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SURVEY ON FUSION OF MULTIMODAL BIOMETRICS USING SCORE LEVEL FUSION

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ABSTRACT

Biometrics is used to uniquely identify a person's individual based on physical and behavioural characteristics. Unimodal biometric system contains various problems such as degree of freedom, spoof attacks, non-universality, noisy data and error rates. so the need of multimodal biometrics system occurred, a multimodal biometric system combines the different biometric traits and provides better performance as compared to a single biometric trait. The paper of different traits are analysed and also discuss the various fusion techniques used for different modalities with the objective of improving performance and robustness at each level of fusion.

Keywords – Multimodal biometrics, Level of fusion, Fusion methods.

Introduction

Biometrics

Biometrics refers to the technology for evaluating and examining a person's physiological or behavioural characteristics. These characteristics are unique for all so can be used to analyse or identify a person.

Biometric systems automatically identify or analyse a person's identity based on his physical and etiquette characteristics such as fingerprint, vein. Iris, palmprint and face. A method of recognizing or analysing the identity of an individual person's physiological and etiquette characteristics, a multimodal biometrics increases the accuracy of specific biological traits to the number of

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applicant for verifying all biometrics traits. A multimodal biometrics system uses more than one physiological or etiquette characteristics for enrolment, verification and identification. The reason to combine different modalities is to improve individual's recognition rate. The aim of multimodal biometrics is to reduce one or more of the following.

- False Accept Rate [FAR]
- False Reject Rate [FRR]

Characteristics of biometrics

Universality: Biometric characteristics of every person are noted.

Uniqueness: No two persons should have the same biometric characteristics.

Permanence: The biometric characteristic must be never changing over time.

Collectability: The biometric characteristic should be determined with some sensing device.

Acceptability: The particular user should have no (strong) objections to the measuring and collection of the biometric characteristic.

Types of biometrics

- Unimodal biometrics.
- Multimodal biometrics.

Unimodal biometrics

The Unimodal reply on the proof of a single source of information for authorization (e.g., single face, iris etc.). These systems have to insist with a variety of problems such as

1. Noise in data sensed: scar or a voice sample altered by smut are examples of noisy data in a finger print image sensed. Noisy data are detected from flawed or improperly deigned sensors (e.g. dust

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accumulation in a fingerprint sensor).

2. Intra-class variations.
3. Inter-class similarities.
4. Non-universality
5. Spoof attacks.

Multimodal biometric

The fusion of different types of information is termed as multimodal biometrics for example fusing two biometrics such as fingerprint and face of the same person or iris and retina etc. multimodal biometric gives a solution for some issue related to Unimodal such as

1. Insufficient population coverage or Non-universality.
2. It is very difficult for the imposter to spoof multiple biometric modalities of a legitimate user.
3. Problem of noisy data can be addressed effectively by multimodal biometric systems (scar affecting fingerprint and affective voice).

Level of fusion in multimodal biometrics

Feature level fusion

The main idea is consolidating the obtained feature set of multiple biometric algorithms into a single feature trait, after the process of normalization, transformation and reduction. Feature normalization: It is a process modifying the location (mean) and the scale (variance) via transform function to generate a feature value in order to group them in a common domain (e.g. Min-Max Normalization, Z-score normalization, median normalization etc.). Feature selection or Feature Transformation: In this algorithm dimensionality of a feature set can be reduced (e.g. Sequential Forward Selection, PCA, Sequential Backward Selection)

Score Level Fusion

From a different multiple biometric classifiers, match scores are combined to generate a new match score

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(scalar). When different biometrics match scores are consolidated to achieve a final recognition decision, thus the fusion is done at the match score level (e.g. distance score, similarity score).

Decision Level Fusion

The fusion is carried out decision or abstract level in the multi biometric system only when decisions are available. AND, Majority Voting, OR, Bayesian Decision Fusion Weighted Majority Voting are some of the available fusion strategy.

Literature Survey

Kalyan Veeramachaneni, Lisa Ann Osadciw [1] proposed a framework for an adaptive multimodal biometric management algorithm. It is a decision level fusion technique. In this framework, it describes a sensor management algorithm and how it is applied to the biometric security applications. In this method they used N biometric sensors, a Mission manager, a Particle Swarm Optimizer (PSO), Bayesian Decision Fusion Processor. The PSO is the key success of AMBM collects different fusion rule from N sensors and searches for an optimal rule by selecting a threshold value for each biometric sensors and passed to the fusion processor. The Bayesian Decision Fusion Processor is used to combine the optimal fusion rule from PSO and decisions from multiple sensors. The Bayesian cost for an optimal fusion rule is monotonic and the optimal rule generated is ALL ONE’s. The most commonly used fusion rules are AND, OR and NAND rule is used rarely due to its poor performance.

Padma Polash Paul, Marina L. Gavrilova, and RedaAlhajj [2] proposed Decision Fusion for Multimodal Biometrics Using Social Network Analysis. This methodology overcomes the problem of dimensionality reduction, classifier selection by employing novel decision fusion using Social Network Analysis. Step 1: Dimensionality reduction can be

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reduced by several feature extractors by Fisher Linear Discriminant Analysis; FLDA is a combination of Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA). K-nearest classifier is used to generate the match score and gives the top matches in the database by majority vote of the neighbours. Construction of Social Networks- Among the features of each biometrics trait calculates the Euclidian distance. Each distance is converted into similarity values and the values are normalized into zero to one. SNA analysis is made to improve the confidence of the classifier. The metrics used to boost the confidences are Degree Centrality (DC), Betweeness Centrality (BC), Clustering Coefficient (CC) and Eigenvector Centrality (EC).

MayankVatsa, Richa Singh, AfzelNoore [3] proposed Unification of Evidence-Theoretic Fusion Algorithms: A Study in Level-2 and Level-3 Fingerprint Features Existing fusion approaches are non-adaptive and do not always guarantee optimum performance improvements. In the first approach, to select a most appropriate fusion algorithm by proposed rule based unification framework, here features are extracted using a feature extraction algorithm then the features are converted into belief assignment as Basic Probability Assignment. If conditions are satisfied means Sum Rule Fusion algorithm else the match score is converted into Generalized Belief Assignment then it is processed by Evidence Theoretic Dezert Smarandache (DSm) theory fusion and decision is made Accept/Reject. Second approach is Adaptive Unification. The trained 2ν-GSVM classifier is used to classify the input probe data. The classification algorithm selects either the evidence-theoretic DSm or sum rule fusion to fuse the probe match scores. Depending on the classification result of the 2ν-GSV classifier, an appropriate fusion algorithm

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is used to evaluate the fused match score, and a decision of accept or reject is made.

L. Mezai and F. Hachouf proposed a Score-Level Fusion of Face and Voice Using Particle Swarm Optimization and Belief Functions The proposed combination approach consists of four steps: 1) Transform the match score into belief assignments using Denoeux and Appriou models; 2) Estimate confidence factors using PSO; 3) Combine masses using DS theory and PCR5 combination rules; and 4) Make a decision about accepting or rejecting a person. Step 1: The initial step in the proposed approach is to transform the match scores of each face and voice classifiers into belief assignments m.

Step 2: PSO is mentioned with a population of particles distributed randomly over the search space. Step 3: the theory of evidence is used in order to combine face and voice modalities, In the proposed multibiometric system, we have used DS theory and PCR5 rules to carry out the fusion of face and voice modalities.. Step 4: Decision - A decision about accepting or rejecting a user is made using a statistical classification technique.

Sumit Shekhar, M. Patel, Nasser M. Nasrabadi and Rama Chellappa proposed Joint Sparse Representation for Robust Multimodal Biometrics Recognition In this paper, it describes feature level extraction and joint sparse fusion method to fuse multiple biometrics traits. In feature extraction step 1 is pre-processing then Gabor features were extracted from the processed images and Circular tessellations were extracted around the core point for all the filtered images. Fusion technique Step 1: Joint Sparsity-Based Multimodal Biometrics Recognition contains C – class specification and D modalities, the objective is to determine the class to which a test sample Y belongs to. Step 2: Multimodal Multivariate Sparse Representation- It says to exploit the joint

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sparsity of coefficients from different biometric modalities to make a joint decision. Step 3: Robust Multimodal Multivariate Sparse Representation we consider a more general problem where the data are contaminated by noise, finally it is removed to have a robust fusion.

Conclusion

The domain of multimodal biometrics is new and existing research area in the information science and they are used to understand the traits, accurate methods and personal reliable information representation of decision making and matching. There is a significance increment in activity over research to understand the biometric information system utilization and representation for decision making which can be used as public and security systems and mainly used to understand the complex processes behind biometric matching and recognition. In future the modelling techniques against forgeries more robust and efficient performance over fusion at decision level fusion. More than two traits cannot be used to identify and difficult to find the forgeries.

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Comparison table

Paper	**Method**	**Advantages**	**Disadvantages**
Kalian Veeramachaneni(2005)	Fusion method: The Adaptive Multimodal Biometric Management (AMBM) contains N biometric sensors. Particle swarm optimization (PSO). Bayesian Decision Fusion Processor	It meets the higher performance needs of a biometric personal identification.	Estimation time for the fusion algorithm is high.
Padma Polash(2014)	Decision fusion method: Feature extraction using Fisher Linear Discriminant Analysis and Fusion algorithm using Social Network Analysis.	1. It improves the performance of the system and reduces the spook attack. 2. It guarantees for high quality and secure data.	The improvement includes the study of different approaches for centrality analysis in the Social Network.
Mayank Vatsa(2014)	Fusion algorithm frameworks: Unification framework to dynamically select the most appropriate Evidence – theoretic fusion, Evidence theoretic Dsm fusion algorithm, 2v-granular Support Vector Machine classifier	To efficiently addresses both accuracy and time complexity of multimodal biometric fusion.	It is difficult to expand the framework to include multi matchers, multilevel fusion. We can generalize the algorithm by mixture model based density estimation.
L.Mezai(2014)	Match score using Particle Swarm Optimization(PSO), Fusion using DS	To improve the verification performance and the fusion at score level	It works on two big DS and PCR5 hence complexity is high in this method.

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	theory (Dempster – shafer theory) and PCR 5 (Proportional Conflict Redistribution)	hasmore significance among the fusion at fusion level. Belief functions can manage the conflict between several classifiers	
Sumit Shekhar (2014)	Feature extraction is done by Fisher Linear Discriminant Analysis and fusion methods: Joint sparsity Based Multimodal Biometrics Recognition, Multimodal Multivariate sparse Representation, Robust Multimodal Multivariate Sparse Representation.	These systems are less vulnerable to spoof attacks and non-universality.	The differences in features extracted in terms of types and dimensions often features have large dimensions and fusion becomes difficult at the feature level.