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# AUTHENTICATION USING MULTIMODAL BIOMETRIC FEATURES

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*Abstract: Multimodal biometric systems is the consolidated multiple biometric sources, which enable the recognition performance better than the single biometric modality systems. The information fusion in a multimodal system can be performed at various levels like data level fusion, feature level fusion, match score level fusion and decision level fusion. In this paper, we have studied the performance of different fusion techniques and fusion rules in the context of a multimodal biometric system based on the finger print, hand geometry, knuckle extraction and speech traits of a user. Experiments showed that these fusion techniques showed a marked performance serial rule showed comparatively better performance.*

*Keywords: multimodal biometrics, fusion strategy, data level fusion, Feature level fusion*

## 1. INTRODUCTION

### 1.1 Authentication

Nowadays with the extending trends of internet and e-commerce people are becoming more and more connected through electronic network. An electronic network connects individuals, and organizations, etc. The ability to automatically recognize the identity of individuals is known as person identification or person authentication. The personal identity is essential for the access of network and reliable transactions. Person authentication can be performed by different methods like knowledge, token, and biometric features. Mostly personal identification is performed using following means as text passwords, personal identification numbers, barcodes and identity cards. The merit of these schemes is that they do not change their value with respect to time and also unaffected by the environment in which they are

used. The main demerit of them is that they can be easily misused or forgotten. When days pass by the range of services offered grows wider over the electronic devices and internet. It becomes unmanageable for a person to keep track of the authentication secrets for different services. The alternative which overcomes all these demerits is the use of biometric features for person authentication. The physiological and behavioural characteristics of human are said to be biometric feature provided it possesses the properties of universality, distinctiveness, permanence, collectability, circumvention, acceptability and performance. Password or card can be shared, forgotten or stolen, but not the biometric features.

### 1.2 Biometric System

Acquisition of biometric is more complex compared to making combinations of digits or stealing the card. In this way, biometric is more secure compared to PIN and password. Passwords are desirable to be different for different applications, but same biometric can be used for most of the applications and hence avoids book keeping. Any human physiological or behavioral characteristic can be used as a biometric characteristic (indicator) to make personal identification Some of the commonly used biometric features include speech, face, signature, finger print, handwriting, iris, DNA, Gait, etc.

### 1.3 Multimodal Biometric system

Biometric systems based on single source of information are called unimodal systems. multimodal biometric systems, which combine information from multiple modalities (like face, fingerprint and iris). Multimodal biometric systems can achieve better performance compared with unimodal systems. The information from the multiple sources are integrated either in the earlier stage of the process or in the later stage of the process.

The rest of this paper is organized as follows: Section 2 reviews the supported literature. Section 3 presents a description of the proposed system. Section 4 is illustrated with the experimental results. The efficiency and effectiveness of the algorithm were discussed. Finally, Section 5 concludes the paper with enhancement that can be extended.

## 2. Literature Review

K.Sasidhar et al[17] had examined large face and fingerprint data sets by using various normalization and fusion techniques. The results of their study showed that the performance of multimodal biometric system is higher than the unimodal performance system.

A.K. Jain et al[2] emphasis fusion of the multiple modalities at the match score level due to the reason of its easiness to access and combine the scores presented by the different modalities . Rukhin and

Malioutov [7] proposed fusion based on a minimum distance method for combining rankings from several biometric algorithms.

Kittler et al. [18] compared the various fusion methods and found that the sum rule outperformed many other methods, Verlinde et al. [8] and Fierrez-Aguilar et al. [9] did the comparison on various fusion methods. While Fierrez-Aguilar et al. [10] and Gutschoven and Verlinde [11] designed learning based strategies using support vector machines.

J.P. Baker and D.E. Maurer [13], applied Bayesian belief network (BBN) based architecture for biometric fusion applications. Bayesian networks provide united probabilistic framework for optimal information fusion. Bigun et al. [12] developed a statistical framework based on Bayesian statistics to integrate the speech (text dependent). Hong and Jain associated different confidence measures with the individual matchers when integrating the face and fingerprint traits of a user [16].

S.Vidhya[1] has studied about preserving the encryption modes.

### 3. Proposed Work

Here in the proposed work we are applying various fusion techniques for creating a multimodal biometric system by combining palm print, hand geometry, knuckles and speech of a single person.

#### 3.1 Palm Print and Hand Geometry

The hand geometry and palmprint of a person were extracted. The pose corrected range and intensity images are processed to locate regions of interest (ROI) for hand geometry and palmprint feature extraction.

##### 3.1.1 3-D Palmprint

3-D palmprints are being extracted from the range images of the hand offer highly discriminatory features for personal identification. Features contained in the 3-D palmprint are primarily local surface details in the form of depth and curvature of palmlines and wrinkles. In this work SurfaceCode 3-D palmprint representation is employed. This compact representation is based upon the computation of shape index at every point on the palm surface.

##### 3.1.2 2-D Palmprint

Personal authentication based upon 2-D palmprint has been extensively researched and numerous approaches for feature extraction and matching are available. Feature extraction techniques based upon Gabor filtering has generally outperformed others. In this work, we employ the competitive coding scheme. Six Gabor filtered images are used to compute the prominent orientation for every pixel in the

palmprint image and the index of this orientation is binary encoded to form a feature representation (CompCode). The similarity between two CompCodes is computed using the normalized Hamming distance.

### 3.1.3 3-D Hand Geometry

3-D features extracted from the cross-sectional finger segments have previously been shown to be highly discriminatory and useful for personal identification. For each of the four fingers (excluding thumb), 20 cross-sectional finger segments are extracted at uniformly spaced distances along the finger length. Curvature and orientation (in terms of unit normal vector) computed at every data point on these finger segments constitute the feature vectors. The details of the 3-D finger feature extraction and matching are discussed.

### 3.1.4 2-D Hand Geometry

2-D hand geometry features are extracted from the binarized intensity images of the hand. The hand geometry features utilized in this work include finger lengths and widths, finger perimeter, finger area and palm width. Measurements taken from each of the four fingers are concatenated to form a feature vector. The computation of matching score between two feature vectors from a pair of hands being matched is based upon the Euclidean distance. Another major contribution of this research is the proposed dynamic fusion strategy to selectively combine palmprint and hand geometry features extracted from the pose corrected 3-D and 2-D hand.

### 3.1.5 Dynamic fusion strategy of hand geometry and palmprint

Researches have come up with fusion approaches that can dynamically weight a match score based upon the quality of the corresponding modality. However, accurately computing the quality of a biometric feature can be very challenging. Therefore, here a simple but efficient approach for combining palmprint and hand geometry scores that are simultaneously extracted from the pose corrected range and intensity images were developed.

### 3.2.1. Extraction of Knuckles

The finger geometry parameters extracted from the hand images in the previous section are employed to locate the graylevel pixels belonging to the four individual fingers. The located finger pixels are used to extract the knuckle regions for feature extraction. A total of six finger geometry features is computed from each of the fingers, resulting in a total of 24 finger geometry features. These include one finger length, three finger widths, finger perimeter, and finger area. The normalization of extracted geometrical

features is essential because of their varying ranges and order. Then the knuckles are to be extracted by using Min-Max normalization and Z-score normalization.

Once the finger regions are segmented, the knuckle regions are located for the extraction of reliable features. It may be noted that the finger images extracted from each hand image vary in size. Here two methods for extracting knuckle regions from the segmented fingers are involved.

### 3.3 Speaker Feature extraction using fMAPLR

We propose a flexible tying scheme that allows the bias vectors and the matrices to be associated with different regression classes, such that both parameters are given sufficient statistics in a speaker verification task. Three sets of parameters are taken, that are 1) the GMM parameter set, 2) the hyper parameter set, and 3) the fMAPLR parameter set. GMM and hyper parameter sets are estimated on the background data, and fMAPLR parameter is estimated on the speaker's data. The hyper parameters and the GMM parameters are jointly estimated to maximize the likelihood on the background data.

### 3.4 Fusion techniques

**3.4.1 Data level fusion:** It is also called as pixel level fusion. It combines several sources of raw data to produce new raw that is expected to be more informative and synthetic than input. It can maintain raw data as much as possible, but have the disadvantage of processing large numbers of data, costing much time, requiring the high sensor matching degree, etc. It is the low level fusion. The proposed biometric data fusion algorithm uses the 3-D and 2-D Palmprint, 3-D and 2-D Hand Geometry, Extraction of Knuckles, Speaker Feature extraction of an image to generate a single composite multimodal biometric image. Figure 1 shows the process of fusing biometric images to form a single image.

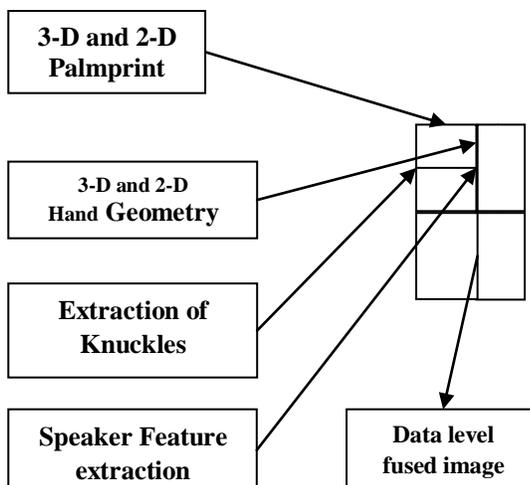


FIG 1: Fusing different levels in data level

**3.4.2 Feature level fusion:** The data obtained from each biometric modality is to compute a feature vector. It is intermediate level fusion. It can compress data to make for processing data real time. Due to the extracted feature have a direct relationship with decision, the result of fusion have more feature information of decision requirement.

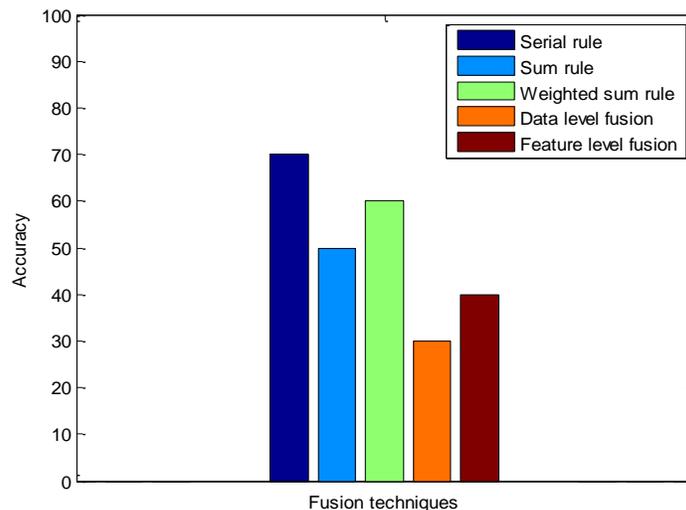
**3.4.3 Match Score Level Fusion:** The main fusion rules in this level are serial rule, parallel rule, and weighted rule. Based on the advantages of feature level fusion, feature level fusion is applied in this paper. Serial rule, Sum rule, and weighted Sum rule fusion algorithms are used in feature level fusion.

#### 4. Experimental Results

Fusion Rule	False acceptance rate	False negative rate	False positive rate	True positive rate	True negative rate
SERIAL RULE	10%	2%	1%	3%	4 %
SUM RULE	40%	1%	4-5%	3%	2 %
WEIGHTED SUM RULE	40%	0%	4-5%	3%	3 %
DATA LEVEL FUSION	40%	3%	4-5%	1%	2 %
FEATURE LEVEL FUSION	40%	3%	3-4%	2%	2 %

Table 1 : Results of various Fusion Rules

The accuracy of the combining palm print, hand geometry, knuckle extraction and speech extraction using various fusion techniques are illustrated with the graph. The accuracy is higher when serial rule is applied. The accuracy is lower when data level fusion is applied. Likewise the error rate is lower when applying serial rule, but it is higher in case of data level fusion.



Normally biometric system can be evaluated by false acceptance rate, false negative rate, false positive rate, true positive rate and true negative rate. On analyzing the above results application of serial rule is found to be more effective.

### 5. Conclusion

Various fusion strategies like serial rule, sum rule, weighted sum rule, data level fusion and feature level fusion are applied to the palm print, hand geometry, speech and knuckle data. Among those techniques serial rule outperformed others. We can combine these biometric features using fusion strategies with encryption in the near future which will enhance the security level.

## REFERENCES

1. Vidhya.S,” A Survey of Format preserving Encryption Modes”, International Journal of Computer Science and Communication Networks Volume 6, Issue 6, January 2017
2. A. K. Jain, A. Ross and S. Prabhakar, “An introduction to biometric recognition”. IEEE Transactions on Circuits and Systems for Video Technology, vol. 14, pp. 4–20, Jan 2004.
3. A.K. Jain, A. Ross, “Multibiometric systems”. Communications of the ACM, vol. 47, pp. 34-40, 2004.
4. Phillips, P.J., P. Grother R.J. Michaels, D.M. Blackburn and E. Tabassi and J.M. Bone, “FRVT 2002: overview and summary”, March 2003.
5. Gokberk, B., A.A. Salah. and L. Akarun, “Rank-Based Decision Fusion for 3D Shape- Based Face Recognition,” LNCS 3546: AVBPA, pp. 1019-1028, July 2005.
6. A. Ross, A.K. Jain, “Multimodal Biometrics: An Overview”, 12th European Signal Processing conference (EUSIPCO), Vienna, Austria, pp. 1221- 1224, 9/2004.

7. L. I. Kuncheva, C. J. Whitaker, C. A. Shipp, and R. P. W. Duin, “*Is independence good for combining classifiers?*”. in Proceedings of International Conference on Pattern Recognition (ICPR), vol. 2, (Barcelona, Spain), pp. 168–171, 2000.
8. L. Rukhin, I. Malioutov, “*Fusion of biometric algorithms in the recognition problem*”. Pattern Recognition Letter, pp. 26, 679–684, 2005.
9. P. Verlinde, G. Chollet, M. Acheroy, “*Multimodal identity verification using expert fusion*”. Information Fusion, vol. 1 (1), pp. 17-33, 2000.
10. J. Fierrez-Aguilar, J. Ortega-Garcia, J. Gonzalez-Rodriguez, “*Fusion strategies in multimodal biometric verification*”. In Proceedings of International Conference on Multimedia and Expo (ICME '03), vol.3(6–9), pp. 5–8, 2003.
11. J. Fierrez-Aguilar, “*Kernel-based multimodal biometric verification using quality signals*”. Biometric Technology for Human Identification, Proceedings of the SPIE, vol. 5404, pp. 544–554, 2004.
12. B. Gutschoven, P. Verlinde, “*Multimodal identity verification using support vector machines (SVM)*”. Proceedings of the Third International Conference on Information Fusion, vol. 2, pp. 3–8, 2000.
13. J. Bigun, et al., “*Multimodal biometric authentication using quality signals in mobile communications*”. Proceedings of IAPR International Conference on Image Analysis and Processing (ICIAP), IEEE CS Press, pp. 2–13, 2003.
14. J.P. Baker, D.E. Maurer, “*Fusion of biometric data with quality estimates via a Bayesian belief network*”. Proceedings of the Biometric Symposium, Arlington, VA, pp. 21–22, 2005.
15. E.S. Bigun, J. Bigun, B. Duc, S. Fischer, “*Expert conciliation for multimodal person authentication systems by Bayesian statistics*”. J. Bigun, G. Chollet, G. Borgefors (Eds.), First International Conference AVBPA Proceedings, Springer Lecture Notes in Computer Science, vol. 1206, pp. 291–300, 1997.
16. R. Brunelli and D. Falavigna, “*Person identification using multiple cues*”. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 12, pp. 955–966, Oct 1995.
17. L. Hong and A. K. Jain, “*Integrating faces and fingerprints for personal identification*”. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, pp. 1295– 1307, Dec 1998.
18. K.Sasidhar<sup>1</sup>, Vijaya L Kakulapati<sup>2</sup>, Kolikipogu Ramakrishna<sup>3</sup> & K.KailasaRao International Journal of Computer Science & Engineering Survey (IJCSSES) Vol.1, No.2, November 2010.
19. Kittler, “*On combining classifiers*”. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20 (3), pp. 226–239, 1998.