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A Person Authentication System using aBiometric Based Efficient Multi-level Integrator

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ABSTRACT

A multi layer multi-classification system has been designed and developedusing a new integration technique of programming based boosting.This system uses different biometrics such as color face, iris and eye alongwith fingerprints of both right and left hands, handwriting, palm-print, gait(silhouettes) and wrist-vein for authentic person identification. In this system, three different super-classifiers individually perform person identification. The individual classifiers corresponding to each super-classifiers identify different respective biometric features and their conclusions are combined together in their respective super-classifiers. The conclusions from individual super-classifiers are fused or integrated together through a mega-super-classifier to perform the final conclusion about person identification using programming based boosting. This mega-super-classifier using different super-classifiers in a compact system is more accurate, efficient and reliable compare to single classifier or even single super-classifier system. The conclusion of mega-super-classifier is fuzzy in nature. Holdout method with confusion matrix is used to evaluate the performances of individual single classifiers and also super-classifiers and fuzzy confusion matrix is used to evaluate the performance of mega-super-classifeir. The different performance evaluations of the system in terms of accuracy, precision, recall and F-score are substantially appreciable with quite affordable learning and testing time.

Keywords: Multi-classification system, OCA, HBC, MOCA, Malsburg learning, SOM, RBFN, Super-classifier, Mega-super-classifeir, Fuzzy Confusion Matrix.

1. INTRODUCTION

Biometrics is the study of defining the identity of a person depending on the behavioral, physical and chemical traits. Single biometric systems have restrictions like uniqueness, high spoofing rate, high error rate, non-universality and noise. Multimodal biometric systems overcome some of these problems by strengthening the proof picked up from various sources to identify a person. Different biometrics can be inspected by a single system or distinctsystems that functions on its own and their conclusions can be fusedtogether.

Most of the multimodal systems are based on few conventional fusion techniques and use two biometric traits for identification. Only two or three biometrics may not be enough to prevent forging. On the other way, say for any accidental reason, one or two biometric traits of a person are damaged or lost. In these cases the conventional multimodal systems which were involved two or three biometric traits may not be appropriate for that person's identification. So, such a system which takes several numbers of different biometric traits for person authentication is appropriate for these consequences as all the required biometric features may not be damaged and these features can compensate over damaged features. Also this kind of system is beneficial to prevent forging as it may not be possible to forge all the required biometric features.

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Various multimodal biometric systems have as of now been created.A multimodal system was presented in [1], where score level fusion was performed on face and fingerprints. Fingerprint recognition was done by minutiae matching and gabor filter and face recognition with Principal Component Analysis (PCA).In another multimodal system [2], Face image was represented by the Active Lines among Face Landmark Points (ALFLP) feature vector and gait image was represented by the Active Horizontal Levels (AHL) feature vector. These two feature vectors were integrated at feature level.A fingerprint and iris feature-level fusion based identification technique was proposed in [3] using traditional Radial Basis Function neural network. Here iris features were extracted by block sum method and fingerprint features were by Haar wavelet method.Iris and face features were combined in [4] as new feature for representing persons which applied on modified PUM for recognition.

The above mentioned multimodal systems are based on few conventional fusion techniques and use two biometric features for identification. These systems may not be extremely secure for high security purpose as these systems may forge by an imposter. So, to overcome this problema multi-classifier based system has been approached which can deal with nine different biometric traits with very high accuracy and low recognition time.

2. SYSTEM OVERVIEWAND APPROACH

2.1. Preprocessing of different biometric features

In different classifiers, individually nine different biometric traits such as color-face, color-iris, color-eye, right and left hand fingerprints, handwriting, palm-print, gait and wrist-vein were used.All the biometric patterns of training and test dataset have to be preprocessed before learning and recognition.

There were eight different preprocessing steps which were applicable on all eight different biometric features except Iris pattern. Also all eight steps of preprocessing were not required for these eight different biometric features. Each step is described below for different biometric patterns.

i) Conversion of RGB images into gray scale images: This step was applicable only on Handwriting patterns.

ii) Removal of noise.

iii) De blurring the patterns.

iv) Background elimination: In this step backgrounds of face, right and left hand fingerprints, and handwriting were removed.

v) Image compression [5].

vi) Image Normalization.

vii) Conversion of Gray scale patterns into Binary patterns:Right and left hand fingerprints, handwriting, palm-print patterns were converted into corresponding binary patterns.

viii) Conversion of RGB/Gray scale patterns into 1D matrix.

These sets were the input to the Clustering Algorithms of corresponding individual classifiers.

- **Preprocessing to extract Color-Iris patterns**

The necessary steps [6] to extract the color-iris patterns from color-eye patterns are given below:

i) Compression of eye images.

ii) Iris Boundary Localization [7, 8].

iii) Extract the iris.

iv) Conversion of RGB images into 1D matrix file.

This set was the input to theclustering algorithm of respective classifier.

2.2. Theoretical Approach of the Present System

This present multiple classification system contains five different single classifiers. Five different classifiers were Optimal Clustering Algorithm(OCA) based Radial Basis Function Network (RBFN), Modified OCA based RBFN, Self Organizing Mapping (SOM) based RBFN, combination of Malsburg learning and Back Propagation Network (BPN), Heuristic Based Algorithm (HBC) based RBFN. First four classifiers were used twice in this multiple classification system. Overall nine different biometric features were identified by nine classifiers.Each and every biometric feature was trained and tested with five different classifiers and finally that classifier was selected for this system which gave best accuracy for corresponding biometric. Color-face, color-iris and color-eye patterns were identified separately using Modified OCA based RBFN, SOM based RBFN and combination of Malsburg learning and BPN respectively and then super-classifier1 conclude the identification of the person based on programming based boosting method. Again OCA based RBFN, HBC based RBFN and combination of Malsburg learning and BPN performed right and left hand fingerprints and handwriting identification respectively and super-classifier2 combine these three individual classifiers conclusion based on programing based boosting logic and conclude the decision. Similarly palm-print, gait(silhouettes) and wrist-vein patterns were identified by Modified OCA based RBFN, SOM based RBFN and OCA based RBFN respectively and super-classifier3 conclude the identification of the person based on programing based boosting method. Finally mega-super-classifier integrates all these three super-classifiers decision based on again programing based boosting method to conclude the final identification/authentication of the person.

The functionalities of each and every single classifiers corresponding to nine different biometric features are described in Table1.

Table 1
Functionalities of different classifiers of the present multi-classification system

Biometric Traits	*Classifiers*	*Training Flow of Individual Classifiers*
Color Face	MOCA based Modified RBFN [5]	Patterns of different expressions and views→ 'person-view' 'person'
Color Iris	SOM based Modified RBFN[9]	Patterns of different expressions of left and right eye → 'person left iris – person right iris' → 'person'
Color eye	Combination of Malsburg learning and BP network [10]	Patterns of different expressions of left and right eye →'person left eye – person right eye' →'person'
Right Hand Fingerprints	OCA based Modified RBFN [11, 12]	Patterns of different qualities of four different fingers →'person-finger' →'person'
Left Hand Fingerprints	HBC based Modified RBFN [13]	Patterns of different qualities of four different fingers →'person-finger' →'person'
Handwriting	Combination of Malsburg learning and BP network	Patterns of different qualities of name and surname → 'person name – person surname' →'person'
Palm-print	MOCA based Modified RBFN	Patterns of different qualities of left and right hands palm print® 'person left hand palm print – person right hand palm print' →'person'
Gait (silhouettes)	SOM based Modified RBFN	Patterns of different gaits of different time slots ®'consecutive gait patterns of particular time slots' → 'person'
Wrist-vein	OCA based Modified RBFN	Patterns of different qualities of left and right hands wrist veins →'person left hand wrist vein – person right hand wrist vein' →'person'

2.2.1. Modifeid Radial Basis Function Network

The RBFN [9, 11, 12, 13] consists of three layers namely an input layer for pattern presentation, a hidden (clustering) layer containing 'basis units' and an output (classification) layer. The clustering outputs (mean "μ", standard deviation "σ" and corresponding approximated normal distribution output functions) are used in 'basis units' of RBFN. Thus, for the above mentioned single classifiers, OCA, MOCA[5, 14, 15], SOM and HBC are the first phase of learning respectively and using BP learning we get the optimal weights, which is the second phase of learning.

2.2.2. Identification Learning with Training Patterns

There were eight different training databases for nine different biometric features, i.e. color-face, color-eye/color-iris (one common training database for these two biometrics), right and left hand fingerprints, handwriting, palm-print, gait(silhouettes) and wrist-vein. Each database contained different biometric patterns of different persons. In color-face database,for every single person's face, six different expressions of face patterns and also three different angular view of face patterns i.e. frontal, left side and right side view were taken. In color-iris/eye database, for each person's iris/eye patterns, eight different expressions of individual left and right eye patternswere taken. In the right and left hand fingerprints individual databases, for each person's fingerprint, three different qualities of fingerprints like hard-press, medium-press and soft-press and for each person, fingerprints of four different fingers (thumb, second, third and fourth finger –as per standard database CASIA version 5) were also included. The handwriting database contains six different qualities of handwritings (name and surname separately) for each person. The palm-print database consists of four different qualities of palm-prints for right and left hands respectively for each person. In the gait database patterns of different time slots were taken for each person. Finally the wrist-vein database contains four different qualities of wrist-vein patterns for right and left hands respectively for each person. (Refer to Figure 1).

After preprocessing, all the patterns were fed separately as input to the different clustering algorithm or clustering networks of individual classifiers. When the networks learned all the different patterns (nine different biometric features) of training databases for all different people, the networks were ready for recognition of learned patterns.(Refer to Figure 2).

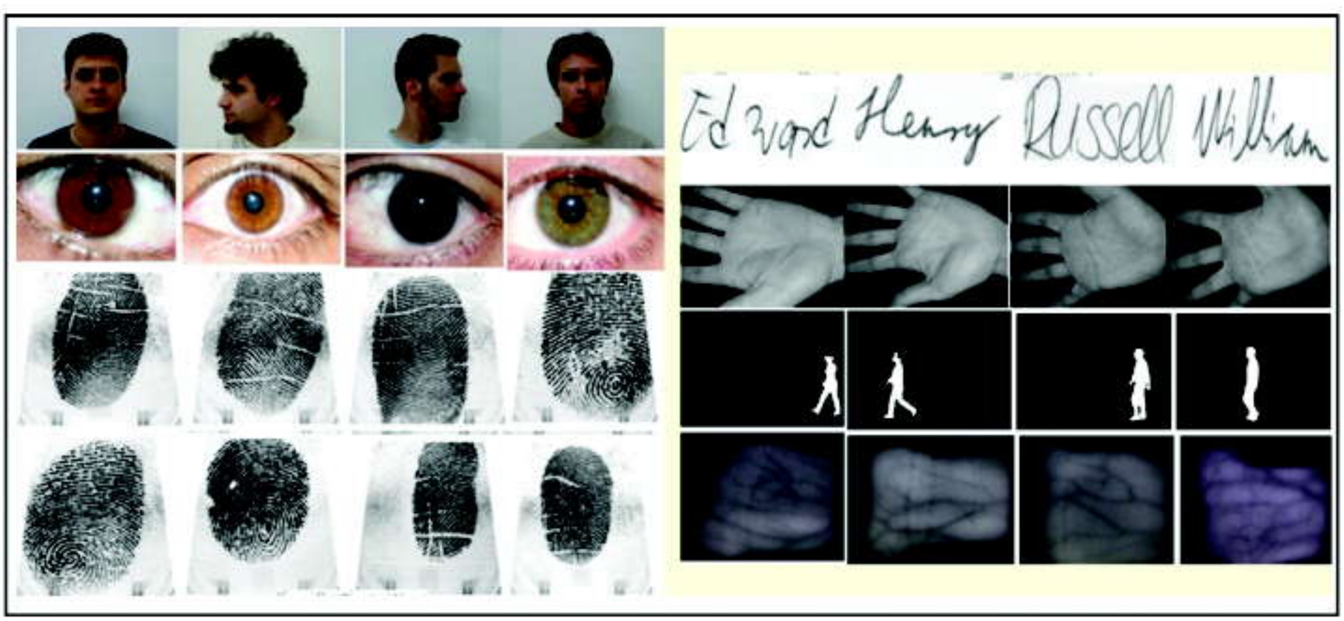

Figure 1: Samples of few training patterns of different biometric features for single classifiers

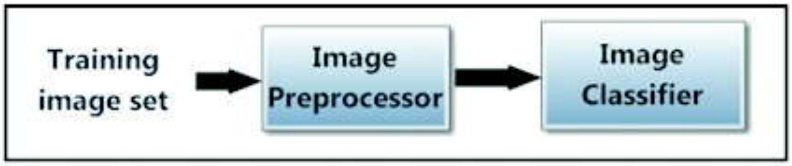

Figure 2: Block diagram for learning identification of individual single classifiers

2.2.3. Identification Testing with Test patterns

The test databases for testing to calculate the performance of individual classifiers with *Holdout method* contained different people's (same as training data set) patterns (color-face, color-eye/color-iris (one common test database for these 2 biometrics), right and left hand fingerprints, handwriting, palm-print, gait(silhouettes) and wrist-vein) of various qualities/expressions. These patterns were completely different from training databases.

The test databases for testing to calculate the performances of three different super-classifiers and mega-super-classifier contained pattern sets of different people (same as training data set). Each test set of super-classifier1 contained one color-face and color-eye. Each test set of super-classifier2 contained one right-hand fingerprint, left-hand fingerprint and handwriting and each test set of super-classifier3 contained one palm-print, gait(silhouette) and wrist-vein pattern. In the test database of mega-super-classifier, each test set comprises of one color-face,color-eye, right-hand fingerprint, left-hand fingerprint, handwriting, palm-print, gait and wrist-vein pattern. The patterns of each test set were also of various qualities/expressions which were completely different from training databases. (Refer to Figure 3).

The test sets for individual nine classifiers, three super-classifiers and mega super classifier also contain some unknown patterns of various qualities/expressions which were not included to train the classifiers.

Figure 3: A sample of test pattern set (person3) of mega-super-classifier for person identification

The test patterns from the test databases were fed as input to nine individual preprocessors. The preprocessed patterns were fed as inputs to the previously trained networks of nine individual classifiers.After training, the networks of all the classifiers gave high output values for known patterns and low output value for unknown patterns. A threshold value was required to differentiate between known and unknown patterns.The threshold was set as the mean of the minimum output value from known patterns and maximum output value from unknown patterns. This threshold value was different for different biometric patterns. The corresponding output value above threshold was considered as corresponding known pattern. TheBP networks produce different output activation indifferent overall output units. The normalizedactivation of each and every output unit represents theprobability of belongingness of the input test patterninto the different classes. The test pattern is considered to belong to a class for which the normalized activation itself representsthe probability of belongingness of that input testpattern into the particular classes. Then three individual super-classifiers conclude the identifications of the person based on *programming based boosting*[6, 16] method considering the decisions of corresponding three individual single classifiers. Finally the mega-super-classifier conclude the final identification of the person based on again *programming based boosting*methodconsidering the decisions of three different super-classifiers. Here, the weight assigned for each link is the normalized*accuracy* of that corresponding classifier/super-classifier. Finally we calculate theprobability of belongingness of the input test pattern for that corresponding class concluded by super-classifiers and mega-super-classifier by taking the minimum value of probability among three different classifiers/super-classifiers.

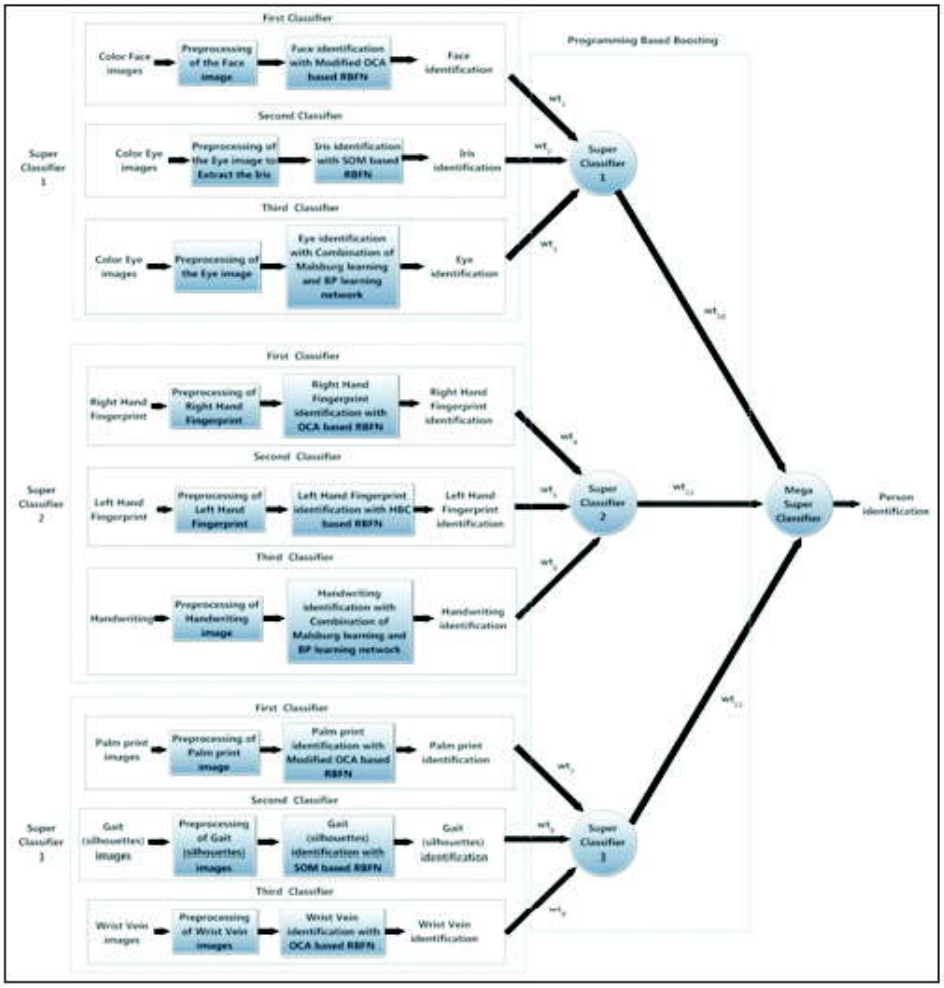

Figure 4: Block diagram of the proposed system for testing identification

If the output of two or more classifiers/super-classifiers are seems contradictory, then the decisions obtain by the classifier/ super-classifier with higher weighted link has to be accepted with minimum probability. So, this system with super-classifier/mega-super-classifier performs well in such contradictory situations. (Refer to Figure 4).

3. RESULT AND PERFORMANCE ANALYSIS

We have taken the patterns of eight different biometric features from eight different standard databases for training and test databases. We were unable to gather all the different biometric patterns from one standard database. That is why it was assumed that, different biometric patterns of different standard databases were of same particular people without losing any generality to evaluate the present system's performance.

We used training and test databases for color-Face samples from FEI database (http://fei.edu.br/~cet/facedatabase.html), Eyes/Irises from UTIRIS database(http://utiris.wordpress.com/), Right and Left hand Fingerprints from CASIA Fingerprint Image Database Version 5.0 (http://biometrics.idealtest.org/dbDetailForUser.do?id=7), Handwritings from IAM handwriting database (http://www.iam.unibe.ch/fki/databases/iam-handwriting-database/download-the-iam-handwriting-database), Palm-prints from CASIA Palm print Image Database (http://biometrics.idealtest.org/dbDetailForUser.do?id=5), Gaits (silhouettes) from CASIA Gait Database (http://www.cbsr.ia.ac.cn/english/Gait%20Databases.asp) and Wrist-veins from CIE Biometrics (http://biometrics.put.poznan.pl/vein-dataset/).

3.1. Performance Evaluation Metrics of the Classifiers

Holdout method [5, 10, 13, 17] has been used to evaluate the performances of the individual classifiers, super-classifiers and mega-super-classifier. Confusion matrices have been implemented in case of individual single classifiers as well as super-classifiers and Fuzzy Confusion Matrix [6] has been implemented in case of mega-super-classifier. Also for all the different biometric features*precision, recall* and *F-score* metrics [5, 6, 10, 13,17] have been evaluated.

3.2. Experimental Results

The proposed system was made to learn on a computer with Intel Core 2 Duo E8400, 3.00 GHz processor with 4 GB RAM and Windows 7 32-bit Operating System.

In Table 2 Fuzzy Confusion Matrix for mega-super-classifier is presented. Each grid of fuzzy confusion matrix is further divided into three grids and each grid represents the fuzzy belongingness for the predicted class of any biometric pattern. Although the different performance measures like*accuracy, precision, recall and F-score* with *holdout* technique are observed a little different with ordinary confusion matrix and fuzzy confusion matrix, since those performance evaluations for fuzzy output with fuzzy confusion matrix is more appropriate and reliable, we are to accept the different performance evaluations with fuzzy confusion matrix for mega-super-classifier.

Table 2
Fuzzy Confusion Matrix for mega-super-classifier

				Actual Class		
		Person1	*Person2*	*Person3*	*Person4*	*Unknown*
Predicted Class	Person 1 High	3	0	0	0	0
	Moderate	32	0	0	0	0
	Low	1	0	0	0	0
	Person 2 High	0	12	0	0	0
	Moderate	0	28	0	0	0
	Low	0	0	0	0	1
	Person 3 High	0	0	6	0	0
	Moderate	0	0	24	0	0
	Low	0	0	4	0	0
	Person 4 High	0	0	0	0	0
	Moderate	0	0	0	34	0
	Low	0	0	0	1	0
	Unknown High	0	0	0	0	0
	Moderate	0	0	0	0	4
	Low	0	0	0	0	15

Table 3
Accuracy of the classifiers (Holdout method)

Classifiers	*Accuracy(%)*
Super-classifier1	95.56
Super-classifier2	97.78
Super-classifier3	97.78
Mega-Super-classifier	99.39

From Table 3, we find the accuracies of three different super-classifiers and mega-super-classifier. The accuracies for three different super-classifiers are >=95% and for mega-super-classifier is 99.39%. Thus, it is evident that the mega-super-classifier is efficient for person identification than considering individual super-classifiers.

Table 4
Performance measurement of the Mega-Super-classifier using Fuzzy Confusion Matrix

Person	*Precision*	*Recall*	*F-score*
Person1	1.00000	1.00000	1.00000
Person2	0.97561	1.00000	0.98765
Person3	1.00000	1.00000	1.00000
Person4	1.00000	1.00000	1.00000
Unknown	1.00000	0.95000	0.97436

Table 5
Learning Time of the Biometric Features (in seconds)

Classifiers	*Training Time*	*Recognition Time (single test sample)*	*Total Time*
Super-classifier1	387.305	0.000001	387.305001
Super-classifier2	65.136	0.000001	65.136001
Super-classifier3	259.412	0.000002	259.412002
Mega-super-classifier	711.867	0.009939	711.876939

Table 6
Comparative study with Accuracy of systems

Multimodal Systems	*Accuracy(%)*
Face-Fingerprint [1]	97.5
Face-Gait [2]	98.6
Fingerprint-Iris [3]	92
Iris-Face [4]	94.2
Present System	99.39

From Table 4, precision, recall and F-score metrics explain the performance of each class with holdout method for mega-super-classifier. Similarly in Table 5, it can be shown that the developed system takes overall low testing time (< 1 sec.) for the standard test data sets.The limitation or drawback of the present system is that, the training time of this system is quite high. But training is only for one time while recognition is for multiple times. Once the training completes, recognition is possible for different inputs many times as per user choice. So with the help of this multi-level multiple classifiers we get accurate recognition with minimum recognition time at the cost of training time.

Table 6 shows a comparative study of the present system in terms of accuracy with other multimodal systems mentioned in section 1 [1, 2, 3, 4], whereas our developed system effectively deals with nine different biometric features to give a very secure person authentication system with higher accuracy. Hence, the proposed approach shows improvement in terms of accuracy as compared to techniques mentioned in the Section 1.

4. CONCLUSION

In the present system, multiple classifiers are utilized with different biometric traits, instead of using a single classifier with only one biometric trait for person identification. In this way, it is not required to depend on single classifier functioning with a particular biometric. Here the conclusions coming out from the different types of classifiers utilizing various biometric traits are properlycombined with voting logic through programmed weights. Thus, the different conclusions from individual classifiers and super-classifiers are integrated together to get the most reliable conclusion. The fuzzy conclusion from the mega-super-classifier is more natural than hard or crisp conclusions.The performance measurement in terms of accuracy, precision, recall, F-score with Holdout method for individual classifiers, super-classifiers and for mega-super-classifier is moderately high for different biometric traits. Also the testing time is moderately low for different biometrics.

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