Integrating Iris and Signature Traits for Personal Authentication using User-Specific Weighting

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***Abstract*—Biometric systems based on uni-modal traits are characterized by noisy sensor data, restricted degrees of freedom, non-universality and are susceptible to spoof attacks. Multi-modal biometric systems seek to alleviate some of these drawbacks by providing multiple evidences of the same identity. In this paper, a user-score-based weighting technique for integrating the iris and signature traits is presented. This user-specific weighting technique has proved to be an efficient and effective fusion scheme which increases the authentication accuracy rate of multi-modal biometric systems. The weights are used to indicate the importance of matching scores output by each biometrics trait. The experimental results show that our biometric system based on the integration of iris and signature traits achieve a false rejection rate (FRR) of 0.008% and a false acceptance rate (FAR) of 0.001%.**

I. Introduction

Multi-modal systems address the problem of non-universality: it is possible for a subset of users to not possess a particular biometrics trait. For example, the feature extraction module of a fingerprint authentication system may be unable to extract features from fingerprints associated with specific individuals, due to the poor quality of the ridges. In such instances, it is useful to acquire multiple biometric traits for verifying the identity. Multimodal systems also provide anti-spoofing measures by making it difficult for an intruder to spoof multiple biometric traits simultaneously [1]. By asking the user to present a random subset of biometric traits, the system ensures that a *live* user is indeed present at the point of acquisition. Thus, a challenge-response type of authentication can be facilitated using multi-biometric systems.

However, an integration scheme is required to fuse the information presented by the individual modalities. Multi-modal biometric systems are expected to be more reliable due to the presence of multiple pieces of evidence [2]. Furthermore, multi-modal systems are able to meet the stringent performance requirements imposed by various applications [3]. In fact, the latest research indicates that using a combination of biometric techniques for human identification is more effective, and far more challenging [6]. Therefore, the problem of information fusion requires much attention in order to optimize the success rate of multi-modal biometric systems.

II. Related Work

Multi-modal biometrics was pioneered by Anil K. Jain; and there has been substantial research carried out in this area. A variety of biometric fusion schemes, which use classifiers, have been described in the literature to combine multiple biometric trait scores. These include majority voting, sum and product rules, k-NN classifiers, SVMs, decision trees, etc, [6], [9], [10]. Ross et al. [1], [7] combine the matching scores of three traits (face, fingerprint and hand geometry) to enhance the performance of a biometric system. Three different techniques (sum rule, decision tree, linear discriminant analysis) are used to combine the matching scores. Experiments indicate that the fusion scheme using the sum rule with normalized scores gives the best performance. These results are further improved by learning user-specific matching thresholds and weights for individual biometric traits.

Other multi-modal biometric fusion approaches include: the HyperBF network approach used to combine the normalized scores of five different classifiers operating on the voice and face feature sets of an individual for identification [11]. Bigun et al. develop a statistical framework based on Bayesian statistics to integrate the speech (text-dependent) and face data of a user [8]. The estimated biases of each classifier is taken into account during the fusion process. Hong and Jain associate different confidence measures with the individual matchers when integrating the face and fingerprint traits of a user [3]. They also suggest an indexing mechanism wherein face information is used to retrieve a set of possible identities and the fingerprint information is then used to select a single identity. A commercial product called BioID [12] uses the voice, lip motion and face features of a user to verify identity. Brunelli and Falavigna also addressed an important aspect of fusion; the normalization of scores obtained from different domains [11]. Normalization maps the scores obtained from different ranges into a common range.

In this paper, an enhanced user-specific weighting technique, which is based on the different degrees of importance for different traits of an individual, to integrate the physiological trait, the *iris* and behavioral trait, the *signature* is proposed. The user-specific weights for individual biometric traits are calculated based on the score of each biometrics trait of an

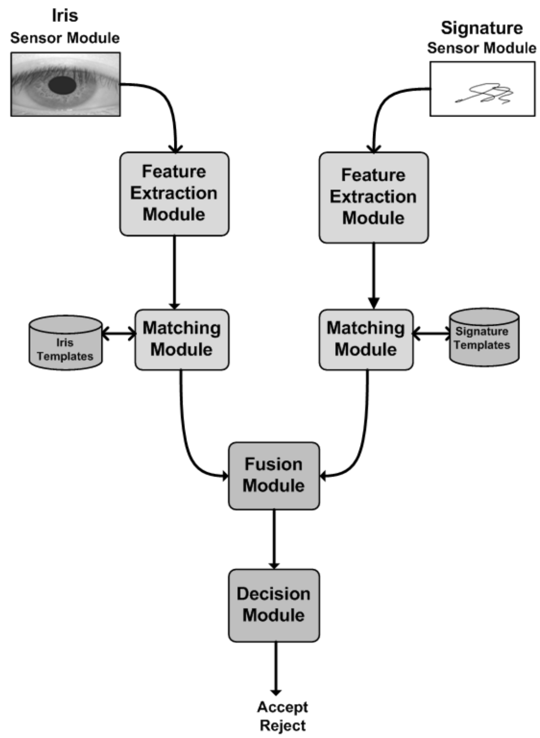

Fig. 1. *Multi-modal Biometrics System (Iris & Signature).*

individual user. The proposed approach is an alternative to the estimation of user-specific weights by exhaustive search.

The rest of the paper is structured as follows: *Section III* explores various fusion techniques for combining biometric traits; *Section IV* describes an overall multi-modal biometrics system; *Section V* describes the weighting techniques and normalization strategies; *Section VI* presents experimental results; and *Section VII* draws the conclusions and future work.

III. Fusion in Biometrics

There are various levels of fusion for combining biometric traits. The three possible levels of fusion are [1]:

1) **Fusion at the feature extraction level**: The data obtained from each sensor is used to compute a feature vector. If the features extracted from one biometric trait are independent of those extracted from the other, it is better to concatenate the two vectors into a single new vector. The new feature vector now has a higher dimensionality and represents a person's identity in a different hyperspace. Feature reduction techniques may be employed to extract useful features from the larger set of features.
2) **Fusion at the matching score level**: Each system provides a matching score indicating the proximity of the feature vector with the template vector. These scores can be combined to assert the veracity of the claimed identity. Fusion techniques such as logistic regression may be used to combine the scores reported by different sensors. These techniques attempt to minimize the FRR for a given FAR [4].
3) **Fusion at the decision level**: Each sensor can capture multiple biometric data and the resulting feature vectors are individually classified into the two classes: *accept* or *reject*. A majority vote scheme, such as that employed in [5] can be used to make the final decision.

IV. Multi-modal Biometrics System

Multi-modal biometric systems are based on the consolidation of information presented by multiple evidences that stem from multiple traits. Some of the limitations imposed by uni-modal biometric systems (that is, biometric systems that rely on the evidence of a single biometric trait) can be overcome by using multiple biometric modalities [6], [8], [11]. Such systems, known as multi-biometric systems, are expected to be more reliable due to the presence of multiple, fairly independent pieces of evidence.

A variety of factors should be considered when designing a multi-biometric system. These include the choice and number of biometric traits; the level in the biometric system at which information provided by multiple traits should be integrated; the methodology adopted to integrate the information; and the cost versus matching performance trade-off.

A simple multi-modal biometrics system has five important components as depicted in **Figure 1**, in which different biometric traits are fused at match score level:

1) **Sensor module**, acquires the biometric data of an individual. An example is the ePadInk tablet that captures the signature.
2) **Feature extraction module**, the acquired biometric data is processed to extract distinctive feature values.
3) **Matching module**, the extracted feature values are compared against those in the template by generating a matching score.
4) **Fusion module**, combines the biometric trait scores.
5) **Decision module**, a claimed identity is either accepted or rejected based on the fusion matching score generated in the fusion module.

V. Integrating Iris and Signature Traits

A brief description of the two biometric traits used in this research work is given below.

A. Iris Recognition

Iris recognition is proving to be one of the most reliable biometric traits for personal identification since iris patterns have stable, invariant and distinctive features. Several techniques have been proposed for iris segmentation, coding and matching. The most common approach used in iris recognition is to generate feature vectors corresponding to individual iris images and perform iris matching based on some distance measures [21], [22]. In this research work, an algorithm that detects the largest non-occluded rectangular part of the iris as region of interest (ROI) is used [13]. A cumulative-sum-based grey change analysis technique is applied to the ROI to extract features for recognition [14]. Then, the Hamming Distance is computed as the iris matching score.

B. Signature Verification

Signatures continue to be an important biometric trait because it remains widely used primarily for authenticating the identity of human beings. An efficient text-based directional signature recognition algorithm which verifies signatures, even when they are composed of symbols and special unconstrained cursive characters which are superimposed and embellished is used [15]. This algorithm extends the character-based signature verification technique. The text-based directional algorithm integrates the direction information extracted from the structure of the whole signature text image contours with the transition information between background and foreground pixels in the signature text image. The extracted features represent the distinguishing cursive handwriting styles. Then, the Mahalanobis Distance is computed as the signature matching score.

C. Combining Iris and Signature Traits

The iris and signature traits are fused at the matching score level, where the matching scores output of each of these two traits are weighted and combined. Fusion at the matching score level is usually preferred, as it is relatively easy to access and combine the scores presented by the different modalities [6]. There are two distinct approaches for the match score level fusion: the *classification problem* approach [10], where a feature vector is constructed using the matching scores output by the individual matchers, and the *combination problem* approach, where the individual matching scores are combined to generate a single scalar score, which is then used to make the final decision. The literature shows that the *combination* approach performs better than the *classification* approach [1]; hence, it is adopted in this paper.

1) Score Generation: Iris matching scores are generated from string iris feature codes extracted by the cumulative-sum-based grey change analysis technique. To verify the similarity of two iris codes, Hamming Distance (HD) based on the matching algorithm [17] is used. The smaller the HD, the higher the similarity of the compared iris codes. The HD denotes the iris raw matching score, S_{iris}, which is computed as:

$$S_{iris} = \frac{1}{2N}[(\sum_{i=1}^{N} A_h(i) \oplus B_h(i)) + (\sum_{i=1}^{N} A_v(i) \oplus B_v(i))] \quad (1)$$

only when $A_h(i) \neq 0 \wedge B_h(i) \neq 0, A_v(i) \neq 0 \wedge B_v(i) \neq 0,$

where $A_h(i)$ and $A_v(i)$ denote the enrolled iris code over horizontal and vertical directions, respectively, $B_h(i)$ and $B_v(i)$ denote the new input iris code over the horizontal and vertical directions respectively. *N* is the total number of cells, and $\oplus$ is the XOR operator.

Signature matching scores are generated from the signature feature vectors. To verify the similarity of two signatures, Mahalanobis Distance (MD) based on correlations between signatures is used. It differs from Euclidean distance in that it takes into account the correlations of the data set and is scale-invariant. The smaller the MD, the higher the similarity of the compared signatures. The MD denotes the signature raw matching score, S_{sig}, which is computed as in equation (2).

$$S_{sig}(\overrightarrow{x}, \overrightarrow{y}) = \sqrt{(\overrightarrow{x} - \overrightarrow{y})^T S^{-1} (\overrightarrow{x} - \overrightarrow{y})} \quad (2)$$

where $\overrightarrow{x}$ and $\overrightarrow{y}$ denote the enrolled feature vector and the new signature feature vector to be verified, with the covariance matrix S.

2) Score Normalization: Given a set of n raw matching scores $\{S_k\}$, $k = 1, 2, ..., n$, the corresponding normalized scores S'_k are given by:

- *Min-max normalization*: retains the original distribution of scores and maps all the scores into the $[0, 1]$ range.

$$S'_k = \frac{S_k - \min(\{S_k\})}{\max(\{S_k\}) - \min(\{S_k\})} \quad (3)$$

  where $\min(\{S_k\})$ and $\max(\{S_k\})$ are the minimum and maximum, respectively, of the given set $\{S_k\}$ of matching scores.
- *Z-score normalization*: transforms the scores to a distribution with arithmetic mean of 0 and standard deviation of 1.

$$S'_k = \frac{S_k - \mu}{\sigma} \quad (4)$$

  where μ and σ are the mean and standard deviation, respectively, of the set $\{S_k\}$.
- *Tanh normalization*: is a robust statistical technique [16] which maps the raw scores into the $[0, 1]$ range.

$$S'_k = \frac{1}{2}\left\{\tanh\left(0.01\left(\frac{S_k - \mu}{\sigma}\right)\right) + 1\right\} \quad (5)$$

  where μ and σ are the mean and standard deviation, respectively, of $\{S_k\}$.

The ROC curves depicting the performance of the individual score normalization techniques is shown in in Figure 2. *Tanh normalization* technique performs better than *min-max* and *Z-score* techniques.

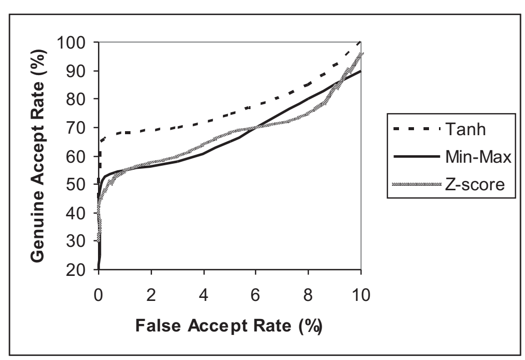

Fig. 2. *ROC curves showing the performance of each of the three normalization techniques on the Iris trait.*

3) Score Weighting: Let s'_{iris} and s'_{sig} be the normalized scores of the iris and signature traits, respectively. The fusion score, s_{fus} is computed as

$$s_{fus} = w_{iris}s'_{iris} + w_{sig}s'_{sig} \tag{6}$$

where w_{iris} and w_{sig} are the *weights* associated with the degrees of importance of the two traits per individual, and

$$w_{iris} + w_{sig} = 1 \tag{7}$$

Different iris scores and signature scores are given different degrees of importance for different users. For instance, by reducing the weight w_{iris} of an occluded iris and increasing the weight w_{sig} associated with the signature trait, the false reject error rate of the particular user can be reduced. The biometric system learns user-specific parameters by observing system performance over a period of time [6]. Two techniques are used to compute the user-specific weights: *an exhaustive search technique*, and *a user-score-based technique*.

The Exhaustive Search Technique: Let w^i_{iris} and w^i_{sig}, be the weights associated with the i^{th} user in the database. The algorithm operates on the training set as follows [7]:

- For the i^{th} user in the database, vary weights w^i_{iris} and w^i_{sig} over the range $[0, 1]$, with the constraint $w^i_{iris} + w^i_{sig} = 1$. Compute $s^i_{fus} = w^i_{iris}s'_{iris} + w^i_{sig}s'_{sig}$. This computation is performed over all scores associated with the i^{th} user.
- Choose that set of weights that minimizes the total error rate. The total error rate is the sum of the false acceptance and false rejection rates pertaining to this user.

The set of weights, $\{w^i_{iris}, w^i_{sig}\}$, that minimize the total error rate, with the constraint $w^i_{iris} + w^i_{sig} = 1$, do not necessarily associate the degrees of importance for iris and signature biometric traits of the i^{th} individual in the fusion score: $s^i_{fus} = w^i_{iris}s'_{iris} + w^i_{sig}s'_{sig}$. An alternative user-score-based weighting technique, which computes the weights, $\{w^i_{iris}, w^i_{sig}\}$, by associating them with the degrees of importance for iris and signature biometric traits, respectively, is proposed. In this method, the weights, $\{w^i_{iris}, w^i_{sig}\}$, which are not constrained to $w^i_{iris} + w^i_{sig} = 1$, are computed in consideration of how close the scores, s'^i_{iris} and s'^i_{sig} are, to the thresholds of the iris and signature traits, respectively. The user-score-based weighting technique is described below.

The User-Score-Based Technique: Let s'^i_{iris} and s'^i_{sig}, be the normalized scores associated with the i^{th} user in the database, and τ_1 and τ_2 are the thresholds of the iris and signature traits, respectively. The preliminary weights w'^i_{iris} and w'^i_{sig} per trait are computed as

$$w'^i_{iris} = \begin{cases} 0.5 & \text{if } s'^i_{iris} = \tau_1 \\ \frac{s'^i_{iris}}{\tau_1 + s'^i_{iris}} & \text{otherwise} \end{cases} \tag{8}$$

and

$$w'^i_{sig} = \begin{cases} 0.5 & \text{if } s'^i_{sig} = \tau_2 \\ \frac{s'^i_{sig}}{\tau_2 + s'^i_{sig}} & \text{otherwise} \end{cases} \tag{9}$$

where w'^i_{iris} and w'^i_{sig} are the initial weights associated with the iris and signature, respectively, **without** the constraint $w'^i_{iris} + w'^i_{sig} = 1$. These weights are assigned to the scores, s'^i_{iris} and s'^i_{sig} after analyzing how close or farther away the scores are from their respective thresholds, τ_1 and τ_2. Then, the fusion weights for the i^{th} user are computed respectively, for the iris and signature as

$$w^i_{iris} = \frac{w'^i_{iris}}{w'^i_{iris} + w'^i_{sig}} \tag{10}$$

$$w^i_{sig} = \frac{w'^i_{sig}}{w'^i_{iris} + w'^i_{sig}} \tag{11}$$

with the constraint $w^i_{iris} + w^i_{sig} = 1$, and the fusion score is computed in equation (12).

$$s^i_{fus} = w^i_{iris}s'^i_{iris} + w^i_{sig}s'^i_{sig} \tag{12}$$

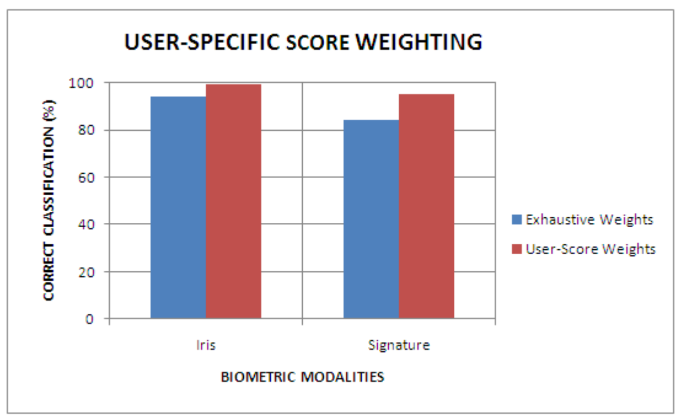

Fig. 3. Average true positive rate of the iris and signature Modalities

4) Score Fusion: The dual ν-Support Vector Machine (2ν-SVM) fusion algorithm [18] is used to integrate the matching scores of the iris s_{iris} and signature s_{sig}, together with their corresponding weights, w_{iris} and w_{sig}. The weighted iris matching score m_{iris} is defined as

$$m_{iris} = s_{iris} \times w_{iris} \tag{13}$$

and the weighted signature score m_{sig} is defined as

$$m_{sig} = s_{sig} \times w_{sig} \tag{14}$$

TABLE I

User-specific Scores and Weights of different traits for 10 users.

User	Iris Score	Signature Score	Normalized Iris Score	Normalized Signature Score	Iris Weight	Signature Weight
1	0.192	0.001	0.487	0.488	0.80	0.20
2	0.277	0.001	0.490	0.488	0.86	0.14
3	0.625	2.054	0.505	0.505	0.50	0.50
4	0.446	2.438	0.506	0.496	0.44	0.56
5	0.232	0.005	0.486	0.492	0.83	0.17
6	0.473	2.383	0.498	0.507	0.47	0.53
7	0.071	0.028	0.484	0.493	0.67	0.33
8	0.522	2.474	0.505	0.507	0.47	0.53
9	0.366	1.358	0.497	0.502	0.48	0.52
10	0.451	1.774	0.502	0.506	0.50	0.50

The weighted matching scores and their labels are used to train the 2ν-SVM for bimodal fusion. Let the training data be

$$Z_{iris} = (m_{iris}, y) \tag{15}$$

and

$$Z_{sig} = (m_{sig}, y) \tag{16}$$

where $y \in \{+1, -1\}$, such that $+1$ represents the genuine class and -1 represents the impostor class. The 2ν-SVM error parameters are calculated using equation (17) and (18).

$$\nu_+ = \frac{n_+}{n_+ + n_-} \tag{17}$$

$$\nu_- = \frac{n_-}{n_+ + n_-} \tag{18}$$

where n_+ and n_- are the number of genuine and impostor, respectively. The training data is mapped into a higher dimension feature space such that $Z \rightarrow \varphi(Z)$, where $\varphi(.)$ is the mapping function. The optimal hyperplane separates the data into two different classes in the higher dimensional feature space.

In the classification phase, the bi-modal fusion matching score s_{fus} is computed in equation (19),

$$s_{fus} = f_{iris}(m_{iris}) + f_{sig}(m_{sig}) \tag{19}$$

where

$$f_{iris}(m_{iris}) = a_{iris}\varphi(m_{iris}) + b_{iris} \tag{20}$$

$$f_{sig}(m_{sig}) = a_{sig}\varphi(m_{sig}) + b_{sig} \tag{21}$$

where a_{iris}, a_{sig}, b_{iris} and b_{sig} are parameters of the hyperplane. The solution of equation (19) is the signed distance of s_{fus} from the separating hyperplane given by the two 2ν-SVM for the two biometric modalities. The decision function defined in equation (22) verifies the identity.

$$Decision(s_{fus}) = \begin{cases} Accept, & \text{if } s_{fus} > 0 \\ Reject, & \text{otherwise} \end{cases} \tag{22}$$

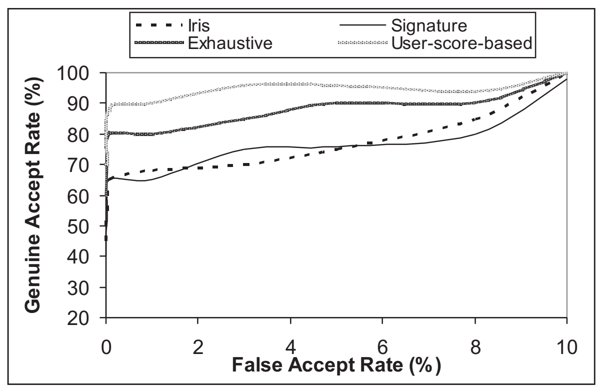

Fig. 4. *Tanh normalized-based ROC curves showing the performance of using Iris, Signature, Iris + Signature (Exhaustive), and Iris + Signature (User-score-based).*

VI. Experimental Results and Discussions

The bi-modal database used in the experiments was constructed by merging *CASIA* iris database [19] with *GPDS* signature database [20]. An alternative bi-modal database was constructed from *CASIA* iris database and a database created from signatures captured using the ePadInk tablet. Seven iris images of the same user were obtained from a set of 50 users from the *CASIA* database. Fifteen signatures (ten genuine and 5 forgeries) were obtained from a different set of 50 users from the *GPDS* database, and another set of signatures were captured using ePadInk tablet. The mutual independence assumption of the biometric traits allows us to randomly pair the users from the two different sets. In this way, two bi-modal databases consisting of 50 users were constructed, either from *CASIA* with *GPDS*, or *CASIA* with signatures captured using ePadInk tablet.

Firstly, the matching scores of the iris and signature traits are computed as defined in equations (1) and (2). These matching scores are normalized and weighted as defined in subsections *V.C.2)* and *V.C.3)*, respectively. Various normalization techniques were investigated. The ROC curves depicting the performance of the individual score normalization techniques is shown in Figure 2. The *Tanh Normalization* technique performs better than the *Min-Max* and *Z-Score* techniques.

Table I shows the scores for the iris and signature biometric traits, and their respective weights, for the sample of ten different individuals. The raw scores are normalized by the tanh technique, and the weights are computed using equations (10) and (11). For instance, from Table I, we observe that for user 5, $W_1^i = 0.83$, a high weight attached to the iris trait, possibly due to the blurred iris. This demonstrates the importance of assigning user-specific weights to the individual biometric trait.

Figure 3 shows the average true positive rates achieved by the exhaustive search technique and the user-score-based approach, respectively, on uni-modal biometric traits based on iris and signature. The exhaustive search technique obtained true positive rates of 92.4% and 82.0% on the iris and signature traits, respectively. The user-score-based approach obtained true positive rates of 99.25% and 94.0% on the iris and signature traits, respectively. The overall average true positive rate achieved by the exhaustive search technique is 87.2%, compared to 96.63% which is obtained by the user-score-based algorithm. Therefore, the results show an improvement in accuracy when the user-score-based weighting technique is used.

The ROC curves in Figure 4, show the performance of the uni-modal biometric traits based on iris and signature, respectively, and the 2ν-SVM fused based bi-modal traits weighted by the exhaustive search technique and the user-score-based approach, respectively. The overall results show an improvement in performance when scores are combined using the user-score-based weighting technique. For a given FAR of 0.001, user-score-based weighting achieve a very low FRR of 0.008, compared to exhaustive search weighting with a FRR of 0.015, as shown in Table II.

TABLE II
Exhaustive search vs User-score-based technique

Weighting Technique	**FAR**	**FRR**
Exhaustive search	0.001	0.015
User-score-based	0.001	0.008

VII. Conclusion

In this paper, an enhanced user-specific weighting technique of integrating a physiological biometrics trait, the *iris*, with a behavioral trait, the *signature*, is proposed. The proposed user-score-based approach calculates weights for each biometrics trait per user in proportion to the scores of the biometric traits of the same user. This enhanced user-specific weighting improves the accuracy rate of bi-modal biometric systems by reducing false reject rate (FRR) on a low false accept rate (FAR). Experimental results show that the proposed approach achieved a minimal FRR of 0.008 on a FAR of 0.01. Further investigation of the effect of the proposed approach with other different biometric modalities is envisaged.

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