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MULTIMODAL BIOMETRIC FEATURES FOR AUTHENTICATION

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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

Increase of transgression with high technology paved the way for awareness of safety in numerous situations. Security has been essential in the observation of privacy protection and information safety. An approach for security, called as biometric individual authentication is used in many fields. Recognition of individuals by a physical or behavioral attribute is the basic for biometrics technology. Examples of recognition of physical characteristics are: fingerprints, iris, face and hand geometry. Behavioral characteristic are the voice, signature or other keystroke dynamics. Recognizing a person based on physiological or behavioral qualities is commencing to get recognition as a genuine technique for determining an individual's uniqueness due to the development in science and technology. A variety of commercial, civilian and forensic applications has been using Biometric systems as a means of establishing identity [1].

The general framework of a typical biometric recognition system is summarized. Here, given some input data (e,g, an image, video or signal), a typical biometric recognition system first performs segmentation or detection, which involves extracting the modality of interest from the input. This is followed by preprocessing, which involves data alignment, noise removal, or data enhancement. Features are extracted from the preprocessed data, which are then used by a classifier for biometric recognition [2]. The recognition process may involve associating an identity with the input data (e.g., biometric identification) or determining if two instances of input data pertain to the same identity (e.g., biometric verification).

A unibiometric system, which utilizes a single biometric cue, may encounter problems due to missing information (e.g., occluded face), poor data quality (e.g. dry fingerprint), overlap between identities (e.g., face images of twins) or limited discriminability (e.g., hand geometry). In such situations, it may be necessary to utilize multiple biometric cues in order to improve recognition accuracy. For example, a border control system may use both face and fingerprints to establish the identity of an individual [3, 4]. In some cases, a biometric cue could be used alongside traditional user-validation schemes such as passwords /pass codes to verify a user's identity. For example, many smart phone devices incorporate such a dual-factor authentication scheme [5, 6]. In other applications, multiple sensors could be used to acquire the same biometric modality, thereby allowing the system to operate in dierent environments. For example, a face recognition system may use both a visible spectrum camera as well as a near-infrared camera to image a person's face and facilitate biometric recognition in a nighttime environment. The term multi biometrics has often been used to connote biometric fusion in the literature [7].

The outline of the paper is as follows: Section II gives review of literature related to different face and palm print multimodal systems. Section III presents the proposed work. Section IV discusses analysis of experimental results. Conclusion and future work are drawn in Section V.

2. RELATED WORK

K.Sasidhar et al 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 a 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 N.Kavitha Devi, International Journal of Computer Science and Mobile Computing, Vol.7 Issue.1, January- 2018, pg. 1-8 © 2018, IJCSMC All Rights Reserved 3 Malioutov proposed fusion based on a minimum distance method for combining rankings from several biometric algorithms. Kittler et al. compared the various fusion methods and found that the sum rule outperformed many other methods, Verlinde et al. and Fierrez-Aguilar et al. did the comparison on various fusion methods. While Fierrez-Aguilar et al. and Gutschoven and Verlinde designed learning based strategies using support vector machines. J.P. Baker and D.E. Maurer , applied Bayesian

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belief network (BBN) based architecture for biometric fusion applications. Bayesian networks provide united probabilistic framework for optimal information fusion. Bigun et al. 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 . S.Vidhya has studied about preserving the encryption modes.

3. PROPOSED METHODOLGY

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-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.

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 (CompCode). The similarity between two CompCodes is computed using the normalized Hamming distance.

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.

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.

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.

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.

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

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.

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.

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. EXPERIMENTATION AND RESULTS

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. Table .1 shows the results of fusion levels of serial rule, Sum rule, weighted rule, Data level rule and Future level fusion.

Table 1. Results of various Fusion Rules

Fusion Rule	False Acceptance Rate	False Negative Rate	False Positive Rate	True Positive Rate	True Negative Rate
Serial Rule	12%	4%	1%	5%	6%
Sum Rule	42%	2%	6-8%	5%	3%
Weighted Sum Rule	42%	1%	6-8%	5%	5%
Data Level Fusion	42%	5%	6-8%	3%	4%
Future Level Fusion	42%	5%	4-5%	4%	4%

5. CONCLUSION

In this work 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 outfitted others. We can combine these biometric features using fusion strategies with encryption in the near future which will enhance the security level.

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