Expert Systems with Applications 41 (2014) 5390–5404

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Multimodal biometrics: Weighted score level fusion based on non-ideal iris and face images

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ARTICLE INFO

Keywords:
Iris recognition
Face recognition
Weighted score level fusion
Multimodal biometrics
Non-ideal biometrics

ABSTRACT

The iris and face are among the most promising biometric traits that can accurately identify a person because their unique textures can be swiftly extracted during the recognition process. However, unimodal biometrics have limited usage since no single biometric is sufficiently robust and accurate in real-world applications. Iris and face biometric authentication often deals with non-ideal scenarios such as off-angles, reflections, expression changes, variations in posing, or blurred images. These limitations imposed by unimodal biometrics can be overcome by incorporating multimodal biometrics. Therefore, this paper presents a method that combines face and iris biometric traits with the weighted score level fusion technique to flexibly fuse the matching scores from these two modalities based on their weight availability. The dataset use for the experiment is self established dataset named Universiti Teknologi Malaysia Iris and Face Multimodal Datasets (UTMIFM), UBIRIS version 2.0 (UBIRIS v.2) and ORL face databases. The proposed framework achieve high accuracy, and had a high decidability index which significantly separate the distance between intra and inter distance.

1. Introduction

Biometrics is about measuring the personal features such as iris, face, fingerprints, retina, hand geometry, voice or signatures and recently drawn extensive concerns in the current security technologies. Biometrics has been the subject of widespread concern in modern society due to its widespread applications, making accuracy an important goal. In recent years, face and iris biometrics have become more popular than other modalities such as the fingerprint, retina, hand geometry, voice or signature (Jain & Kumar, 2011; Yunhong, Tieniu, & Anil, 2003). However, for systems that use unimodal biometrics, the recognition accuracy is sometimes questionable and is often affected by small sample size, noisy sensor data, low error rate, poor robustness, and spoofing attacks (Cui & Yang, 2011). A multimodal biometric system can alleviate some of these problems by utilizing and fusing two or more biometric modalities. Dass, Nandakumar, and Jain (2005) stated that a multimodal biometric system based on different biometric traits performs better and thus, can fulfill tighter real-world requirements. In the study reported in this paper, two biometrics were chosen to perform the fusion, namely, the face and iris biometrics.

Iris pattern is absolutely unique (Daugman, 2002). The chance of finding two randomly formed identical irises is almost astronomical order. Iris is formed since embryonic stage until age of 1 (Daugman, 2002). It will become constant after that till the end of the human life unless there are accidents or surgery. This is one of the main advantage of choosing iris biometric since almost every other biometric template would change significantly over certain time. In the past, iris recognition systems managed to authenticate accurately in cooperative environment. However, it is strictly in a constraint where the iris acquisition is in an ideal condition and imaginary setup (Farouk, 2011). Iris recognition performance may be in a very low accuracy especially when it faces a non-cooperative environment. In addition, probability of obtaining non ideal iris image is very high (Roy & Bhattacharya, 2010). Non-ideal iris image is defined as dealing the acquired iris images with off angle, occluded, blurred, reflection and noisy images captured in non-cooperative environment. Comparing different noise factors, the focus for this study is the off-angle iris. Off-angle iris is due to the rotation of the subjects head and eyes where iris images is capture with the iris not properly aligned with the imaging direction. These off-angle iris images have the elliptical shape for the region corresponding to the iris (Proenca & Alexandre, 2006).

Face recognition is the problem of verifying or identifying a face from its image. It has received substantial attention over the last

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http://dx.doi.org/10.1016/j.eswa.2014.02.051
0957-4174/

three decades as well as in addressing many challenging real-world applications, identity documents (e.g. passport, driver license, access control, and video surveillance. It is an automated technique that human implicitly use their visual and cognitive capabilities to recognize a person (Modi, 2011) and also one of the nonintrusive modalities in biometrics. The most stable and distinctive information contained in the face is focused on the region that is unlikely to change such as eyes, nose and mouth. Although face recognition in controlled conditions (frontal face of cooperative users and controlled indoor illumination) has already achieved impressive performance, there still exist many challenges for face recognition in uncontrolled environments, such as partial occlusions, large pose variations, and extreme ambient illumination. Uncontrolled environment in face recognition is a very complex problem, where faces appear in different position and orientation, make up, facial hair, and a face can even be partially occluded.

Multi-biometric is an emerging technologies which attracts increasing attention of researcher. The multi-biometric main purpose is to overcome the shortcoming of the unimodal biometric system. Generally, there are five types of multi-biometric system which includes multi-sample (Poh, Bengio, & Korczak, 2002), multi-instance (Yuille et al., 2007), multi-sensor (Kisku, Sing, Tistarelli, & Gupta, 2009), multi-algorithm (Burge, Bowyer, Connaughton, & Flynn, 2012) and multi-modal (Lee et al., 2007). As reported in the literature of the biometric system, results provided by multimodal biometrics is much more accurate due to the availability of richer information (Rattani, Kisku, Bicego, & Tistarelli, 2007). Therefore, in this study, we propose the multimodal biometric system of iris and face biometrics. Combining the biometric information obtained from different modalities using an effective fusion scheme can significantly improve the overall accuracy of the biometric system. Multimodal approach proposes a fusion of different biometric traits and usually can be categorized into three main level which are score level fusion, feature level fusion, and decision level fusion (refer Table 1).

Feature level fusion method extracts the different features from biometric modalities and combines the feature set to create single temple. The difficulty of feature level fusion is the incompatible of various feature sets or having high dependencies between each other. In addition, most commercial system do not provide the access to the raw feature sets. Score level fusion method calculates the match score based on the degree of similarity between two biometric samples and the scores are integrated to generate a single matching scores. The effectiveness of score level fusion techniques depends on the accurate information of the score range and performance parameters. Score fusion level can be categorized into classification and combination approach. Classification formulate problem as diving the decision into two classes, the "Accept" genuine and "Reject" imposters. The combination approach is a techniques which combines the multiple scores and calculate a single match scores. Several research using classifiers to consolidate the matching scores of the biometrics. YunHong et al. (2003) used the Fisher's discriminant analysis and Neural Network classifier for the classification of the face and iris matching score results. Lee et al. (2007), Chen and Chu (2005) and Eskandari, Toygar, and Demirel (2013) also presents the score level fusion based on face and iris biometrics using the classification approach. Classification methods requires larger amounts of training data to determine its optimal decision boundary. There are also some study which demonstrates the score level fusion in the combination approach. Dass et al. (2005) combines the matching scores of the multi biometric traits based on generalized density estimation. Robert, Umut, Alan, Michael, and Anil (2005) demonstrate a good results with the multimodal fingerprint and face biometrics through the matching score fusion algorithms using the elaborate evaluation. Slobodan, Ivan, and Kristina (2008) acquired the fingerprints and palm prints and used the extracted eigenpalm and eigenfinger features to perform the score level fusion. Another more recent combination approach with the fusion of face and iris biometrics using Iris on the Move (IOM) sensor are presented by Burge et al. (2012). This sensor is designed for high throughput stand-off iris recognition which features a portal of subjects walk through at normal walking pace. On the other hand, decision level fusion is the easiest fusion level among the others which applied a Boolean response indicating whether or not the comparison is matched. As fusion level progresses from feature level to decision level, the amount of information deceases (Monwar & Gavrilova, 2009). Fusion at decision level is less studied in literature, as it is often considered inferior to matching score-level fusion, on the basis that decisions are too "hard" and have less information content compared to "soft" matching scores (Tao, 2009).

The main goal of this study is to develop a unified framework which: (1) correctly localizes iris boundaries of the off-angle iris images; (2) integrates more features to increase the limited discriminant ability of unimodal biometrics. This research study was done to contribute to the domains of biometric recognition and its practical application to the general population. The framework of biometric recognition proposed had achieved minimal intra-class variations and maximal inter-class variations. In terms of theoretical knowledge, a better segmentation method that has combined geometric calibration and direct least square ellipse fitting has been proposed to correctly localize non-circular boundary of unconstrained off-angle iris images. Another significance of this study is that the proposed "NeuWave Network" to extract features of unconstrained off-angle iris images. Both proposed methods had demonstrated high segmentation and iris recognition accuracy.

Table 1
Related studies of different level of multimodal biometric recognition.

Category	Fusion traits	Related study	Techniques/algorithm	Pros/Cons
Feature level fusion	Face and iris	Tistarelli, Nixon, and Rattani (2009), Byungjun and Yillbyung (2005), Ross and Govindarajan (2005)	Transformation-based score fusion and classifier-based score fusion; scale-invariant feature transform (SIFT) features extractor; Daubechies wavelet transform	Incompatible of various feature sets or having high dependencies
Score level fusion	Face and iris	Eskandari et al. (2013), YunHong et al. (2003), Lee et al. (2007), Chen and Chu (2005)	Fisher's discriminant analysis and neural network; local bit pattern histogram matching; unweighted average based neural network	Best tradeoff between information content and fusion complexity
	Face and speech	Sanderson and Paliwal (2004)	Support vector machine	
	Fingerprints and palmprints	Slobodan et al. (2008)	Eigenpalm and Eigenfinger extractor	
Decision level fusion	Iris and face	Kapale, Kankarale, and Lokhande (2011)	PCA, Haar wavelet and morphological method	Least information content available

Another significance of the proposed method is the weighted score level fusion for the multimodal biometrics that had integrated features of iris biometrics with information from face biometrics. From a technical perspective, this increases the performance by resolving the limited discrimination capability and insufficient accuracy of unimodal biometrics, and thus lowers false rejection rates and false acceptance rate. The dataset use for the experiment is self established dataset named Universiti Teknologi Malaysia Iris and Face Multimodal Datasets (UTMIFM). For the purpose of comparison, experiment is also done based on "chimeric dataset" where we combine the non-ideal iris datasets, UBIRIS v.2 with the common use face datasets, ORL face database. The remainder of this paper is organized as follows. Section 2 provides the details of the acquired datasets for both iris and face images, and Section 3 provides an overview of the proposed method and technique for the whole multimodal biometric approach. The experimental design and results are presented and analyzed in Section 4. Section 5 concludes the entire paper.

2. Multimodal biometric dataset

In multimodal biometric research, the main problems most researchers facing are the lack of real-user databases (Jain & Kumar, 2011). As far as our knowledge, there are no free available multimodal real-user database which combines face and iris modalities. However, there is well established datasets for face and iris images which results in the creation of chimeric users (the virtual subjects created with biometric traits of different users) (Burge et al., 2012). According the Nicolas and Jerome (2008), such assignments are commonly used in the recent multimodal literature and was questioned during the 2003 Workshop in Multiodal User Authentication. Therefore, to overcome this issue, there is a need to established a multimodal biometric datasets of iris and face from the same subject. In conjunction to assess the efficiency of the proposed method and overcome issues by the creation of chimeric users due to shortage of available multimodal datasets, UTMIFM datasets was collected and used in this experiment. In order to facilitate the fusion of face and iris biometrics from a single sensor, the Iris Guard IG-AD100 device was used for the data acquisition. The device is designed for iris image acquisition and to capture face images. At present, multi-biometrics fusion from a single sensor device is an under-studied challenge.

The datasets consist of users from Asian with different ethnics and they are the students of Universiti Teknologi Malaysia. The Iris Guard-AD100 is an USB 2.0 biometric device that is able to capture eye iris and face images. The device optics allow to capture images of both eyes simultaneously with the user face image. At the same time, this iris camera is able to determine eye liveness to prevent spoofs with contact lenses and uses direct and crossed illumination that allows to capture irises through eye glasses. Our datasets consist not only the ideal face and iris images, but also the images taken under non-ideal environments (off-angle, motion blur, reflection, occlusion, pose variation, and differ facial expression).

Most of the images of non-cooperative iris images are off-angle with the angle between (0° and 45°) with right off-set angle, left off-set angle, and also rotated-ellipse off-set angle. During the iris capturing process, iris images captured in non-cooperative environments, that is, with varying degrees of pupil and iris direction. The same applied to the face image capturing process wherein the subjects captured with a variety of poses and facial expressions. The overall dataset collected for testing included 300 face and 300 iris images. Five images taken individually of the right and left eyes (making a total of ten) as shown in Fig. 1. The face images were then grouped into several categories based on the pose and expression which includes serious (Category F_A), shocked (Category F_B), smiling (Category F_c), and looking upwards (Category F_D) shown in Table 2. The iris images were captured with tolerance given for some tilting and rotation of the iris to obtain off-angle iris images. These iris images were grouped into several categories including: 0° offset angle (Category I_A), rotated ellipse with upper angle (Category I_B), right-side offset angle (Category I_C), and left-side offset angle (Category I_D) shown in Table 3.

In order to compared the efficiency of the proposed approach with other researcher, we had also run the experiment using the "chimeric" datasets where we combined the UBIRIS v.2 iris dataset (Proenca, Filipe, Santos, Oliveira, & Alexandre, 2010) with the ORL face dataset (Samaria & Harter, 1994). For iris, there are two types of light wavelengths can be use to capture eye images which are the near infrared and visible light. Our self established datasets, UTMIFM capture eye images using near infrared light wavelengths. Among the databases which are available (refer Table 4) to public for iris recognition purposes, examples of other near infrared light databases for iris are the University of Bath (BATH) (Nicolaie & Valentina, 2010), the Institute of Automation, Chinese Academy of Sciences (CASIA) (CASIA., 2010), the Multimedia University (MMU) (MMU., 2004), version one of the University of Beira Interior (UBIRIS v.1) (Proenca & Alexandre, 2005) and the West Virginia University (WVU) (WVU-IBIDC., 2004). On the other hand, the visible light wavelength datasets include the University of Olomuc (UPOL) (Dobes & Machala, 2004) and the University of Beira Interior version 2.0 (UBIRIS v.2) (Proenca et al., 2010). Between these datasets, CASIA version four (CASIA-Iris-Distance) and UBIRIS v.2 are the two databases containing eye images captured at different distances. In this study, we choose UBIRIS v.2 for the comparison purpose because it included eye images captured under visible light which allow comparison with our self established near infrared datasets UTMIFM, and contained large amount of iris with off-angle and with different distances.

The UBIRIS v.2 datasets contained of 11,102 eye images and 522 irises with different noisy effects such as off-angle, reflection, blurring, and occlusion by hair, glasses and contact lenses. It captured 261 subjects using Canon EOS 5D camera at different distances range from four to eight meters with moving subjects. Each session captured 15 left and right eye images. In this study, we randomly choose about 1000 eye images with off-angle iris and categorized according to their captured distances (refer Table 5).

For face images, ORL database (shown in Table 6) is chosen to combine with the UBIRIS v.2 iris datasets to form the chimeric datasets. ORL database contains of ten different images for each of the 40 distinct subjects. For some subjects, the images were taken at different times and with different lighting conditions, facial expressions (open/closed eyes, smiling/not smiling) and facial details (with/without glasses) (Samaria & Harter, 1994). All the images were taken against a dark homogeneous background with the subjects in an upright, frontal position (with tolerance for some side movement).

3. The multimodal biometric authentication

The fusion of multimodal biometrics in this study consist of several stages, as illustrated in Fig. 2.

3.1. Iris recognition method

In non-ideal scenarios, the inner and outer boundaries of iris images are often in non-circular and non-concentric form. The Hough Transform and some other existing techniques work well when the iris images are acquired from closely controlled environments. However, this technique has its limitations and often yields incorrect segmented iris images in non-cooperative environments

Fig. 1. UTMIFM dataset image acquisition.

Table 2
Different categories of training images with various facial expressions.

Samples / Category Types	*Example of face expression variations images*			
	Category F_A (Serious)	**Category F_B** (Shocked)	**Category F_C** (Smiling)	**Category F_D** (Looking upwards)
Sample 1 				
Sample 2 				
Sample 3 				

(Proenca & Alexandre, 2006). In this study, the upper and lower eyelids were first separated using the linear Hough Transform (Daugman, 1993) while a simple thresholding method which uses the variance of the intensity provided comparing with the threshold to determine existence of eyelashes and was used to remove the eyelashes from the eye images. To accurately segment iris images from non-cooperative (off-angle) environments, we additionally propose an ellipse localisation boundary technique which combines the calibration algorithm and direct least square ellipse (DLSEFGC). The iris can be localized easily since the pupil is normally much darker than the surrounding area in an ideal iris image. However, the pupil shape and size may vary under non-cooperative (off-angle) environment. For off-angle images, the geometric calibration technique was first attempted to compensate for the distortion by restoring the pupil shape to be as circular as possible. Then, the image was rotated around the horizontal and vertical coordinates of the pupil center (c_x, c_y) through a scaling transformation as Eq. (1).

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}, \tag{1}$$

where x and y denotes the horizontal and vertical coordinates.

By applying this scaling transformation, the ellipse shape of the (x, y) became (x', y'). The given parameters of the scaling transformation are expressed in Eq. (2).

$$\cos\theta = \frac{r_x}{r_y}, \tag{2}$$

where r_x and r_y are the short and long axes of the ellipse shape and is calculated as $\cos\theta$. When the calibration for the pupil ellipse was successful, we proceed to the ellipse fitting for the iris using the obtained parameters by adjusting and scaling up the value using the calculated ratio, $\cos\theta$. The direct least square ellipse would then iteratively fitted the ellipse around the iris. This direct least square ellipse would returned five parameters, namely, the coordinates of the ellipse center (c_x, c_y), the length of the axes (r_x, r_y) and the orientation of the ellipse itself $(\cos\theta)$. The next step is the normalization step. This was an important step because the optical size of every person's eye and iris, as well as the pupil's position, are different. Therefore, the same representation and similar dimensions have to be assigned to all the final iris images. In this study, we adopted the Daugman (1993) homogenous rubber sheet model to perform the normalization process for the iris image to remap and unwrap the iris region from the (x, y) Cartesian coordinates and produce a non-concentric polar representation. The coordinates of the pupil and iris boundaries are x_p, y_p, x_i, y_i along the θ directions, and Daugman (1993) derived the formula as Eqs. (3)–(5):

Table 3
Different categories of iris variations based on angles.

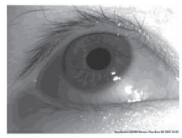
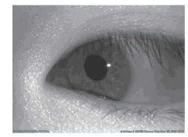
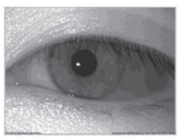
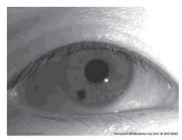
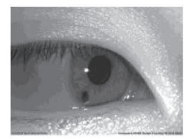
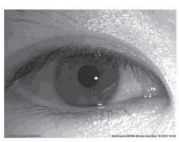
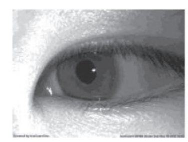
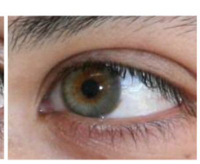
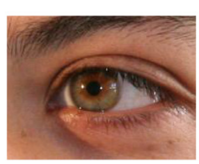
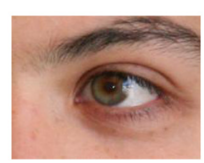
Samples / Category Types	*Examples of iris variations based on different angles*			
	Category I_A (0° offset angle)	**Category I_B** (Rotated ellipse with upper angle)	**Category I_C** (Right-side offset angle)	**Category I_D** (Left-side offset angle)
Sample 1 				
Sample 2 				
Sample 3 				

Table 4
Overview of the noise factors in public and free iris image databases. Parashar and Joshi (2012).

Iris database	Occlusion	Reflection	Motion blurred	Off-angle	Poor focused
CASIA http://www.sinobiometrics.com		–	–	–	–
MMU http://pesona.mmu.edu.my/~ccteo	✓	–	–	–	–
UPOL http://phoenix.inf.upol.cz/iris	–	–	–	–	–
UBIRIS v.1 http://iris.di.ubi.pt/ubiris1.html	✓	✓	✓	–	✓
UBIRIS v.2 http://iris.di.ubi.pt/ubiris2.html	✓	✓	✓	✓	✓
WVU http://www.citer.wvu.edu/biometric_dataset_collections	✓	–	–	✓	✓

Table 5
Different categories of distances for the visible reflection eye images that have been selected from UBIRIS v.2 database.

Type	Distance (meter)				
	4	5	6	7	8
Example of off-angle eye images					
Total eye images	200	200	200	200	200

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta), \quad (3)$$

with:

$$x(r,\theta) = (1-r)x_p(\theta) + rx_i(\theta), \quad (4)$$

$$y(r,\theta) = (1-r)y_p(\theta) + ry_i(\theta). \quad (5)$$

Each iris image consists of a fairly large number of pixel matrices that correspond to the iris image. The feature extraction method was used to extract significant iris features to produce a useful and relevant iris template. In this study, we propose the combination of Haar Wavelet decomposition and Neural Network (which we indicated as "NeuWave Network") for the feature extraction (template formation). The segmented and normalized iris image was transformed into wavelet coefficients $(\psi_1, \psi_2, \ldots, \psi_n)$ where a higher coefficient represented the relevant iris data while the small part of the coefficient represented the noise. Each of the different angles from the datasets would have its own significant coefficient

Table 6
Different categories face images from ORL face database.

Examples of face images in ORL face databases

with a set of weights to form the iris template. The method of wavelet networks is developed based on the idea of (Aditya & Stephanie, 2010). The bit patterns that were formulated are known as the "iris templates" and are formed and are carried out as follows:

Step 1: transformed the segmented and normalized iris images into wavelet domain using Haar Wavelet. The Haar Wavelet is a good wavelet decomposition choice for encoding of the segmented iris information.

Step 2: the encoded iris images are then used to formulate a template using the wavelets. The template generated into a sequence of wavelet coefficients ($\psi_1, \psi_2, \ldots, \psi_n$) where a higher coefficient represents the relevant iris data while the small part of the coefficient represented the noise.

Step 3: wavelet networks combines the wavelet decomposition properties with the characteristic of Neural Networks as in Eq. (6).

$$f(x) = \sum_i w_i \varphi_i(x), \tag{6}$$

with w_i represents the weights coefficient of the network.
The w_i is to be tuned as the network learns to give the preference for the set of wavelet function $\psi = (\psi_1, \psi_2, \ldots, \psi_n)$.

Step 4: the input signal is decomposed into the wavelet basis of the hidden layer as shown in Fig. 3. Next, the wavelet coefficient will then output one or more weight where the input weight is changes accordance with the learning process. The output would be a weighted sum of the wavelet coefficient.

The detailed flows of the formation of iris template for our proposed framework (*iris_temp_form*(*image*)) are describe as follows:

Step 1: separate upper and lower eyelids with linear Hough Transform and simple thresholding for eyelashes removal.

Step 2: geometric calibration and direct least square ellipse algorithm to segment, localized and fit the pupil and iris boundary for ideal or non-ideal iris images.

Step 3: normalization of iris images to produce a same representation and similar dimension normalized polar images by adopting Daugman's Rubber Sheet Model (Daugman, 1993).

Step 4: feature extraction using Haar Wavelet decomposition and Neural Network by transformed the normalized polar image into different wavelet coefficient which forms the bit patterns (*iris_temp*).

Step 5: find the matching value using hamming distance (HD) as the matching algorithm for the iris recognition of two samples shown in Eq. (7).

$$\mathrm{HD} = \frac{1}{n}\sum_{i=1}^{n} P_i \oplus Q_i. \tag{7}$$

3.2. Face recognition method

For the recognition of face biometrics, face images are normally projected into the feature space which best encodes the variation of the image. This feature space is also known as the eigenface, which is the eigenvector of the set of faces. Suppose we have Eq. (8):

$$X_i = [A_i \ldots A_n]^T, \quad i = 1 \ldots n, \tag{8}$$

where $[A_i, \ldots, A_n]^T$ represents the input signal of the face images.

During empirical mean detection and calculation phase, the face images are being mean centred by subtracting the mean image from each image vector. The mean, υ, will represent the mean image as Eq. (9):

$$\upsilon = \frac{1}{n}\sum_{i=1}^{n} X_i, \tag{9}$$

where the mean centred image is $X_i - \upsilon$. Next, the eigenvectors and eigenvalues calculation process being executed. Eigenvectors of the covariance matrix, Y ($m \times n$) give the eigenfaces, where $Y = XX^T$ are generated, and these eigenvectors are sorted from high to low following the eigenvalues calculated from the covariance matrix. The highest eigenvalues give the largest variance in the image. The training sets of face images were acquired and the eigenfaces were calculated using Principal Component Analysis (PCA) projections. A 2-D facial image was represented as a 1-D vector. Each of the eigenfaces can be viewed as a feature and is expressed by eigenface coefficients (weight).

The steps of the projections for the face are as follows:

Step 1: calculate the average face and the empirical mean to generate the median face.

Step 2: collect the difference between the training images and the average face in a matrix, X ($m \times n$), where m is the number of pixels and n is the number of images.

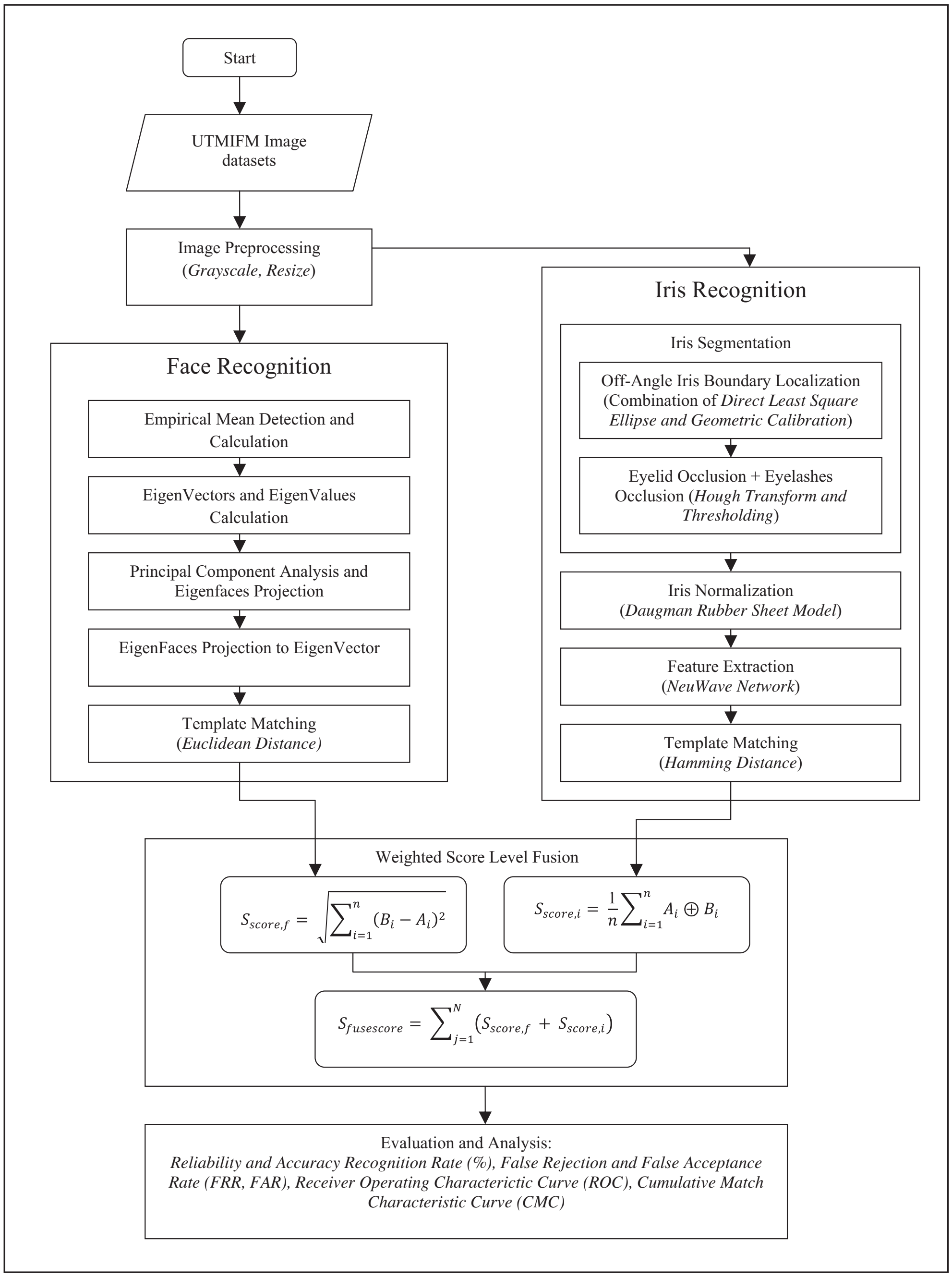


Fig. 2. Overall proposed framework.

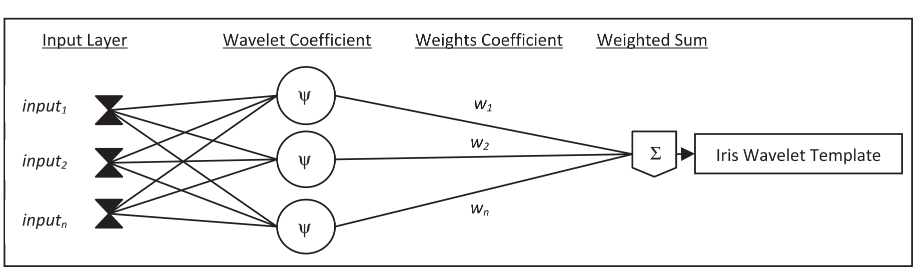


Fig. 3. NeuWave Networks.

Step 3: the eigenvectors are then generated with covariance matrix Y $(m \times n)$ which produce the eigenfaces, where $Y = XX^T$
Step 4: find the eigenvalues of the covariance matrix and arrange accordingly.
Step 5: take the largest eigenvalue as the basis of the eigenface space.

For face authentication, the face images will undergoes the PCA projection on the acquired training sets for the generation of eigenfaces. The detailed steps to generate the eigenfaces is explained belows:

Step 1: read the face image and get the number of rows and colums.
image = im_read ('image.bmp')
[row, col] = size(image)
Step 2: creates a matrix based on rows and columns $(N_1 \times N_2)$ for the image.
Step 3: adjust the mean and standard deviation for all the images (normalization to reduce lighting error).
Step 4: get the normalized training set for the training images.
Step 5: create a matrix by tranposing the image $(N_2 \times N_1)$ by getting the mean of each row and columns and generate a mean image.
Step 6: get the covariance matrix and sort with ascending sequence. Normalized the eigenvectors and obtained the eigenfaces.
Step 7: matching of face images was done by retrieving the enrolled image from the dataset and calculated using the Weighted Euclidean Distance, Eq. (10) with the image of the tester subjects.

$$WED = \sqrt{\sum_{i=1}^{n} w_i (P_i - Q_i)^2}, \tag{10}$$

where P and Q represents the enrolled and testing biometric images.

3.3. Matching fusion score for multimodal biometric

In this stage, we combined the iris and face modalities at the weighted score level to fuse the matching scores obtained from the face and iris recognition matching processes. Dissimilarity scores were obtained from each modality by matching the input data with the stored dataset using the distance measures mentioned in the previous section:

$$P_i(genuine|A) = \text{probability of being a genuine user given iris sample of } A, \tag{11}$$

$$P_f(genuine|A) = \text{probability of being a genuine user given face sample of } A, \tag{12}$$

$$P_i(genuine|B) = \text{probability of being a genuine user given iris sample of } B, \tag{13}$$

$$P_f(genuine|B) = \text{probability of being a genuine user given face sample of } B, \tag{14}$$

$$\text{Matching Score Iris}, S_{iscore} = f\{P_i(genuine|A) + \eta(Z)\}, \tag{15}$$

$$\text{Matching Score Face}, S_{fscore} = f\{P_f(genuine|A) + \eta(Z)\}, \tag{16}$$

where $\eta(Z)$ is the error due to the noise introduced by the sensor during acquisition or the errors made by the feature extraction and matching process. When $\eta(Z)$ is zero, it becomes approximately

$$P(\text{genuine}|A) \approx P(\text{genuine}|B). \tag{17}$$

Using the calculation from the experimented results with prior knowledge of the average score and score variations, the normalized score for both iris and face, S'_{iscore}, and S'_{fscore} is calculated as in Eqs. (18) and (19).

$$S'_{iscore} = \frac{S_{iscore} - \mu_i}{\sigma_i}, \tag{18}$$

$$S'_{fscore} = \frac{S_{fscore} - \mu_f}{\sigma_f}, \tag{19}$$

where μ_i and μ_f is the arithmetic means and σ_i and σ_f is the standard deviation of the iris and face data.

Next, we describe the procedure of the proposed fusion rule. Let S'_{iscore} and S'_{fscore} be the normalized scores of the biometric matcher's face (f) and iris (i), respectively. Let $w_{1,j}$ and $w_{2,j}$ be the weight of the face and iris modalities, respectively. For the jth user, the weight was determined based on the preliminary results from the experiments. The fusing score can be computed as in Eq. (20):

$$S_{fusedscore} = \sum_{j=1}^{N} \left(w_{1,j} S'_{fscore} + w_{2,j} S'_{iscore} \right). \tag{20}$$

In this work, we empirically chose the weights by experimenting with each matcher to find the maximum accuracy recognition rate. The weight used for both databases is different and they are computed twice in the experiments. By using Matlab to run our system, the time needed for the computation search for each set of the data is 8–12 s. Scores of both iris and face biometric are weighted based on the multimodal dataset characteristic and their score distributions comparison. Initially the weights for each the individual matcher (both iris and face) are set to be equal. Both $w_{1,j}$ and $w_{2,j}$ are 0.5. The method requires learning of the specific weights from the training score and the score distributions for each of the database. After a detailed analysis and experimenting with the weight values, we propose the method as the weight can be tuned for both datasets which we assign lower weight to which datasets with maximum, and mean (distance value during unimodal verification) is higher and higher weight for the lower maximum and mean (distance value during unimodal verification) iris datasets.

The process to compute the weights is as follows:

(i) Weight are varied over a range of [0, 1] such that the constraint is satisfied with $(\boldsymbol{w_{1,j}} + \boldsymbol{w_{2,j}} = \mathbf{1})$
(ii) The S'_{iscore} and S'_{fscore} which are the score provided by the two biometric matchers iris and face is computed as $S_{fusedscore} = \left(\frac{S_{iscore} - \mu_i}{\sigma_i}\right)\boldsymbol{w_{1,j}} + \left(\frac{S_{iscore} - \mu_i}{\sigma_i}\right)\boldsymbol{w_{2,j}}$, where the mean and standard deviation of the associated genuine and impostor distribution is estimated through the experimentation.
(iii) Set of weight with the minimal total error rate by calculation of the sum of false acceptance and false rejection rate is chosen at specified threshold (τ) value. For multimodal datasets of UTMIFM, the chosen set of weight is $w_{1,j} = 0.5$ and $w_{2,j} = 0.5$ whereas for multimodal biometrics datasets for (UBIRIS v.2 + ORL face database), the $w_{1,j}$ and $w_{2,j}$ are 0.6 and 0.4, respectively. The set of weight is determined through the observation of the minimal total error rate.

Depending on the weight of the face and iris biometrics, if both of them were equal, Eq. (20) can be derived or simplified into Eq. (21):

$$S_{fusedscore} = \sum_{j=1}^{N} \left(S'_{j\,fscore} + S'_{j\,iscore} \right). \tag{21}$$

Through the steps described in the following section, the unified fusing score, $S_{fusedscore}$, was evaluated based on the pre-specified threshold value, τ. The τ value is defined based on the average value obtained for the overall results. We declared the user to be genuine when $S_{fusedscore} \leqslant \tau$, otherwise the user was an impostor.

4. Experimental performance analysis

This research is conducted in a Matlab (R2012a) environment tested using self acquired UTMIFM datasets. Details on the datasets can be found in http://sites.google.com/site/utmifm/. Result analysis was initially done on the off-angle iris image and on variety posing and expression of face image individually. For comparison purposes, we also conducted experiment using "chimeric datasets" which combines the UBIRIS v.2 iris datasets with ORL face databases. The analysis of the UTMIFM datasets, "chimeric datasets" of UBIRIS v.2 and ORL face databases were evaluated based on several performance measurements such as the accuracy (ACC) and the receiver operating characteristic curve (ROC) and the decidability index (DI). The experiments were conducted for genuine and impostor identification.

4.1. Result analysis on off-angle iris image

Tables 7 and 8 shows the results of ACC for the eye images captured at different distances for UBIRIS v.2 and eye images with different off-angle quality of UTMIFM (iris images). Results show that an overall 94.4% accuracy rate which is much better compared to Kumar et al. (2011) works with 89.7% using the same UBIRIS v.2 iris datasets. Kumar et al. (2011) proposed to extract iris features captured during non cooperative environments using a sparse representation of local radon transform. For, UBIRIS v.2 datasets, during four to five meters, our proposed method obtained the most accurate result as the accuracy rates approach 98.4% and 97.6%. The rate was then fell to 90.2% and 88.5% for seven and eight meter. On the other hand, for our self established datasets, UTMIFM, the overall results obtained for the iris image authentication is 98.6%. Example of iris segmentation, normalization and noise removal image for datasets using UBIRIS v.2 for off-angle images based on different distances from four to eight meters are shown in Table 9. Table 10 shows the example results of iris images with different category of (I_A, I_B, I_C, I_D) on angle, rotated ellipse upper angle, right side offset angle and left side offset angle after the iris image segmentation, image normalization and noisy removal and covered with black rectangles. It is more difficult for iris and pupil to be localized when it is in non-ideal (off-angle) situation. However, when the localization is improved with geometric calibration and direct least square ellipse, the inner and outer iris boundaries were accurately localized. Iris were normalized by adjusting dimensions of each iris to allow comparisons to be made between iris templates.

Intensity results of each of the off-angle iris image are generated to enhance the performance of the iris localization. Dark color of the pupil gives higher intensity compared to the other. The intensity graph based on different off-angle degrees for 3 different subjects is shown in Table 11. From the table, it is clearly show that it is rather high intensity values when it comes to darker pixel where the iris can be located.

4.2. Result analysis on variety posing and expression face image

Each posing and face expression variations was the input of the PCA training and testing datasets. Features of each face represents by the Eigenface coefficients. PCA store the set of known patterns in a compact subspace representation of the images space, where the subspace is spanned by the Eigenvectors of the training image set (Agarwal, Agrawal, Jain, & Kumar, 2010). Accuracy results are highly coordinated with a well generated eigenface. Without a good training data of eigenfaces, the recognition might suffer from high false rejection or false acceptance rates. PCA was chosen due to its efficient technique in its useful statical analysis, and also the ability of represent high dimension data by lower dimension by reducing the complexity of the grouping of face images.

4.3. The discussion and results impact of weighted matching score fusion on multimodal iris and face recognition

The results of the accuracy for different fusion categories for the UTMIFM dataset are illustrated in Fig. 4. The average accuracy rate of recognition for all fusion category was approximately 99.8%. This was due to the ability of our proposed framework to reduce the level of noise, enhanced in the level of segmentation for either ideal or non-ideal images, and also the distribution of the weighted score level fusion of the face and iris biometric traits. The implementation of Neuwave Network also creates an great advantage during the extraction of iris features where each different angles of the iris has also being used as the features of the iris images.

Table 7
Result of accuracy for different levels of distance and methods for UBIRIS v.2 iris database.

Measurements	Datasets	Distances (m)	Proposed method (%)	Kumar et al. (2011) (%)
Accuracy	UBIRIS v.2	4	98.4	90.0
		5	97.6	89.0
		6	97.3	88.0
		7	90.2	87.8
		8	88.5	87.0
		Overall	94.4	89.7

Table 8
Result of accuracy at different quality for UTMIFM iris database.

Measurements	Datasets	Quality	Proposed method (%)
Accuracy	UTMIFM (iris images)	0° offset angle	99.2
		Rotated ellipse with upper angle	97.2
		Right side offset angle	98.3
		Left side offset angle	98.6
		Overall	98.6

Table 9
Different distances of eye image of UBIRIS v.2.

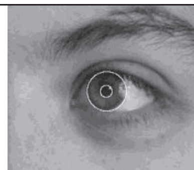
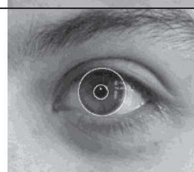
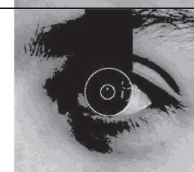
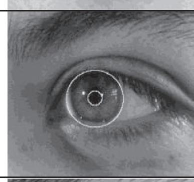
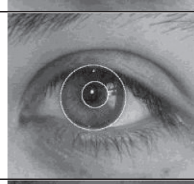
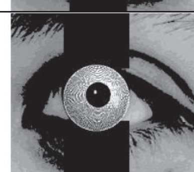
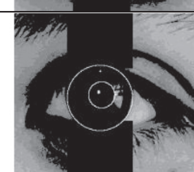
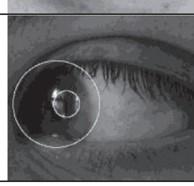
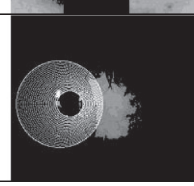
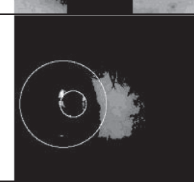
Different distances of eye image UBIRIS v.2	Sample of eye images from UBIRIS v.2 visible light wavelength		
	Segmented Image	Normalized Image	Noisy Removed Image
8 meters			
7 meters			
6 meters			
5 meters			
4 meters			

Table 10
Different category of eye image after iris segmentation, image normalization, and noisy removal.

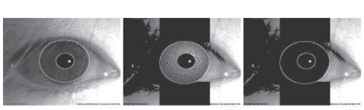
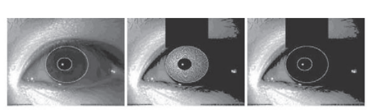
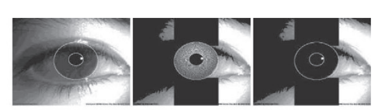
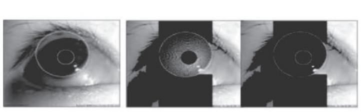
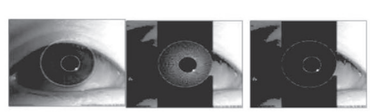
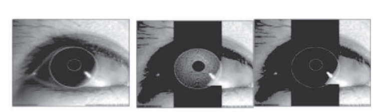
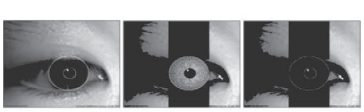
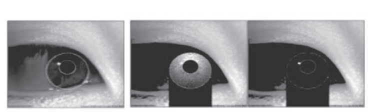
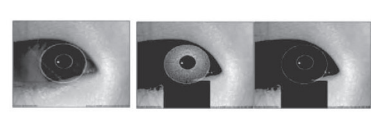
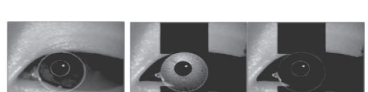
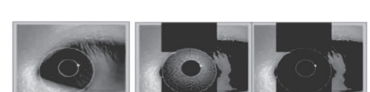
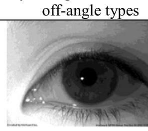
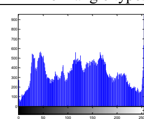
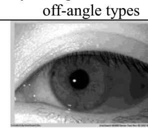
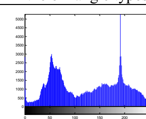
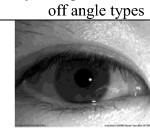
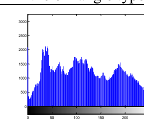
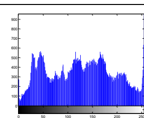
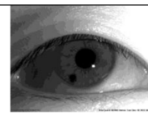
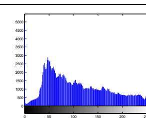
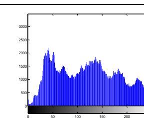
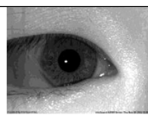
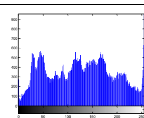
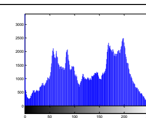
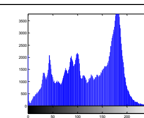
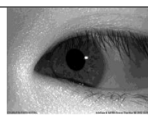
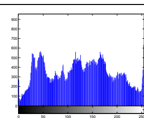
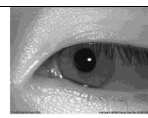
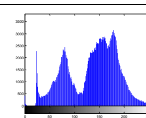
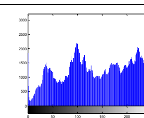
Different category of eye image	Sample 1			Sample 2			Sample 3		
	Segmented Image	Normalized Image	Noisy Removed Image	Segmented Image	Normalized Image	Noisy Removed Image	Segmented Image	Normalized Image	Noisy Removed Image
0° offset angle (Category I_A)									
Rotated ellipse with upper angle (Category I_B)									
Right-side offset angle (Category I_C)									
Left-side offset angle (Category I_D)									

Table 11
Example of intensity graph based different off-angle type of UTMIFM.

Different category of eye image	Sample 1		Sample 2		Sample 3	
	Eye Image with different off-angle types	Intensity graph based on the off-angle types	Eye Image with different off-angle types	Intensity graph based on the off-angle types	Eye Image with different off angle types	Intensity graph based on the off-angle types
0° offset angle (Category I_A)						
Rotated ellipse with upper angle (Category I_B)						
Right-side offset angle (Category I_C)						
Left-side offset angle (Category I_D)						

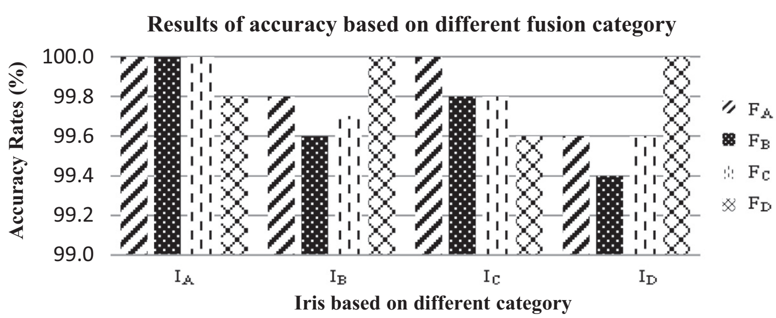


Fig. 4. Results of accuracy for different fusion categories for the UTMIFM dataset.

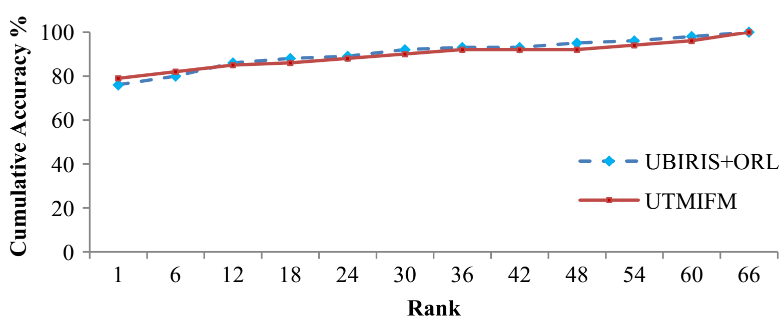


Fig. 5. CMC curve for UTMIFM datasets and UBIRIS v.2 + ORL datasets.

Beside this, PCA for the eigenfaces generation also plays an high impact roles in extracting the features of the face image for the accurate recognition. However, as the degree of off angle increase, the performance of UTMIFM biometric recognition decreased. Despite this challenge, our proposed framework still greatly performed with results of at least 99.4% of accuracy.

To estimate the cumulative match characteristics, the matching scores between all iris and face samples were stored. A curve was then plotted to represent the probability of identification against the returned 1:N subject list size (Bowyer, Hollingsworth, & Flynn, 2008). The lower the rank of the genuine matching biometrics in the enrollment database, the better the 1:N recognition system. Fig. 5 shows the results for the CMC curve of the UTMIFM datasets. The results show that the approach obtained an accurate result with an average rank of one, showing that the approach can perform well in one-to-many identification.

The ROC curve is important for measuring the one-to-one verification of false acceptance rates and false rejection rate tradeoffs. The ROC curve of the iris, face and fusion of the iris and face using the UTMIFM dataset, chimeric datasets combining UBIRIS v.2 iris

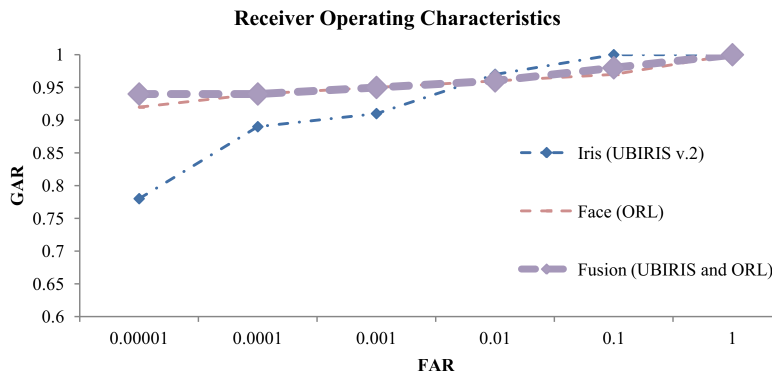


Fig. 6a. Receiver operating characteristics (ROC) of iris, face, and fusion of iris and face using the UBIRIS v.2 and ORL face dataset.

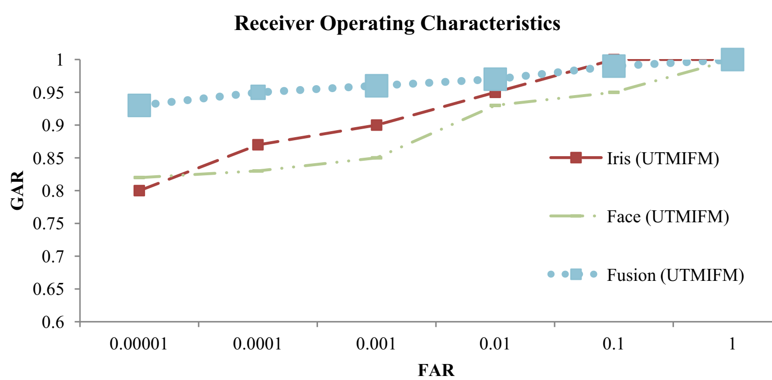


Fig. 6b. Receiver operating characteristics (ROC) of iris, face, and fusion of iris and face using the UTMIFM dataset.

and ORL face datasets are shown in Figs. 6a and 6b. The overall performance results based on false acceptance rate and genuine acceptance rate is also shown in Table 12. The robustness and security levels of a recognition approach are essentially influenced by the false acceptance rate (FAR) and the false rejection rate. Based on the graph in Figs. 6a and 6b, it shows the comparison between the performance of the unimodal iris, unimodal face recognition and the accuracy after the fusion process based on the FAR and the genuine acceptance rate (GAR). GAR is equivalent to (1-FRR). In the graph and based on the table, it is clearly seen that the fusion using weighted score level in our framework outperformed the individual performances of both the iris and face biometric matchers. This shows a great improvement, as shown in the equal error rate (EER) in the ROC curve.

Table 13 shows the results of the accuracy and decidability index for our proposed framework. The accuracy results for unimodal iris and unimodal face based on our datasets, UTMIFM are 98.6% and 98.9% of accuracy while chimeric datasets UBIRIS v.2 + ORL datases are 94.4 and 99.0, respectively. Decidability index, DI, is a factor which determines the separation distance between the intra-class and the inter-class distribution and is calculated as follows, Eq. (22):

$$\mathrm{DI} = \frac{|\pi_m - \pi_n|}{\sqrt{\frac{\sigma_m^2 + \sigma_n^2}{2}}}, \tag{22}$$

The DI for unimodal iris and face (UTMIFM) is 2.523 and 1.256, respectively. After the multimodal fusion, the decidability index for UTMIFM datasets has increased to 2.9988. From Table 13, it is noticed that the decidability index increase significantly after the weighted score level fusion proposed in our framework compared to unimodal recognition. Separation of the hamming distance value between two templates which indicates by the DI is directly proportional to the accuracy performance of the recognition. As the DI increase, accuracy rates will also increase. After the enhancement with the multimodal biometric fusion, we can see a good increase in the accuracy value. The same increment in accuracy and decidability index can also be seen in the chimeric

Table 12
Overall performance results based on FAR and GAR(1-FRR).

False acceptance rate (%)	Genuine acceptance rate (1-false rejection rates)					
	Iris (UBIRIS v.2)	Iris (UTMIFM)	Face (ORL)	Face (UTMIFM)	Fusion (UBIRISv.2 + ORL)	Fusion (UTMIFM)
0.00001	0.78	0.8	0.92	0.82	0.94	0.93
0.0001	0.89	0.87	0.94	0.83	0.94	0.95
0.001	0.91	0.9	0.95	0.85	0.95	0.96
0.01	0.97	0.95	0.96	0.93	0.96	0.97
0.1	1	1	0.97	0.95	0.98	0.99
1	1	1	1	1	1	1

Table 13
Results of accuracy and decidability index for the proposed framework.

Biometric category	UTMIFM			UBIRIS v.2 and ORL face		
	Minimum matching values	ACC (%)	DI	Minimum matching values	ACC (%)	DI
Unimodal iris	0.3308	98.6	2.523	0.3467	94.4	2.568
Unimodal face	1.1905	98.9	1.256	1.2963	99.0	2.312
Multimodal biometric fusion	0.0869	99.6	2.998	0.158	99.4	2.778

Table 14
Results of accuracy, FAR, FRR of fusion for different biometrics and methods.

Measurements	Different biometric traits fusion of methods using score level matching fusion				
	Arun et al. (2001) (face, fingerprints, hand geometry)	Mehrotra et al. (2006) (iris and fingerprints)	Mingxing et al. (2010) (fingerprint, face, fingervein)	Proposed framework (face and iris)	
				UTMIFM	UBIRIS v.2 and ORL Face
FAR (%)	0.1	1.58	0.99600	0.10	0.09
FRR (%)	0.1	6.34	0.00005	0.01	0.01
ACC (%)	98.6	96.04	99.40000	99.6	99.4

datasets (UBIRIS v.2 and ORL face). The total accuracy for multimodal biometric fusion for the chimeric datasets is 99.4% with 2.778 decidability index. Comparing with related work (refer Table 14) combining different biometric traits with the methods of matching score level fusion, our proposed framework has achieved better enhancement in terms of ACC (%) and DI compared to Arun, Anil, and Jian-Zhong (2001), Mehrotra, Rattani, and Gupta (2006), and Mingxing et al. (2010) in the overall performance. Arun et al. (2001) propose the biometric combination of face, fingerprints and hand geometry using score level matching fusion. Mehrotra et al. (2006) proposed the same method using score level matching fusion but with iris biometric and fingerprints while Mingxing et al. (2010) combines fingerprint, face and fingervein.

5. Conclusions remarks

Iris recognition are among the most promising biometric traits and able to accurately identify a person due to its unique textures. Most of the current iris recognition system captured images in cooperative environment. Nevertheless, the current biometric security requirement which identify a person by capture using surveillance system or capture at a distance results in non-ideal issues such as off-angle, occlusion, reflection, or motion blurred. These factors have declined the performance and accuracy of the current iris recognition. Consequently, the direction of the iris recognition research has diverged to solution of capture eye image in non-cooperative environment. Simultaneously, the goal of this study is to develop a unified framework which can correctly localize iris boundaries of the off-angle iris images, and integrates more features to increase the limited discriminant ability of unimodal biometrics. In conjunction with these, the first challenge in this study focused on the off-angle iris images where a more appropriate image segmentation and feature extraction technique has been proposed and implemented. Despite that the segmentation and feature extraction methods can recover some of the off-axis angle iris features, there is still high possibility of lost and non-recoverable features especially for larger off-angle degree iris images which cause limited discriminant ability in the biometric recognition. These limited discriminant ability also happen in most unimodal biometrics. Therefore, the second challenge in this study is to integrates more biometric features where a new fusion methodology combining two biometric traits by weighted score level fusion is proposed to enhance the discriminant ability.

Firstly, off-angle iris images cause the inner (pupilarly) and outer (limbic) boundaries to be in non-circular and cause difficulty in segmentation. The incorrect segmentation may leads to lost of significant features. In real-world iris image acquisitions, it is common and unavoidable to capture off-angle iris images. It can easily happens when actions such as tilting the head, gaze direction, inexact positioning angle or even the variations in user's height. To accurately segment the iris images from off-angle environments, an DLSEFGC which combines the calibration algorithm and the direct least square ellipse was proposed. The geometric calibration technique was first use to compensate for the distortion by restore its pupil shape to as circular as possible. After the successful calibration, the ellipse fitting is proceeded by using the obtained parameter to adjust and scaling up the value to fit the ellipse around the iris. Unlike ideal iris images that can easily localized using circular metrics, off-angle iris images needs calibration and ellipse fitting due to its non-circular and non-concentric forms. In addition, a method of wavelet networks which combines the Haar Wavelet and Neural Network (known as NeuWave Network) was propose to extract the significant iris features which form the iris codes template. It transformed the segmented iris into wavelet coefficients where higher coefficient represent relevant iris data and small coefficient represent the noise. These coefficient represents as the weight coefficient of the Neural Network. The results was tested using UBIRIS v.2 datasets with large number of off-angle iris images, and also the self-established datasets, UTMIFM which also consist of different off-angle iris images. Compared to other algorithms, results of the proposed approach using DLSEFGC and NeuWave Network algorithm demonstrated the effectiveness and efficiency. The develop algorithm shows highest rate of iris boundaries detection especially on non-ideal cases as well as the feature extraction. Based on these findings, it is is optimistic that the subsequent step added to the segmentation and feature extraction produces good quality textural features for further analysis.

Secondly, in unimodal iris recognition, it still consist high possibility of lost and non-recoverable features. For example, most of the iris especially with off-axis angle more than approximate 30°, it face difficulty in the segmentation and exact feature extraction. Some important features might be completely lost and these leads to limited discriminant ability of the unimodal biometrics. Multimodal biometric system can alleviate the unimodal problems by integrates two or more biometric modalities. It provide extra significant features to increase the discriminant ability for the recognition. Therefore, the second contribution of this study is to develop a method to integrates complementary information comes primarily from the different modality (face biometrics) with the iris biometrics. Initially, the iris biometric features and the face biometric features will be extracted into the matrix codes and each of the matching score will be generated. The score is needed for the developed weighted score level fusion method. In this study, the weighted score level fusion was proposed for the fusion of the iris and face biometrics score. After obtaining the normalized scores each from the biometric matcher's face and iris respectively, the weight was determined based on the preliminary results obtained from the experiments. The normalized score is obtained based on the average score and the score variations. Weight was then assigned using an exhautive search to find the maximum accuracy rate. Lastly, the unified fusing score will be evaluated based on the pre-specified threshold value. Using the multimodal datasets of UTMIFM and the chimeric datasets (UBIRIS v.2 and ORL face datasets), it shows a significant increment in the recognition accuracy compared to the unimodal iris and unimodal face biometrics with 99.6% accuracy for UTMIFM and 99.4% accuracy for the chimeric datasets (UBIRIS v.2 and ORL face datasets). Compared with other related work which uses the score level matching fusion techniques with other biometric traits, the measurements illustrates that the weighted score level fusion method with iris and face biometric provides the highest accuracy in terms of FAR and FRR. Based on this findings, it demonstrate that fusion using iris and face produces a better matching results which provides better discriminant ability for the biometric authentication.

5.1. Contributions of the research

The essential goal of current research work is to examine whether the performance of a biometric recognizing system can be improved by proposing a new computational framework which can correctly localize iris boundaries of the off-angle iris images, integrates more features which comes primarily from two different modalities which increases the limited discriminant ability of unimodal biometrics.

(i) For first contribution, the method by combining the geometric calibration and direct least square ellipse fitting and the method of NeuWave Network by fusion of Haar Wavelet and Neural Network has been introduced as the segmentation and feature extraction method, respectively for the iris recognition. The algorithm is specifically designed for better localization of the non-circular boundaries from the off-angle iris images and to extract the most significant features.
(ii) For second contribution, the weighted score level fusion has been introduced as the method to integrates iris biometrics traits with the face biometric traits to provide extra significant features to increase the discriminant ability for the recognition. Based on the experimental investigation, it is shown that the new fusion methodology which proposed based on weighting rule based model has managed to offers considerable improvement to the accuracy by providing the extra complementary information and resolved the limited discrimination capability especially compared to the unimodal recognition approach.

By considering several issues occurred in biometric recognition to identify a person, the proposed framework offer a better solutions to the problems of iris images captured in non-cooperative (off-angle) environment, and unimodal biometric limitations. As a result, the proposed framework has manage to provide capability to recognize errors cause by unconstrained environments, provides more difficulty in falsifying biometric templates with multimodal recognition approach and provides higher reliability to the system with relatively low false rejection rates and false acceptance rates. The potential applications which is suitable to be use with the proposed framework in this study are such as criminal history registry enrollment system, bank security storage system, immigration system, Automatic Teller Machine (ATM) banking system, or for university, school and employee attendance system.

5.2. Future works

Further works and possible directions that can be completed based on this work and results in this study are as follows:

(i) The authentication results presented in this paper can be validated with more public multimodal real-user datasets. Specifically, it would be more significance to measure the performance of the suggested approaches with larger datasets containing more individuals with more different ethnics and environments. As far as our knowledge, there are still no public free real-user dataset which combines iris and face modalities of the same individuals which could be used to evaluate the proposed work instead of chimeric datasets.
(ii) The proposed techniques in this paper can also be applied to other kinds of biometric trait and it would be interesting to integrate other biometrics either physiological or behavioral biometrics such as iris and voice biometric determines on the application needs to enhance the recognition performance.
(iii) Other non-cooperative environment factors especially in iris such as occlusion, reflection, motion blurred and distance on-the-move can be further focus and extended to enhance the accuracy by minimizing the possibility of false rejection rate.

Acknowledgments

The authors highly appreciate the contribution of University of Beira Interior for providing the UBIRIS v.2 database and appreciation for the contribution by Cambridge University Computer Laboratory for the ORL face database. The authors would like to acknowledge the Grant from the GATES Scholars Foundation of GATES IT Solution Sdn. Bhd. (Grant no. LTRGSF/SU/2011-04) and also highly appreciation to the Universiti Teknologi Malaysia Research University Grant with the Grant no. PY/2011/00367 for the research funding.

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