Multi-modal Biometric Recognition using Human Iris and Dynamic Pressure Variation of Handwritten Signatures

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Abstract—**Physiological traits containing information extracted from human organs such as fingers, ears, eyes, palm prints, and knuckles can be used for biometric recognition. In addition, behavioural biometric traits such as speech, gait, handwritten signature, and keyboard dynamics while typing a text can provide reliable biometric features. In the current research, texture information extracted from iris data, and dynamic pressure variation data extracted from online signatures was combined to form a reliable biometric system. In this view, this paper is proposing a multi-modal biometric recognition architecture, which utilises a new feature vector extraction mechanism based on the Webber Local Descriptor and the k-NN machine learning classifier. The proposed architecture was evaluated using multi-modal data obtained from 64 users. The TAR-TRR results when using iris recognition alone reached 88.39%. When using dynamic pressure variation data extracted from online signatures TAR-TRR reached 75.89%. When combining the data of the two modalities the recognition TAR-TRR increased to 90.18%. The proposed architecture revealed that biometric systems which perform recognition using two different data channels are more reliable that when using single channel data.**

Keywords- Webber Local Descriptor, Biometics, multi-modal, multi-instance, Signature pressure variation, iris.

I. Introduction

Biometric authentication systems are based on the principle of authenticating a human based on "What he or she is?" rather than "What they remember?" or "What they carry?". This aspect makes the biometric authentication systems far better than traditional password and token based systems. Biometric authentication systems have become ubiquitous in the domain of border control, public surveillance, online transactions and other security related tasks. Biometric systems are difficult to circumvent and have a non-repudiate nature of authentication [1][2][3]. However, as the population increases or the number of users enrolled to the system grows, the rate of detection deteriorates and complexity of identification by biometric systems increases. In such case the challenge of keeping the accuracy as per the standards arises. To address this and have increased accuracy and better support for large populations, multiple biometric traits can be combined to build intelligent biometric systems [4][5][6].

There are different types of biometric implementations multi-modal or multi-biometrics, multi-algorithmic, multi-sensorial and multi-instance biometrics [3][6]. In this work multi-modal systems are discussed, and these systems deal with multiple biometric traits of the same person for improving the accuracy of authentication. Humans have multiple organs such as fingers, ears, eyes, palm prints, and knuckles and these are called physiological biometric traits. Furthermore, how a specific human behaves is also unique and there exist biometric traits derived from such behaviours known as behavioural biometric traits. Behavioural biometric traits include speech, gait, handwritten signature, and keyboard dynamics while typing a text. In the current research, human handwritten signature is combined with iris to build a multi-modal biometric authentication system.

Webber Local Descriptor is a dense global descriptor, which evaluates orientation and excitation based features at pixel level and derives a global histogram, which can be used for classification [7]. This paper proposes an architecture which embeds a Webber Local Descriptor for extracting features from signatures and the iris; and the features are fed into a machine learning classifier which is trained using the extracted features to evaluate biometric recognition performance. Section II provides a literature survey; Section III describes the proposed system architecture; Section IV provides the results and discussion; and Section V provides a conclusion and future work.

II. Literature Survey

Bharadi et al. [5] proposed an architecture for biometric authentication. The architecture has two parts: enrolment and verification. User biometric samples are captured, pre-processed, and thereafter feature extraction is performed. The extracted features are stored in a database in the enrolment phase. In the verification phase the extracted feature vector is input into the classifier for the matching phase. This full process forms a unimodal biometrics system [5][6][8][9]. In case of multi-modal biometrics, such multiple modalities are combined

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at various levels of fusion such as sensor level, feature level, matching score level and decision level [1][2][3][4][6], to make the system more accurate, difficult to circumvent and deceive, and suitable for a large population. In the current work, one channel is based on Dynamic Signature Recognition [9][10][11][12] and another channel is based on Iris Recognition. Online signatures or dynamic signatures are regular handwritten signatures which are captured through specific devices called as Digitizers or pressure sensitive pads. This gives additional information such as, pressure, azimuth, and altitude information about each point in the signature.

In an attempt to make the biometric systems more secure for non-repudiate and suitable for banking, finance and commercial transactions [1][2][9][10][11][12], in their previous work, the authors have proposed signature recognition systems based on Vector Quantization [9][11], Wavelets-based feature vector extraction [9], and Transform complex plane [12]. These were all unimodal systems. Similarly, iris recognition is also implemented using Vector Quantization and Transform based feature vector generation [13][15]. These systems gave False Acceptance Rate (FAR), False Rejection Rate (FRR) Crossover in the range of 85-90%. Furthermore, in [6] the authors combined Iris and fingerprint features to build an algorithm for multi-modal biometric recognition to improve the performance of detecting biometric trait. The system described in [6] used a Score and Decision fusion and texture information based feature vector.

Jie et al. [7] proposed the Webber Local Descriptor as a Robust Local Image Descriptor, and used it for image texture classification. Webber Local Descriptor (WLD) consists of two mechanisms: differential excitation and orientation. It is motivated by Weber's Law, which is a psychological law [7]. WLD is evaluated using the ratio between the two expressions: one is the relative intensity differences of a current pixel against its neighbours; and the other expression is the intensity of the current pixel. Differential excitation gives the local distinct features of the biometric data. In addition, the gradient information is also evaluated. The WLD histogram is built for each trait point. The WLD descriptor exploits the benefits of Scale Invariant Fourier Transform [4] in evaluating the histogram using the gradient and its orientation. WLD is a dense descriptor evaluated for every data point, and depends on both the local intensity variation and the magnitude enters point data.

The work described herein is extending the use of WLD for texture information analysis of biometric traits. WLD can be used to extract the texture information from iris data, and dynamic pressure variation data from online signatures. In this view this paper is proposing a new feature vector extraction mechanism based on WLD.

III. Proposed System Architecture

The proposed system has two distinct channels, one channel is responsible for evaluating behavioural traits and another channel is responsible for handling physiological biometric traits, these are namely Online Signature and Iris, respectively. The proposed architecture is presented in Fig. 1.

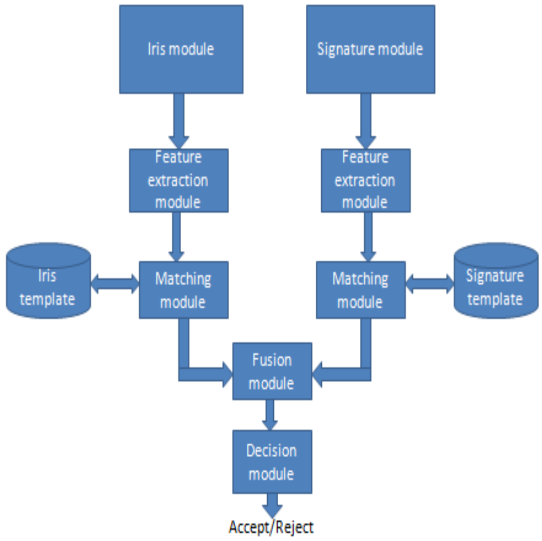


Figure 1: Proposed Biometric System Architecture

A. *Signature Module: Extraction of Dynamic Pressure Variation traits from signatures*

The online signature system under consideration is using a Wacom Intuos 4 Digitizer [9] [11] to capture dynamic data from a signature. Fig. 2 shows an example of the signatures and illustration of the pressures applied when creating the signatures. This digitizer sends the data in packets at a rate of 100 packets/second and each packet consists of X, Y Z, Pen tip Pressure, Azimuth Angle and Altitude angle of the pen while signing.

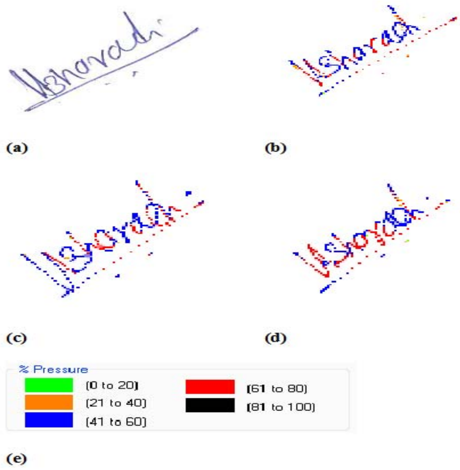


Figure 2: Signatures and illustration of the pressures applied when creating the signatures.

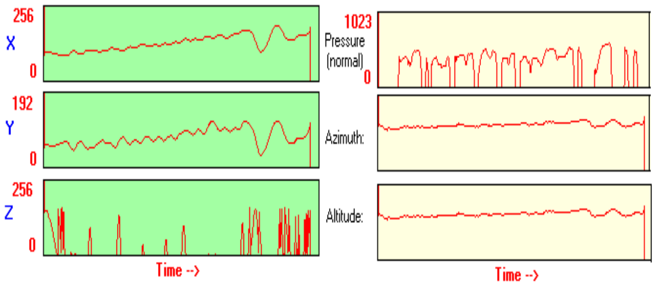


Figure 3: Signature Feature Plot for Multidimensional features- X,Y,Z Co-ordinates, Pressure Azimuth and Altitude parameter for signature sample shown (a) Offline Scanned Signature (b)-(d) Dynamic Signature shown in Fig. 2.

A typical signature, its offline and online versions and the data plots are shown in Fig. 3. Preprocessing the signatures [9] gives a WxH template of 540x340 pixels, which is used for feature extraction.

Signature template: A signature template of size 540x340 with information of Pressure, Azimuth and Altitude information is used for WLD based Feature Vector Extraction. Fig. 4 shows a signature template along with information on the different pressure levels applied during the signing process. The pressure information matrix is taken for the generation of the Histogram feature vector, illustrated in Fig. 5.

Figure 4. Signature Template with Pressure Levels

Three histograms are generated for the signature pressure information of size Hs=8x120 for three scales (neighbourhood of 3x3, 5x5 and 7x7 pixels while applying the orientation calculation operators), one histogram has 960 elements, such three histograms are there hence total elements are 960x3=2880. The feature vector size for one signature is 2880 elements as derived from [17]. Each element represents occurrence of orientation and excitation in a specific range (of the respective sub-histogram bins). This will be used for recognition of the signature.

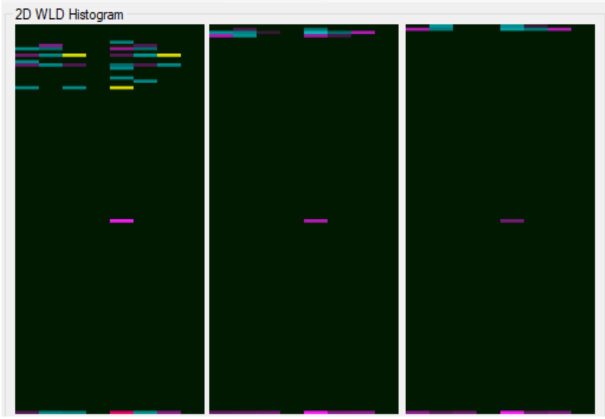
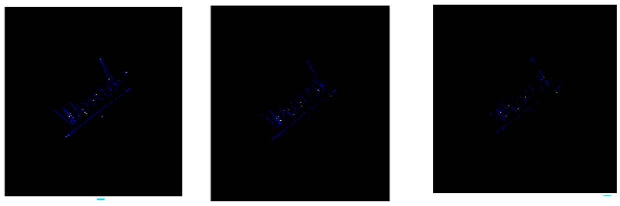


Figure 5. WLD Histograms for the signature shown in Fig. 4.

(a) Orientation Plots



(b) Excitation Plots

Scale 1 Scale 2 Scale 3

Figure 6. Orientation and Excitation plots for the signature shown in Fig. 4.

B. *Iris Module: Extraction of Physiological Biometric traits*

The human iris is rich in texture and has high degree of uniqueness. Iris based biometrics are resilient to rotation and aging as well as more stable and highly reliable [4][5][6][13][14][15][16]. Fig. 6(a) depicts a typical iris with texture information.

The Phoenix database [18] is used for storing the features extracted from WLD, and the database contains iris data of 64 candidates. For each candidate, three images of the left and three images of the right eye are stored. Thus, in total there are 384 such images in the database. Each image is resized to a 128x128 matrix. Iris normalization is often carried out via three main steps: Canny Edge Detection, Iris Localization and Unwrapping [6] [13] [15] [16]. The iris normalization process provides an iris template of size 180x380 pixels. Feature extraction is performed on the template. Fig. 6 shows the steps in iris pre-processing, localization and unwrapping of the iris data.

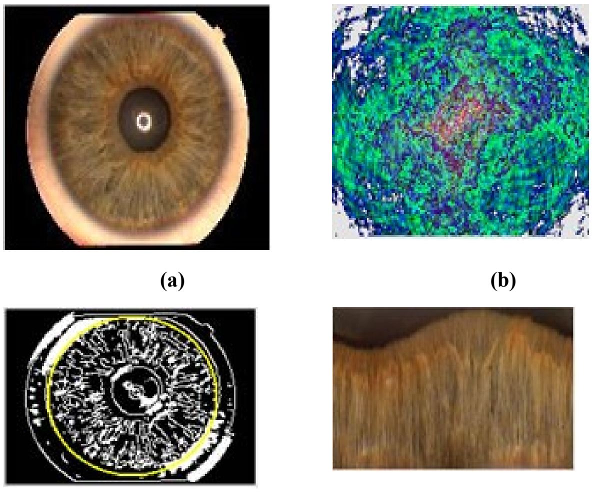


Figure 7: Unwrapping Iris (a) Input Iris Image (b) Corresponding Hough Magnitude (c) Localized Iris Region (d) Unwrapped (Normalized) Iris [6],[13],[15],[16]

Figure 8. (a) Input Iris Image[18]

Figure 8. (b) Normalized Iris image, with normalization parameters

Iris template: The Phoenix Iris Database [18] is used in the current research. One the iris is normalized, as discussed, it gives 180x360 pixels image. The normalized iris is rich in texture and will be used as a biometric trait. This image is used for calculation of excitation (ξj) and orientation (Φt) and construct the Histogram (H). For each iris feature vector of size 2880, as discussed earlier and derived from [16], elements is extracted and used for verification purposes. Fig. 8 shows the interface of the tool which was built for pre-processing the iris images. Fig. 9 shows a 2D WLD Histogram of Iris at three different scales.

A. *Multi-modal fusion of Dynamic Signature and Iris data*

Data extracted from the iris and signature channels provides the feature vectors which are then given to classifiers for training. Fig. 1 shows the proposed system, and the scores of the two channels is then fused to perform score fusion [19] [20]. The summarised process is as follows.

Step 1 - Matching Module: Matching of biometric trait against the stored template using a Euclidean distance formula.

Step 2 - Fusion Module: Fusion of iris and signature traits using the Score level fusion technique.

Step 3 -Decision Module: Decision making for a legitimate user. Each biometric system makes an independent decision about the identity of the user or verifies the claimed identity.

Step 4 - Performance improvement: In cases where the quality of a biometric sample is unacceptable, the alternative biometric trait can be used. For example, if the signature module rejects the signature image due to poor quality the decision can be made using the other biometric modality. In this case the iris module's matching percentage can be used for better estimation and this will lower the false rejection rates.

As previously mentioned, the data of 64 different users is stored in the Phoenix database - three left iris images and three right iris images. The feature vectors are extracted as discussed for all the users, and out of the three Left+Right (L+R) image pairs, only two pairs for training and one pair for testing are utilised for the experiments. The signature samples of the 64 users are associated with the iris data, and this result in multi-modal user enrolment data.

The record of each user contains three L+R iris samples and 10 dynamic signatures. The system was developed in Microsoft Visual Studio 2015 community edition, and tested on a machine running Windows 10 64-bit Professional Edition, with 4GB RAM and 500GB HDD.

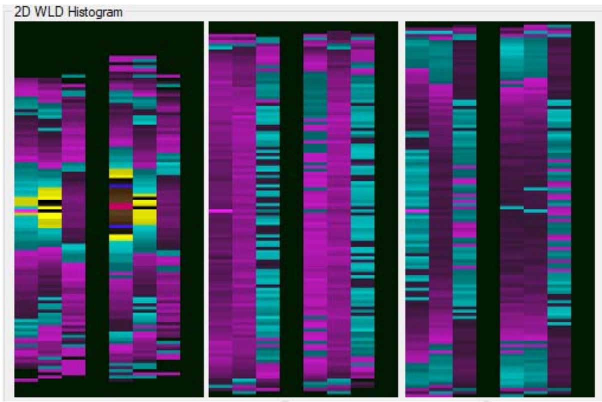


Figure 9. 2D WLD Histogram of Iris at three different scales

B. *Verification Process (Part of the Matching Module)*

The k-NN machine learning classifier is used for the proposed multi-modal biometric system as a part of the matching module in Fig. 1. In the proposed experiments, the value of nearest neighbours was set to *k=3*, and this value was chosen experimentally. To compute the distance between iris and signature based biometric traits I1 and I2, their WLD histogram features H1 and H2 are extracted [16]. The similarity between H1 and H2 is then evaluated. Normalized Histogram Intersection [16] is used as a similarity measure [4] shown in Function (1).

$$\Pi(H^1, H^2) = \sum_{i=1}^{L} \min(H^{1,i}, H^{2,i}), \tag{1}$$

Experiments are performed using Iris unimodal (L, R) data Iris multi-modal (L+R) data, Signature Unimodal (S) data, and Signature-Iris multi-modal (L+R+S) data. There are total 64 users enrolled to the system. For each user, ten signature samples and six iris samples (three right and three left) are used. For each user, seven signatures and four (two right + two left) iris samples are used for training. The remaining samples were used for testing. A total of 11718 signature matching tests and 3906 iris matching tests were performed, the results are discussed in Section IV.

IV. EXPERIMENTAL RESULTS

This section presents the performance evaluation metrics used for evaluating the system, and presents the results of the experiments.

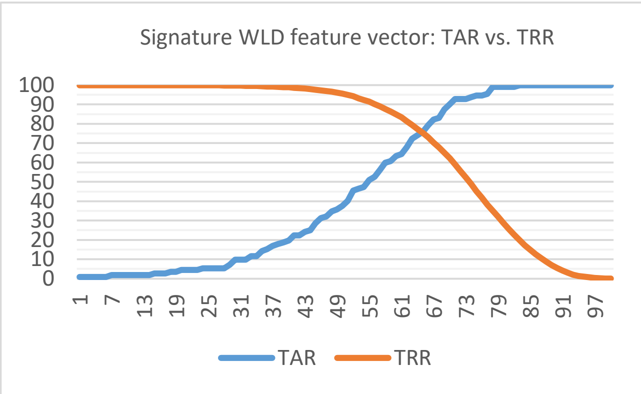


Figure 10. TAR-TRR Plot (ROC Plot) for Pressure, Normalized Histogram Intersection

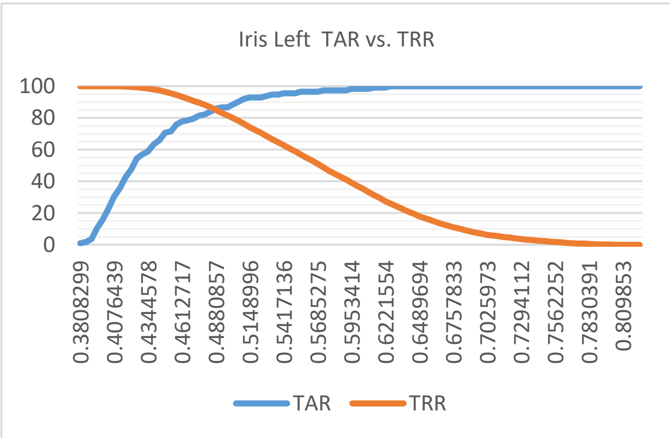


Figure 11. TAR-TRR Plot for Left Iris

A. *Performance Evaluation Metrics*

False Accept Rate or False Match Rate (FAR or FMR) is the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted.

False Reject Rate or False Non-Match Rate (FRR or FNMR) is the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected.

Equal Error Rate or Crossover Error Rate (EER or CER) is the rate at which both accept and reject errors are equal. The value of the EER can be easily obtained from the ROC curve. The EER is a quick way to compare the accuracy of devices with different ROC curves. In general, the device with the lowest EER is most accurate. Obtained from the ROC plot by taking the point where FAR and FRR have the same value.

Security Performance Index (SPI) is a new measure proposed by Dr. H. B. Kekre [21], which indicates how fast the EER is achieved. In Fig. 11 a typical FAR-FRR curve, the EER is given by the value at the crossover point. The Security Performance index is defined as,

$$SPI = AB/AC \qquad (2)$$

A perfect system would return an SPI =1 (or 100%). The SPI can be used to compare the performance of Biometric Authentication Systems when two system have equal EER. The higher the performance of the system, the higher the SPI value. SPI was used to evaluate the performance of the system using different feature vectors.

A. *Signature Recognition Results*

The graph in Fig. 10 shows the TAR versus TRR characteristics when using signature features alone as input into the biometric recognition system. The EER is 75.89%.

B. *Iris Recognition Results*

Similar analysis is performed for Left and Right Iris as well as L+R Iris multi-modal implementation. Compared to the results obtained using dynamic signature data, the multi-modal feature vector for iris has improved the performance by 14.29%. This is shown in Table 2, Fig. 11 shows TAR vs. TRR plot for the Left Iris feature vector. Furthermore, when the signature and iris multi-modal feature vectors are fused, TAR-TRR =1.79% improvement in biometric recognition performance was observed, when compared to performance using the iris unimodal data (Iris L+R). In addition an overall TAR-TRR=27.69% increase in performance was observed when using the signature multimodal feature vector. Furthermore, an overall 1.88% (multi-modal vs. iris) and 18.3% (multi-modal vs. signature) improvement in security performance index (SPI) was observed when using the multi-modal iris and signature features, compared to when using the iris and signature features, respectively. The best performing biometric system was the multi-modal ones which took as input iris and signature data.

V. CONCLUSIONS AND FUTURE WORK

In this paper a multi-modal biometrics system based on iris and signature dynamic biometrics is presented. The multi-modal system has given EER 90.18% with k-NN Classifier. The multi-modal combination has given 14.29% and 1.79% improvement in EER (TAR-TRR) of signature and iris data respectively and an 18.3% and 1.88% increase in the SPI of signature and iris data respectively. Future work includes evaluating the suitability of deep learning methods and other advanced deep learning classifiers for the task. The importance of this work is that unimodal biometric systems may not be suitable for the entire population, for example, an amputee will not be able to provide fingerprint or dynamic signature data; a blind person may not be able to provide iris data. Thus having a multi-modal biometric system is beneficial. Significant challenges in iris recognition still exist and future work also involves focusing on overcoming such challenges.

TABLE I
UNIMODAL FEATURE VECTOR VARIATIONS FOR SIGNATURE DATA

EER TAR-TRR %	EER FAR-FRR %	SPI %
75.89	24.10	67.09

TABLE II
MULTI-MODAL FEATURE VECTOR VARIATIONS FOR IRIS AND SIGNATURE

Traits	EER TAR-TRR%	EER FAR-FRR%	% SPI
Iris L	85.71	14.29	81.69
Iris R	83.04	16.96	79.50
Iris L+R	88.39	11.61	83.51
Sign	75.89	24.11	67.09
Iris + Sign	90.18	9.82	85.39

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