RANK LEVEL FUSION USING FINGERPRINT AND IRIS BIOMETRICS

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Abstract

Authentication of users is an essential and difficult to achieve in all systems. Shared secrets like Personal Identification Numbers (PIN) or Passwords and key devices such as Smart cards are not presently sufficient in few situations. The biometric improves the capability to recognize the persons. A biometric identification system is an automatic recognition system that recognizes a person based on the physiological (e.g., fingerprints, face, retina, iris, ear) or behavioral (e.g., gait, signature, voice) characteristics. In many real-world applications, unimodal biometric systems often face has significant limitations due to sensitivity to noise, intra class variability, data quality, non-universality, and other factors. Multimodal biometric systems overcome some of these limitations. Multimodal biometric system provides more accuracy when compared to unimodal biometric system. The main goal of multimodal biometric system is to develop the security system for the areas that require high level of security. The proposed system focused on developing a multimodal biometrics system, which uses biometrics such as fingerprint and iris. Fusion of biometrics is performed by means of rank level fusion. The features from the biometrics are obtained by using the FLD (Fisher Linear Discriminant). The experimental result shows the performance of the proposed multimodal biometrics system. In this paper, the decision is made using rank level fusion and the ranks of individual persons are calculated using the Borda count, and Logistic regression approaches.

***Keywords*:** Multimodal Biometric System; Rank Level Fusion; Logistic Regression; PCA (Principal Component Analysis); FLD (Fisher Linear Discriminant).

1. Introduction

Each biometric feature has its own strengths and weaknesses and the choice typically depends on the application. The better biometric characteristic has five qualities: robustness, distinctiveness, availability, accessibility and acceptability [1, 2].

Robustness: Unchanging on an individual over time. It is measured by “false non-match rate”.

Distinctiveness: Showing great variation over the population. It is measured by “false match rate”.

Availability: This means that the entire population should ideally have this measure in multiples. It is measured by “failure to enroll rate”.

Accessibility: It is easy to image using electronic sensors. Accessibility can be quantified by the “throughput rate” (measuring the number of users that can be processed in a time period) of the system.

Acceptability: the user perceives it as non-intrusive. Accessibility is measured by polling the device user.

Fingerprints are unique and it is most widely used to identify the person. Its matching accuracy was very high [3]. Iris is the ideal part of the eye in human body. It contains many distinctive features such as furrows, ridges and rings etc [4]. Iris technology provides greater unique identification. According to the above features fingerprint and iris are taken to develop the proposed system. A Multibiometric system combines characteristics from different biometric traits. A reliable and successful multimodal biometric system needs an effective fusion

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scheme to combine biometric characteristics derived from one or modalities. It also improves the template security by combining the feature sets from different biometric sources using appropriate fusion scheme. In multimodal biometrics, the fusion scheme can be classified as sensor level, feature level, match score level, rank level and decision level. Multibiometric system integrates information at the following two categories [5].

(1) **Prior to matching fusion:** In this category, fusion integrates the information of biometric before matching. This includes the following fusion levels.

(i) Sensor level fusion: this system fuse raw data obtained from the sensors without any feature extraction and represented as a single unit. This level of fusion is also known as data level fusion or image level fusion (for image based biometrics).

(ii) Feature level fusion: Data obtained from different sensors are first subjected to feature extraction algorithms and the feature vector that is subsequently used for recognition.

(2) **After matching fusion:** In this category, fusion integrates the information of biometric after matching. This includes the following fusion levels.

(i) Match-score level fusion: Features extracted from individual biometric modalities are first matched to compute the corresponding match scores. Match scores obtained from different biometric systems are then combined to generate a fused match score.

(ii) Decision level fusion: Decisions of individual biometric classifiers are fused to compute a combined decision. This level of fusion is also known as abstract level fusion because it is used when there is access to only decisions from individual classifiers.

(iii) Rank level fusion: Rank level fusion involves combining identification ranks obtained from multiple unimodal biometrics. It consolidates a rank that is used for making final decision. Sensor fusion address the problem of noise in sensed data because improper maintenance of sensors. Feature level fusion is difficult to achieve in such cases because of the relationship between the features spaces of different biometric systems may not be known and concatenating two feature vectors might lead to the dimensionality problem. In score level fusion matching scores of the different biometric modalities are heterogeneous. Normalization is required to transform these scores into a common domain before combining them. Choosing inappropriate normalization technique result leads to very low recognition performance rate. Fusion at the decision level contain only limited amount of information about the data. This is the main problem of this level. Rank level fusion is efficient technique, which is used to consolidate the multiple unimodal biometric matcher outputs. In this paper, the rank of two separate unimodal biometrics (fingerprint and iris) is considered and also discussed its efficiency. The rank of each biometric modality is combined using borda count method and logistic regression method. All biometric traits are considered as images and PCA (Principal Component Analysis**)** and FLD (Fisher Linear Discriminant) methods are used for the enrollment and recognition of biometric traits. Section II describes related works of multibiometric system. Section III describes rank level fusion and its methods. Section IV describes PCA, FLD and eigenimage methods for recognition purpose. Section V will summarize the results of the experiments in terms of error rates. The main goal of this paper is to improve the recognition performance. The performance of the proposed system is measured in terms of error rates (FAR, FRR, EER and GAR) [6].

False Rejection Rate (FRR): The valid user may be rejected as an invalid user. This must be low to achieve good Performance.

False Acceptance Rate (FAR): The Non-authorised user is accepted as authorised user while authentication. In a good authentication system this rate must be low.

Equal Error Rate (ERR): This can be determined by the ratio FRR: FAR**.**

Genuine acceptance Rate (GAR) - It is used to measure the genuine acceptance rate of a valid user.

2. Related works

Several approaches have been developed for multibiometric system using different biometric modalities. M. Nageshkumar et al. [7] have presented an authentication method utilizing two features i.e. face and palmprint for multimodal biometric system identification. The robustness of the person authentication has been enhanced by the combination of both palmprint and face features. The final evaluation was made by fusion at matching score level. Ross and Jain [8] use decision tree and linear discriminant classifiers for combining the scores of face, fingerprint, and hand-geometry modalities. T. Wang et al. [9] developed a multimodal system of face and iris verification system with match score level fusion using methods unweighted and weighted sum rules. Rattani et al. [10] proposed a multibiometric system of face and fingerprint using feature level fusion. The proposed system obtained accuracy of 96.66%. Ajay kumar and sumit shekhar [11] developed a biometric system of palmprint recognition using rank level fusion. Snelick et al. [12] proposed a multimodal system for face and fingerprint, with fusion methods at the score level. Asim Baig et al. [13] developed a multimodal system for fingerprint and iris using score level fusion, which utilizes a single hamming distance matcher. The EER of the proposed system is 2.86%. Srinivasa Reddy [14] generates revocable iris templates and secured them using password hardened fuzzy vault. Feng Hao et al. [15] have presented a biometric based cryptographic key generation method utilizing the iris feature. They generated key, which were created reliably from a legitimate iris codes and hence achieved a 99.5% accuracy rate. They generated up to 140 bits of biometric key that is adequate for a 128- bit AES.

3. Rank Level Fusion

In multimodal biometric system, rank level fusion is the method of consolidating ranks from different biometric modalities (fingerprint, iris, retina etc) to identify an individual. Fig. 1 shows an example of multimodal biometric system of fingerprint and iris using rank level fusion.

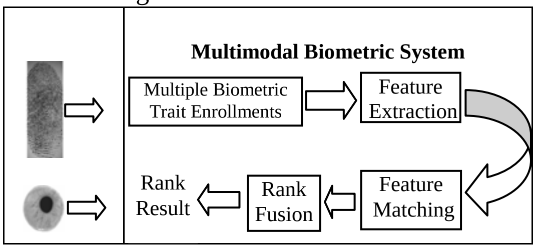


Fig. 1. Multimodal biometric system using rank level fusion approach

Ross et al. [16] describe three methods to combine the ranks assigned by different matchers. Those are the highest rank method, the Borda count method, and the logistic regression method.

Highest Rank Method: In the highest rank method, the fused rank of a user is computed as the lowest (minimum) rank generated by different matchers.

Borda Count Method: This method uses the sum of the ranks assigned by individual matchers to calculate the final rank.

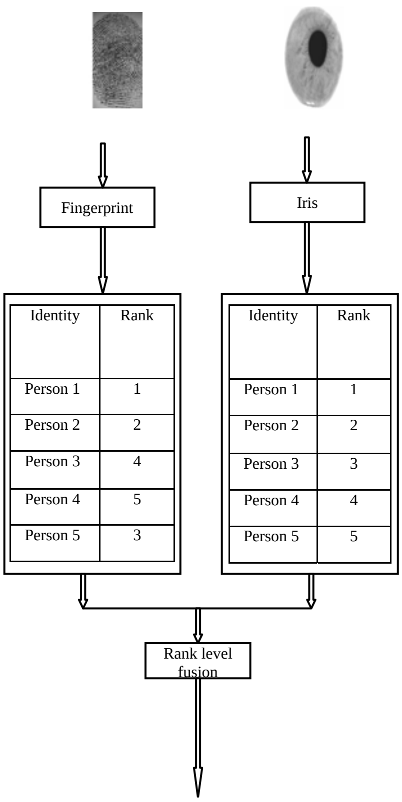
Logistic Regression Method: The performance of the different biometric is not uniform. For example a biometric iris image is performing better than hand geometry or face. Therefore assigning the corresponding biometric weights to the rank of individual matchers have been mostly used modifies the borda count method. The weights are calculated during the training phase using logistic regression method. Figure 2 shows an example for proposed system using borda count method and logistic regression method of rank level fusion.

The value of the less rank will be the more accurate result. In Fig. 2 ranks for "Person 1" are 1, and 1 from the fingerprint, and iris. In the Borda count method, these ranks are added and then divided by 2 (number of biometrics). Here the one, which is the first rank. For the logistic regression method, the assigned weights are 0.3 and 0.15 for fingerprint and iris. For "Person 3," the obtained ranks are 4 and 3 for Fingerprint and iris. For the reordered rank calculation, initial ranks are multiplied by their respective weights **(4 multiplied by 0.3, 3 multiplied by 0.15).** Then, these two new ranks of "Person 3" is added and divided by 2 (number of biometrics), the result is 0.825, which is considered as rank 3 (Third from the lowest).

4. Proposed System

Eigenimage and fisherface techniques are used in this system for recognition of biometric traits. Two types of recognition approaches are used for images (appearance based and model based). PCA and FLD are example of appearance-based system. Figure 3 is the representation of the proposed system. All biometric traits are considered as eigenimages. The extracted features from the eigen image is based on the K–L transform (Karhunen-Loeve or Hotelling transform). These features are obtained by projecting the original sub images into

the corresponding subspaces. The proposed system is initialized with a set of training images. Eigenvectors and eigenvalues are computed from the covariance matrix of these images. Eigenimages with low eigenvalues can be omitted because, it has only a small part of the features of the images. The chosen eigen values are those which has highest value. Finally, the known images are projected onto the image space, and their weights are stored. A threshold determines an acceptance or rejection. The following steps show the recognition process.
(1) Project the test image into the eigenspace, and calculate the distance between the unknown image position and all the known image's positions in the eigenspace.
(2) The image closest to the unknown image in the eigenspace as the match.



Identity	Borda Count Method		Logistic regression method (Finger Print=0.3, iris=0.15)	
	Fused score	Recorded rank	Fused score	Recorded rank
Person 1	2/2= 1	1	0.45/2= 0.22	1
Person 2	4/2= 2	2	0.9/2= 0.45	2
Person 3	7/2= 3.5	3	1.65/2= 0.82	3
Person 4	9/2= 4.5	5	2.1/2= 1.05	5
Person 5	8/2= 4	4	1.7/2= 0.85	4

Fig. 2. Example of rank level fusion.

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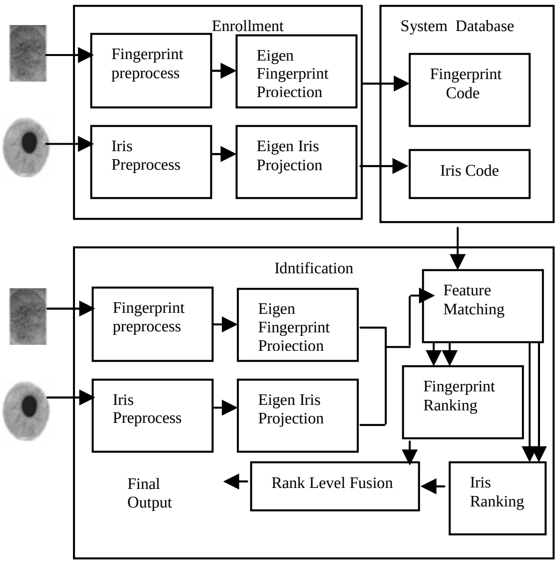

Fig. 3. Proposed system.

5.1. *Recognition Using Fisherface*

The fisherface method use both PCA and FLD to produce a subspace projection matrix. Fisherface method is able to take advantage of within-class information, minimizing variation within each class. Scatter matrices, representing the within-class (SW), between-class (SB). Two scatter matrices are computed, representing the within-class (SW), between-class (SB) and total (ST) distributions of the training set is,

$$S_W = \sum_{i=1}^{C} \sum_{\Gamma_k \epsilon X_i} (\Gamma_k - \Psi_i)(\Gamma_k - \Psi_i)^{\mathrm{T}} \quad (1)$$

$$S_B = \sum_{i=1}^{C} |X_i|(\Psi_i - \Psi)(\Psi_i - \Psi)^{\mathrm{T}} \quad (2)$$

$$S_T = \sum_{n=1}^{M} (\Gamma_n - \Psi)(\Gamma_n - \Psi)^{\mathrm{T}} \quad (3)$$

Where $\Psi = (1/M)\sum_{n=2}^{M}\Gamma_n$ the average image vector of the entire training is set and $\Psi_i = (1/|X_i|)\sum_{\Gamma_i \in X_i}\Gamma_i$ is the average of each individual class X_i (person).

6. Experimental Results

The proposed system has been implemented using this MATLAB. The biometrics obtained from 100 persons is used for evaluation. For convenient use of the system, the proper database consisting of subdirectories of training fingerprint, iris will be automatically connected to the system. The proposed system is evaluated using the parameters such as False Rejection Rate (FRR) and False Acceptance Rate (FAR). For fingerprint the FVC2000 data set and iris the **Cuhk**(University of hongkong) database is used. Figure 4 shows the false rejection rate of the proposed system, from this logistic regression method has lesser FRR and it provides better result than borda count method. Fig 5 shows the false rejection rate of the proposed system. It shows the logistic regression method has lesser FAR and it provides better result than borda count method.

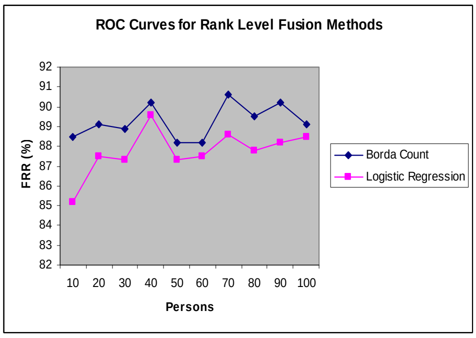

Fig. 4.

7. Conclusion and Future Work

Multibiometrics is a new technique used to accurate identification of the person. In this paper, we present a comparison between borda count method and logistic regression methods are obtained. From the comparison results that rank-level fusion with the logistic regression approach provided the better performance in terms of error rate and increase the recognition rate of multibiometric systems, because in this approach, weights are assigned to different matchers according to their performance. Some of the future enhancements that can be incorporated to improve the security and performance of the system are given below:

(1) Other biometric features like nose, face, palm print etc can be used in this research, which may provide better results.

(2) Cryptographic techniques can be incorporated in this research, which would increase the security.

(3) Better multimodal fusion technique can be used for better results in the biometric fusion.

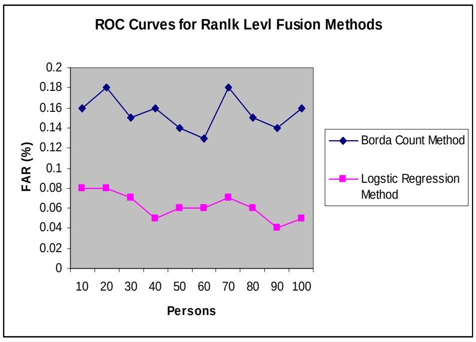

Fig. 5.

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