Multi-modal Authentication System for Smartphones Using Face, Iris and Periocular

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Abstract

Secure authentication for smartphones is becoming important for many applications such as financial transactions. Until today PIN and password authentication are the most commonly used methods for smartphone access control. Specifically for a PIN and limited length passwords, the level of security is low and thus can be compromised easily. In this work, we propose a multi-modal biometric system, which uses face, periocular and iris biometric characteristics for authentication. The proposed system is tested on two different devices - Samsung Galaxy S5 smartphone and Samsung Galaxy Note 10.1 tablet. An extensive set of experiments conducted using the proposed system shows the applicability for secure authentication scenarios. The proposed system is tested using uni-modal and multi-modal approach. An Equal Error Rate (EER) of 0.68% is obtained from the experiments validating the robust performance of the proposed system.

1. Introduction

Smartphones are rapidly becoming a key platform for many authentication processes in a large number of applications. However sensitive data on smartphones is at risk, if a smartphone is protected with methods providing an insufficient level of security. Since the advent of mobile phones, PIN and password authentication using a mix of alphanumerics and symbols were the most commonly used methods for access control. In order to avoid the risk of short passwords, one can use cumbersome and long passwords with a mix of special characters at the cost of inconvenience [26]. Most recent smartphones also offer an option to authenticate the owner based on a swipe pattern [10]. However, all these methods could be compromised by using brute force attack as the entropy of the knowledge-based authentication is significantly lower than the entropy of a biometric characteristic [22, 7]. As smartphones are also being used as the authentication factor in financial transactions, the need for robust methods to authenticate towards the personal device has gained importance recently.

Major stakeholders in the smartphone market such as Apple, Samsung, Huawei and Motorola have provided an integrated fingerprint sensor to facilitate biometric authentication. Advances on smartphone based authentication systems have successfully demonstrated the use of smartphone cameras for capturing high quality images of biometric characteristics [8, 24, 14, 20]. Most popular approaches have investigated face based authentication on smartphones, as it is convenient and can be easily integrated in the interaction process with the device.

In this work, we explore multi-modal biometrics as a means for secure authentication. The proposed system employs face, periocular and iris images all captured with embedded smartphone cameras. As the face image is captured from a close distance, one can always obtain periocular and iris information with significant details. Under difficult conditions for the capture process such as partially illuminated faces, accuracy for facial recognition systems is known to degrade [27]. Hence, using in addition periocular information under such circumstances can maintain and even improve the recognition accuracy. Further within the face image one can obtain the visible spectrum iris representation with sufficiently high resolution. As iris is known to provide very robust recognition performance, we make use of the iris pattern, whenever this can be segmented reliably. Additionally, iris and periocular information can be combined in visible spectrum to improve the recognition accuracy [21]. Thus, the current work employs face, periocular and iris information for our authentication system. The contributions of this work can be summarized as:

- This is the first work employing multi-modal biometrics for authentication on smartphones using face, periocular and iris characteristics. The proposed system is tested extensively using 78 subjects on two different devices.
- This work explores various score level fusion schemes to use the complementary information from all three modalities.

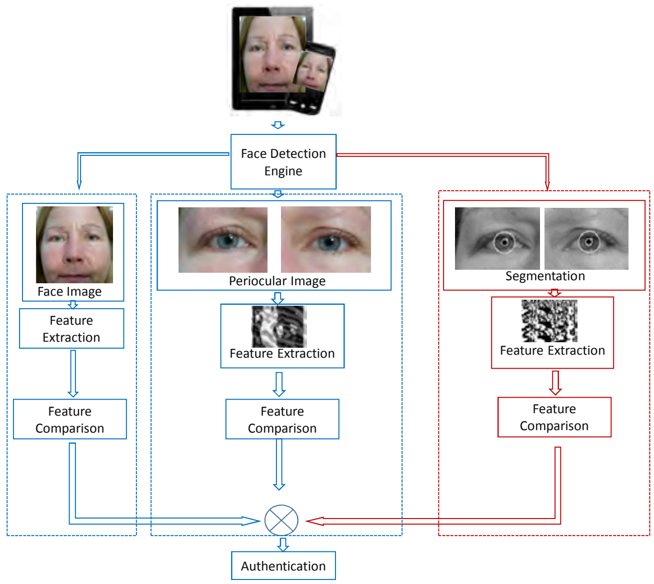


Figure 1: Proposed multi-modal authentication system; The blocks in blue color indicate imperative contributions to the authentication process (i.e. to the decision subsystem) and the blocks in red color indicate an optional contribution in case the iris pattern has been segmented successfully.

- Another contribution of this work lies in implementing the open source iris segmentation algorithm, OSIRIS v4.1 [23] on Android operating systems. The segmentation scheme can now be used as a standalone tool on smartphones and tablets under the Android operating system.

In the remainder of the paper, Section 2 presents the proposed system employing multi-modal approach. Section 3 presents the employed feature extraction schemes and the comparison subsystem. Section 5 presents the details of our experiments and the results obtained. Section 6 provides the conclusive summary of the presented work.

2. Proposed Multi-modal Authentication System on Smartphones

The proposed multi-modal authentication system for smartphones is illustrated in the Figure 1. The proposed system combines a face, periocular and iris recognition subsystem as the core components. When a particular subject wishes to enroll, the image is captured and provided to face detection subsystem. This subsystem works synchronously with the capture device or camera by providing continuous feedback. If the face is not detected in the captured frame, the face detection subsystem sends continuous feedback to recapture. Once the captured face sample is of sufficiently high quality, the face is localized using the Haar cascade based face detector [4].

The localized facial region is further submitted to the face recognition and periocular recognition subsystems. Along with the processing in these two subsystems the iris recognition subsystem is activated, if the iris is represented with sufficiently high quality. For a data subject to whom the visible spectrum representation of the iris pattern is insufficient, as in the case of dark irises, the iris recognition subsystem shall not attempt to enroll an iris reference. The OSIRIS v4.1 segmentation tool based on the viterbi search algorithm has demonstrated robust segmentation performance even for visible spectrum iris samples [23]. Motivated by the robustness, we have implemented OSIRIS v4.1 for Android based devices. As the segmentation task of the iris on smartphones is a challenging problem, this work has contributed significantly by providing the open source iris segmentation scheme for smartphone environments operating at minimal response time. The segmented iris texture is further processed using Daugman's rubber sheet expansion technique [6]. The iris pattern is normalized to a dimension of 512×64 pixels. Once the subject is enrolled, all templates corresponding to face, periocular and iris are stored in the smartphone embedded database.

When the subject wants to authenticate, the image is acquired and the face is detected as illustrated previously. The features are extracted from the face and periocular region. Depending on the visibility and quality of the iris texture pattern, iris features are extracted as well. Probe feature vectors are compared against the reference templates stored on the smartphone. The scores obtained from all modalities are fused and submitted to the decision subsystem to finally authenticate the data subject.

3. Components in the Proposed System

This section provides a brief description of the employed feature extraction and feature comparison techniques. Based on the robust feature description and reduced computation, we have employed Scale Invariant Feature Transform (SIFT), Speeded Up Robust Features (SURF) and Binarized Statistical Image Features (BSIF). We have used Fast Approximate Nearest Neighbor Search for comparing the SIFT and SURF features and histogram matching for BSIF features.

3.1. Feature Extraction Subsystems

3.1.1 Scale Invariant Feature Transform

Scale Invariant Feature Transform (SIFT) extracts scale and rotation invariant features from the image, which are robust against a substantial range of distortions such as affine transformations and change in view-point [15]. The extracted features are well represented in both spatial and frequency domains, which minimize the impact of occlusion, noise and illumination changes. The SIFT features obtained on an image compose a high dimensional feature vector (generally 128) that is highly distinctive. It has been reported that SIFT features provide robustness, when employed for face recognition [3]. Further an extensive study has shown the benefit of using SIFT features for periocular recognition [17, 25].

3.1.2 Speeded-Up Robust Features

Speeded Up Robust Features (SURF) provides the features based on the spatial distribution of gradient information within the point of interest vicinity. As compared to SIFT features, SURF descriptors are more robust to rotation, scale, illumination and contrast changes [2]. SURF feature vectors have 64 dimensions in the general case. Consequently, similarity computations are more efficient as compared to the 128-dimensional SIFT feature vectors. Earlier work has successfully employed SURF descriptors for robust face recognition under difficult lighting and pose variations [9]. Further, SURF feature descriptors were employed for periocular recognition with high verification performance [17, 25].

3.1.3 Binarized Statistical Image Features

Binarized Statistical Image Features (BSIF) are another well known unsupervised feature extraction technique [12]. A set of filters with different dimensions and scales are learnt using image statistics and independent component analysis of natural images [12]. It was shown recently that the set of pre-trained filters performs well for face, iris and periocular recognition [12, 13]. Motivated by these studies, we have integrated BSIF as a feature extraction technique in our approach. Further, in this work, the BSIF feature extraction technique has been ported to the Android platform. Specifically, we have employed a filter of size 9×9 pixels with a bit depth of 8.

3.2. Comparison Subsystem

3.2.1 Fast Approximate Nearest Neighbor Search

Fast Approximate Nearest Neighbor Search uses a Hierachical K-means Tree to determine the similarity of feature vectors. Nearest neighbors are obtained by examining the branch, which are not visited along the nodes. FLANN uses a priority-queue (Best-Bin-First) to approximate the Hierachical K-Means Tree [16].

3.2.2 Histogram Matching

As features resulting from BSIF are gray level values ranging from $0 - 255$, we find the histogram bins between two images and perform histogram matching using the Bhattacharya distance [5].

4. Multi-modal Smartphone Database Construction

Table 1: Total images from each device in the database

Device	Back Camera	Rear Camera (Assisted)
Samsung Galaxy S5	2340	2340
Samsung Galaxy Note 10.1	2340	2340

The proposed system was tested using two different devices, namely the smartphone Samsung Galaxy S5 and the tablet Samsung Galaxy Note 10.1. for which the hardware specification is listed in the Table 2. The proposed multimodal authentication system was evaluated using the data captured from 78 subjects in total. The database was divided into a development and testing dataset. The development database consisting of 32 subjects is used to tune the feature extraction algorithms and weights for different fusion schemes. As there is no training involved in this work, we have no requirement to reserve a partition of the database for training purposes. The partition of the database can be obtained from the Table 3.

For both the development and testing set, each subject was enrolled into the system by capturing 5 reference samples on each of the two different portable devices as mentioned in the Table 2. The enrolled subject on each of the device was authenticated by using 10 probe samples. For both reference and probe samples the image was acquired using

Table 2: Specifications of different hardware in this work

Device	Operating System	Screen Size	Back Camera
Samsung Galaxy S5	Android v4.4.2	1080 x 1920 pixels 5.1 inches	16 MP, 5312 x 2988 pixels
Samsung Galaxy Note 10.1	Android v4.4.2	800 x 1280 pixels, 10.1 inches	5 MP, 2592 x 1944 pixels

Table 3: Division of database into development and testing; *Note: 15 indicates 15 different sessions of which 5 correspond to reference image and 10 correspond to probe images

Camera	Total Subjects	Development set		Testing set	
		Subjects	Subjects * Images	Subjects	Subjects * Images
Smartphone - Samsung S5					
Back	78	32	32*15	46	46*15
Back Assisted	78	32	32*15	46	46*15
Tablet - Samsung Note 10.1					
Back	78	32	32*15	46	46*15
Back Assisted	78	32	32*15	46	46*15

the back camera of the device, as of today the back camera provides higher image resolution. For user convenience we expect in future hardware specification to see the same resolution for the front camera as for today's back camera. Thus in order to obtain an optimal baseline performance of the system, images were also captured by a trained expert. Thus, for each device, two set of reference images were acquired. For each user, there are in total 60 images (30 from smartphone and 30 from tablet) as given in Table 1. The images from each capture mode (non-assisted or assisted) for each device are 2340 in number corresponding to 78 subjects. The experimental protocol for this database and work is explained in the upcoming section.

5. Experiments and Results

The proposed system was evaluated as a standalone biometric recognition system. The system was evaluated seeking the biometric performance for three unimodal and the multi-modal approach. (i) In the first set of experiments, the system was evaluated using face recognition only. (ii) The second set of experiments relates to periocular based recognition. (iii) The third set of experiments indicates reliability of iris based recognition. Each of these experiments is described in the sections below. (iv) Further experiments were conducted employing multi-modal biometrics with score level fusion, which are detailed in Section 5.5.

5.1. Database and evaluation protocol

All experiments in this work are based on the database described in the Section 4. Each subject enrolled in the database has 5 reference images obtained from back camera in expert assisted and non-assisted mode. 10 probe images are obtained in similar fashion at different time instances. Thus, from each of the captured image, we obtain face, periocular and iris images. Each of the image from the reference set is compared against the probe image to obtain the genuine and imposter score. Thus, for each subject, a set of 50 genuine scores and 750 imposter scores are obtained for each modality. The results are reported in terms of Equal Error Rate (EER) and Genuine Match Rate (GMR) at various False Match Rate (FMR) [11]. For the simplicity and space limitations of this paper we present limited graphical illustration of the results related to the Samsung Galaxy S5.

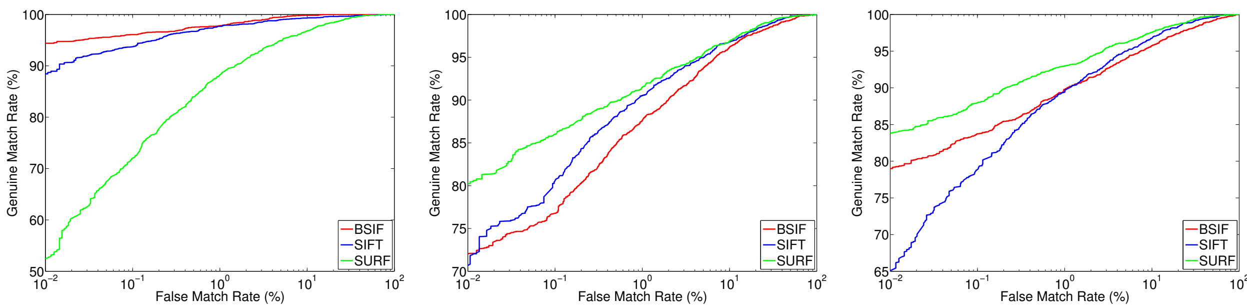
5.2. Experiments on smartphone based face recognition

The proposed system captures the image with the back camera based on the optimal focus computed using the preview frame in the camera's view. Once the image is captured, the user is presented a choice to either keep or discard the image in order to have sufficient visible quality. Capturing facial images is very challenging with respect to pose and illumination changes. In this set of experiments, we explore the face recognition performance accuracy under the assumption that neither pose and illumination are explicitly controlled nor that we deliberately introduce weak poses or ill-suited lighting. Table 4 presents the performance for face recognition.

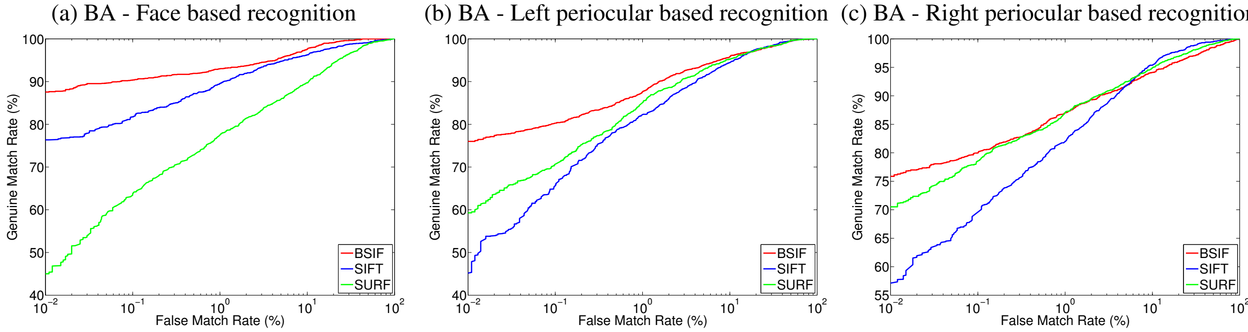
The data obtained from the back camera in self aquisition (i.e. non-assisted capture mode) provides an EER of 4.65% corresponding to GMR of 87.55% at FMR = 0.01% with BSIF features. The data obtained in the assisted mode has an EER of 1.61% corresponding to a GMR of 94.39% at FMR = 0.01%. Figure 2 (a) and (d) present the Receiver Operating Characteristic (ROC) curves for face based recognition for self acquisition and assisted acquisition from Samsung S5. It can be observed that the face recognition has a promising recognition performance. It can also be noted that when the subject uses the back camera to capture the face image in a self acquisition mode, the challenges due to pose alignment cause a slightly lower performance as compared to the images captured under the same settings by a trained expert.

Table 4: Biometric performance in terms of Genuine Match Rate and Equal Error Rate for unimodal approaches.

Camera	Feature Extraction	Face		Right Periocular		Left Periocular		Both Periocular	
		FMR @ 0.01%	EER	FMR @ 0.01%	EER	FMR @ 0.01%	EER	FMR @ 0.01%	EER
Smartphone - Samsung S5									
Back	SIFT	76.36	5.18	57.34	**6.63**	45.35	7.07	65.89	4.40
	SURF	45.03	10.21	70.56	6.55	59.28	6.20	76.00	4.52
	BSIF	**87.55**	**4.65**	**75.86**	7.01	**76.00**	**5.80**	**83.24**	**4.14**
Back Assisted	SIFT	88.43	1.88	65.43	5.00	70.83	5.03	82.04	3.04
	SURF	52.91	5.13	**84.04**	**4.00**	**80.22**	**4.86**	**90.52**	**3.13**
	BSIF	**94.39**	**1.61**	79.00	5.56	72.09	5.73	83.96	3.57
Tablet - Samsung Note 10.1									
Back	SIFT	92.83	2.62	31.43	9.40	61.91	8.40	72.96	6.85
	SURF	81.83	3.34	77.26	6.01	74.30	7.54	85.35	5.04
	BSIF	**94.61**	**2.43**	**77.39**	**5.91**	**77.30**	**6.75**	**87.04**	**4.71**
Back Assisted	SIFT	95.57	**1.81**	30.83	8.79	48.52	6.87	72.17	5.18
	SURF	79.91	1.96	71.30	5.31	51.09	5.47	82.00	3.87
	BSIF	**96.65**	2.03	**82.91**	**5.00**	**85.78**	**4.78**	**89.96**	**3.74**



(a) BA - Face based recognition (b) BA - Left periocular based recognition (c) BA - Right periocular based recognition



(d) BS - Face based recognition (e) BS - Left periocular based recognition (f) BS - Right periocular based recognition

Figure 2: ROC curves for various unimodal recognition employing face and periocular characteristics on Samsung S5; (a)-(c) correspond to assisted acquisition using the back camera; (d)-(f) correspond to self acquisition using the back camera; *BA - Assisted acquisition from back camera, *BS - Self acquisition from back camera

5.3. Experiments on smartphone based periocular recognition

The problem of non-uniform illumination, pose changes and various expression is known to degrade the performance of face recognition systems [27]. The problem becomes more prominent, when the capture device is not fixed as in a border crossing scenario. Under non-uniform illumination of the face, one of the two periocular regions can still be used to perform robust recognition. The intrinsic advantage in using periocular information is that two periocular regions can be used for one subject complementing or substituting the information from the overall face image. Various studies have indicated the preference to use periocular information in such scenarios of non-uniform illumination [17, 18]. Thus, we employ periocular based recognition subsystem to address the challenges arising out of non-uniform illumination.

Table 4 presents the recognition performance in terms of EER and GMR for periocular features with various feature extraction techniques. Images of periocular region from right side of the face provides an EER of 6.55% with back camera (SURF) and 4% with assisted acquisition (SURF). Table 4 also presents the recognition performance when the left periocular image is used. An EER of 5.80% is obtained with back camera (BSIF) and EER of 4.86% is obtained with back camera in assisted mode (SURF). Similar results can be seen for the periocular recognition with tablet device. Combining both the periocular region further boosts the authentication performance as indicated in the Table 4. An average gain of around 1.5% can be seen when both periocular information is fused.

Figure 2 present the ROC curves for periocular based recognition for different acquisition modes with Samsung S5. The periocular based recognition can perform close to the level face based recognition as it can be observed from the experiments. The obtained periocular scores can also be fused with the scores obtained from complete face information.

5.4. Experiments on smartphone based iris recognition

Iris recognition is known to be the modality with higher recognition performance and thus very popular in deployed biometrics systems [6, 7]. To capture iris information in the visible spectrum domain has been well explored [19]. More recent works have explored the possibility of using the iris information on a smartphone [8, 1]. As described in the earlier sections, the iris recognition pipeline including the segmentation has been implemented on the smartphones in this work. Further, since each person has two unique iris patterns, we have explored the performance of the smartphone based iris recognition using each individual eye. We have employed 2D Gabor features with Hamming distance for similarity score computation [7].

Table 5: Performance of iris recognition

Camera	Smartphone - Samsung S5			Tablet - Samsung Note 10.1		
	Iris	GFMR @ 0.01%	GEER	Iris	GFMR @ 0.01%	GEER
Back Assisted	Left	38.95	22.67	Left	35.93	24.20
	Right	48.80	23.72	Right	32.67	26.44
Back	Left	42.56	23.85	Left	39.70	22.74
	Right	39.90	22.89	Right	43.16	21.88

Unlike the case of periocular region where both the images can be used for recognition purpose, the availability of iris depends highly on the accuracy of the segmentation algorithm. Due to unconstrained nature of iris imaging in the visible spectrum, a number of challenges regarding the sample quality must be expected. Out-of-focus imaging and motion blur are more prominent under smartphone based iris imaging than it is the case for conventional near infrared iris imaging. Thus, the general algorithm performance metrics FMR and FNMR are insufficient to report the effective performance under the presence of iris images that can not be segmented. All the non-segmented iris images are treated as Failure-to-Acquire (FTA). Data subjects that due to dark iris patterns can not be enrolled with the visible spectrum samples must be treated as Failure-to-Enroll (FTE) . According to the International Standard ISO/IEC 19795-1 [11], the effective system performance can be reported as Generalized Equal Error Rate (GEER), which can be obtained using the Generalized False Accept Rate (GFAR) and the Generalized False Reject Rate (GFRR) where

$$GFAR = FMR * (1 - FTA) * (1 - FTE)^2 \quad (1)$$

$$\begin{aligned} GFRR = FTE + (1 - FTE) * FTA \\ + (1 - FTE) * (1 - FTA) * FNMR \end{aligned} \quad (2)$$

where $GFAR$ is the generalized false accept rate; $GFRR$ is the generalized false reject rate; FMR is the false match rate; $FNMR$ is the false non-match rate; FTE is the failure-to-enrol rate and FTA is the failure-to-acquire rate [11].

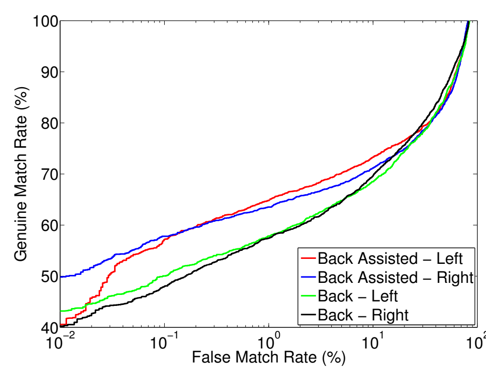


Figure 3: ROC plots of iris recognition

Table 5 lists the algorithmic performance of iris based recognition for right and left iris of both smartphone and tablet device. A GEER of 22.67% is obtained for left iris and 23.72% is obtained for right iris related to smartphone data. Almost comparable GEER is obtained for the back camera in self acquisition mode. Similar results are achieved for the tablet as indicated in the Table 5. Figure 3 provides the detailed graphical illustration of the iris based recognition performance.

5.5. Experiments on Multi-modal recognition

As the iris and face data contribute complementary information, we perform multi-modal fusion using the face, periocular and iris data. Thus, under the non-uniform illumination on face, at least one of the features, either face, periocular or iris provides good comparison scores for recognition. We fuse the comparison scores obtained from different feature extraction techniques using the weighted fusion

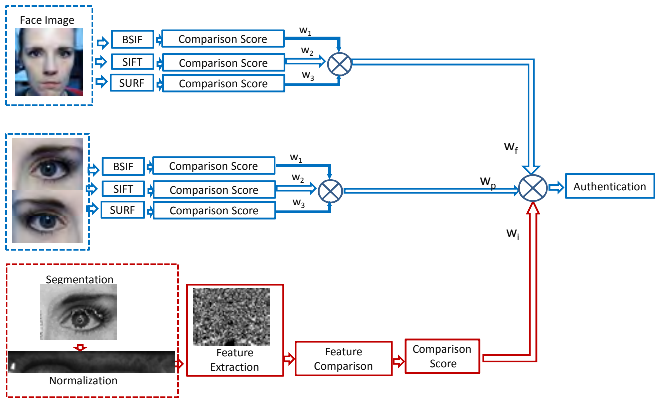


Figure 4: Illustration of employed fusion scheme

scheme as shown in the Figure 4. The weights for the scores for different features are determined experimentally by employing the development database. If the comparison scores from BSIF features are represented by C_1, SIFT features are represented by C_2 and SURF features are represented by C_3, then the weighted fused score F_m is computed for each modality according to:

$$F_m = 0.7 * C_1 + 0.15 * C_2 + 0.15 * C_3 \tag{3}$$

Moreover it is straightforward to fuse the information from the represented different biometric characteristics.

If the fused score of face is provided as F, the fused score of periocular region is provided as P_l for left periocular and P_r for right periocular region and the comparison score for iris is represented as I_l for left iris and I_r for right iris respectively, then the final comparison score F_c can be obtained using one of the schemes given in the following subsections.

5.5.1 Min-score Fusion Rule

In this fusion scheme, the score corresponding to the minimum of all the obtained scores is used. The final score is obtained in accordance to Min-rule given by F_c as:

$$F_c = \arg\min\{F, I_l, I_r, P_r, P_l\}; \tag{4}$$

5.5.2 Max-score Fusion Rule

Under the Max-score fusion rule, the score corresponding to the maximum in the set of modality specific scores is used. The obtained final score in accordance to the Max-score rule is given as below:

$$F_c = \arg\max\{F, I_l, I_r, P_r, P_l\}; \tag{5}$$

5.5.3 Product-based Fusion Rule

Further, the product rule has been popularly explored in biometrics. In this scheme we compute the product score by multiplying the scores obtained for each modality. The obtained final score under the product rule is given as:

$$F_c = F * I_l * I_r * P_r * P_l; \tag{6}$$

5.5.4 Dynamic Weighted-score Fusion Rule

Since the scores of each modality contribute to the performance in various degrees, we explore a dynamic weighting scheme to make the recognition system robust. As discussed earlier, the performance of the system can be improved by incorporating multiple modalities. At the same time, due to the various issue regarding capturing iris textures in the visible spectrum, it is likely that no iris data is available for a portion of subjects. Thus, in this work we propose a dynamic weighting scheme, where each modality is assigned a weight such that sum of all weights equals 1. Under circumstances where a particular modality does not contribute to the comparison score, the weight of that particular score is set to 0 and the weights are redistributed equally among all other modalities contributing to the recognition. Thus the dynamic weighted fusion scheme is given as below:

$$F_c = w_1 * F + w_2 * I_l + w_3 * I_r + w_4 * P_r + w_5 * P_l; \tag{7}$$

where $w_1 + w_2 + w_3 + w_4 + w_5 = 1$. For instance, if the score from right iris is missing, the weight w_3 is set to 0 and the new assignment of the weight is computed such that $w_1 + w_2 + w_4 + w_5 = 1$.

Table 6: Multi-modal Fusion obtained by employing face, periocular and iris characteristics on the complete database

Fusion Scheme	Camera	Samsung S5		Samsung Note	
		FMR @ 0.01%	EER	FMR @ 0.01%	EER
Min Rule	Back Assisted	99.17	0.43	88.57	3.43
	Back	97.12	0.93	88.13	4.34
Max Rule	Back Assisted	50.78	10.71	11.65	25.93
	Back	52.94	12.10	17.74	22.59
Product	Back Assisted	84.13	15.34	50.65	47.96
	Back	84.81	14.37	44.61	48.08
Weighted Fusion	Back Assisted	**99.13**	**0.43**	**95.52**	**2.39**
	Back	**97.98**	**0.68**	**93.52**	**2.69**

Table 6 presents the results for various multi-modal fusion schemes. It can be observed that the proposed system based on multi-modal biometric characteristics is robust in terms of recognition accuracy. The dynamic weighting fusion scheme provides best performance with an EER of 0.43% under assisted acquisition and an EER of 0.68% for data obtained in the self acquistion mode. Further, Figure 5 presents the ROC plots for multimodal biometric performance under dynamic weighted fusion.

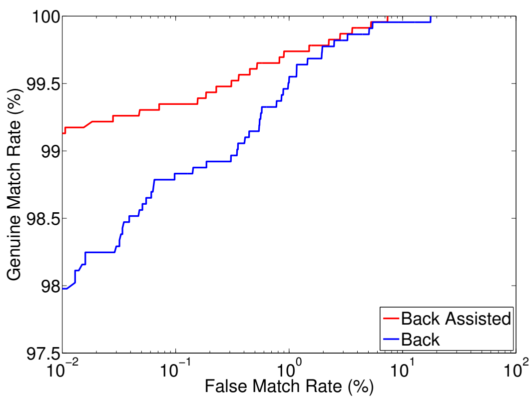


Figure 5: ROC plots for recognition based on multi-modal fusion

6. Conclusions

Secure applications such as financial transactions need strong authentication processes. In order to overcome the necessity of cumbersome passwords, one can use biometric characteristics. In this work, we have proposed a new smartphone based recognition system employing multi-modal biometric characteristics. The proposed system uses face, periocular and iris characteristics. An important contribution of this work is in implementing the open source iris segmentation algorithm - OSIRIS v4.1 to Android platforms.

An extensive set of experiments were conducted by employing the data acquired from 78 subjects. The obtained EER of 0.68% with dynamic weighted fusion provides the experimental evidence for the applicability of the proposed recognition system on smartphones.

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