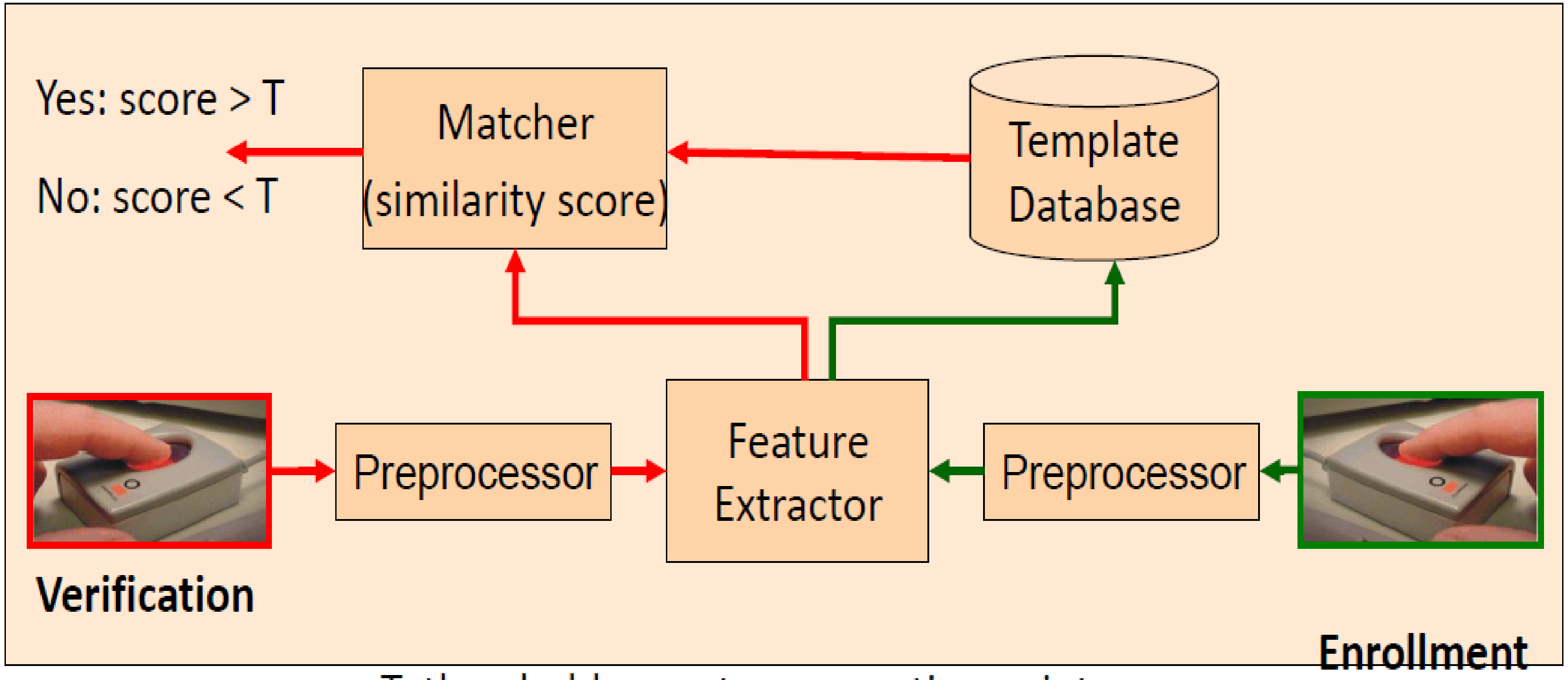
Case Studies

Multi Classifier System

Biometrics as a Pattern Recognition System

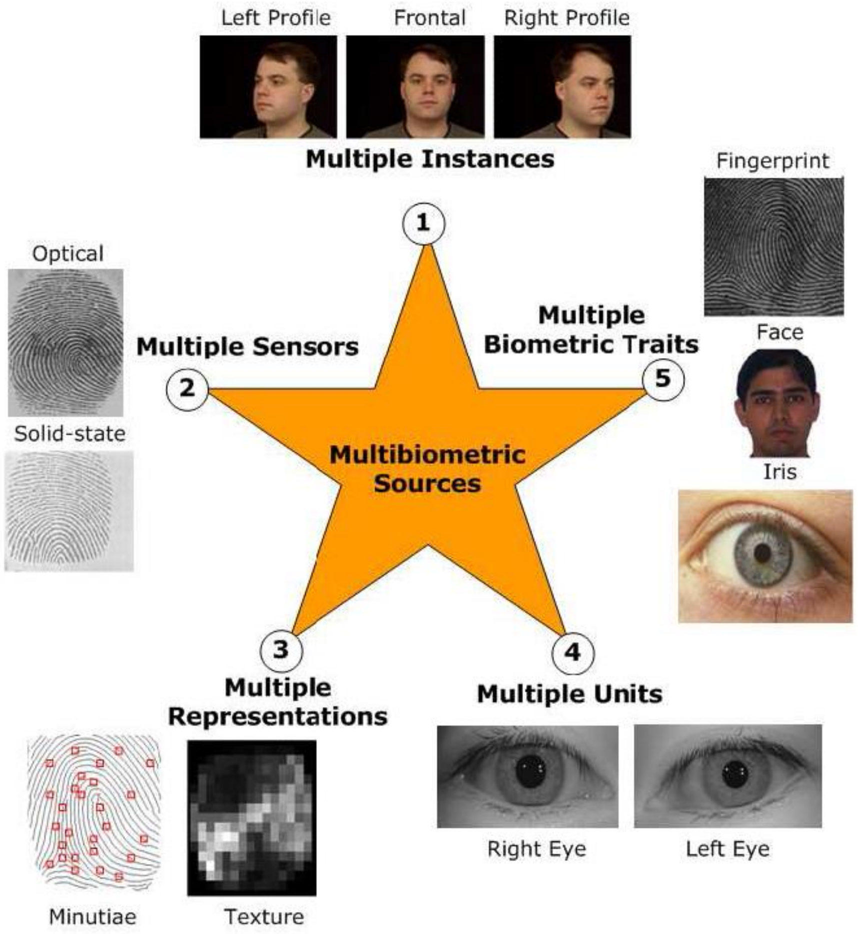


T: threshold or system operating point

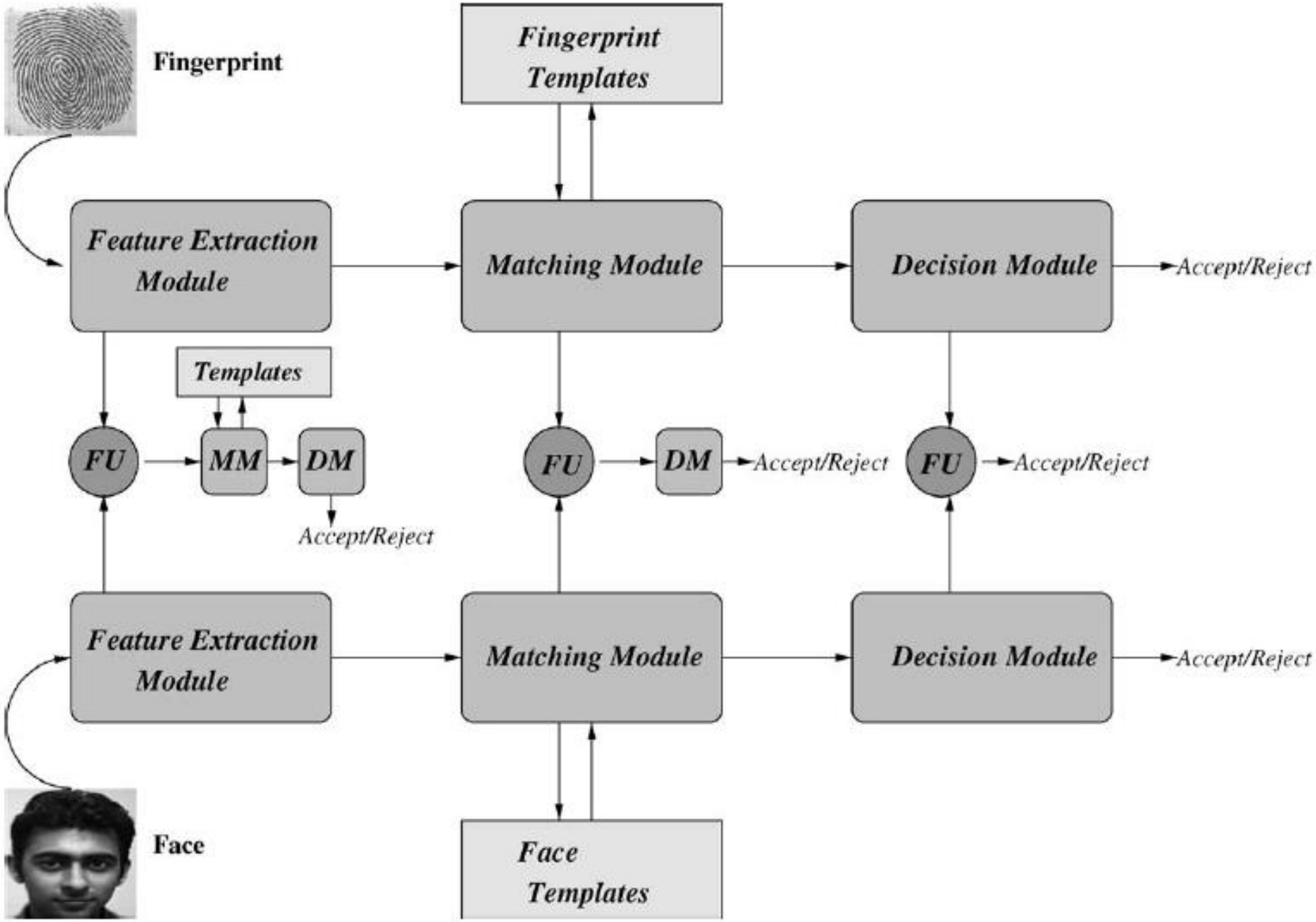
Verification : 1:1 matching (you claim who you are)

Identification: 1:N matching (you do not claim your identity)

Multimodal Biometric Systems (Information Fusion)



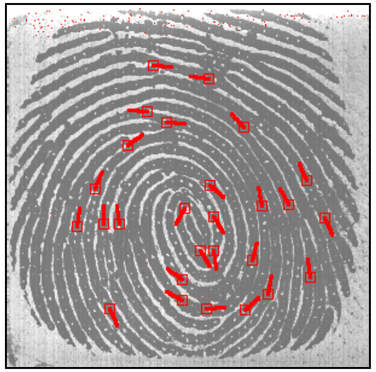
- DATA level
- FEATURE level
- SCORE level
- DECISION level

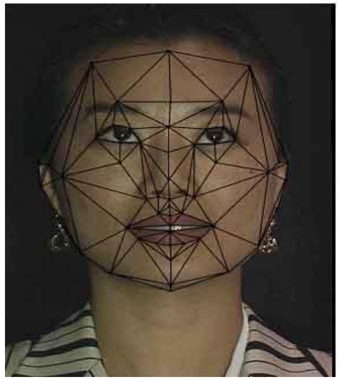


Arun Ross, Anil Jain, Information fusion in biometrics, Pattern Recognition Letters, 24(2003), 2115 – 2125.

Steps: Feature level fusion

The *"feature space"* of two modalities are combined





X1	X2	X3	X4	X5	X6	…	Xn

Y1	Y2	Y3	Y4	Y5	Y6	…	Ym

Normalization of feature values

Normalization of feature values

Compatibility and Concatenation

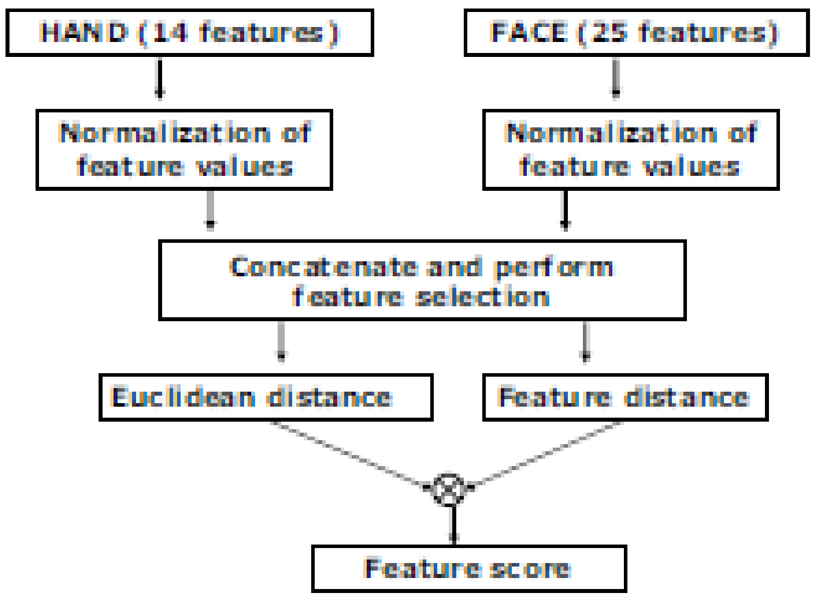
SUPER FEATURE VECTOR

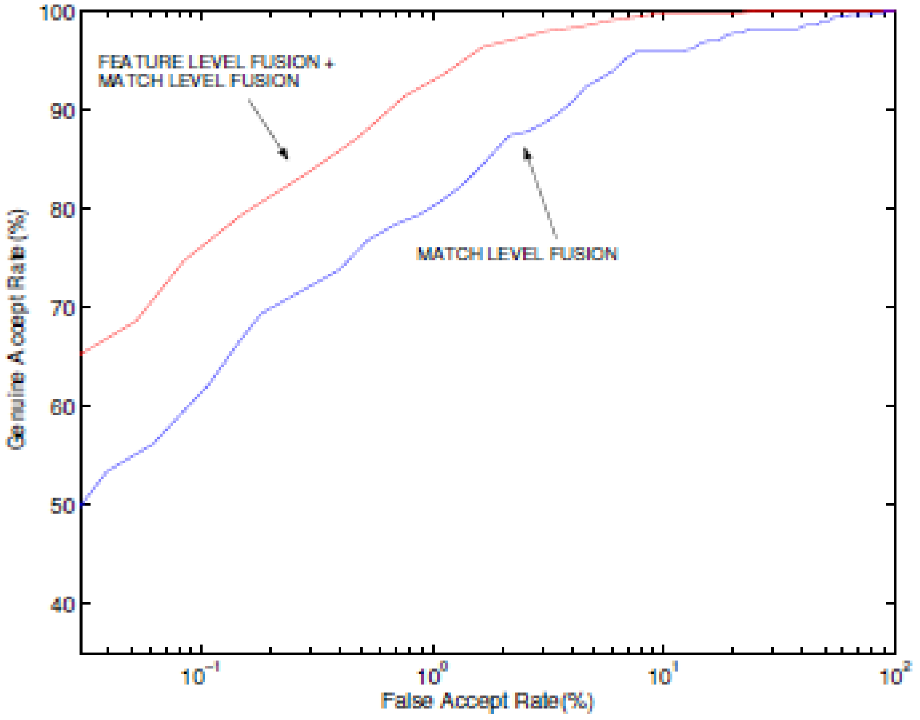
X1	X2	X3	X4	X5	X6	…	Xn	Y1	Y2	Y3	Y4	Y5	Y6	…	Ym

A. Rattani, D. R. Kisku, M. Bicego, M. Tistarelli, "**Feature Level Fusion of Face and Fingerprint Biometrics**", In Proc. of IEEE BTAS, Washington DC, USA, pp. 1--6, 2007.

A. Rattani, D. R. Kisku, M. Bicego, M. Tistarelli, "**Robust Feature Level Multibiometrics Classification**", In Proc. of IEEE BSYM, USA, pp. 1--6, 2006.

Feature Level Fusion in Biometric Systems





Arun Ross and Rohin Govindarajan, Feature Level Fusion Using Hand and Face Biometrics, Proc. of SPIE, 2005

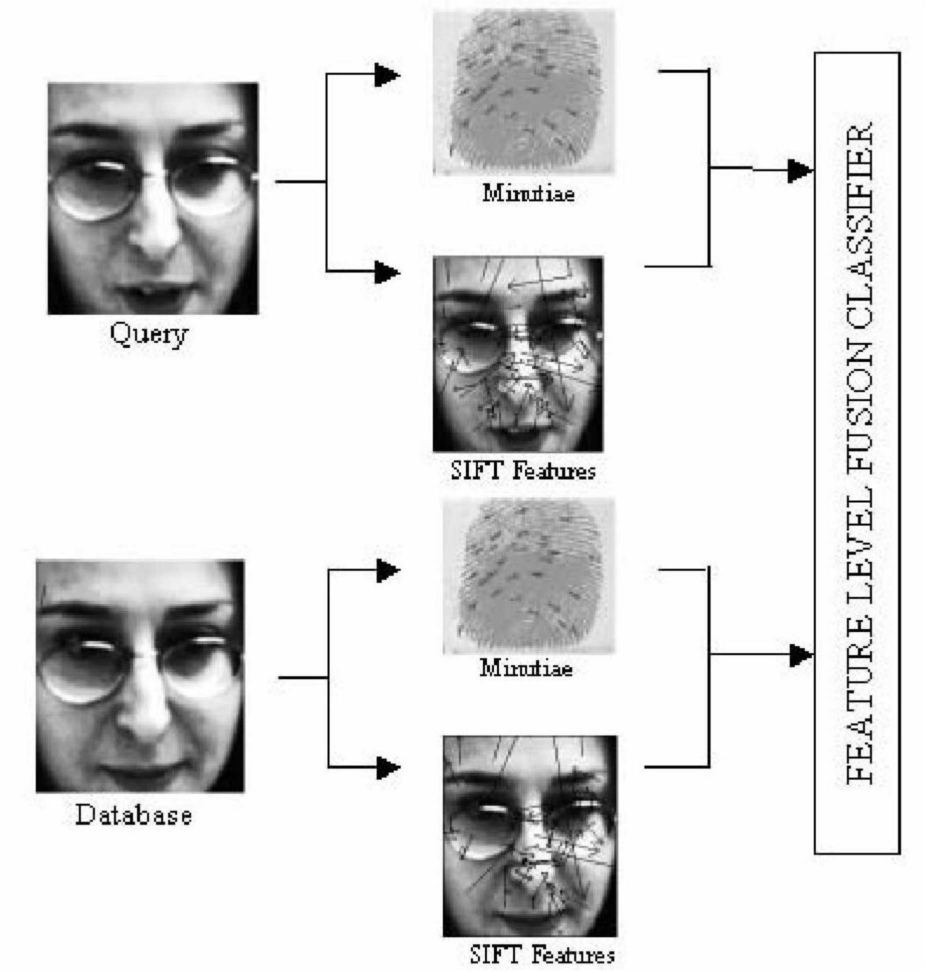


Table 1: FRR , FAR and Accuracy values

Algorithm	FRR(%)	FAR(%)	Accurac y
Face SIFT	11.47	10.52	88.90
Fingerprint	5.384	10.97	91.82
Face+Finger at Matching score level	5.66	4.78	94.77
Face+Finger at Feature Extraction Level	1.98	3.18	97.41

A. Rattani, D. R. Kisku, M. Bicego and M. Tistarelli, "Robust Feature-Level Multibiometric Classification," *2006 Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference*, Baltimore, MD, 2006, pp. 1-6.

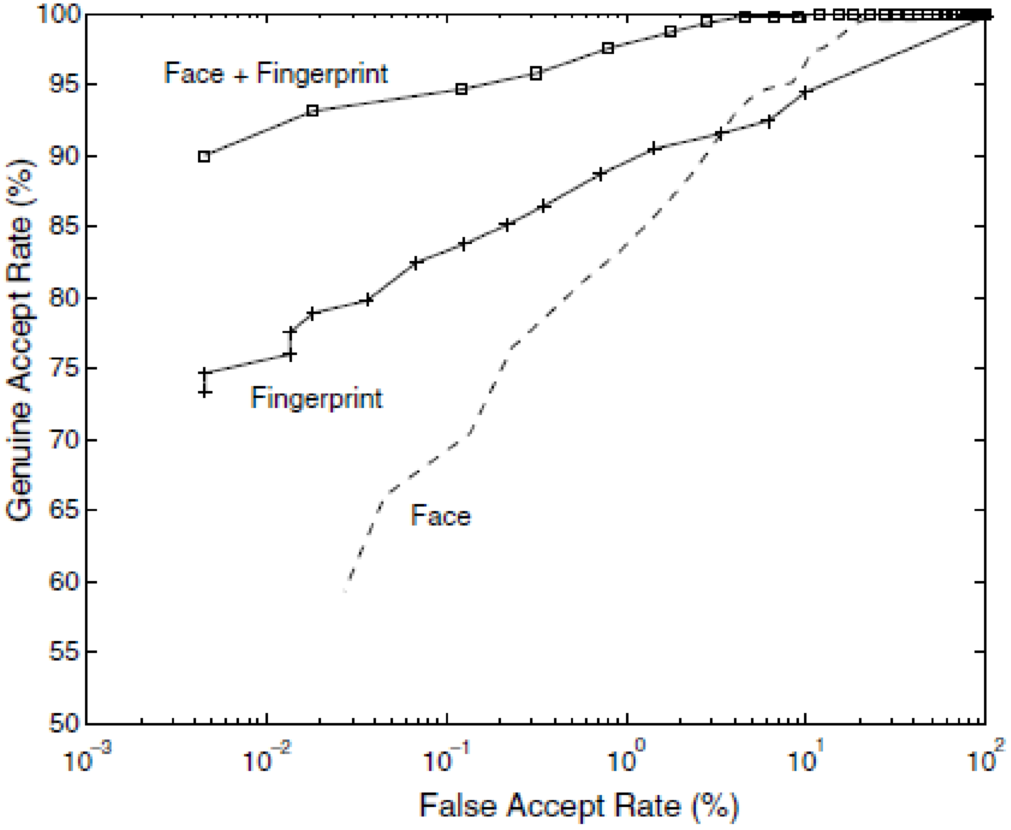
Score-level Fusion

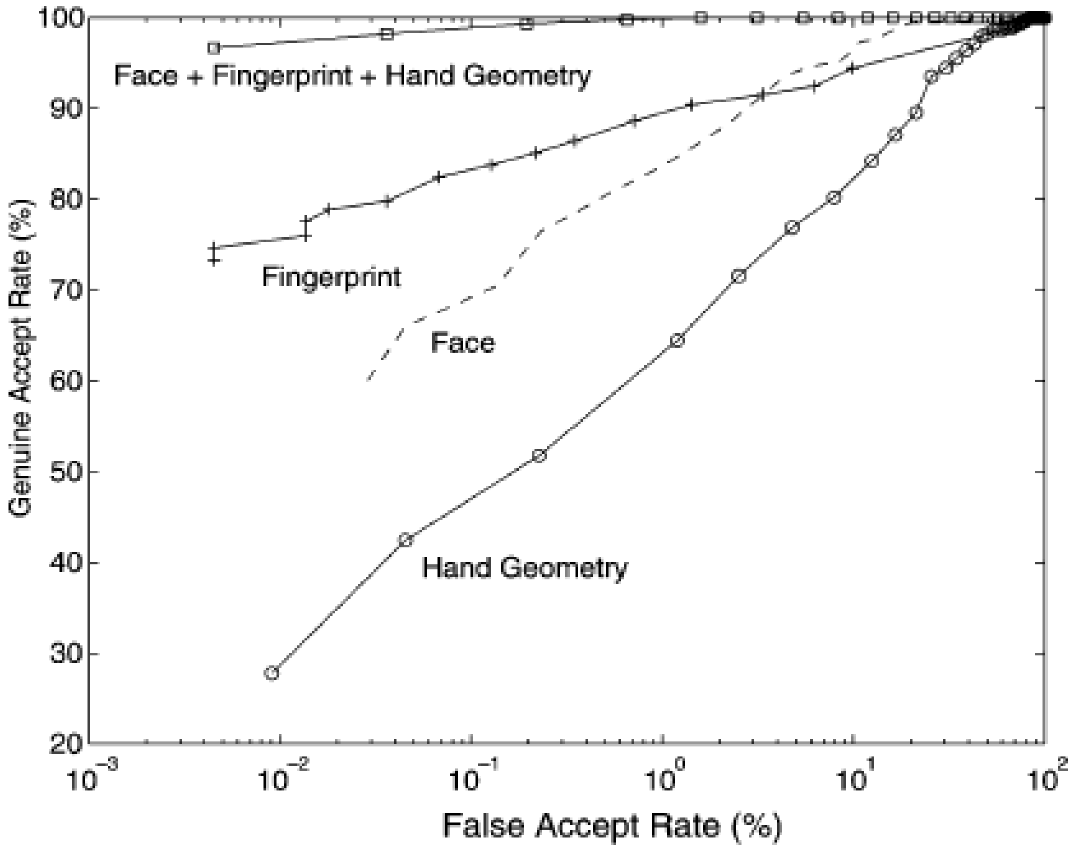
1.	Sum	$s = s_1 + s_2$
2.	Product	$s = s_1 \times s_2$
3.	Bayesian	$s = (s_1 \times s_2) / [(1- s_1)(1- s_2) + (s_1 \times s_2)]$
4.	Weighted Sum (LDA)	$s = w_0 + w_1 s_1 \times w_2 s_2$
5.	Weighted Product	$s = s_1^{w} \times s_2^{1-w}$
6.	Likelihood ratio (LLR)	$s = p(s_1,s_2 \mid G) / p(s_1,s_2 \mid I)$
7.	Exponential Sum	$s = w_1 \exp(s_1) + w_2 \exp(s_2)$
8.	Exponential Product	$s = w_1 \exp(s_1) \times w_2 \exp(s_2)$
9.	Min	$s = \min(s_{1,} s_2)$
10.	Max	$s = \max(s_{1,} s_2)$

P. Gupta, A. Rattani, H. Mehrotra & A. K. Kaushik, "**Multimodal Biometrics System for Efficient Human Recognition**", In Proc. of SPIE Defense, Security and Sensing (SPIE DSS 2006), Florida, USA, 2006

A. Ross, A. Rattani and M. Tistarelli, "**Exploiting the Doddington Zoo Effect in Biometric Fusion**," In Proc. of 3rd IEEE International Conference on Biometrics: Theory, Applications and Systems (BTAS'09), pp. 1-7, Washington DC, USA, September 2009

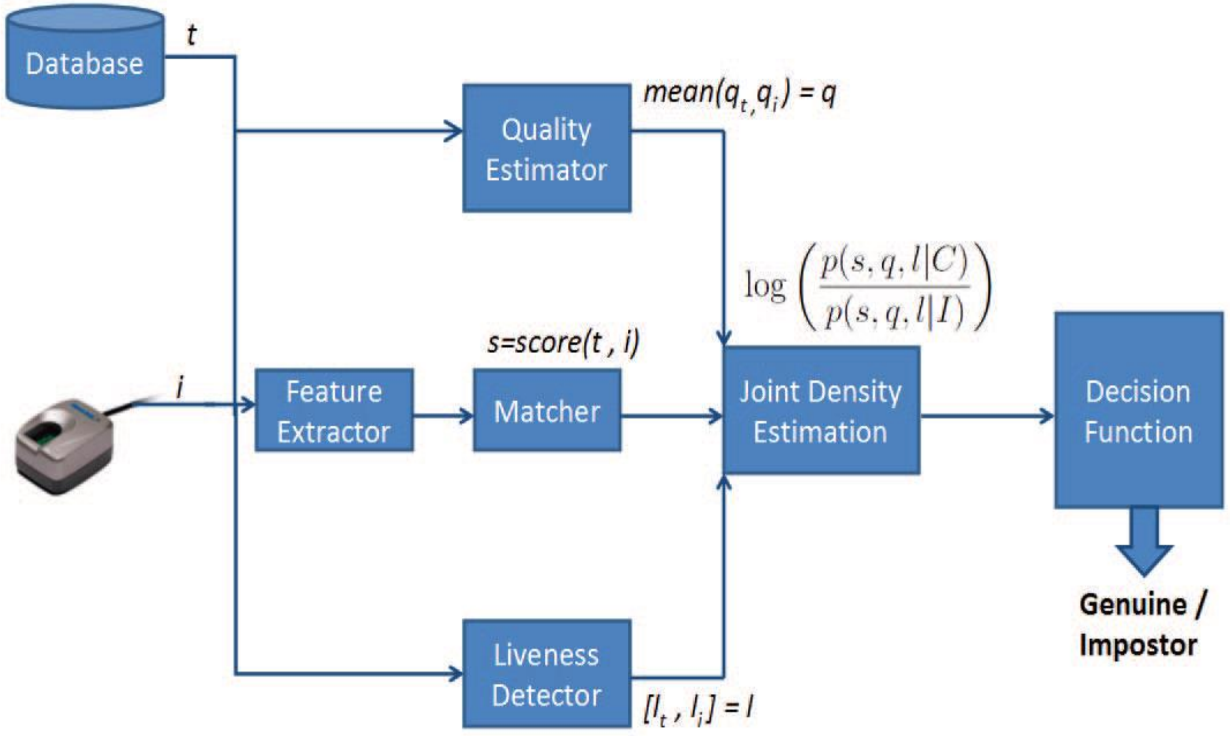
Fixed Sum Rule

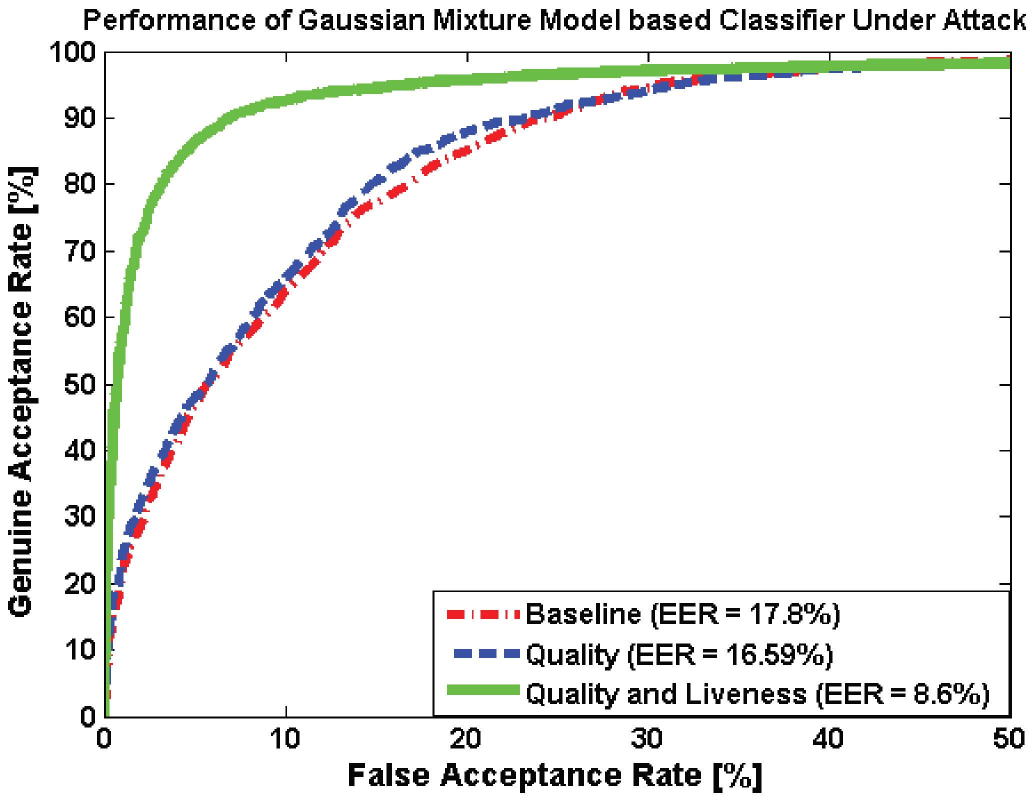




Arun Ross, Anil Jain, Information fusion in biometrics, Pattern Recognition Letters, 24(2003), 2115 – 2125.

Training based fusion





A. Rattani and N. Poh, "Biometric system design under zero and non-zero effort attacks," *2013 International Conference on Biometrics (ICB)*, Madrid, 2013, pp. 1-8

On Combining Classifiers

Josef Kittler, *Member, IEEE Computer Society*, Mohamad Hatef, Robert P.W. Duin, and Jiri Matas

Abstract—We develop a common theoretical framework for combining classifiers which use distinct pattern representations and show that many existing schemes can be considered as special cases of compound classification where all the pattern representations are used jointly to make a decision. An experimental comparison of various classifier combination schemes demonstrates that the combination rule developed under the most restrictive assumptions—the sum rule—outperforms other classifier combinations schemes. A sensitivity analysis of the various schemes to estimation errors is carried out to show that this finding can be justified theoretically.

Index Terms—Classification, classifier combination, error sensitivity.

1 Introduction

The ultimate goal of designing pattern recognition systems is to achieve the best possible classification performance for the task at hand. This objective traditionally led to the development of different classification schemes for any pattern recognition problem to be solved. The results of an experimental assessment of the different designs would then be the basis for choosing one of the classifiers as a final solution to the problem. It had been observed in such design studies, that although one of the designs would yield the best performance, the sets of patterns misclassified by the different classifiers would not necessarily overlap. This suggested that different classifier designs potentially offered complementary information about the patterns to be classified which could be harnessed to improve the performance of the selected classifier.

These observations motivated the relatively recent interest in combining classifiers. The idea is not to rely on a single decision making scheme. Instead, all the designs, or their subset, are used for decision making by combining their individual opinions to derive a consensus decision. Various classifier combination schemes have been devised combination with a reject option. For the more difficult objects more complex procedures, possibly based on different features, are used (sequential or pipelined [17], [7], or hierarchical [24], [16]). Other studies in the gradual reduction of the set of possible classes are [8], [6], [14], [21]. The combination of ensembles of neural networks (based on different initialisations), has been studied in the neural network literature, e.g., [11], [4], [5], [10], [15], [18].

An important issue in combining classifiers is that this is particularly useful if they are different, see [1]. This can be achieved by using different feature sets [23], [13] as well as by different training sets, randomly selected [12], [22] or based on a cluster analysis [3]. A possible application of a multistage classifier is that it may stabilize the training of classifiers based on a small sample size, e.g., by the use of bootstrapping [27], [19]. Variance reduction is studied in [30], [31] in the context of a multiple discriminant function classifier and in [35] for multiple probabilistic classifiers. Classifier combination strategies may reflect the local competence of individual experts as exemplified in [32] or the training process may aim to encourage some experts to

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Pattern Recognition   Machine Learning

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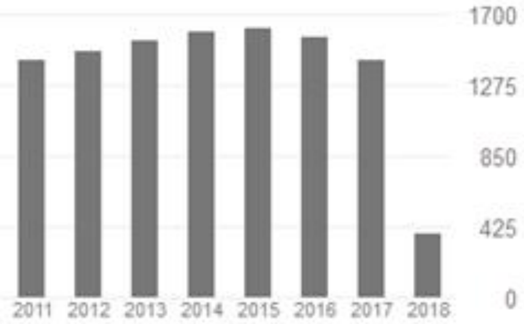

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Biometrics Computer vision Pattern recognition Machine learning Image processing

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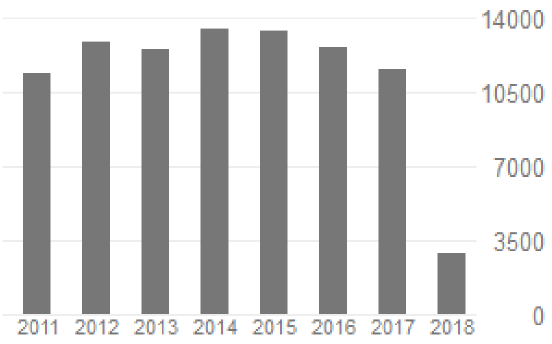

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