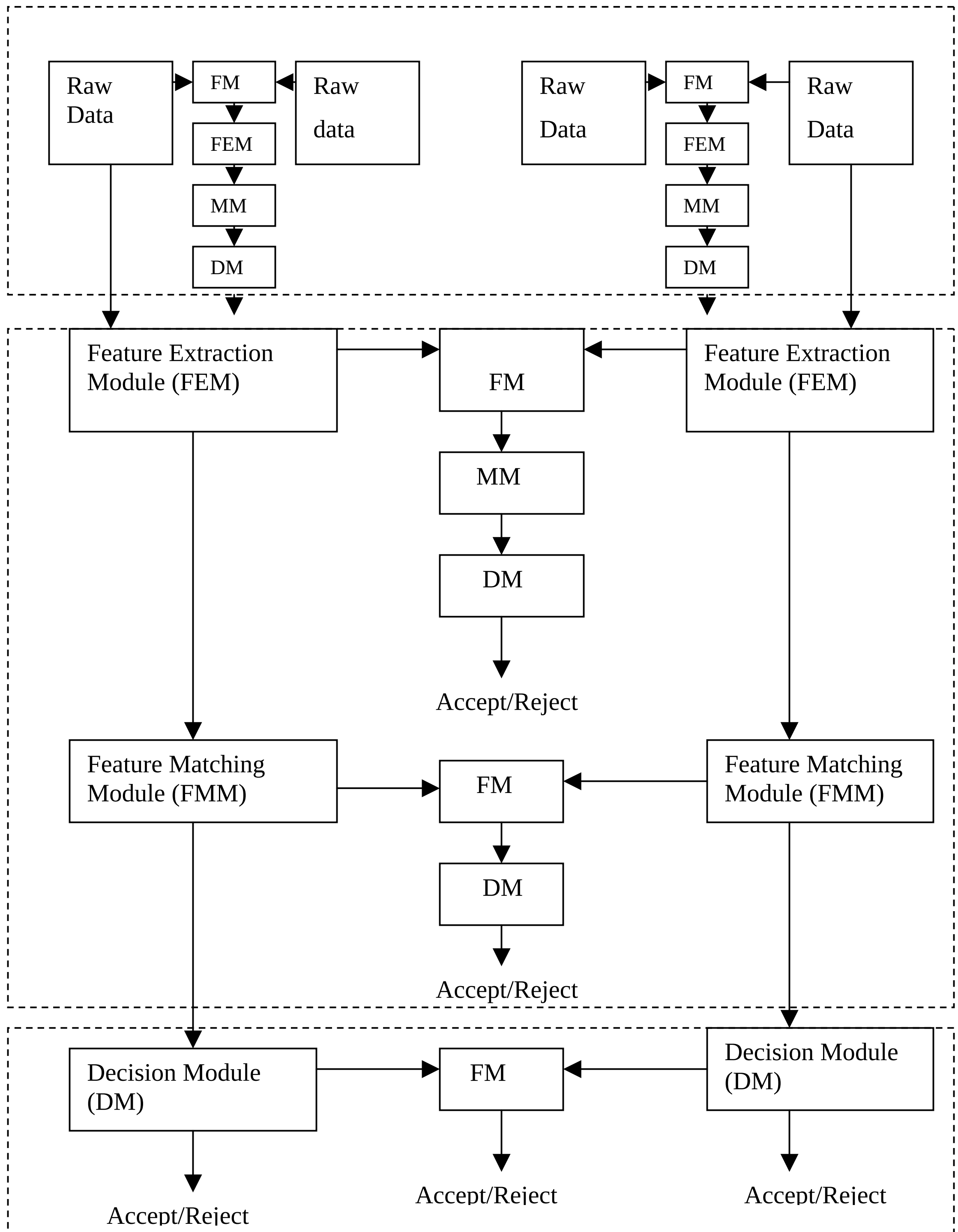


Figure 3. *Different levels of information fusion (FM: fusion module, MM: matching module, DM: decision module)*

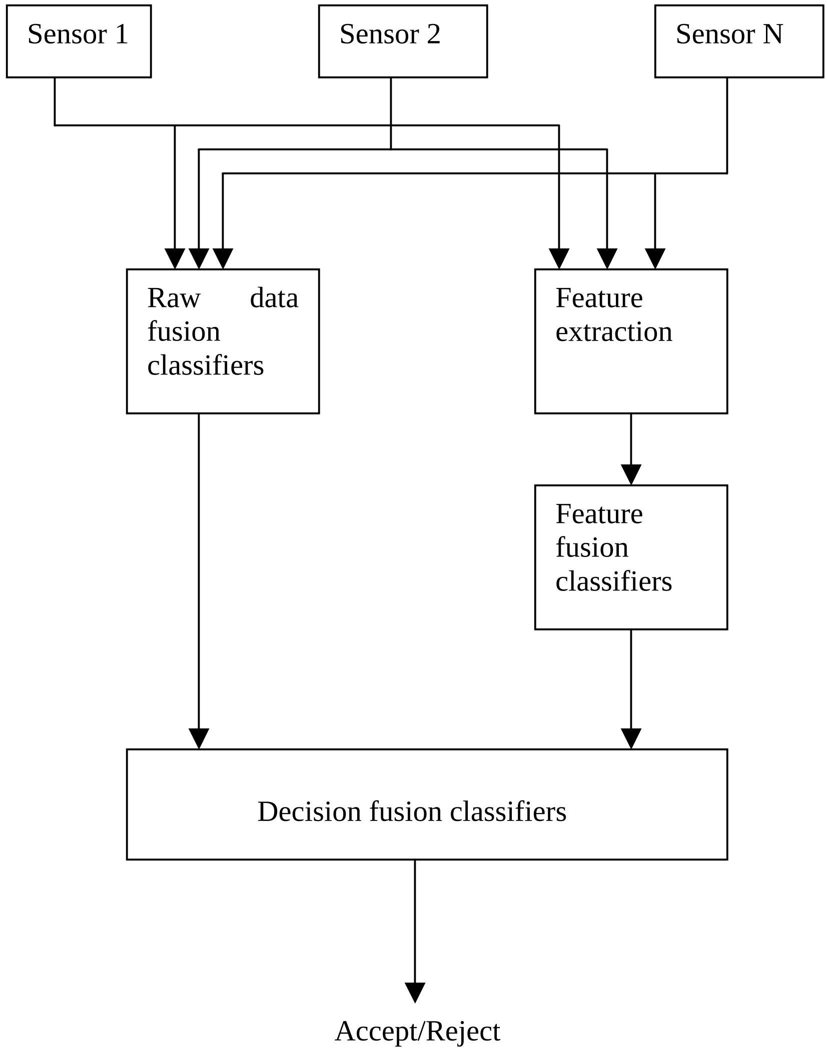


Figure 4. *The multi-level integrated fusion structure*

Some researchers have proposed multi-level integrated schemes for information fusion. Three-level integrated information fusion for classification problems is shown in Figure 4. One classifier utilizes the raw data from multiple sensors directly for classification. Another classifier utilizes the features from multiple sensors for classification. The outputs from raw data-level and feature-level fusion are then input into the decision fusion module to make a final decision – accept or reject.

3. Information Fusion for Dependent Sources

3.1 Raw data level

Different applications require different levels of information fusion. Raw data-level fusion has been widely applied for multi-sensor fusion in target-tracking, remote sensing image fusion, medical image fusion, GPS/INS navigation, etc. Although raw data-level fusion can also applied to biometric fusion, it is a less popular method compared with feature-level and decision-level fusions. In this section, raw data-level fusion techniques for non-biometric applications are reviewed. Then biometric fusion techniques are introduced.

Compared with biometric fusion, multi-sensor fusion has been employed for many applications including the most popular target-tracking application. Many multi-sensor fusion based target-tracking methods have been elaborated in [3]. The most widely used one among them is the extended Kalman filter (EKF) method, which utilizes the raw measurements of multiple sensors to estimate the states of the target. The second important application of non-biometric fusion is navigation. A comprehensive review of various methods to fuse GPS and INS sensors was given in [22]. The fusion techniques were divided into three categories as: (1) Probabilistic model; (2) Least-squares techniques: EKF, weighted EKF, fuzzy EKF, adaptive EKF [24], and optimal theory; (3) Intelligent fusion: fuzzy logic [26], neural network [23], and genetic algorithms. An optimal nonlinear filtering to integrate GPS and INS sensors was utilized in [25], while a constrained unscented Kalman filter (UKF) was used in [27] to fuse GPS, INS, and digital map information for vehicle localization. An UKF method to register and fuse dissimilar sensors was proposed in [28] for cooperative driving application. Although multiple dissimilar sensors have been fused for tracking and navigation applications, the measurements are based on the same source and hence they can be considered as dependent sources based fusion. Some dynamic modeling methods, such as gait recognition, have been proposed for biometrics and hence EKF and UKF based methods can be used for biometric fusion.

A biometric system is essentially a pattern-recognition system that recognizes a person based on a feature vector derived from specific physiological or behavior characteristic that the person possesses [13]. Biometric system can be operated in two modes: verification and identification. The commonly used biometrics include fingerprint, face, hand geometry, finger geometry, iris, voice, palmprint, DNA, ECG, signature, etc. The comparison of various biometric techniques is given in [13] and is presented in Table 1. Since, each biometric technique has its own limitations and advantages, multi-modal biometric fusion for improved performance is gaining popularity. A comprehensive overview of different multi-modal biometric fusion techniques is given in [12-16]. Raw data fusion can be used for unimodal biometric fusion. For example, multiple fingerprint images can be obtained from different sensors. Averaging of these fingerprint images can reduce the random measurement noise.

Table 1. *Comparison of various biometric technologies [2]*

Biometric characteristic	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention
Facial thermogram	H	H	L	H	M	H	L
Hand vein	M	M	M	M	M	M	L
Gait	M	L	L	H	L	H	M
Keystroke	L	L	L	M	L	M	M
Odor	H	H	H	L	L	M	L
Ear	M	M	H	M	M	H	M
Hand geometry	M	M	M	H	M	M	M
Fingerprint	M	H	H	M	H	M	M
Face	H	L	M	H	L	H	H
Retina	H	H	M	L	H	L	L
Iris	H	H	H	M	H	L	L
Palmprint	M	H	H	M	H	M	M
Voice	M	L	L	M	L	H	H
Signature	L	L	L	H	L	H	H
DNA	H	H	H	L	H	L	L

Legend: H – High M – Medium L – Low

3.2 Feature-Level

Feature-level fusion is the second category of information fusion. Based on different combination of features, we can divide it into two schemes as:

1. Features from multiple sensors are concatenated to form a new feature vector with larger dimension. The concatenated feature vector is input into a feature matching module and decision module for decision making.
2. Each feature vector from individual sensor is input into a feature matching module first. The outputs (i.e., matching scores) of the feature matching modules are fused through some methods. Feature-level fusion has been widely used for biometric fusion and target identification. We mainly discuss the biometric fusion problem here.

3.2.1 Fusion at the feature extraction level

The data obtained from each sensor and the same biometrics is used to compute a feature vector. Feature vectors from different sensors are concatenated together to form a single new feature vector. PCA and LCA may be required to reduce the dimension of the concatenated feature vector before input into a classifier. Target recognition and biometric verification and identification problems can be considered as a classification problem. The following classifiers can be used based on the concatenated feature vector [29]:

- Nonparametric techniques:
  - Nearest-Neighbor rule, k-Nearest-Neighbor rule, Parzen window, Metrics classifier
- Soft computing techniques:
  - MLP, Recurrent NN, RBF, SVM, Probabilistic NN, Fuzzy NN, ANFIS, GA
- Stochastic methods:
  - Bayesian classifier, Maximum likelihood, Component analysis, Expectation-maximization, Hidden Markov Model
- Non-metric based methods:
  - Decision trees, CART (classification and regression trees), Recognition with strings, Grammatical methods, Rule-based methods
- Unsupervised learning and clustering:
  - FCM, Unsupervised Bayesian classifier, Graph-theoretic methods.

Compared to the classifier fusion level, concatenated feature scheme is less popular. We found only two references that employ this approach to multimodal biometric fusion for independent sources and no reference was found for dependent sources based biometrics fusion.

3.2.2 Classifier fusion level

Classifier fusion and decision fusion are two of the most popular schemes for pattern recognition problems such as target classification in military applications and biometric verification and identification. Dependent sources based classifier fusion techniques can be categorized as:

- Rule based algorithms:
  - Majority voting [9, 31, 33]
  - Aggregation rules: minimum, maximum, averaging (simple averaging, optimal averaging [31], product [34], logistic rule [38], Borda count [9, 35]
- Statistical decision based algorithms:
  - Bayesian estimation [4]
  - Dempster-Shafer (DS) evidential reasoning [9]
  - Non-parametric density estimation [9]
- Information based algorithms:
  - Expert systems [34]
  - Combination by fuzzy integral [3]
  - Fuzzy sets and possibility theory [36]
- Learning-based fusion:
  - SVM, feed forward neural network, MLP, RBF [9]
- Others:
  - Linear regression [33]
  - Logistic transform [9, 37].

A Bayesian frame and DS theory was used in [31] to fuse Bayesian classifier, k-NN, and distance-based classifiers for handwriting recognition. Using some individual classifier, handwriting words were first recognized. Then the scores of the individual classifiers were combined by the Bayesian and DS methods. Their experiments showed that the correct recognition rates could be improved by about 5% compared with the individual classifiers. A method for fusing multiple instances of biometric data to improve the performance of a personal verification system was proposed in [33]. The fusion problem was formulated in the framework of Bayesian estimation theory. Experimental studies on the M2VTS database [32] showed that a reduction in error rates is up to about 40%. Four combination strategies are [32]:

Averaging

$$\hat{P}(w_j|\boldsymbol{x}) = \frac{1}{R}\sum_{j=1}^{R} P(w_j|\boldsymbol{x}) \tag{1}$$

Max rule

$$\hat{P}(w_j|\boldsymbol{x}) = \max{}_{j=1}^{R}\ P(w_j|\boldsymbol{x}) \tag{2}$$

Min rule

$$\hat{P}(w_j|\boldsymbol{x}) = \min{}_{j=1}^{R}\ P(w_j|\boldsymbol{x}) \tag{3}$$

Median rule

$$\hat{P}(w_j|\boldsymbol{x}) = median_{j=1}^{R}\ P(w_j|\boldsymbol{x}) \tag{4}$$

Expert fusion strategies, including product, min, max, median and vote, and single expert scheme were compared in [34]. It was also shown that there exists a noise level boundary across which the relative performance of classifier combination rules changes. For expert fusion techniques affected by uniform noise, it was found that the minimum and product rules were best for noise less than a particular threshold. When the noise level was greater than the threshold, the performance of these two rules degraded and the sum rule became the best one.

Borda count was used in [35] to fuse multiple algorithms for word recognition. A novel Borda count for fusion based on ranks and confidence was proposed. All experiments were performed on real-world handwritten words taken from the CEDAR benchmark database. The word recognition results were the highest (91%) among published results for handwritten words (before 2001). The proposed technique was shown in Figure 5.

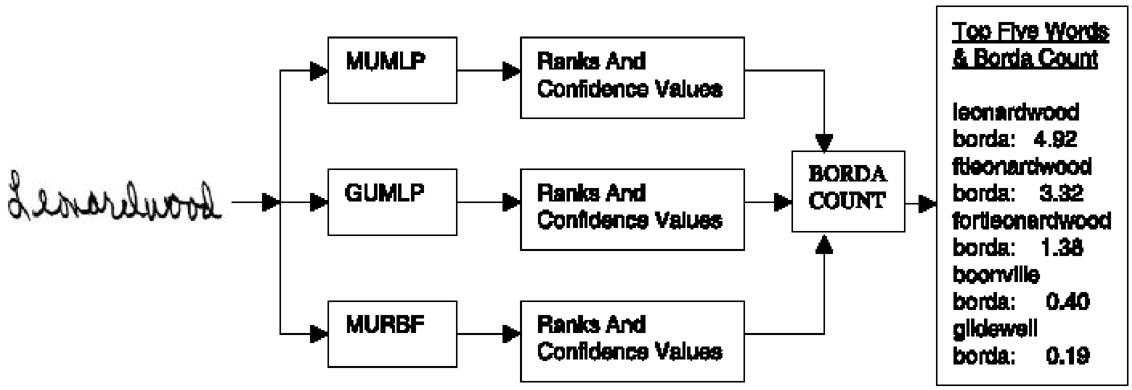


Figure 5. *The Borda count method for handwritten recognition [35].*

A method to fuse multiple handwritten word classifiers based on data-dependent densities in a Choquet fuzzy integral was proposed in [36] that outperforms neural networks, Borda count, weighted Borda counts, and Sugeno fuzzy integral (about 2% improvement). The Choquet fuzzy integral of the function *h* with respect to a fuzzy measure *g* is defined as follows:

$$e = \sum_{i=1}^{n} \left[h(x_i) - h(x_{i-1}) \right] g_i^n , \tag{5}$$

where

$$h(x_0) = 0, h(x_1) \le h(x_2) \le \Lambda \le h(x_n) ,$$

and
$$g_i^n = \begin{cases} g(\{x_i, x_{i+1}, \Lambda , \Lambda\ x_j\}), & i \le j \\ 0, & otherwise. \end{cases}$$

When fuzzy integral is applied to classifier fusion, every classifier produces a confidence value for each class. These confidence values are represented by the function *h*. The overall confidence for that class is the fuzzy integral value. The class with the largest integral value can be taken as the final decision if a crisp decision is needed.

Fingerprint matching algorithms are often based on different representations of the input fingerprints and hence complement each other. A logistic transform was used in [37] to integrate the output scores from three different fingerprint matching algorithms. Let $I_i(x_i)$ and $G_i(x_i)$ be the imposter and genuine distribution of the i^{th} matcher, *i* = 1, 2. The logistic function was used to map the output scores of these two matching algorithms into a single score. The integration scheme is shown in Figure 6. An experimental result is given in Figure 7.

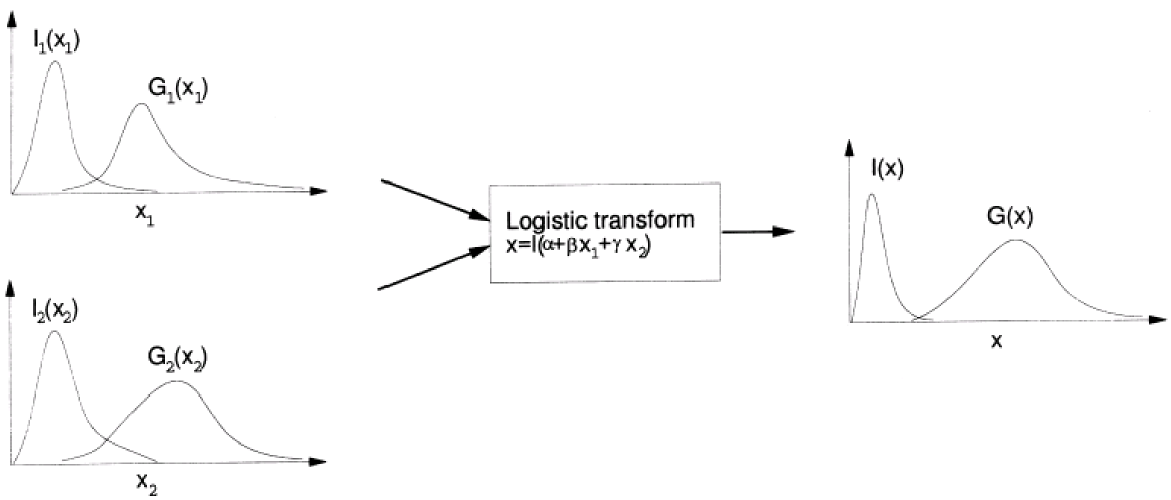


Figure 6. *Integration of two fingerprint matching algorithms using the logistic transform*

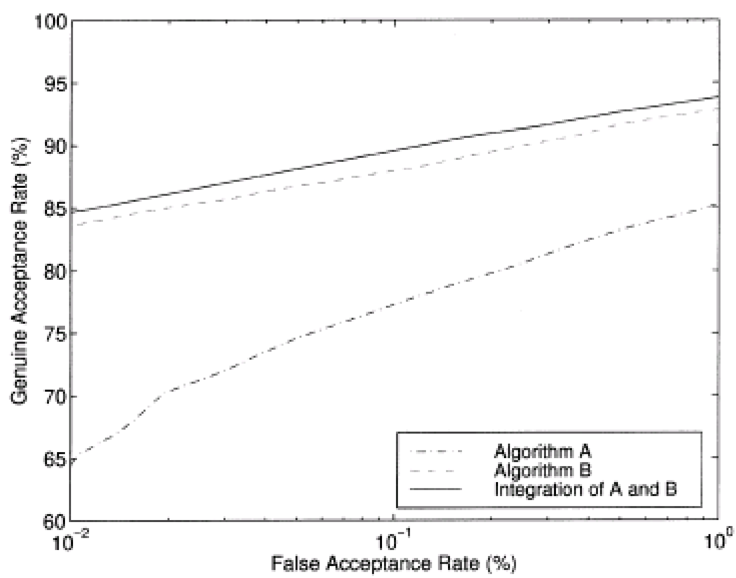


Figure 7. *ROC curves of integration of algorithms A and B*

A logistic transform method similar to [37] was proposed in [38] to fuse optimal and capacitive sensors for fingerprint verification. The logistic transformation function is defined as

$$s = \frac{1}{1 + \exp[-(w_0 + w_1 s_0 + w_2 s_c)]}. \qquad (6)$$

The ROC curves of the fusion methods are shown in Figure 8. The performance of the fusion method is better than the performance of the single classifiers.

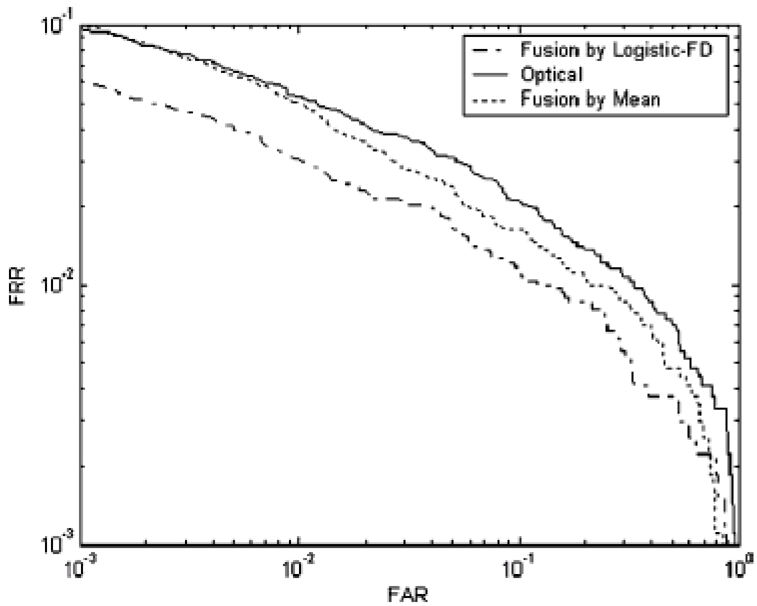


Figure 8. *ROC curves of the optical sensor and two fusion methods*

A multi-channel approach to fingerprint identification was proposed in [39]. This method was tested on 4000 images in the NIST4 database. A two-stage classifier method is proposed. This method uses K-nearest neighbor classifiers in the first stage and a set of neural network classifiers in the second stage to classify a feature vector into one of the five classes. The classification accuracy was improved from 94.8% to 96% for the five-class classification problem.

Highest rank, Borda count, and linear regression were used in [40] for word recognition. The performance of different methods was compared in Table 2. The recognition rates are improved greatly by the fusion method.

Table 2. *Performance comparison of character classifiers*

		Correct Rate (%) at Top N Choices					
Model	Classifier(s)	1	2	3	4	5	10
	PBC	79.3	87.8	91.2	92.8	94.3	97.6
	PNC	85.3	91.3	93.3	94.7	95.4	97.7
	P2N	85.8	91.9	93.9	94.9	95.7	97.9
	BBC	79.1	87.5	90.7	92.4	93.9	97.1
	BNC	84.3	90.8	93.3	94.6	95.4	97.7
	B2N	85.4	91.7	93.9	95.1	95.7	98.0
	Logistic Regression						
1	PBC, PNC	85.4	92.2	94.5	95.7	96.7	98.5
2	PBC, P2N	86.3	92.8	94.7	95.9	96.8	98.6
3	BBC, BNC	85.3	91.8	94.1	95.3	96.1	98.3
4	BBC, B2N	86.0	92.3	94.5	95.7	96.4	98.4
5	PBC, BBC	81.3	89.8	92.7	94.5	95.8	98.3
6	PNC, BNC	86.7	92.6	94.6	95.6	96.2	98.4
7	P2N, B2N	86.9	92.9	95.0	95.9	96.5	98.5
8	PBC, BBC, PNC, BNC	88.1	93.8	95.7	96.6	97.2	98.8
9	PBC, BC, P2N, B2N	88.8	94.1	95.7	96.7	97.4	98.9

3.3 Decision-Level

Very few published papers have been found for decision-level biometric fusion based on dependent sources. An optimal Neyman-Pearson rule [59] was used to combine multiple fingerprint matching algorithms at the decision-level. Experimental results conducted on a large fingerprint database (with about 2700 fingerprints) showed that the average matching performance increased by about 3%. They further showed that a combination of multiple impressions and multiple fingers improved the verification performance by more than 4% and 5%, respectively.

This method estimates the Parzen window density function based on *n* observations given by

$$P(\boldsymbol{X}) = \frac{1}{nh^d}\sum_{j=1}^{n}\left\{\frac{1}{(2\pi)^{d/2}\left|\boldsymbol{\Sigma}\right|^{1/2}}\exp\left[-\frac{1}{2h^2}(\boldsymbol{X}-\boldsymbol{X}_j)^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{X}-\boldsymbol{X}_j)\right]\right\}. \qquad (7)$$

Then the likelihood ratio $L = P(\boldsymbol{X}^d \big|_{w_0}) / P(\boldsymbol{X}^d \big|_{w_1})$ is used to make the final decision for a two-class problem: Decide D_0 (person is an imposter) for high values of *L*; Decide D_1 (person is genuine) for low values of *L*.

3.4 Multi-Level integrated fusion

A few papers were published to discuss multi-level integrated sensor fusion. Multi-level fusion was utilized in [74] for target discrimination, while it was used in [75] to gradually update the performance of identity verification systems. A distributed data fusion structure was proposed in [76] for autonomous systems, while [77] used a two-level belief function model to detect anti-personnel mines. A multi-level data fusion for intelligent navigation of telerobot was discussed in [78].

4. Information Fusion for Independent Sources

4.1 Raw data-level

Raw data-level fusion is not suitable for multi-modal biometric fusion since the raw measurements from different biometrics such as face and fingerprint cannot be combined to form a new measurement.

4.2 Feature-Level

4.2.1 Fusion at the feature extraction level

Compared with the score level fusion, concatenated feature schemes are less popular. Only a few papers were published about information fusion in the feature extraction level. A concatenated feature vector and Parzen classifier were used in [42] to fuse fingerprint and iris for improved identity verification. A new feature vector $\boldsymbol{x} = (\boldsymbol{x}_1, \boldsymbol{x}_2, \boldsymbol{x}_3)$ was formulated based on the feature vectors $\boldsymbol{x}_1$ (fingerprint), $\boldsymbol{x}_2$ (iris), and $\boldsymbol{x}_3$ (iris color). The classification rates of the fusion method are compared with single classifiers in Figure 9.

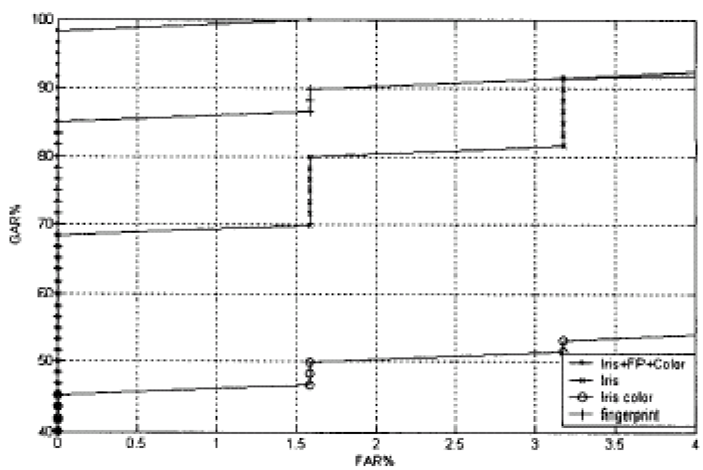


Figure 9. *Comparison of fusion method and single classifiers*

In [43], a concatenated feature scheme was proposed on fusing speech and face for person verification. The experimental results showed that for high SNRs, correct classification rates of the fusion methods were higher than that of the individual classifiers. However, for low SNRs, the correct classification rates of the fusion methods were worse than the best individual classifier.

4.2.2 Classifier fusion level

Independent sources based classifier fusion techniques can be classified as follows:

- Rule based algorithms:
  - Majority voting [51, 52, 53]
  - Aggregation rules: sum [50], minimum, maximum, averaging (simple averaging, weighted averaging [49, 52], Borda count [53], Mixed group ranks (MGR) [55]
- Statistical decision based algorithms:
  - Probabilistic fusion [52]
  - Bayesian estimation [50, 52, 53]
  - Dempster-Shafer evidential reasoning [52, 57]
  - Adaptive decision [52]
- Information based algorithms:
  - Behavior-knowledge space (BKS) [52]
  - Combination by fuzzy integral [53]
  - Fuzzy sets and possibility theory [53]
- Learning-based fusion:
  - SVM, Feedforward neural network, MLP, RBF [50, 54]
- Others:
  - Combination by Zimmermann's compensatory operator [53]
  - Score transformation
  - Reduced multivariate polynomial model for multimodal biometrics and classification fusion, [49, 56]

Face and speech was combined in [44] for person identification. The classifiers used include SVM, Bayesian classifier, decision tree, and MLP. Bayesian method is used to fuse the multiple classifiers. The ROC curves of the Bayesian fusion and single modalities are compared in Figure 10. The performance of identity verification is improved greatly by Bayesian fusion.

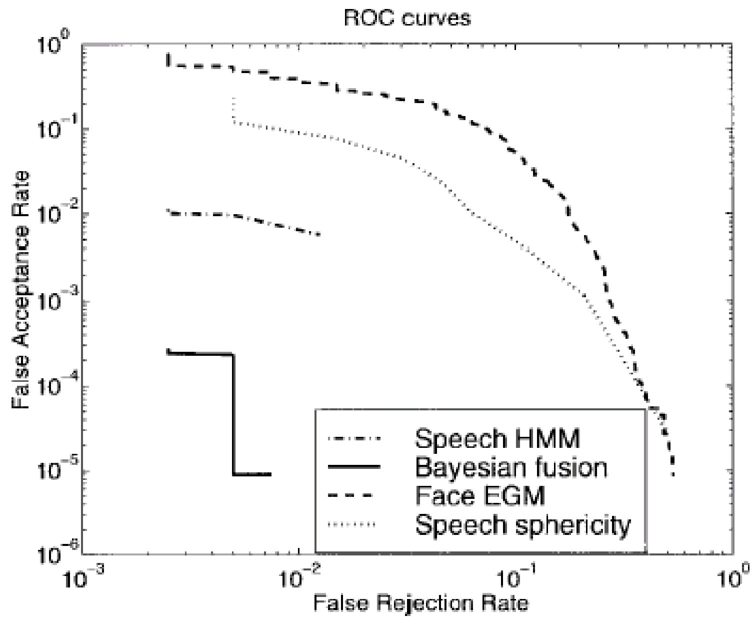


Figure 10. *ROC curves of Bayesian fusion and single modalities*

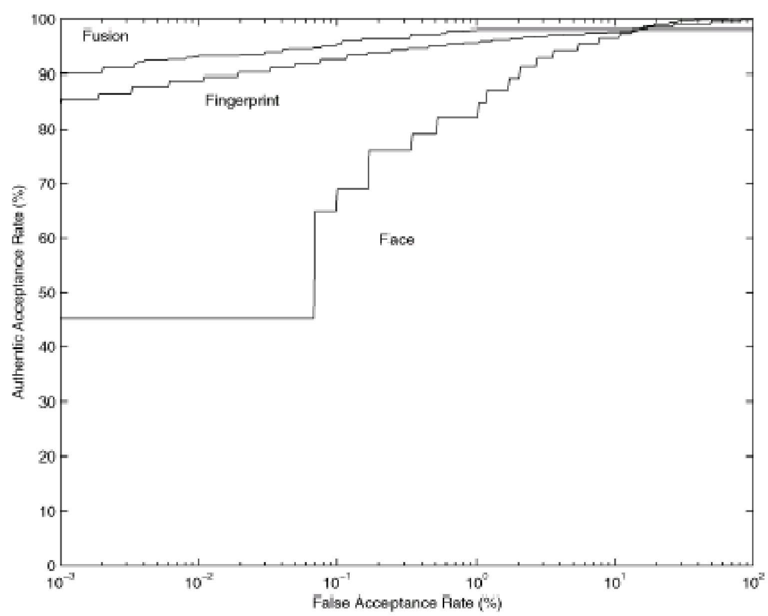


Figure 11. *ROC curves of fusion, face, and fingerprint*

Bayesian statistics fusion was used in [45] for multi-modal person authentication. HyperBF networks were used in [46] to fuse audio and video features for person identification. Faces and fingerprints were integrated in [47] for person identification. Statistical estimation method was used for fusion. The ROCs of the fusion method, face, and fingerprint are shown in Figure 11. For low acceptance rates, the performance of the fusion method is improved effectively than face-only based and fingerprint-only based methods.

A multi-modal biometric system was introduced in [48], which integrates face recognition, fingerprint verification, and speaker verification for person identification. This system takes advantage of the capabilities of each individual biometrics. It can be used to overcome some of the limitations of a single biometrics. Preliminary experimental results demonstrate that the identity established by such an integrated system is much more reliable than the identity established by a single face recognition system, fingerprint verification system, or speaker verification system.

A reduced multivariate polynomial model for classifier fusion was proposed in [49]. This method overcomes the shortcomings related to complexity of conventional multivariate polynomial model for high-dimensional problems. The authors applied the new model to fuse fingerprint and voice data for person identification. The second-order (RM2) and third-order (RM3) multivariate polynomial models are compared with unimodal biometric systems in Figure 12. The identification performance can be improved greatly by the fusion methods for low acceptance rate cases.

SVM and sum rule for fusion of fingerprint and signature were proposed in [50]. The output scores of single classifiers are used as the input of the SVM network. The output of the SVM is the final decision score. Before testing, the SVM network must be trained by some training data sets.

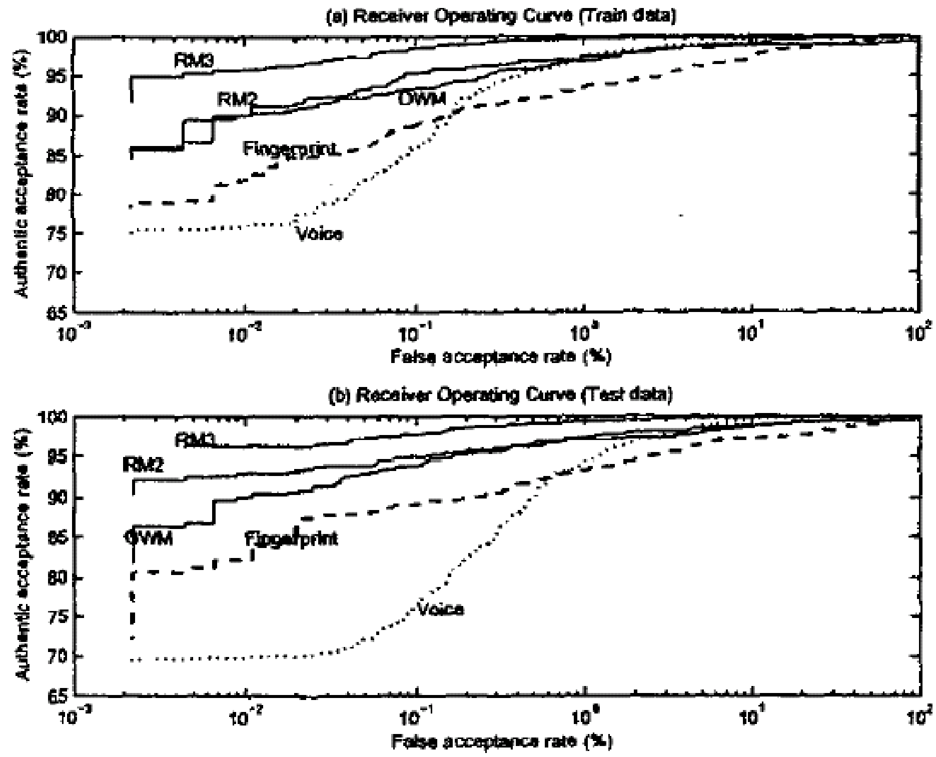


Figure 12. *ROC curves of second-order and third-order multivariate polynomial model fusion methods*

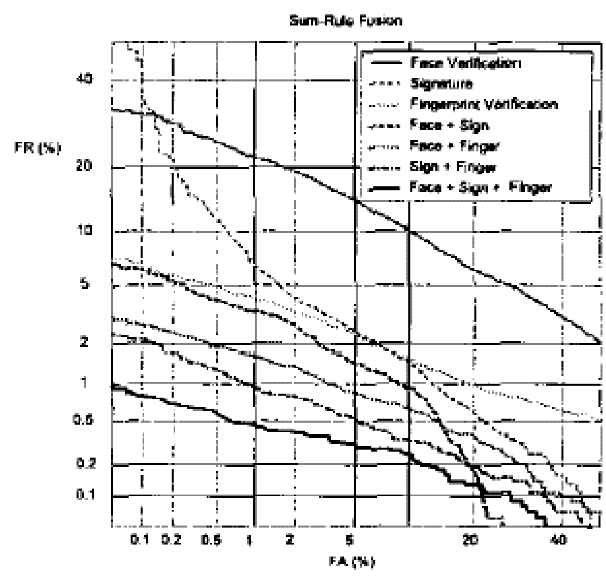


Figure 13. *ROC curves of the sum rule based fusion method*

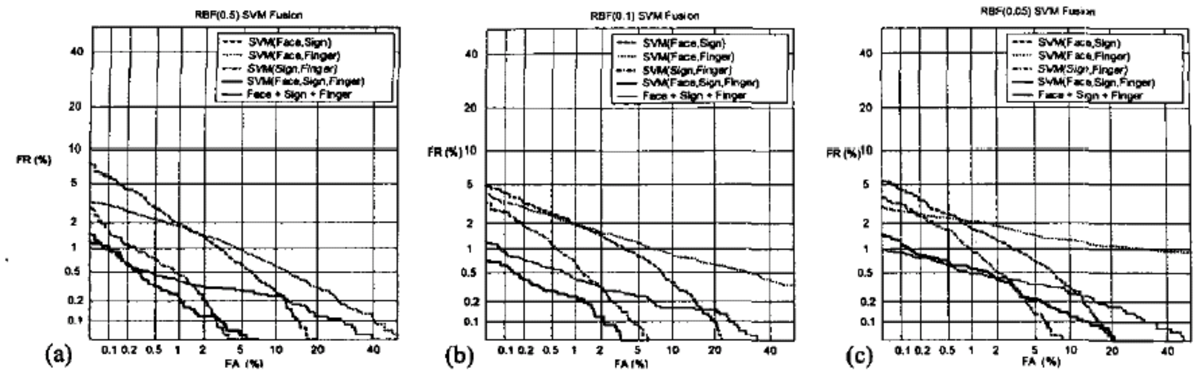


Figure 14. *ROC curves of the SVM method*

Reference [52] proposed decision templates for multiple classifier fusion, and compared it with C1: MAJ, majority voting. C2: NB, Naïve Bayesian; BKS, Behavior knowledge space method. CC1: MAX, maximum aggregation rule; MIN, minimum aggregation rule; AVR, average aggregation rule; PRO, product aggregation rule. CC2: PPR, probabilistic product; FI, fuzzy integral. CI2: DS, Dempster-Shafer, LDC, Linear discriminant classifier on the intermediate-output space; QDC, Quadratic discriminant classifier; LOG, logistic classifier; FSH, Fisher linear classifier. DT: decision templates with different models. The comparison is shown in Table 8 in [52].

Eleven classifier fusion methods were compared in [53]. The comparison included majority rule, averaging, Borda count, Bayesian combination, weighted averaging, combination by fuzzy integral, combination by fuzzy integral with data-dependent densities, combination by weighted averaging with data-dependent weights, combination by the BADD defuzzification strategy, combination by Zimmermann's compensatory operator and optimizing the fuzzy measure.

Hyperbolic function network, forward neural network, and SVM were used in [54] for classifier fusion of fingerprint and face. They treated the problem of combining fingerprint and speech biometrics decisions as a classifier fusion problem. The output scores of individual classifiers are used as the input of the neural networks, and the output scores of the NN are the final decision scores. The different NN fusion methods can improve the identification performance effectively as shown in Figure 15. The reduced multivariate polynomial model is also used in [56] for fusion of fingerprint and speaker.

A mixed group rank (MGR) method for classifier fusion was proposed in [55]. A unifying framework was proposed in this paper for combination rules of rank-based classifiers. Borda count, logistic regression, and highest rank combination are just special cases of this framework. MGR improves the correct classification rates on all tested data sets as shown in Figure 16.

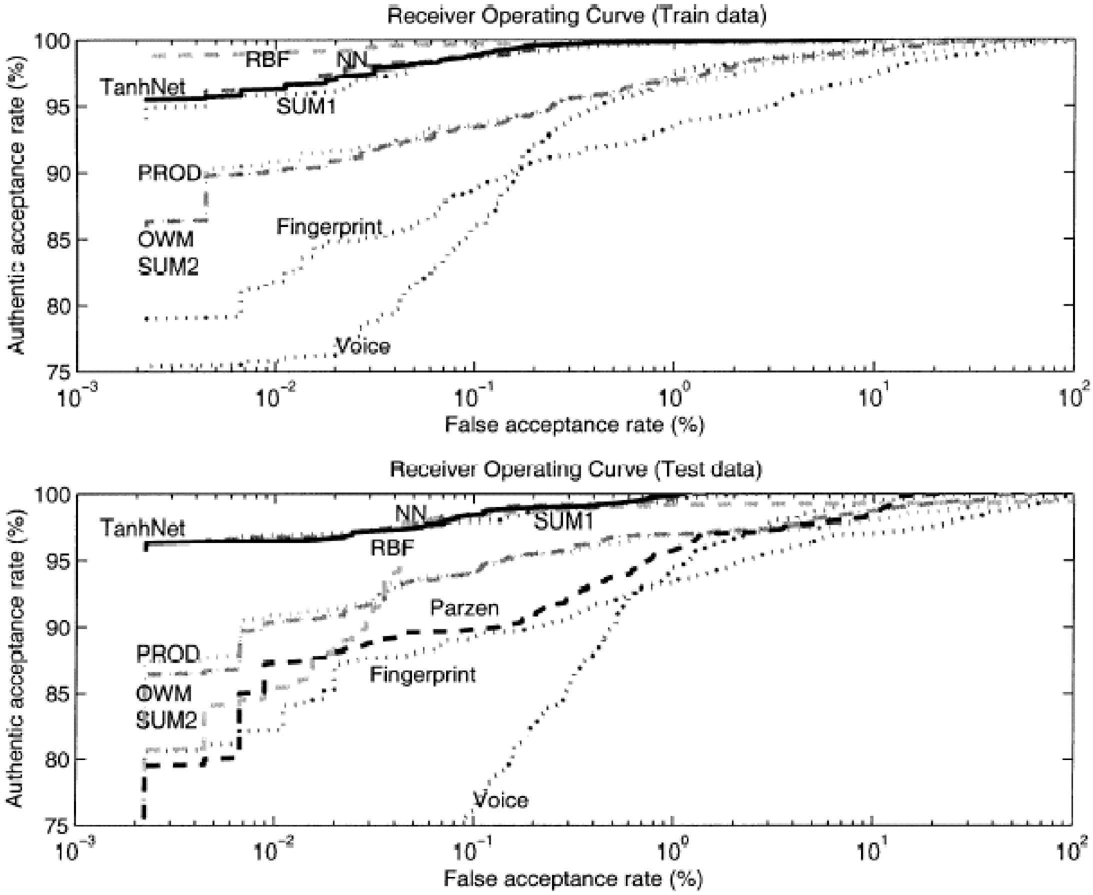


Figure 15. *ROCs of different fusion methods*

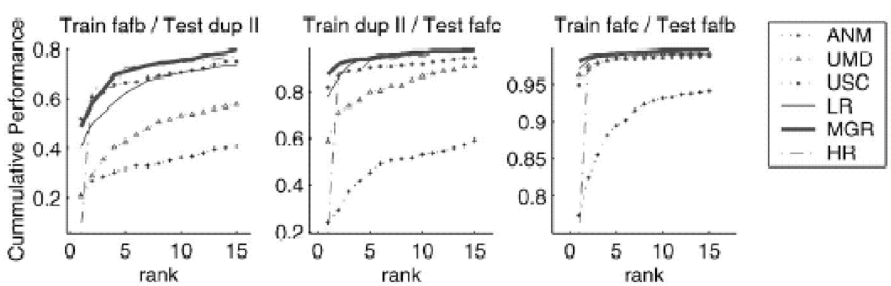


Figure 16. *The combination of three classifiers by MGR consistently demonstrates improved performance on different data sets*

4.3 Decision-Level

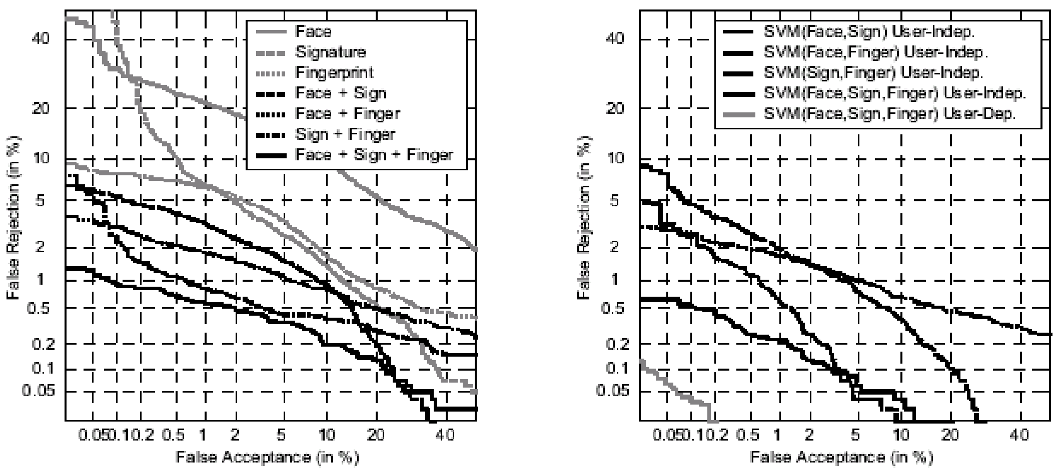
Decision-level fusion can be considered as a pattern classification problem such as biometrics fusion and target recognition. The independent sources based decision-level fusion schemes include:

- Rule based:
  - Majority voting [72], AND/OR and PROD/SUM rules [61, 73]
- Machine learning and neural network [58, 73]:
  - Expert [65], FFNN, SVM, MLP [60], fuzzy set [68], particle swarm [70, 71]
- Classifier based:
  - Linear classifier, Quadratic classifier, k-NN based classifiers, decision trees [62, 64, 66]
- Statistical decision theory [58, 67]:
  - Maximum a posterior, maximum likelihood, minmax, Bayesian [68, 70, 71], Dempster-Shafer (DS) evidence theory [68]
- Clustering for decision level fusion [69]:
  - Fuzzy k-means, fuzzy vector quantization, median radial basis function
- Others:
  - Logistic regression [58].

SVM used in [60] for decision-level multi-modal biometric fusion. Face, fingerprint and signature were used as the three biometric signals. Fusion of face, fingerprint, and signature was considered as a pattern classification problem in this paper, which was implemented through SVM. The SVM classification problem can be changed into a quadratic programming problem as shown in the following equation

$$\begin{aligned} &\textit{Minimize} \quad \frac{1}{2}\|\boldsymbol{W}\|^2 + C\sum_{i=1}^{l}\xi_i \\ &\textit{with} \quad y_i(<\boldsymbol{W}, \Phi(\boldsymbol{X}_i)>_F + b) \geq 1 - \xi_i, \quad i = 1, \Lambda\ , l\ . \\ &\qquad\quad \xi_i \geq 0, \quad i = 1, \Lambda\ , l \end{aligned} \tag{8}$$

The classification scores of unimodal biometrics are input into the SVM network, and the outputs of the SVM network are the final fused score. A training data set is first formulated and used to train the SVM network. The testing data set is then used to test the performance of the SVM fusion method. The ROC curves of fusing different sets of biometrics by SVM are shown in Figure 17. When the false acceptance rate is lower than 20%, the fused results are consistently better than that of the unimodal biometrics techniques.



(a) (b)

Figure 17. *ROC curves of SVM based multimodal biometric fusion*

Voting was used in [61] to increase the decision reliability. In majority voting, a consensus on the decision is reached by having a majority of the classifiers declaring the same decision. Decision-level fusion was considered as a classifier problem in [62]. It used k-NN, decision trees, and logistic regression in a multi-modal identification problem. An adaptive model was proposed for person identification by combining speech and image information [63]. The flowchart of the integration process is shown in Figure 18. The performance of the integration method is compared with face recognition model and speck recognition model. The average recognition rate of the integration method is about 91.6% while the recognition rates for the voice and face models are about 85% and 79.29%, respectively.

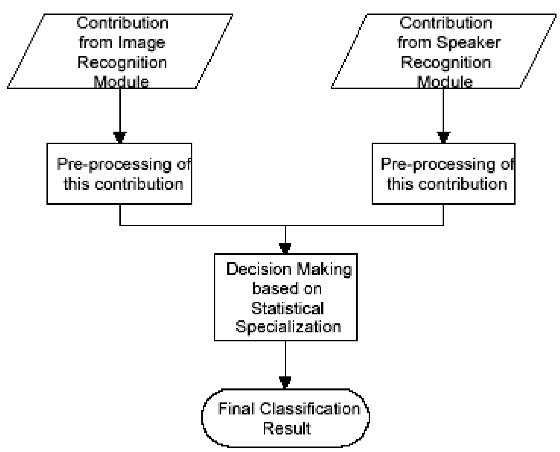


Figure 18. *Flowchart of the integration process [63]*

Table 3. *Performance of the speaker recognition, face recognition and integration models*

Person	Speaker recognition model (%)	Face recognition model (%)	Integration Model (%)
A	90	75	90
B	80	80	90
C	70	65	80
D	85	90	95
E	90	80	95
F	85	85	90
G	95	80	100
Average	85	79.29	91.43

MLP was used in [64] to implement decision fusion using face, voice, and signature. The classification scores of three classifiers for face, voice, and signature, are respectively used as the input of the MLP neural network, and the outputs of the MLP are the fused decision scores. Before testing, the MLP network must be trained by some training data sets. Without fusion, the recognition rates for voice, face, and signature are 89%, 99.5%, and 93%, respectively. The recognition rate with fusion is 100%.

Speech and face were fused in [65] by expert systems. SVM and vote rules were used for expert fusion. The authors investigated the behavior knowledge space and decision templates methods of classifier fusion in the context of multi-modal personal identity verification. The two fusion rules have been compared to simple combination rules, namely sum and vote, which do not require any training. Through extensive experiments on the XM2VTS database, they found that all these four combination methods yielded performance improvement. But no strong evidence had been found to support the hypothesis that trainable fusion strategies could offer better performance than simple rules.

Both global and local decisions for person identification based on multivariate polynomial model was exploited in [67]. The general multivariate polynomial model can be expressed as

$$g(\boldsymbol{\alpha}, \boldsymbol{x}) = \sum_{i=1}^{K} \alpha_i x_1^{n_1} x_2^{n_2} \Lambda \ x_l^{n_l} . \tag{9}$$

The computation complexity of the model represented in (9) is very high for high dimensional data sets. So a reduced multivariate polynomial model was proposed for multi-biometric fusion. This new model was defined as

$$g_{RM}(\boldsymbol{\alpha}, \boldsymbol{x}) = \alpha_0 + \sum_{k=1}^{r}\sum_{j=1}^{r}\alpha_{kj}x_j^k + \sum_{j=1}^{r}\alpha_{rl+j}(x_1 + x_2 + \Lambda + x_l)^j + \sum_{i=2}^{r}(\boldsymbol{\alpha}_j^T \boldsymbol{x})(x_1 + x_2 + \Lambda + x_l)^j. \quad (10)$$

Experiments showed that the fusion methods can improve the performance of person identification effectively (as shown in Figure 19).

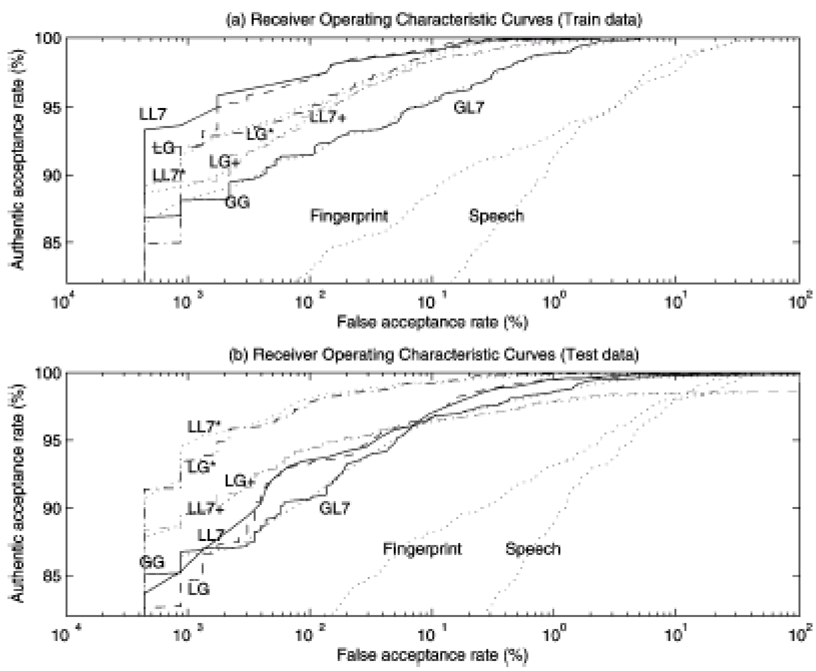


Figure 19. *ROC curves of the fusion methods*

An overview of different decision level fusion techniques including Bayesian estimation, DS, and fuzzy sets was given in [68]. Clustering was used in [69] for multi-modal decision fusion. Person authentication results coming from several modalities are combined by using fuzzy k-means (FKM), fuzzy vector quantization (FVQ), and median radial basis function (MRBF) network. Simulations showed that MRBF had better performance. Both [70] and [71] proposed a particle swarm optimization method to search for the best Bayesian decision rule which was used for fusing face, voice, and hand. The flowchart of this method is shown in Figure 20.

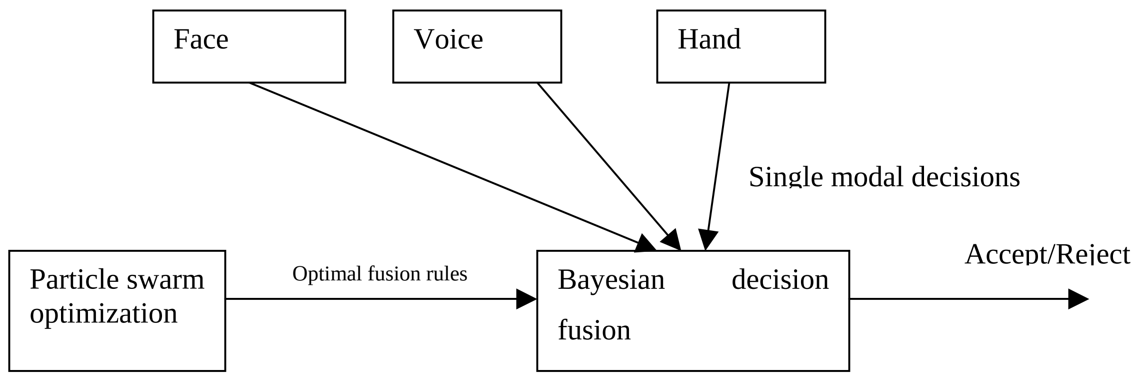


Figure 20. *Flowchart of particle swarm optimization and Bayesian fusion*

Face and ECG were fused in [72] for person identification. Mono-modal biometric identification systems exhibit performance that may not be adequate for many security applications. Face and fingerprint modalities dominate the biometric verification / identification field. However, both face and fingerprint can be compromised using counterfeit credentials. Previous research has demonstrated the use of the electrocardiogram (ECG) as a novel biometric. This paper explored the fusion of a traditional face recognition technique with ECG. System performance with multi-modality fusion can be superior to reliance on a single biometric trait.

A multi-modal approach for speaker verification was described in [73]. The system consists of two classifiers, one using visual features and the other using acoustic features. A lip tracker is used to extract visual information from the speaking face which provides shape and intensity features. They used a weighted summation method to integrate the scores of multiple classifiers. The performance of the integrated system outperformed each sub-system and reduced the false acceptance rate of the acoustic sub-system from 2.3% to 0.5%.

5. Theoretical Analysis for Decision Level Fusion

Decision level fusion of independent sources is considered here. For instance, two independent sources are face and voice. Fusion scheme using these two sources is denoted by A. Verification system based only on face is denoted by A_1, while on voice by A_2. If A_1 provides 95% correct classification rate (CCR) and A_2 provides only 80% CCR individually, then it is interesting to find if A can provide CCR higher than 95%, if so, what is any condition or what kind of algorithm can reach this confidence level. If Γ is an algorithm, then the task is to find Γ which acts on independent sources so that the output is maximized. This can be written as

$$\hat{\Gamma} = \max_{\Gamma \in \Omega} \Gamma(A_1, A_2) . \tag{11}$$

At first, we give two important performance indices in biometrics authentication system. The first is false acceptance rate denoted FAR hereafter which means wrongly identifying an imposter to be an enrollee. The other index is false rejection rate denoted by FRR which means wrongly identifying an enrollee as an imposter.

$$FAR(t) = P(\hat{w}_1 | w_0) = \int_{R_1} p(X | w_0) dX = 1 - \int_{R_0} p(X | w_0) dX , \tag{12}$$

$$FRR(t) = P(\hat{w}_0 | w_1) = \int_{R_0} p(X | w_1) dX \tag{13}$$

where w_1 denotes the genuine user while w_0 denotes the imposter. R_0 and R_1 are two exclusive set in the real axis. Both FAR and FRR are desirable to be as low as possible in authentication system. In some systems, a low value for FAR is emphasized. Such systems include bank authentication system, military access control unit, etc. For any biometrics authentication system, whatever classifier takes, there exists a great risk of error. From the viewpoint of Bayesian decision theory, this is represented by the following equations for a two class problem,

$$E(t) = C_r \times FRR(t) + C_a \times FAR(t) , \tag{14}$$

$$E_i(t_i) = C_r^i \times FRR^i(t_i) + C_a^i \times FAR^i(t_i), \; for \; i = 1, \Lambda , N \tag{15}$$

where, N is the total sensor number, C_r denotes the loss function pertinent to the false rejection, and C_a denotes the loss function for the false acceptance. For simplicity, we assume that $C_a = C_a^i$ and $C_r = C_r^i$.

5.1 Using AND rule

First we analyze the performance of fusing two biometric signals. In this case, the relationships of FAR and FRR between two individual classifiers and the integrated classifier are represented by the following formulas, respectively,

$$FAR(t) = FAR^1(t_1) \times FAR^2(t_2)\,, \tag{16}$$

$$FRR(t) = FRR^1(t_1) + FRR^2(t_2) - FRR^1(t_1) \times FRR^2(t_2)\,. \tag{17}$$

Remark 1 Using an example to explain (16) and (17) clearly, we assume that $FAR^1 = 0.01$ and $FAR^2 = 0.05$. If there are 10000 imposters presented to B_1, then according to FAR^1 there will be 100 imposters passed by B_1. Because of the AND rule, only five imposters of 100 imposters can pass B_2 by FAR^2. Thus the false acceptance rate of the integrated system is calculated by

$$\frac{Number\ of\ \ false\,accept}{Number\ of\ imposter} = \frac{5}{10000} = 0.0005$$

which can be calculated from (16) as $FAR(t) = 0.01 * 0.05 = 0.0005$.

In a similar way, we assume that $FRR^1 = 100/1100 = 0.091$ and $FRR^2 = 50/1000 = 0.05$. Then it follows by the AND rule that if 1100 genuine users present, as a result there are 950 users passed by the integrated system which gives the false rejection rate

$$FRR\,\frac{Number\ of\ \ false\,rejections}{Number\ of\ genuine} = \frac{1100 - 950}{1100} = 0.136\,.$$

It is calculated by (17), i.e., $FRR(t) = 0.091 + 0.05 - 0.091 \times 0.05 = 0.136$.

Lemma 1 If using AND rule on the independent sources, then for fixed operating point of B_2, the integrated system can improve the performance over the individual classifiers under the following condition in the sense of the total error.

$$(1 - k_1 FAR^1(t_1)) \le FRR^1(t) \le k_2(1 - FAR^1(t_1)) \tag{18}$$

where

$$k_1 = \frac{C_a}{C_r} \frac{1 - FAR^2(t_2)}{FRR^2(t_2)}, \tag{19}$$

$$k_2 = \frac{C_a}{C_r} \frac{FAR^2(t_2)}{1 - FRR^2(t_2)}. \tag{20}$$

However, the integrated system will increases FRR while decreases the FAR.

Proof: It is enough to prove that $E(t) \le E_i(t_i)$. This leads to the following equations by substituting (16) and (17) into $E(t)$,

$$C_r FRR^2(t_2)(1 - FRR^1(t_1)) \le C_a FAR^1(t_1)(1 - FAR^2(t_2)), \tag{21}$$

$$C_r FRR^1(t_1)(1 - FRR^2(t_2)) \le C_a FAR^2(t_2)(1 - FAR^1(t_1)). \tag{22}$$

From (21) and (22), it can be easily seen that to get improved performance, a proper relationship should be developed between the operating points of two systems. In fact, at some operating points, (21) and (22) will not hold, which indicates that the performance cannot be improved for the AND rule based fusion.

If the classifier B_2 operates at some fixed $(FAR^2(t_2), FAR^2(t_2))$ we can derive conditions for B_1 from (21) and (22). That is,

$$1 - k_1 FAR^1(t_1) \le FRR^1(t_1) \le k_2(1 - FAR^1(t_1)). \tag{23}$$

From (16), it is straightforward that $FAR(t) < FAR^1(t_1)$ and $FAR(t) < FAR^2(t_2)$. This means the integrated system decreases FAR. But from (17), $FRR(t) > FRR^1(t_1)$ and $FRR(t) > FRR^2(t_2)$ hold. Thus, the FRR increases.

Equations (16) and (17) can be easily generalized to the cased with more than two biometrics. For $N = 3$, we have,

$$FAR(t) = FAR^1(t_1) \times FRR^2(t_2) \times FRR^3(t_3), \tag{24}$$

$$\begin{aligned} FRR(t) = {} & FRR^1(t_1) + FRR^2(t_2) + FRR^3(t_3) \\ & - (FRR^1(t_1) \times FRR^2(t_2) + FRR^1(t_1) \times FRR^3(t_3) + FRR^2(t_2) \times FRR^3(t_3)). \\ & + FRR^1(t_1) \times FRR^2(t_2) \times FRR^3(t_3) \end{aligned} \tag{25}$$

5.2 Using OR rule

For the OR rule, similar to the AND rule, we can easily derive the following relationships of FAR and FRR between the individual classifiers and the integrated classifier.

$$FRR(t) = FRR^1(t_1) \times FRR^2(t_2)\,, \tag{26}$$

$$FAR(t) = FAR^1(t_1) + FAR^2(t_2) - FAR^1(t_1) \times FAR^2(t_2)\,. \tag{27}$$

Therefore, without any further proof, we can state the following conclusion similar to Lemma 1.

Lemma2 If using OR rule on the independent sources, then for fixed operating point of B_2, the integrated system can improve the performance over the individual classifiers under the following condition in the sense of total error.

$$k_2(1 - FAR^1(t_1)) \le FRR^1(t_1) \le (1 - k_1 FAR^1(t_1))\,. \tag{28}$$

However, the integrated system will increases FAR while decreases the FRR.

Equations (26) and (27) can be generalized for the cases with more biometrics. For N = 3, we have

$$FRR(t) = FRR^1(t_1) \times FRR^2(t_2) \times FRR^3(t_3)\,, \tag{29}$$

$$\begin{aligned} FAR(t) = {} & FAR^1(t_1) + FAR^2(t_2) + FAR^3(t_3) \\ & - (FAR^1(t_1) \times FAR^2(t_2) + FAR^1(t_1) \times FAR^3(t_3) + FAR^2(t_2) \times FAR^3(t_3))\,. \\ & + FAR^1(t_1) \times FAR^2(t_2) \times FAR^3(t_3) \end{aligned} \tag{30}$$

5.3 Using majority voting rule

Assume that there are N independent sources. For the i^{th} source, an individual classifier B_i exists with false accept rate and false rejection rate $\{FAR^i(t_i), FRR^i(t_i)\}$. If at least $\frac{N+1}{2}$ classifiers wrongly accept an imposter simultaneously, then by the majority voting rule, the integrated system will accept the imposter. Since each individual classifier is independent, the joint probability of the classifiers is represented by

$$P(r_1,\Lambda\ , r_N) = \left[FAR^1(t_1)\right]^{r_1}\left[1-FAR^1(t_1)\right]^{1-r_1}\left[FAR^2(t_2)\right]^{r_2}\left[1-FAR^2(t_2)\right]^{1-r_2} \\ \times\Lambda\ \times\left[FAR^N(t_N)\right]^{r_{N1}}\left[1-FAR^N(t_N)\right]^{1-r_N}. \tag{31}$$

The probability of at least $\frac{N+1}{2}$ classifiers wrongly identifying an imposter is then calculated by

$$\begin{aligned} FAR(t) &= \sum_{r_1+\Lambda\ +r_N>(N+1)/2} P(r_1,\Lambda\ , r_{N)} \\ &= \sum_{r_1+\Lambda\ +r_N>(N+1)/2} \begin{matrix} \left[FAR^1(t_1)\right]^{r_1}\left[1-FAR^1(t_1)\right]^{1-r_1}\left[FAR^2(t_2)\right]^{r_2}\left[1-FAR^2(t_2)\right]^{1-r_2} \\ \times\Lambda\ \times\left[FAR^N(t_N)\right]^{r_{N1}}\left[1-FAR^N(t_N)\right]^{1-r_N}. \end{matrix}. \end{aligned} \tag{32}$$

For $N = 3$, we have,

$$\begin{aligned} FAR(t) &= FAR^1(t_1)FAR^2(t_2) + FAR^2(t_2)FAR^3(t_3) - 2FAR^1(t_1)FAR^2(t_2)FAR^3(t_3) \\ &= FAR^1(t_1)FAR^2(t_2)(1-FAR^3(t_3)) + FAR^1(t_1)(1-FAR^2(t_2))FAR^3(t_3) \\ &\quad + (1-FAR^1(t_1))FAR^2(t_2)FAR^3(t_3) + FAR^1(t_1)FAR^2(t_2)FAR^3(t_3). \end{aligned} \tag{33}$$

Similarly, for $N = 3$, we have

$$\begin{aligned} FRR(t) &= FRR^1(t_1)FRR^2(t_2) + FRR^2(t_2)FRR^3(t_3) - 2FRR^1(t_1)FRR^2(t_2)FRR^3(t_3) \\ &= FRR^1(t_1)FRR^2(t_2)(1-FRR^3(t_3)) + FRR^1(t_1)(1-FRR^2(t_2))FRR^3(t_3) \\ &\quad + (1-FRR^1(t_1))FRR^2(t_2)FRR^3(t_3) + FAR^1(t_1)FAR^2(t_2)FAR^3(t_3). \end{aligned} \tag{34}$$

If the integrated system $FAR(t) \le FAR^1(t_1)$, then we have

$$FAR^1(t_1)FAR^2(t_2) + FAR^2(t_2)FAR^3(t_3) - 2FAR^1(t_1)FAR^2(t_2)FAR^3(t_3) \le FAR^1(t_1). \tag{35}$$

The following equation can be derived from (35),

$$FAR^1(t_1) \ge \frac{FAR^2(t_2)}{1+\left(1-FAR^2(t_2)(1-2FAR^3(t_3)\right)/FAR^3(t_3)}. \tag{36}$$

For $FAR(t) \le FAR^2(t_2)$, we have

$$FAR^2(t_2) \geq \frac{FAR^1(t_1)}{1+\left(1-FAR^1(t_1)(1-2FAR^3(t_3)\right)\big/FAR^3(t_3)}. \tag{37}$$

For $FAR(t) \leq FAR^3(t_3)$,

$$FAR^3(t_3) \geq \frac{FAR^1(t_1)}{1+\left(1-FAR^1(t_1)(1-2FAR^2(t_2)\right)\big/FAR^2(t_2)}. \tag{38}$$

If the FRR of the integrated system is smaller than that of the individual classifier, the following conditions should be satisfied.

For $FRR(t) \leq FRR^1(t_1)$,

$$FRR^1(t_1) \geq \frac{FRR^2(t_2)}{1+\left(1-FRR^2(t_2)(1-2FRR^3(t_3)\right)\big/FRR^3(t_3)}. \tag{39}$$

For $FRR(t) \leq FRR^2(t_2)$, we have

$$FRR^2(t_2) \geq \frac{FRR^1(t_1)}{1+\left(1-FRR^1(t_1)(1-2FRR^3(t_3)\right)\big/FRR^3(t_3)}. \tag{40}$$

For $FRR(t) \leq FRR^3(t_3)$,

$$FRR^3(t_3) \geq \frac{FRR^1(t_1)}{1+\left(1-FRR^1(t_1)(1-2FRR^2(t_2)\right)\big/FRR^2(t_2)}. \tag{41}$$

5.4 Soft decision level fusion

For simplicity, we discuss integration of two biometric systems denoted by Ψ_1 and Ψ_2, respectively. The integrated system is denoted by Ψ. The outputs by individual systems Ψ_1 and Ψ_2 are called scores, which stand for the probability of claimant to be a genuine or an imposter. Then for any fusion strategies, an error is expressed as (14) and (15). If we assume that $E_1(t_1) \le E_2(t_2) \le \Lambda \le E_N(t_N)$, then it is easily known it is sufficient to prove that $E(t) \le E_1(t_1)$. For a two-sensor fusion, if Bayesian rule is chosen, then this means that

$$\begin{array}{ll} \text{Decide} & w_0, \text{if } (X_1, X_2) \in R \\ \text{Decide} & w_1, \textit{otherwise} \end{array} \tag{42}$$

where $R = \left\{(X_1, X_2) \middle| C_r\, p(X_1, X_2|w_0) \ge C_a\, p(X_1, X_2|w_1)\right\}$. Since Ψ_1 and Ψ_2 are independent, we have

$$p(X_1, X_2|w_0) = p_1(X_1|w_0)\, p_2(X_2|w_0),$$

$$p(X_1, X_2|w_0) = p_1(X_1|w_0)\, p_2(X_2|w_0). \tag{43}$$

Then

$$\begin{aligned} FAR(t) &= 1 - \int_{R_0} p(X_1, X_2|w_0)\, dX_1 dX_2 \\ &= 1 - \int_{R_0} p_1(X_1|w_0)\, dX_1 \int_{R_0} p_2(X_2|w_0)\, dX_2 \\ &= 1 - (1 - FAR^1(t_1))(1 - FAR^2(t_2)). \end{aligned} \tag{44}$$

It can be easily seen from (44) that $FAR(t) \ge FAR^1(t_1)$ and $FAR(t) \ge FAR^2(t_2)$. Thus the two-sensor configuration cannot improve the false acceptance rate by the Bayesian decision rule.

From the definition of the false rejection rate and with the help of the independence of the individual classifiers, we have

$$
\begin{aligned}
FRR(t) &= \int_{R_0} p(X_1, X_2 | w_1) dX_1 dX_2 \\
&= \int_{R_0} p_1(X_1 | w_1) dX_1 \int_{R_0} p_2(X_2 | w_1) dX_2 \\
&= FRR^1(t_1) FRR^2(t_2).
\end{aligned} \tag{45}
$$

From (45), it is obvious that $FRR(t) \le FRR^1(t_1)$ and $FRR(t) \ge FRR^2(t_2)$. Thus the false rejection rate of the integrated system is reduced compared to individual sub-classifiers.

The exact way as to how the integrated system performs better in terms of the smaller total error is described in [81]. The Bayesian decision rule is adopted to prove that the error is minimized. That is, assume that

$$
\frac{C_r p(X_1, X_2 | w_0)}{C_a p(X_1, X_2 | w_1)} \ge 1. \tag{46}
$$

That is

$$
\frac{C_r p_1(X_1 | w_0) p_2(X_2 | w_0)}{C_a p_1(X_1 | w_1) p_2(X_2 | w_1)} \ge 1 \tag{47}
$$

which is equivalent to

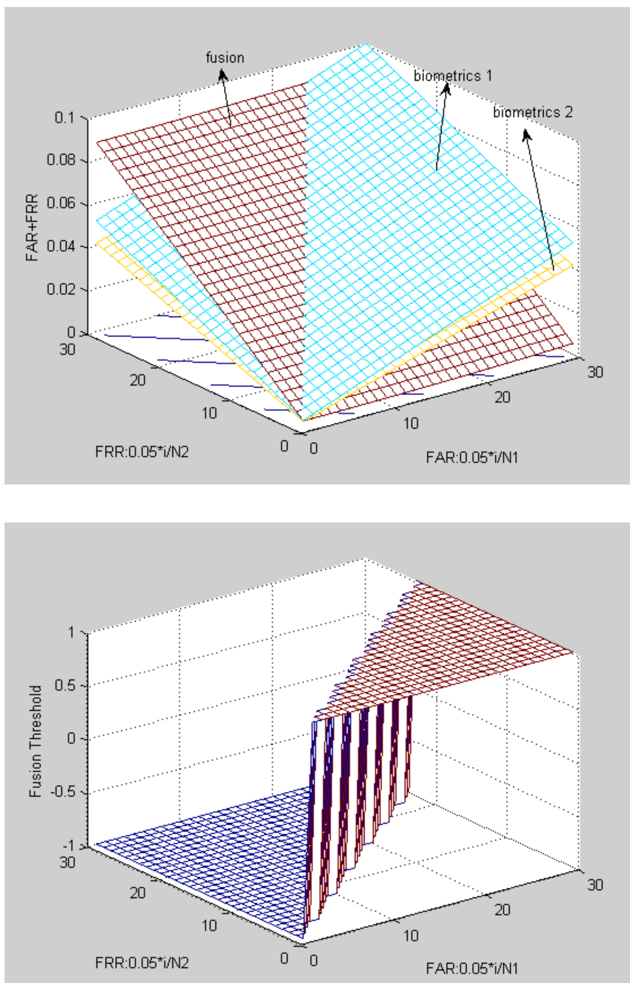
$$
\frac{C_r p_2(X_2 | w_0)}{C_a p_2(X_2 | w_1)} \ge \frac{p_1(X_1 | w_0)}{p_1(X_1 | w_1)}. \tag{48}
$$

It was claimed in [81] that from the Bayesian rule, the total error will be smaller than the other rules. This claim needs further theoretical proof.

6. Simulation Results

6.1 AND rule

The first experiment shows the performance of the AND rule for fusing two biometrics. Figure 21(a) compares the fused result with that of the individual biometrics. In Figure 21(b), region with fusion threshold “1” represents the region in which performance of the AND rule based fusion is better than all individual classifiers. The region with “-1” represents the area where the fused result is worse than the best individual biometrics. FRR and FAR vary from 0.05 (*N* = 0) to 0.0 (*N* = 30). We can observe that the fused result is better than all individual biometrics only in some regions for the AND rule for fusing two biometrics.

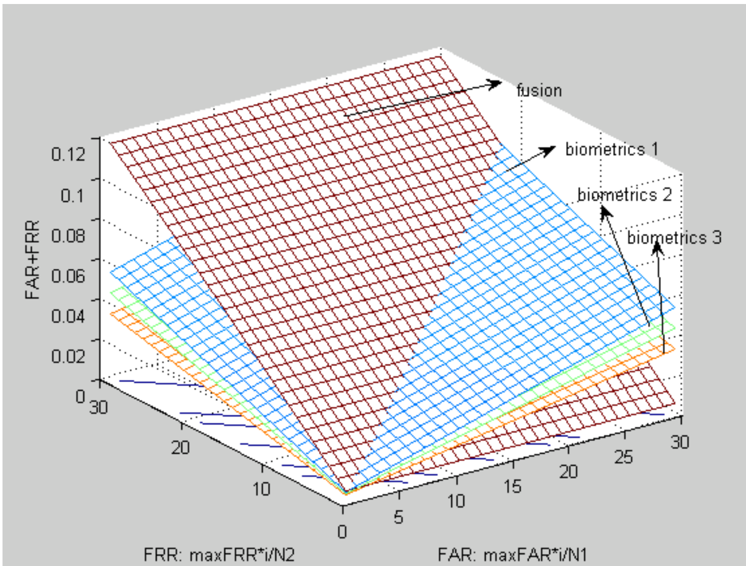


(a)

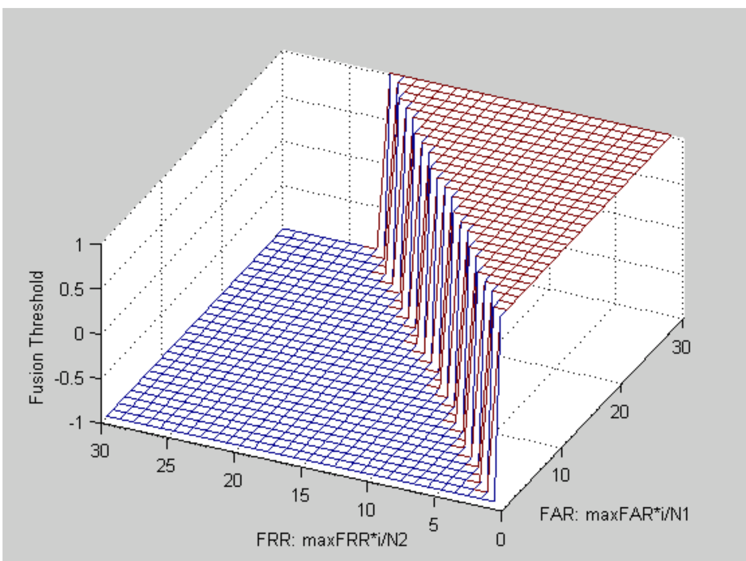
(b)

Figure 21. *AND rule for fusing two biometrics*

The second experiment shows the performance of the AND rule for fusing three biometrics. Figure 22(a) compares the fused result with that of the individual biometrics. In Figure 22(b), region with fusion threshold "1" represents the region in which performance of the AND rule based fusion is better than all individual classifiers. The region with "-1" represents the area where the fused result is worse than the best individual biometrics. The FRR and FAR of three biometrics were changed as follows: FAR1: [0, 0.05]; FRR1: [0, 0.05]; FAR2: [0, 0.04]; FRR2: [0, 0.04]; FAR3: [0, 0.03]; FRR3: [0, 0.03]. Even in this case, we can notice that the fused result is better than all the three individual biometrics only in some areas.



(a)

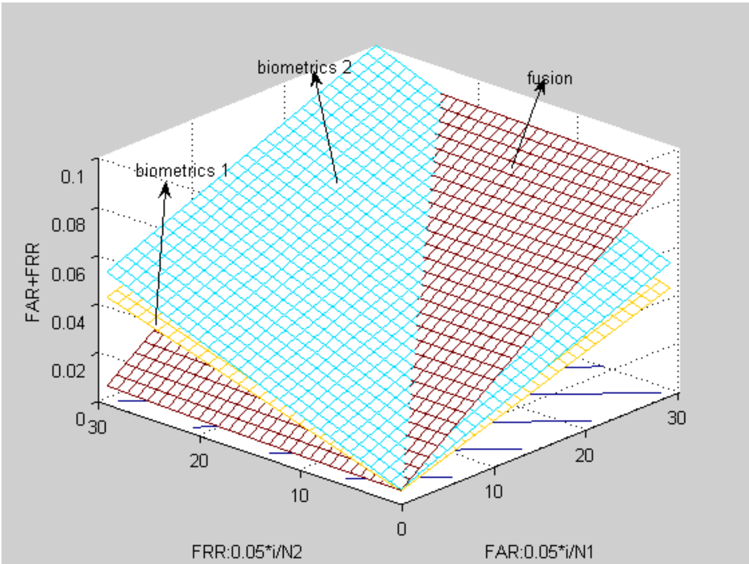


(b)

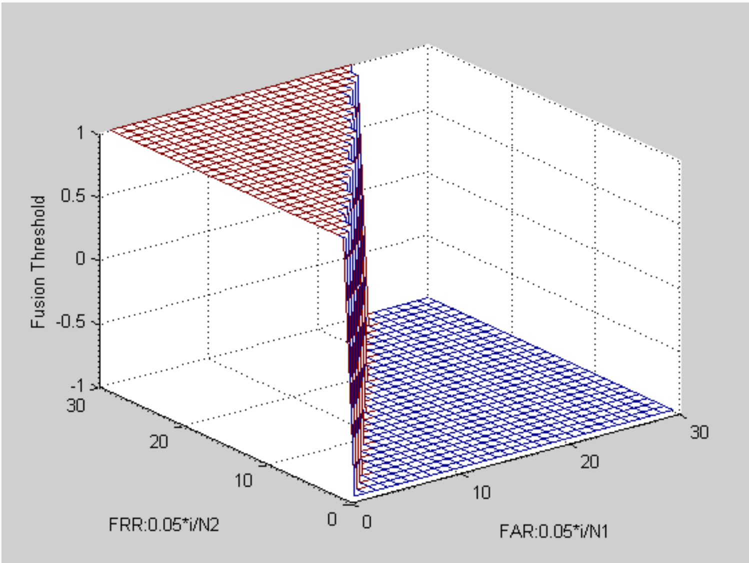
Figure 22. *AND rule for fusing three biometrics*

6.2 OR rule

The third experiment shows the performance of the OR rule for fusing two biometric signals. Figure 23(a) compares the fused result with that of the individual biometrics. In Figure 23(b), region with fusion threshold “1” represents the region in which performance of the OR rule based fusion is better than all individual classifiers. The region with “-1” represents the area where the fused result is worse than the best individual biometrics. FRR and FAR vary from 0.05 (N = 0) to 0.0 (N = 30). We can observe that the fused result is better than all individual biometrics only in some regions for the OR rule for fusing two biometrics.



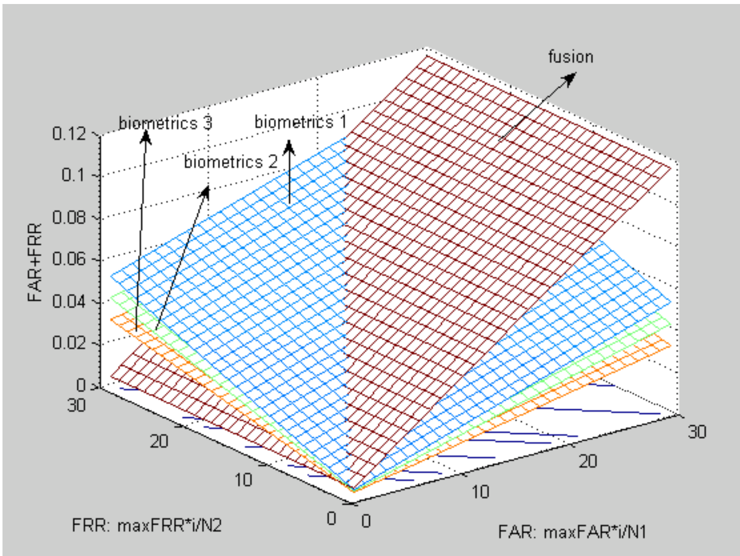
(a)



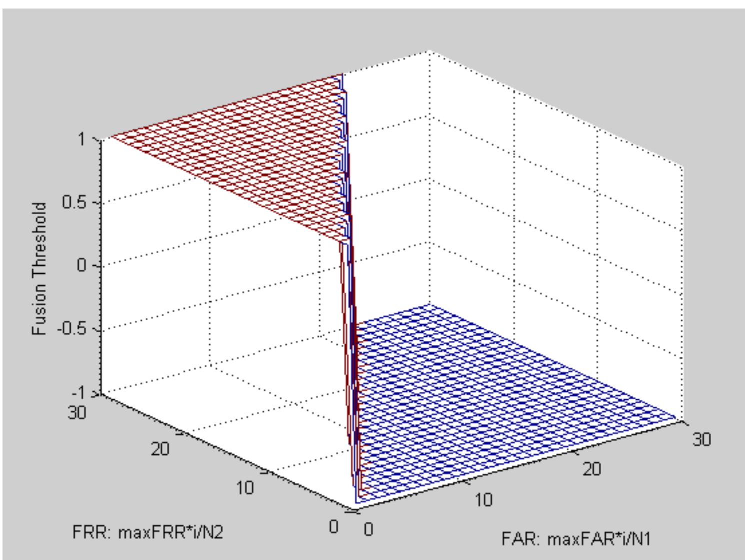
(b)

Figure 23. *OR rule for fusing two biometrics*

The fourth experiment shows the performance of the OR rule for fusing three biometric signals. FRRs and FARs of the three biometrics were changed as follows: FAR1: [0, 0.05]; FRR1: [0, 0.05]; FAR2: [0, 0.04]; FRR2: [0, 0.04]; FAR3: [0, 0.03]; FRR3: [0, 0.03]. We can see that the fused result is better than all individual biometrics only in some areas for the OR rule with three biometrics.



(a)



(b)

Figure 24. *OR rule for fusing three biometrics*

6.3 Majority voting rule

The fifth experiment shows the performance of the Majority Voting Rule for fusing three biometric signals. The FRRs and FARs of the three biometrics were changed as follows: FAR1: [0, 0.05]; FRR1: [0, 0.05]; FAR2: [0, 0.04]; FRR2: [0, 0.04]; FAR3: [0, 0.03]; FRR3: [0, 0.03]. The comparison results are shown in Fig. 25. It is apparent from the figure that the fused result is better than all individual biometrics over the entire region. On the other hand, the AND and OR based fusion were better over only a portion of this entire region.

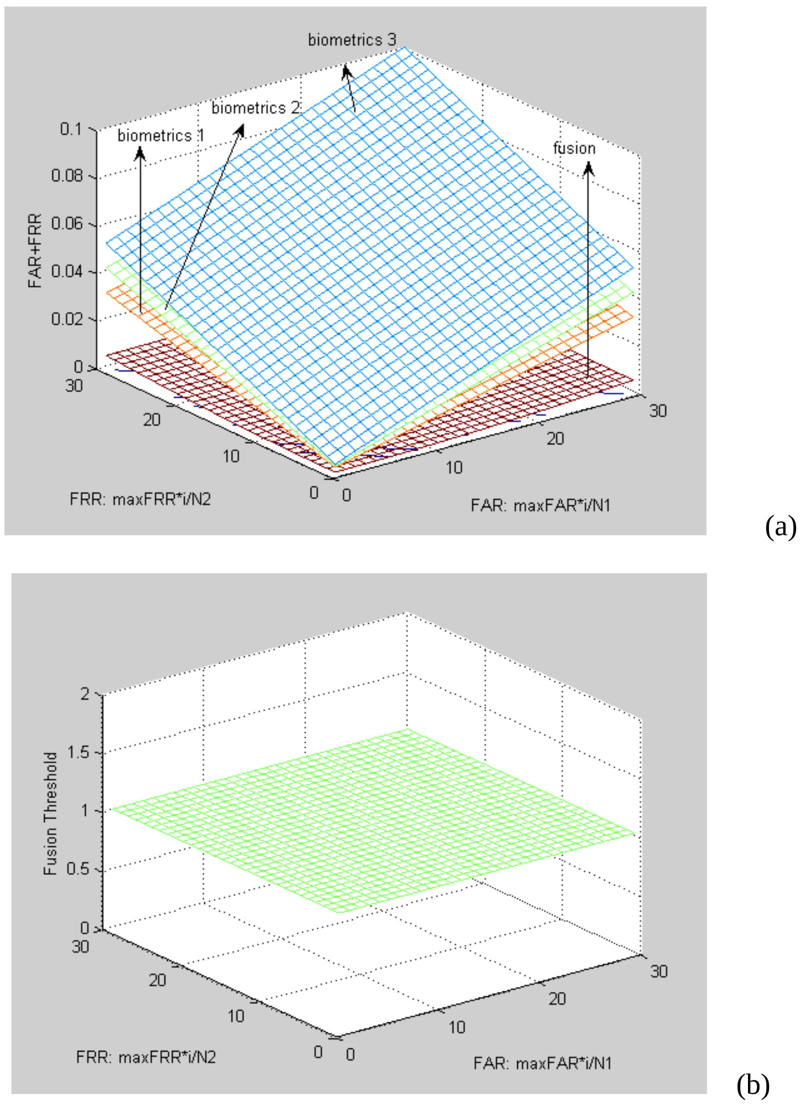
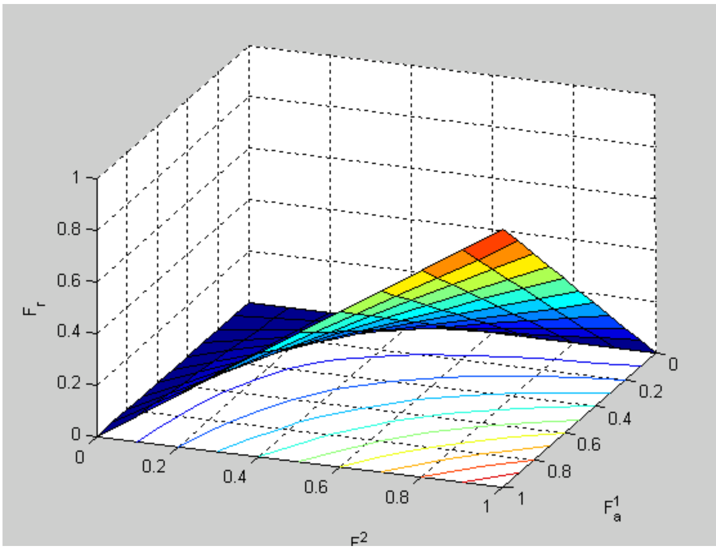


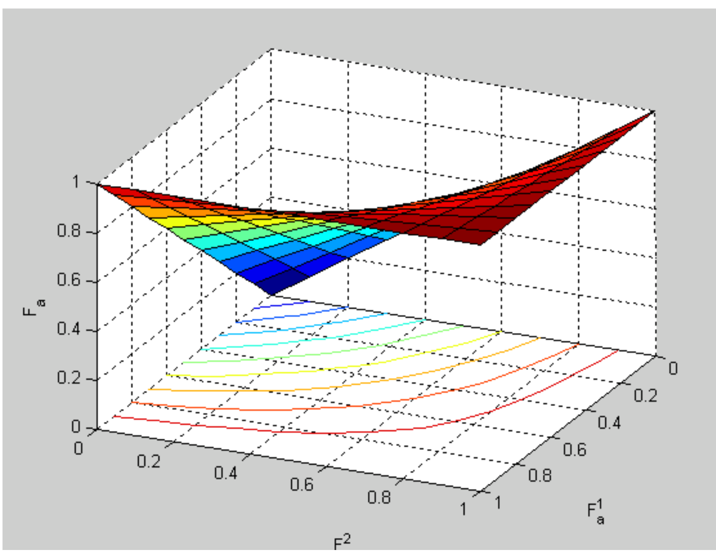
Figure 25. *Majority Voting rule for fusing three biometrics*

6.4 Soft decision-level fusion

The sixth experiment shows the FRR and FAR of the Bayesian soft decision-level fusion of two biometrics. Figure 26(a) shows that the FRR of the integrated system is reduced compared to the individual classifiers while the FAR of the integrated system is increased as shown in Figure 26(b).



(a)



(b)

Figure 26. *Bayesian soft decision-level fusion of two biometrics*

7. Conclusion

This report reviewed the basic structure for information fusion including raw data level fusion, feature level fusion (feature concatenation and classifier fusion), decision level fusion, and multi-level integrated fusion for dependent and independent sources. The raw data level fusion is mainly applied to the fields of multi-sensor fusion in the literature for target-tracking, navigation, and image fusion. Feature level and decision level fusions are more popular for unimodal biometric fusion (dependent sources) and some are applied to multi-modal biometric system (independent sources). Different techniques for biometric fusion at these levels were reviewed and briefly explained in this report.

In the latter part of this report, some preliminary performance analyses on fusion of independent sources were presented. It was shown that under certain conditions, fusion of independent sources at the decision level can in fact improve the performance from the total error point of view. Simple rules such as AND, OR and majority rules were employed. Both theoretical and simulated results were obtained. It was also shown that for fusing two biometric traits the FAR and FRR cannot be simultaneously decreased. Although it is desirable to decrease both FAR and FRR, this might not be a big problem since for many applications, either FAR or FRR is of particular emphasis.

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Fusion of Dependent and Independent Biometric Information Sources Scientific Report (U)

4. AUTHORS (Last name, first name, middle initial)

Huang, Dongliang; Leung, Henry; Li, Winston

5. DATE OF PUBLICATION (month and year of publication of document) March 2005	6a. NO. OF PAGES (total containing information. Include Annexes, Appendices, etc.) 55	6b. NO. OF REFS (total cited in document) 83

7. DESCRIPTIVE NOTES (the category of the document, e.g. technical report, technical note or memorandum. If appropriate, enter the type of report, e.g. interim, progress, summary, annual or final. Give the inclusive dates when a specific reporting period is covered.)

Contractor Report

8. SPONSORING ACTIVITY (the name of the department project office or laboratory sponsoring the research and development. Include the address.)

DEFENCE R&D CANADA - OTTAWA
3701 Carling Avenue, Ottawa, Ontario, K1A0Z4

9a. PROJECT OR GRANT NO. (if appropriate, the applicable research and development project or grant number under which the document was written. Please specify whether project or grant) 15BF27	9b. CONTRACT NO. (if appropriate, the applicable number under which the document was written) W7714-4-0-9130
10a. ORIGINATOR'S DOCUMENT NUMBER (the official document number by which the document is identified by the originating activity. This number must be unique to this document.) DRDC Ottawa CR 2005-052	10b. OTHER DOCUMENT NOS. (Any other numbers which may be assigned this document either by the originator or by the sponsor)

11. DOCUMENT AVAILABILITY (any limitations on further dissemination of the document, other than those imposed by security classification)

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In this report, an overview of information fusion techniques for dependent and independent sources, specifically for biometric applications, is provided. The information fusion architecture is presented for both dependent and independent sources addressing in detail the various fusion techniques at four different levels namely: raw data or signal level, feature level, decision level and multi-level integrated fusion. Furthermore, the report addresses the question of whether independent biometric sources can be fused to provide multi-modal biometric system with enhanced performance. The report shows that even when the sources are independent, the performance of a multi-modal biometric system can be better than that of a biometric system based on single source. The performance is measured in terms of total false accept rate (FAR) and false rejection rate (FRR). The conditions for achieving an improved performance for the decision level fusion using AND, OR and majority voting are derived theoretically and confirmed through computer simulations.

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Information Fusion, Biometrics, Dependent, Independent, Signal Fusion, Feature Fusion, Decision Fusion