

Multimodal Biometric System for Voters Verification in an Electioneering Process

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Abstract— Electioneering process in many developing countries results in election frauds such as double registration, ballot stuffing, under-age voting and other forms of election drawbacks during registration of voters and casting of votes by eligible voters. In some developing countries, electronic biometric registration and verification system have been introduced during the registration and verification of voters. In many cases, some of the genuine registered voters were not recognized by the biometric machine. However, the rules and regulations pertaining to the elections stipulated that a voter would not be allowed to vote until he/she had been registered and verified. This means that before a voter could be allowed to cast his/ her vote, the biometric machine is supposed to recognize him/her first. Furthermore, some citizens that are physically challenged would also be denied the opportunities of exercising their franchise because the system used for the registration made use of fingerprint only. A Multi-modal biometric system is designed to eradicate the problem of eligible registered voters being disenfranchised by the current biometric system. This work presents a multi modal system that allows citizens to use their iris and fingerprint to go through the registration and verification process instead of their fingerprints alone as in the case of Nigeria electioneering process. The introduction of this system for general elections is expected to create room for full participation of all eligible voters, eliminate multiple voting and also increase the confidence of the people in electioneering processes.

Keywords— Electioneering, Biometrics, Fingerprint, Iris, Multi-modal biometrics

Introduction

Election is the procedure that allows members of an organization or community to choose representatives who will hold positions of authority within it (Chaum, 2004). The chance to decide who will govern at these levels, serves as an opportunity for the public to make choices about the policies, programs, and future directions of government action. The threat of defeat at the polls exerts pressure on those in power to conduct themselves in a responsible manner and take account of popular interests and wishes when they make their decisions.

The electoral process includes the selection of candidates, the registration of voters and the voting procedures. The need for a secure electoral process cannot be over-emphasized as the absence of this will not only bring about the possibility of

abuse, but the process and the result may be open to legal challenge.

According to Jegede et al (2006), Registration in electoral systems is the method usually used to identify voters who are qualified to participate in an election. It is a technique for determining that prospective voters are properly qualified according to law. Historically, election systems have been undergoing evolutionary and architectural changes to enable election bodies deliver results, since a thriving democracy is a gauge of a nation's development. Bubeck (2003) observed that, several Election Management Bodies have had to discard manual data entry method and adopt some form of automation in order to make the voters roll more credible. Computer application was expected not only to make the process more efficient, but also to avoid having a bloated register. Hence, the introduction of biometrics to voters registration.

Biometric is an identity verification of living, human individuals based on physiological and behavioural characteristics. In general, biometric system is not easily duplicated and it is unique to each individual. (Adewole et al, 2014). While biometric systems have their limitations, they have an edge over traditional security methods in that they cannot be easily stolen or shared. Biometrics uses physical characteristics and personal traits, some of the modalities are Facial features, Gait, Keystrokes, Voiceprint, body Odour, Hand geometry, Fingerprint, Iris, Retina, Handwriting or signature (Iwasokun et al 2013).

In electioneering processes, there is need for accurate authentication techniques to prevent unregistered voters from voting. To meet accuracy requirements of today's applications, relying on a single biometric can be challenging. Therefore, a multimodal biometric system that use more than one biological identifier, can improve the accuracy of biometric systems. This work proposes a multi-modal biometric system that allows citizens to use their fingerprints and iris for registration and verification processes instead of fingerprints alone as it is being practiced in the present Nigerian electioneering processes. The process is expected to create room for full participation of all eligible voters, eliminate multiple voting and also increase the confidence of the people in the electioneering process. The objectives of this work are to design a multimodal Iris and fingerprint biometrics system for voters' verification and post-election data analysis, create a hypothetical database of voters' registration system and implement the system developed using JAVA.

System Design

A multimodal biometric system based on fingerprint and iris characteristic is proposed. Fusion process at the matching level as well as the related comparisons against the unimodal elements were adopted. Tests were performed on the public CASIA-Iris database V1 and V2 and the official FVC 2004 Fingerprint database (Fingerprint verification

competition). The proposed population is about 600 images of 50 subjects (from FVC 2004 and CASIA – Iris VI&VII).

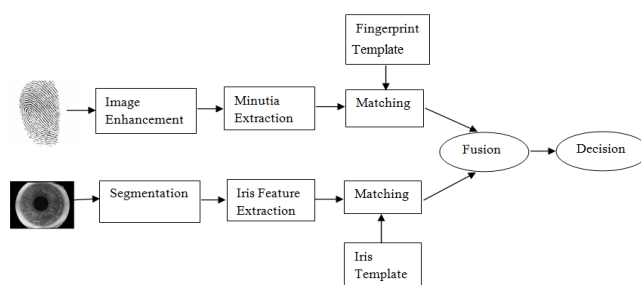


Figure 1. Schematic Diagram of the Proposed Multimodal System.

The multimodal system involves series of stages, ranging from the acquisition of images, processing and matching of features from the two modalities iris and Fingers.

Iris system

Iris modality, involved acquisition, pre-processing and matching. Images were captured using infrared camera which produces good quality with high contrast and low reflections images. Image pre-processing involved image localization and segmentation; image normalization; feature extraction or encoding.

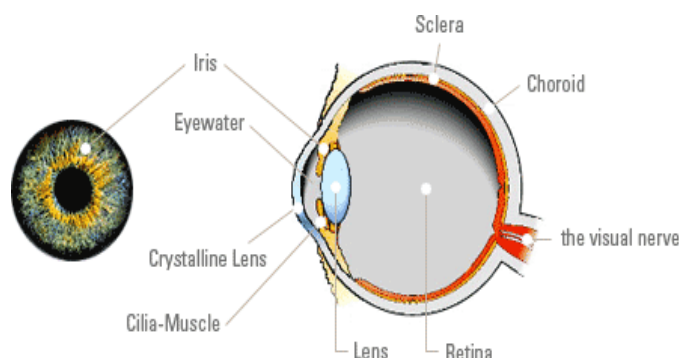


Figure 2. Parts of the eye (Daugman, 2004)

Finding an iris in an image

To capture the rich details of iris patterns, an imaging system should resolve a minimum of 70 pixels in iris radius. In the field trials to date, a resolved iris radius of 100 to 140 pixels has been more typical.

Iris Recognition System

For the purpose of this research, the work of Daugman (2004) was adopted. Daugman made use of an integro-differential operator for locating the circular iris and pupil regions, and also the arcs of the upper and lower eyelids. The integro-differential operator is

$$\text{Max}_{(r,x_0,y_0)} \left| G_\sigma * \frac{\partial}{\partial r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right| \quad (1)$$

$I(x, y)$ represents the original grayscale eye image; r denotes the radius of various circular regions with the center coordinates at (x_0, y_0) ; The symbol $*$ denotes convolution;

σ is the standard deviation of the Gaussian distribution; $G_\sigma(r)$ is a radial smoothing Gaussian function; and s is the contour of the circle given by the parameters (r, x_0, y_0) . The one-dimensional Gaussian filter has an impulse response given

$$g(x) = \sqrt{\frac{a}{n}} \cdot e^{-a \cdot x^2} \quad (2)$$

a denotes the height of the curve's peak (magnitude of the impulse response) and has a value greater than zero. In two dimensions, it is the product of two such Gaussians, one per direction:

$$g(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

x and y denote the distance from the origin towards the edges of the filter in the horizontal axis and vertical axis directions, respectively; and σ is the standard deviation of the Gaussian distribution (Kisku et al, 2016).

Iris normalization

For normalization of iris region, a technique based on Daugman's rubber sheet model was employed. The centre of the pupil was taken as the reference point, and radial vectors passed through the iris region. A number of data points were selected along each radial and defined as the radial resolution. The number of radial lines going around the iris region was defined as the angular resolution. Since the pupil can be non-concentric to the iris, a remapping formula was needed to rescale points depending on the angle around the circle. This is given by:

$$r^1 = \sqrt{\alpha\beta} \pm \sqrt{\alpha\beta^2 - \alpha - r_1^2} \quad (4)$$

$$\alpha = \sigma_x^2 + \sigma_y^2 \quad (5)$$

$$\beta = \cos\left(\pi - \arctan\left(\frac{\sigma_y}{\sigma_x}\right) - \theta\right) \quad (6)$$

displacement of the centre of the pupil relative to the centre of the iris is given by $(0_x, 0_y)$; r' is the distance between the edge of the pupil and edge of the iris at an angle θ around the region; r_1 is the radius of the iris. The remapping formula first gives the radius of the iris region 'doughnut' as a function of the angle θ . The homogenous rubber sheet model devised by Daugman remaps each point within the iris region to a pair of polar coordinates (r, θ) where r is on the interval $[0, 1]$ and θ is angle $[0, 2\pi]$.

The remapping of the iris region from (x, y) Cartesian coordinates to the normalised non-concentric polar representation was modelled as

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad (7)$$

$$x(r, \theta) = rx_s(\theta) + (1 - r)x_p(\theta) \quad (8)$$

$$y(r, \theta) = ry_s(\theta) + (1 - r)y_p(\theta) \quad (9)$$

where $x(r, \theta)$ and $y(r, \theta)$ are defined as linear combinations of both the set of pupillary boundary points $(x_p(\theta), y_p(\theta))$ and the set of limbus boundary points along the outer perimeter of the iris $(x_s(\theta), y_s(\theta))$ bordering the sclera, both of which are detected by finding the maximum of the operator. The rubber sheet model takes into account pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimensions. In this way the iris region is modelled as a flexible rubber sheet anchored at the iris boundary with the pupil centre as the reference point.

Feature extraction/encoding

To ensure accurate recognition of individuals, the most discriminating information present in an iris pattern were extracted. A number of wavelet filters, also called a bank of

wavelets, is applied to the 2D iris region, one for each resolution with each wavelet a scaled version of some basis function. The output applying the wavelets is then encoded in order to provide a compact and discriminating representation of the iris pattern. Log-Gabor filters – a modified version of Gabor wavelet was used in the feature encoding. The frequency response of a log-Gabor filter is given as:

$$G(f) = \exp\left(\frac{-(\log(f/f_0))^2}{2(\log(\sigma/f_0))^2}\right) \quad (10)$$

Where f_0 represents the centre frequency and σ gives the bandwidth of the filter.

Matching Algorithm

The matching algorithm that was used as pattern matching method to verify a person’s identity based on the iris code is Hamming Distance. Using the HD of two bit patterns, a decision can be made as to whether the two patterns were generated from different irises or from the same one. The two phase code bit vectors are denoted *code A*, *code B* and whose mask bit vectors are denoted {*mask A*, *mask B*}:

$$HD = \frac{||(\text{codedA} \otimes \text{codedB}) \cap \text{maskA} \cap \text{maskB}||}{||\text{maskA} \cap \text{maskB}||} \quad (11)$$

If two iris patterns are completely independent, such as iris templates generated from different irises, the Hamming distance between the two patterns should equal 0.5. To reduce noise and enhance the definition of ridges against valleys, various techniques include Image segmentation, Image normalization, Image filtering(Orientation Estimation, Ridge Frequency Estimation, Gabor Filtering), and Image binarization/Thinning were applied.

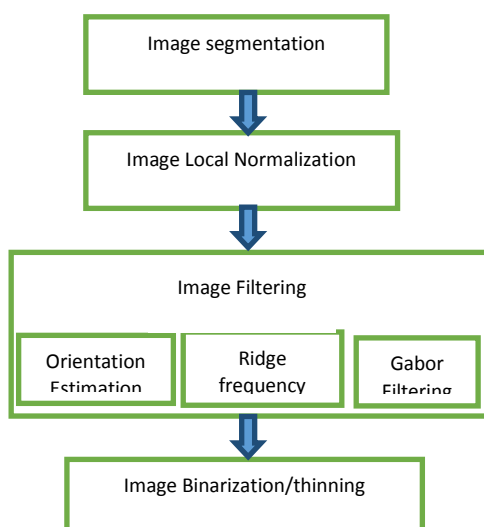


Figure 3: The conceptual diagram of the fingerprint enhancement algorithm (Adapted from Iwasokun et al, 2011)

Image segmentation separates the foreground regions and the background regions in the image. The foreground are the area of interest. Firstly, the image is divided into blocks and the grey-scale variance is calculated for each block in the image. If the variance is less than the global threshold, then the block is assigned to be part of background region or else it is part of foreground.

Normalization is a process of standardizing the intensity values in an image so that these intensity values lies within a certain desired range. It can be done by adjusting the range of grey-level values in the image. Normalized fingerprint image is filtered for enhancement through removal of noise and other spurious features. Filtering is also used for preserving the true ridge and valley structures. The least mean square estimation method used by Raymond Thai (Thai, 2007) was used to compute the orientation image. However, instead of estimating the orientation block-wise, the method was extended into a pixel-wise scheme, which produces a finer and more accurate estimation of the orientation field. The ridge frequency is obtained from the extraction of the ridge map from the image.

Gabor filters (Wildes et al, 2007) was used because they have orientation-selective and frequency-selective properties. Gabor filters are called the mother of all other filters as other filter can be derived using this filter. Therefore, applying a properly tuned Gabor filter can preserve the ridge structures while reducing noise.

The method of image binarization proposed by (Rahda and Kavita, 2012) was employed. The method sets the threshold (T) for making each cluster in the image as tight as possible, thereby minimizing their overlap. To determine the actual value of T, the following operations are performed on set of

presumed threshold are the pixels are separated into two clusters according to the threshold, the mean of each cluster are determined, the difference between the means is squared and the product of the number of pixels in one cluster and the number in the other is determined. The within-class variance each of the cluster is then calculated as the weighted sum of the variances. Thinning is a morphological operation which is used to remove selected foreground pixels from the binary images. A standard thinning algorithm from (Baig et al, 2009) is used, which performs this operation using two sub iterations.



Figure 4: (a) Original Image, (b) Enhanced Image,
 (c) Binarised Image, (d) Thinned Image

Feature Extraction

After improving quality of the fingerprint image we extract features from binarised and thinned images. We extract reference point, minutiae and key (used for one to many matching).

Multimodal System: Fusion

Prior to combining the scores of different traits into a single score, we need to normalize the scores of different traits because the match scores at the output of the individual trait may not be homogeneous. The normalization of both scores by the min-max rule is given by:

$$N_{Iris} = \frac{MS_{Iris} - min_{Iris}}{Max_{Iris} - min_{Iris}} \quad (12)$$

$$N_{Finger} = \frac{MS_{Finger} - min_{Finger}}{Max_{Finger} - min_{Finger}} \quad (13)$$

where MS_{iris} and MS_{finger} , are the matching scores obtained from Iris and fingerprint modalities, respectively. min_{iris} and max_{iris} are the minimum and maximum scores for iris recognition; min_f and max_f are the corresponding values obtained from fingerprint trait.

Fusion

Weighted sum rule-based method

In this work, iris trait has more weight in fusion with fingerprint. We adopted the user-score-based technique. Let s'_{iris} and s'_{fing} be the normalized scores of the iris and fingerprint traits, respectively. The fusion score, $sfus$: is computed as;

$$sfus = w_{iris}s'_{iris} + w_{fing}s'_{fing} \quad (14)$$

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

$$w_{iris} + w_{fing} = 1 \quad (15)$$

Different iris and fingerprint scores are given different degrees of importance for different users. For instance, by reducing the weight w_{iris} of an occluded iris and increasing the weight w_{fing} associated with the fingerprint trait, the false reject error rate of the particular user can be reduced. The biometric system learns user-specific parameters by observing system performance over a period of time (Besbes et al, 2008)

Two techniques are used to compute the user-specific weights: An exhaustive search technique, and a user-score based technique. We adopted the user-score based technique.

The User- Score-Based Technique Let s'_{iris} and s'_{fing} be the normalized scores associated with the i^{th} user in the database,

and r_1 and r_2 are the thresholds of the iris and fingerprint traits, respectively. The preliminary weights w'_{iris} and w'_{fing} per trait are computed as;

$$W'_{iris} = \frac{S'_{iris}}{T_1 + S'_{IRIS}} \quad (16)$$

$$f'_{iris} = \frac{S'_{fing}}{T_2 + S'_{fing}} \quad (17)$$

where W'_{iris} and W'_{fing} are the initial weights associated with the iris and fingerprint, respectively, without the constraint

These weights are assigned to the scores, S'_{iris} and S'_{fing} after analyzing how close or farther away the scores are from their respective thresholds, T_1 and T_2 . Then, the fusion weights for the i^{th} user are computed respectively, for the iris and fingerprint as:

$$w'_{iris} = \frac{W'_{iris}}{W'_{iris} + W'_{fing}} \quad (18)$$

$$w'_{fing} = \frac{W'_{fing}}{W'_{fing} + W'_{iris}} \quad (19)$$

With the constraint $W'_{iris} + W'_{fing} = 1$ and the fusion score is computed in the equation below:

$$W'_{iris} = S'_{iris} + W'_{fing} + S'_{fing} \quad (20)$$

Score fusion

The dual v -support Vector Machine (2v-SVM) fusion algorithm (Vatsa et al, 2007) is used to integrate the matching scores of the iris s_{iris} and fingerprint s_{fing} , together with their corresponding weights, w_{iris} and w_{fing} .

The weighted iris matching score m_{iris} is defined as:

$$m_{iris} = s_{iris} \times w_{iris} \quad (21)$$

and the weighted fingerprint score m_{fing} is defined as:

$$m_{fing} = s_{fing} \times w_{fing} \quad (22)$$

For the weighted matching scores and their labels are used to train the 2v-SVM for multimodal fusion. Let the training data

$$Z_{iris} = (m_{iris}, y) \quad (23)$$

be

$$Z_{fing} = (m_{fing}, y) \quad (24)$$

where
 $y \in \{+1, -1\}$

such that +1 represents the genuine

class and -1 represents the impostor class. The 2v-SVM error parameters are calculated using equations (55) and (56)

$$v_+ = \frac{n_+}{n_+ + n_-} \quad (25)$$

$$v_- = \frac{n_-}{n_+ + n_-} \quad (26)$$

where n_+ and n_- are the number of genuine and impostor,

respectively. The training data is mapped into a higher

dimension feature space such that $Z \rightarrow \phi(Z)$, where $\phi(z)$ is the mapping function. The optimal hyper plane separates the

data into two different classes in the higher dimensional

feature space. In the classification phase, the multi-modal

fusion matching score s_{fus} , is computed in Equation (52),

$$s_{fus} = f_{iris}(m_{iris}) + f_{fing}(m_{fing}) \quad (27)$$

where

$$f_{iris}(m_{iris}) = a_{iris} \varphi(m_{iris}) + b_{iris} \quad (28)$$

$$f_{fing}(m_{fing}) = a_{fing} \varphi(m_{fing}) + b_{fing} \quad (29)$$

where a_{iris} , a_{fing} , b_{iris} and b_{fing} are parameters of the hyper plane. The matching process results in a score that is compared against a threshold. If the score exceeds the threshold, the result is a match; otherwise it is considered a mismatch. The decision function defined in Equation (20) verifies the identity.

$$Decision_{(s_{fus})} = \begin{cases} \text{Accept,} & \text{if } s_{fus} > 0 \\ \text{Reject,} & \text{otherwise} \end{cases} \quad (30)$$

System Implementation

The algorithms was tested on two databases FVC2004 and FVC2000 databases. The application was written using the Java programming language. The System is configure with the following specification: (HP 630) Intel CORE 13 with 2Gigabyte of RAM and 320Gigabyte hard drive disk HDD and has a 2.40 GHz speed. Requirements necessary are Microsoft windows vista or later, Java runtime environment (JRE). The minimum required material characteristics for the application are 512Megabyte of RAM and 80Gigabyte hard drive. Other requirements are fingerprint and iris scanners, and Internet connectivity. The hardware include the optical fingerprint biometric scanner SecuGen, 500 dpi (SecuGen Biometric Solutions). The image size used was 72 kB, 292x248. For the iris system the OKI IRISPASS-h handheld device [Human Recognition Systems, "OKI IRISPASS-h," <http://www.oki.com/en/>], was used. The size of the picture is 302 kb, 480x640 and 2 kb for the log file. The log file contains information about the device settings when data is collected, such as focus value, specula height and aperture value etc. Two images of each eye were taken. The Registration page is shown below where the user is to provide his/her bio-data and biometric samples.

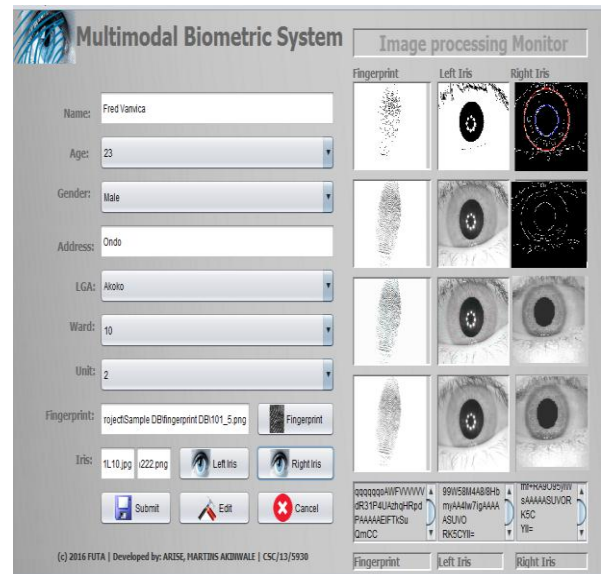
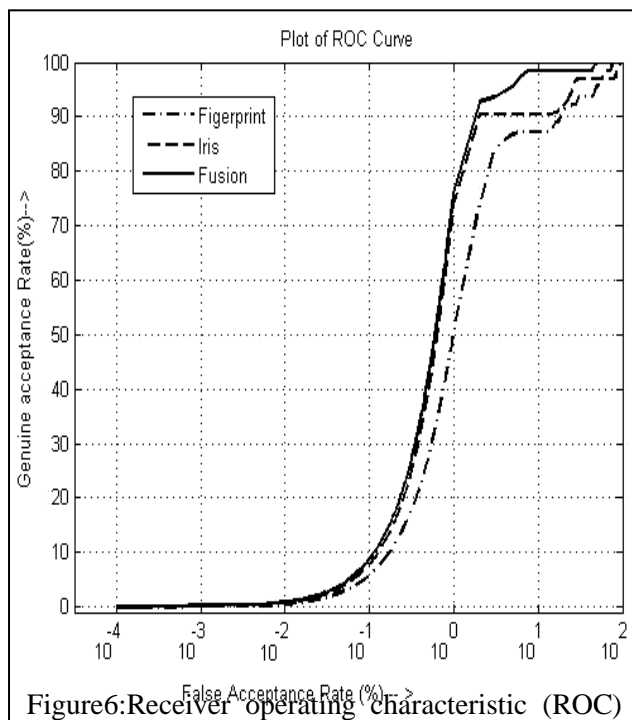


Fig 5: Registration Page

Experimental Results and Analysis

Our verification process is implemented within a multimodal biometric recognition system of combined iris and fingerprint using the weighted sum rule based matching. The experiment uses an equivalent number of images from CASIA Iris –VI & VII and FBVC2004 fingerprint databases. The performance of the investigated multi -modal biometrics system is evaluated by calculating its false acceptance rate (FAR) and false rejection rate (FRR) at various thresholds. These two factors are integrated together in a receiver operating characteristic (ROC) curve that plots the FRR or the genuine acceptance rate (GAR) against the FAR at different thresholds. The FAR and FRR are computed by generating all possible genuine and impostor matching scores and then setting a threshold for deciding whether to accept or reject a match. For the purpose of allowing comparison, two level of experiments are performed. At first level, iris and fingerprints algorithms are tested individually. At second level, the matching score of both traits are combined and final accuracy graph is plotted as shown Experimental results achieved best compromise between FRR and FAR (0% FAR and 0.05% FRR) with accuracy 99.95%. The results show a remarkable improvement in the accuracy as well as a

considerable decrease in the Equal Error Rate (EER) equal to 0.4 and matching time equal to 0.1754s as compared to existing experiments involving iris and fingerprint



Kankrale and Sapkal (2012)	Feature Extraction	300 images of 50 subjects (from CASIA-fingerprint V5 and CASIA-iris V1)	Minutia based extractor + Daugman's iris extractor	AND rule	FAR = 0%, FRR = 5.12% Match time = 3.56s
Proposed System	Matching Score	600 images of 50 subject (from FVC 2004 and CASIA-Iris V2)	Minutia based extractor + Daugman's iris extractor	User-Score-based Weighted 2v-SVM	FAR = 0% FRR = 0.05% Match time = 0.1754 s

CONCLUSION

A framework was established with assessing the performance of multimodal biometric systems. The results of this study shows multimodal biometric systems perform better than unimodal biometric systems especially the fusion of iris and fingerprint. An improved and faster Iris-Fingerprint based voters' verification system was developed using JAVA.

Future scopes include investigating alternative normalization and fusion methods and to also expand the test databases to attain larger sizes in order to give room for system scalability.

Table 1 Performance Comparison With Related Systems

System	Fusion Level	Database	Extractor	Matcher	Results
Gawande et al. (2012)	Feature extraction	500 images of 50 subjects	ID log Gabor filter for both modalities	HD (hamming distance)	FAR=0% FRR=4.3% Match time=0.14s
Abdolahi et al. (2013)	Decision	Not given	Modified minutia based extractor + iris extractor not given	Fuzzy rules + weighted code	FAR = FRR = 2% Match time not given.

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