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Fusion in Multimodal Biometric System: A Review

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Abstract

Objectives: The use of multimodal biometric has been introduced recently owing to use of multiple biometric modalities. Here we perform in-depth review of the various methods used for multimodal biometric technology. **Methods/ Statistical Analysis**: Here we present a systematic review of various methods used for fusing multiple biometric modalites. Specifically, fusing at various levels such as, before matching and after matching. Score level, feature level, rank level and decision fusion is followed by feature optimization using methods such as genetic algorithms and artificial neural networks. **Findings**: Single biometric based methods suffer from lack of security and efficiency. This leads to advent of multimodal biometric systems. However, fusing various biometric modalities is being persued with very high interest. We describe the granular nature of several methods used to fuse multiple biometric modalities. A wide range of methods are being employed to fuse biometric data. These methods vary in efficiency and are highly dependant upon the selection of type of biometric chosen for fusion. **Application/Improvements**: As computational efficiency increases, there increase in more secure and efficient biometric systems that use multiple sources of biometric identification and access authorization.

Keywords: Biometric Modality, Fusion, Multimodal Biometric, Optimization

1. Introduction

A multimodal biometric system combines two or more features extracted from a person to determine a person's authentication[1–3]. Multimodal biometric systems can considerably improve the system recognition performance and improve population coverage. It helps in preventing spoof attacks, increase the degrees of freedom, reduce the failure-to-enroll rate and hence make system secure[4–8].The multimodal biometric system shows several advantages as compared to that of a unimodal biometric system due to multiple sources. Multimodal biometric system fusion techniques refer to how the information is fused when obtained from different biometric modalities. This can be divided into five main types but mainly can be subdivided into two categories:

1.1. Fusion just before Matching:

It includes all the schemes which involve fusion techniques before matching stage (Figure 1) as follows:

1.1.1 Feature Extraction Level Fusion:

This fusion mainly involves the fusion of feature vectors extracted from different biometric traits for further processing[3]. The new concatenated feature vector developed has higher dimensions. Further, feature reduction techniques could be applied on large feature set so as to obtain meaningful feature set. It is assumed that this feature

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extraction level fusion performs better than other fusion techniques[9].

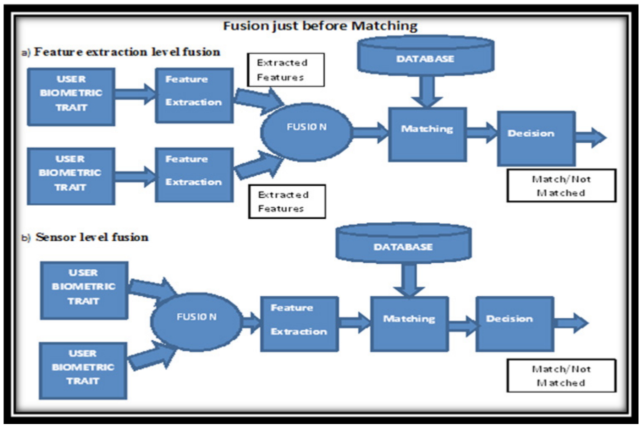

Figure 1. Shows fusion scenarios for fusion just before matching a) Feature extraction level and b) Sensor level fusion.

1.1.2 Sensor Level Fusion:

In this fusion technique, the data obtained from different sensors is combined as raw before hand[10]. It results in better information than to be used individually.

1.2 Fusion just after Matching:

It includes all the schemes which involve fusion after matching stage (Figure 2) as follows:

1.2.1 Matching Score level Fusion:

This fusion scheme provides a matching score which indicates better proximity of feature vector with the template. The scores can be combined to show the conformity of claimed user identity[11].

1.2.2 Decision Level Fusion:

In this fusion scheme the information is captured from various biometric modalities and the resulting feature vector is classified into two main classes i.e. reject or accept. This fusion level technique is quite rigid because of availability of limited information[9].

1.2.3 Rank Level Fusion:

In this fusion scenario, a classifier associates a rank to each and every enrolled biometric identity. It has been suggested that high rank is good indicator of good match.

Different multimodal biometric system using different biometric traits at different levels of fusion are shown in Table 1.

In the present study, most articles related to multimodal biometrics were collected and research advances and methodologies/algorithms used for fusion have been summarized. Also, the work discusses the level of fusion of different biometric modalities used in the research.

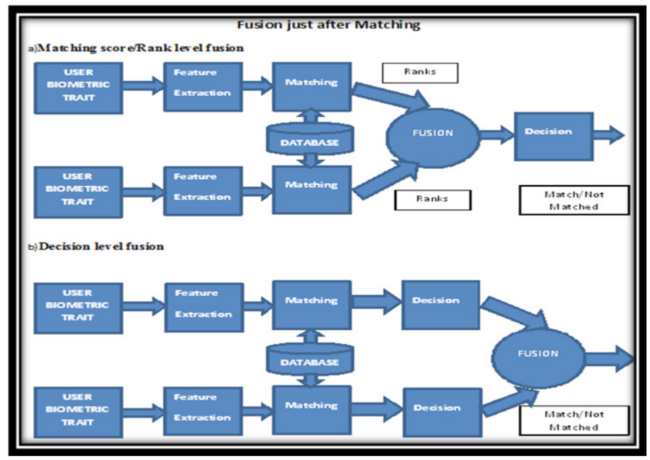

Figure 2. Shows fusion scenarios for fusion just after matching a) Matching Score level and b) Decision level fusion.

Table 1. Different Multimodal Biometric System using different levels of fusion

Biometric Modalities Used for Fusion	Level of Fusion	Reference Number
Face, fingerprint and hand geometry	Match score level	3
Face and iris	Match score level	11
Face and ear	Sensor level	14
Face and gait	Match score level	15
Fingerprint, hand geometry and voice	Match score level	16
Face and palm print	Feature level	17
Fingerprint and signature	Match score level	18
Palm print and hand geometry	Feature level, Match score level	19
Face and voice	Match score level	20
Speech and Signature	Score level	21

2. Multimodal Biometric Systems for Different Fusion Levels

Multimodal biometric system mainly relies on information fusion schemes and information types used from different biometric modalities. The first application using information fusion was reported in 1965[12] that was further used for pattern recognition, information retrieval, machine learning etc[13]. Voluminous literature is available which deals with different fusion schemes like sensor level[14], match score level[15,16,18–21,23–26], feature level[17,19,27,28], rank level fusion[22], decision level[29,30] involving different biometrics. The following sub-sections discuss some of the research employing different fusion methods for multimodal biometric systems.

2.1 Fusion at Score Level in Multimodal Biometric Systems

As stated above a lot of work has come up in recent decade in the field of multimodal biometric systems. Investigation of a multimodal biometric system comprising face, speech and signature was built at score level[31]. Sum rule was used for fusion of scores obtained. The system proved robust in noise too. Fusion of two biometric modalities iris and ear was achieved at score level using sum rule[32]. The iris system was built by extracting features using Principal Component Analyis (PCA). The performance accuracy of the system was 95%. While investigation of information-fusion using face, fingerprint and hand geometry at matching score level was performed, wherein, sum rule was applied for fusion[8]. And results outperformed the fusion results using decision tree and linear discriminant classifiers. The FAR was 0.03% while FRR was 1.78%. Score level and feature level fusion was performed on face, voice and online signature biometrics[33]. Speech and signature fusion at score level was reported byKartik[34]. Speech recognition used MFCC for feature extraction and VQ (vector quantization) for modeling. An offline signature recognition system was built using DCT for feature extraction. Further VPP and HPP were applied. Finally, sum rule was used for fusion of biometric scores. Face, signature and fingerprint biometrics were used for fusion using learning based fusion strategy based on SVM[35]. The results showed that EER using sum rule was 1% while using SVM was 0.3%.

In another study, score level fusion was performed using PSO on iris, palmprint and finger knuckle biometrics[36]. PolyU database for palmprint was used in this work. The work focussed on single biometric as well as the multimodal biometric system. The score was combined using min, weighted sum rule, sum and product rule. The identification rate came out to be 98.4%. A study in 2011 performed comparison of five fusion techniques: Brute force, Genetic Algorithm (GA), Particle Swam Optimization (PSO), Support Vector Machine(SVM) and adaptive neuro fuzzy inference system at score level[37]. The score was first normalized using Min-Max. The results proved that GA and PSO outperformed other techniques even in degraded conditions. A study investigated the multimodal biometrics for voice and fingerprints with the graphical structure of bayesnets[38]. Quality was main measurement criteria for the performance evaluation which mainly refers to accuracy and Signal to Noise ratio. Performance comparison of fusion using Bayesian Belief Net (BBN) and sum rule was found using FAR and FRR. While in another study performed an efficient fusion of face and palm print was done at score level and at feature level using log gabortransformations[39]. Large databases were used for the research. Finally, the PSO technique was applied for reducing the complexity of the features during fusion. Better computation time was shown by both schemes using PSO technique. It was found that hybrid fusion scheme where features were fused using log Gabor space showed tremendously good results with GAR of 97.25%. Multivariate polynomial fusion was also performed on fingerprint and speaker verification system[40]. The work used linear classifiers like weighted averaging and Optimal Weighted Method (OWM). The reduced multivariate polynomial model was tested on Iris dataset to know the classification capabilities before fusion. The dataset has 150 samples which belonged to three subspecies of dimension four. The average classification error was computed. Also for the same dataset different classifiers like Naïve-Bayes, SVM and neural network were applied to compute the error rate for training and testing dataset. Receiving Operating Characteristics (ROC) curves for the speaker and fingerprint verification using the above-mentioned classifiers were also computed. It was found that OWM method to be efficient. Examination of the performance of multimodal biometric authentication systems using state-of-the-art Commercial Off-The-Shelf (COTS)revealed important performacematrices[41]. Fingerprint and face biometric matches were used on a population approaching 1,000 individuals. New normalization and fusion methods were attributed to matching score level fusion of multimodal biometrics. It was found that COTS-based multimodal fingerprint and face biometric

Table 2. Various multimodal biometric systems using different fusion level and fusion approach

S.No.	Year	Multimodal Fusion Level	Multimodal Fusion Approach	Biometric Modalities Used	Reference Number
	2005	Match score Level	Sum-rule, max-rule and min-rule	Face, fingerprint and hand geometry	6
	2003	Match score level	Sum rule , decision rule and Linear Discriminant Analysis	Face, fingerprint and hand geometry	3
	2014	Score Level	Weighted score level fusion	Iris and face	11
	2003	Sensor level	Principal component analysis (PCA)	Face and ear	14
	2005	Match score level	SVM classifiers	Fingerprint and signature	18
	2009	Decision Level	AND rule, OR rule, majority voting	Hand biometrics (palm print, fingerprint, finger geometry)	19
	1998	Match score level	Sum rule, product rule, maximum median and minimum rule	Face and voice	20
	2010	Score level	Product of likelihoods	Speech and Signature	21
	2008	Feature level	Neyman-Pearson theorem	Face and iris	22
	2000	Match score, Decision level	Sum rule	Face, voice and lip movement	23
	1995	Score Level	Weighted geometric average	Speech and face	24
	2011	Score Level	Weighted Fusion	Fingerprint and finger vein	25
	2008	Match score Level	Likelihood ratio	Fingerprint, face and hand geometry	26
	1997	Decision Level	Bayesian supervisor	Speech and face	29
	1998	Decision Level	Bayesian supervisor, Averaging	Face and speech	30
	2014	Feature, Score Level	Max-of-scores	Face, Voice, and Online Signature	33
	2004	Match score level	Local and global decision parameters	Fingerprint, hand geometry and voice	40
	2011	Score Level	Z-Score normalization and Sum rule	Speech, Signature and Handwriting Features	43
	2010	Rank Level	Borda count, weighted Borda count, maximum rank, nonlinear weighted rank	Two palm print images	46
	2012	Feature Level	Sum rule	Palm veins and signature	62
	2007	Feature Level	Delaunay triangulation	Fingerprint and face	63
	2003	Feature level, Match score level	Similarity measure	Palm print and hand geometry	64
	2004	Feature level	Principal Component Analysis (PCA) and Independent Component Analysis (ICA)	Face and palm print	65
	2013	Decision Level	Maximum Likelihood Parameter Estimation	Speech and Signature	66
	1999	Decision-level	AND, OR OPERATOR, Fuzzy k-means and fuzzy vector quantization	Face and Voice	67
	1998	Match score Level	Product-based composite imposter distribution	Face and fingerprint	68
	1999	Match score level	Support Vector Machines, Minimum cost Bayesian Classifier, Fisher's linear discriminant, decision trees, Multi Layer Perceptron	Face and speech	69
	2004	Match score level	Sum, Min and Product Rule	Face and gait	71
	2009	Sensor Level	Particle swarm optimization	Face and palm print	77

systems can achieve better performance than unimodal COTS systems. Meanwhile, person identification was performed using three modalities viz face, mouth and audio[42]. The score level late-integration based on the weighted sum rule was purposed in work. For testing system robustness, acoustic babble noise and JPEG compression to degrade the audio and visual signals were used. Experiments were carried out on a 248-subject subset of the XM2VTS database. The multimodal expert system outperformed each of the single experts in all comparisons.

Eventually, a robust multimodal biometric person authentication system was developed using speech and signature biometric features at score level[43]. Experiments were performed on a bimodal biometric system with and without noise to check system accuracy. The random noise added to the speech files under testing in the speaker recognition case. Similarly, in the signature recognition case, salt and pepper noise (3%) to the signature files under testing was added. The IITG standard database and SSIT database was used to check the performance of bimodal system. In score level fusion using sum rule was applied on speech, signature and handwriting biometrics.

2.2 Fusion at Rank Level in Multimodal Biometric Systems

Also, a study reported research suggested several modifications that enhance the performance of a quality based rank-level fusion scheme in the presence of weak classifiers or low quality input images[44]. Their experimental outcomes have demonstrated a significant performance gain, including image quality, when the fusion scheme is utilized. In another report, researchers investigated a new approach for person recognition using a combination of multiple palm print representations at rank level[45]. They used Borda count, weighted Borda count, maximum rank and nonlinear weighted ranking method. Two palmprint image databases were used in work. Among all of the fusion approaches the authors investigated, the usage of nonlinearities in combination with the weights which resulted in improving the performance. Rank level fusion for ear, face and signature was performed and individual ranks of biometric modalities were fused using highest rank, Borda count method[46]. 300 face samples from 30 randomly chosen subjects (10 from each) were taken. For ear and signature, the database had 240 training samples. A new method proposed a new nonlinear rank-level fusion for multiple palm print representation[47]. While, another study proposed a novel approach for rank level fusion for palm print biometric[48]. The proposition involved K partitions of the template. Proposed algorithm iteratively generates ranks for each partition of the user template. Finally, ranks from template partitions were fused to evaluate the fusion rank for the classification. Experimental results on 100 users showed performance with recognition accuracy of 99 %. It is also believed that rankings of documents should be combined in order to produce a consensus ranking[49]. They proposed method which was based on decision rules which exhibited better performance over former positional data fusion methods. A study reported another important contribution in this area. The work discussed rank aggregation from partial ranking lists[50]. The main conclusions of the research were two approximation algorithms for aggregating partial rankings.

2.3 Fusion at Feature Level in Multimodal Biometric Systems

Feature level fusion of ear and iris biometrics was employed feature level fusion to fuse feature vectors extracted using PCA technique[25]. The accuracy of the system came to be 93% with FAR and FRR as 0.05 and 0.075. While in another work publishedused iris and fingerprint feature level fusion was done using Mahalanobis distance technique and later SVM classifier was applied for matching. The database consisted of 100 genuine and 50 impostor samples. The system accuracy during testing and training time was found for the system. FAR and FRR was also calculated. In another study, the two modalities finger vein and fingerprint were reported for enhancing the multimodal biometric system[51]. The performance was compared with the other methods of fusion like LDA, CCA LPCCA and Kernel-CCA. It was found that the accuracy of fusion at feature level was more than matching score level and FAR, FRR of SLPCCA method came to be best. The palm print fusion was performed at feature level[52].This study used 284 individual images were captured using palm print capturing device as the database. It consisted of 186 male. The size of test image was 384*284 and resolution was 75dpi. Gabor filter banks were applied to preprocessed image. The execution time was calculated for preprocessing, feature extraction and matching separately which came to be 267ms, 123 ms and 18μs. Whereas, A new technique to fuse the feature vectors of hand geometry and face was proposed[53]. EER for the system was 1.58% while FAR was close to 0.01% and

GAR was 50 to 65%. Similarly, palm print texture feature extraction methods based on the variance value calculated for each of the image blocks, Haar Wavelets and PCA[54]. Karhunen-Loeve Transform (KLT) algorithm was applied for palm print feature extraction. The work was tested all the captured images from database. They took 20% of dataset for impostors i.e. 16 individuals. Rest other images were divided into a genuine set of 23 individuals and training set of 45 individuals. False Rejection Rate (FRR) and False Acceptance Rate (FAR) were calculated in the work.

In order to enhance the security in Automated Teller Machine (ATM) system, there different biometrics were employed, namely, 1) fingerprint and iris 2) iris and face and 3) face and fingerprint along with email verification code which provides two level security to the system[55]. Similarly, a study proposed a novel feature level fusion that combines the information of palm print and iris biometric[56]. This system extracts Gabor texture from the pre-processed palm print and iris images. Since it was found that feature vectors attained from different methods are in different sizes and the features from an equivalent image may be correlated. Therefore, wavelet-based fusion techniques were used. Lastly, the feature vector is matched using KNN classifier with stored template. The proposed approach was authenticated on PolyU palm print database fused with IITK iris database of 125 users for their accuracy. The experimental results establish that the proposed multimodal biometric system achieves recognition accuracy of 99.2% and with False Rejection Rate (FRR) of 1.6%. Recently, the feature of face and signature were combined, both of which are from a different domain[57]. Correlation pattern recognition with MACE filter was employed to overcome the problem of the different domain of face and signature. MACE filter was able to extract the feature from face and signature and finally produce a new fused feature vector in a frequency domain. The proposed work achieved GAR of 85.71% and FAR of 14.29%-20%. A feature level fusion of face features and the online handwritten signature features was also proposed[58]. Linear Discriminant Analysis (LDA) was applied in the feature extraction phase to solve the problem of high dimensionality of the combined features. Feature selection using GA with modified fitness function was used to get significant features used for classification from the concatenated features. The recognition accuracy of 97.50% was achieved.

Interesting, on study used finger vein and palmprint biometric for fusion[59]. Contourlet Transform was used to reduce the dimensionality and computational complexity of the features extracted from the preprocessed finger vein and palmprint images. Discrete Stationary Wavelet Transform (DSWT) was used for fusion in the system. While another study preferred face and signature biometrics for the fusion[60]. They proposed an algorithm which fuses wavelet-based features of face and signature and showed promising results. Further, hamming distance classifier was used to take the decision. The performance in terms of false acceptance rate of 5.99% and 3% for multibiometrics system for ORL databases was calculated. Similarly, fingerprint and iris features were fused at the feature extraction level. Extensive study of fusion at the feature level in three different scenarios a) fusion of PCA and LDA coefficients of face b) fusion of LDA coefficients corresponding to the R,G,B channels of a face image and c) fusion of face and hand modalities revealed important insights into the robustness of fusion at feature level. In another research, feature level fusion of palm veins and signature biometrics was performed[61]. While work in papers[62,63,64] discuss feature level fusion using different modalities.

2.4 Fusion at Decision Level in Multimodal Biometric Systems

Decision level fusion oftwo behavioral biometrics, speech and signature were used in a novel multimodal system[65]. Decision level fusion based on Gaussian mixture models was applied. They used the Detection Error Tradeoff (DET) curve to visualize and compare the performance of the system. The EM and GEM estimation algorithms were used to achieve performance rates. The EER=0.0 % for "EM" and EER=0.02 % for "GEM" came for the combined modalities. In another study,Fuzzy k-Means (FKM) and fuzzy vector quantization (FVQ) algorithms, and Median Radial Basis Function (MRBF) network were used for combining the results of face and speech modalities[66]. The quality measure of the modalities data is used for fuzzification. It was found that fuzzy clustering algorithms have better performance compared to the classical clustering algorithms and other known fusion algorithms. Several fusion techniques were tested for face and voice biometrics,including sum, product, minimum, median, and maximum rules and it was found that the sum rule outperformed others[20].

Another study proposed an identification system based on face and fingerprint which used decision based fusion and where fingerprint matching is applied after pruning the database via face matching[67]. Similarly, several fusion strategies, such as support vector machines, tree classifiers, and multilayer perceptrons were deliberated for face and voice biometrics[68]. The Bayes classifier was found to be the best method. Whereas, fusion of face and voice biometrics using The Adaptive Multimodal Biometric Management Algorithm (AMBM) algorithm, containted three major components, a Particle Swarm Optimizer (PSO), a mission manager and the Bayesian fusion processor[69]. The PSO has been designed to search the global fusion rule space. The optimum rule is selected and passed to the fusion processor. Finally, as users access the system, the Bayesian fusion processor applies the optimum rule to make global decisions from the local decisions. In another work use decision level fusion to combine the gait recognition algorithm and a face recognition[70] NIST database which has outdoor gait and face data of 30 subjects was employed to get the fusion results. Some multimodal biometric system with different fusion levels and approaches has been summarized in Table 2.

2.5 Multimodal Biometrics Fusion using Optimization Techniques

Implementation of fingerprint matching approach based on genetic algorithms to find the optimal transformation between two different fingerprints was one of the initial optimization techiniques[71]. NIST-4 database was used in research. While some applied genetic approach for fingerprint authentication[72]. They tested the results on a database of 12 people consisting 1200 fingerprints. Whereas, fuzzy fusion approach for face and fingerprint biometrics and compared with LLR and weighted sum fusion schemes. The results showed fuzzy fusion performed better in terms of accuracy[73]. Fusion of three modalities viz facial features of face, visual features of speech relating to the location of eyes and mouth.Morphological operations were used to extract features. Third acoustic features represented by WLPCC. A five layered Auto-Associative Neural Network (AANN) model was used for distribution of extracted features. The system worked very well with EER of 0.45% for 50 test images[74]. Additionally, genetic algorithm was also used for feature selection of face and signature biometrics[75]. While in[76] sensor fusion technique for face and palmprint biometrics using Particle Swarm Optimisation (PSO). The proposed method included two main steps first decompose the face and palmprint image which obtained from different sensors using wavelet transformation secondly, used PSO to select most edifying wavelet coefficients from face and palmprint biometrics to yield a new fused image. Further Kernel Direct Discriminant Analysis was employed for feature extraction and the decision was obtained using Nearest Neighbour Classifier.

3. Conclusion

We provided a detailed review of feature, rank and decision level fusion. Additionally, we discussed optimization techniques to improve system efficiency. Collectively, this study suggests that as computational efficiency increases along with highly optimized algorithms, biometrics systems will increasingly use multimodal fusion. Addition of novel biometric modalities will increase the complexity in these systems.Fortunately, with security will rise proportionally with the complexity of these systems.

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