Volume 5, Issue 2, February 2015 ISSN: 2277 128X
International Journal of Advanced Research in Computer Science and Software Engineering
Research Paper
Available online at: www.ijarcsse.com

Fusion of Fingerprint, Iris and Face Biometrics at Decision Level

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Abstract* — Multimodal biometric systems can effectively solve limitations and challenges in single biometric such as noisy data, non-universality and spoof attacks. In this paper fusion of fingerprint, iris and face traits are used at decision level in order to improve the accuracy of the system. Each subsystem gives its individual binary decision (either low or high), and then these decisions are fused using Fuzzy and weighted logic. Experimental results show that weighted fuzzy logic gives excellent accuracy equal to 99.99 %.

Keywords— multimodal, fusion, fingerprint, face, iris, fuzzy logic.

I. INTRODUCTION

Many decades ago, biometric characteristics have become very important tools in field of identity verification or identification. This is for its stability for long time and the ability to cope with theft or forgery or forgetfulness [1]. Due to most of biometric systems are far from satisfactory in terms of user confidence and user friendliness and have a false rejection rate (FRR). So there is a need to develop novel algorithms for human recognition. Multimodal biometric systems use multiple modalities to overcome the challenges that arise when use single biometric trait such as: noise, non universality, lack of individuals and spoof attacks. Multimodal biometric systems perform better than unimodal biometric systems [2]. In our work, three public biometrics are used "fingerprint, iris and face”. In first stage image pre-processing is performed on fingerprint, iris and face images using different techniques for each biometric. In the second stage three feature extraction techniques are applied: Minutia based algorithm are used for fingerprint which extracts two types of points, ridge ending and ridge bifurcation [11]. Modified Daugman’s algorithm is used for iris recognition where enhanced iris image is segmented first to localize circular iris and pupil region, The extracted iris region was then normalized into a rectangular block with constant dimensions to account for imaging inconsistencies. Finally, the phase data from 1D Log-Gabor filters were extracted and quantized to four levels to encode the unique pattern of the iris into a bit-wise biometric template using Daugman's rubber sheet model [12],[13]. Local binary pattern LBP is performed for face images where face image is divided into cells then for each cell an 8-digit binary number is computed which converted to decimal form then histogram is computed over cells, finally all histograms are concatenated to give feature vector [14]. In the third stage: matching scores from each matcher are arrived [4]. In the fourth stage: each subsystem produce its individual decision, in our work every subsystem has two decision values either low or high. Then fusion of these decisions is executed using Fuzzy logic to get unary decision in the end. The objective of this research is as follow: Designing and implementing a multimodal biometric system of the combined biometrics "fingerprint, iris and face" and then fusing them at the decision level by fuzzy logic. The reason to use three biometric traits is the desire to get high degree of discrimination when we have large number of users or population. The paper is organized as follows: in section 2 related works are presented; in section 3 previous works in fingerprint, iris and face recognition systems are given; in section 4 state of the art of multimodal biometric; in section 5 the research methodology are presented; fuzzy logic concept in section 6, the experimental results and analysis are reported in section 7; conclusion is given in the last section.

II. RELATED WORKS

Different literatures can be found which present variety of approaches for unimodal and multimodal biometric systems. Multimodal biometrics has been proposed by Ross and Jain in 2003 [3]. regarding fingerprint, iris and face biometrics fusion any pair of them” fingerprint and iris ” , ” iris and face” or ”fingerprint and face” has attracted a lot of attention and different researches have proposed many of approaches. Houda benaliouchi et al. [35] in 2014 presented comparative study on fusing iris and fingerprint at score level and decision level. Experimental results have shown that fuzzy logic method at decision level is more accurate than weighted sum rule at score level. Mohamed abdolahi et al. [4] in 2013 had used two uni-modal biometrics, iris and fingerprint as multi-biometrics and found that using these biometrics give good result with high accuracy. Decision level is used for fusion and each biometric result is weighted for participate in final decision. Fuzzy logic is used for the effect of each biometric result combination. Yang and Fan [5] in 2007 used fingerprint, palmprint and hand geometry to implement personal identity verification. These three biometric traits can be taken from the same image. they perform matching score fusion at different levels to establish person, performing a first fusion of the fingerprint and palm print features, and then a matching score fusion between the multimodal system and hand geometry system .the system was tested on a database containing the features selfconstructed by 98 subject. Mohamed et al. [6] in 2013 multimodal biometric system fusion using fingerprint and iris are proposed, decision level is used for fusion and each biometric result is weighted for participate in final decision .fuzzy logic is used for the effect of each biometric result combination. The proposed method has achieved high accuracy comparing with unimodal systems. Byungium and Yillbyung [7] in 2005 were presented biometric authentication system based on iris and face; they applied 2-D discrete wavelet transform to extract the feature sets from iris and face. And then Linear Discriminant Analysis is applied to obtain reduced joint feature vector from these feature sets. Databases which used to show experimental results are ORL for face images, and for iris database the images are acquired through CCD camera with LED lamp around lens under indoor light. Ajita and Massimo [9] in 2009 addressed the feature level fusion of multi-modal and multi-unit sources of information by proposing approach computes the SIFT features from both biometric sources. For each biometric trait feature selection on the extracted SIFT features was performed by spatial sampling then the features are concatenated to form a single vector using serial fusion. L.Latha and S.Thangasamy [10] in 2010 they have used left and right irises and retinal features, and after matching process the scores are combined using weighted sum rule. To validate their approach, experiments were conducted on the iris and retina images obtained from CASIA and VARIA database respectively**.**

III. FINGERPRINT RECOGNITION

A fingerprint is the feature pattern of one finger. It is believed with strong evidences that each fingerprint is unique. Each person has his own fingerprints with the permanent uniqueness. So fingerprints have being used for identification and forensic investigation for a long time [15]. Fingerprint is composed of ridges and furrows which are parallel and have the same width. In fingerprint recognition, fingerprint is distinguished by minutiae, which are points on the ridges. There are many types of minutia, but the two basic types are: termination which represent the ending of the ridge and the other is called bifurcation which is the point of the ridge from which two branches derive [16], [6] as in figure (1).

Fig 1: Fingerprint image and minutia points

Fingerprint identification system has three parts as follow:

A. Fingerprint Acquisition

Image capture devices include different categories of fingerprint capture devices, such as: optical, solid-state and ultrasonic [11]. Optical fingerprint capture devices have the longest use history of these categories.

B. Feature Extraction

In this work minutia based algorithm are used, in this method, the resulting feature vector is containing for each minutia point the following parameters: 1) x-coordinate, 2) y-coordinate, and 3) orientation.

C. Pre-processing

Histogram equalization and Fast Fourier transform (FFT) are used for image enhancement [17]. Histogram equalization is employed to expand the pixel value distribution of an image so as to increase the perceptional information. FFT is used to connect false broken points of ridges and increase the contrast between ridges and furrows. Binarization is then performed using locally adaptive thresholding to transform the 8-bit gray scale fingerprint image into a binary image where 0s indicate ridges and 1s furrows. Image segmentation is achieved through a three step approach: (1) block direction estimation, (2) segmentation by direction intensity and (3) morphological open and close operations to extract regions of interest (ROI).

D. Minutia Extraction

Before minutia extraction, Ridge thinning is performed first to remove the redundant pixels of ridges till the ridges wide are just one pixel. Now fingerprint image is ready to extract minutia. The simple algorithm for minutia extraction is: if a pixel with 1 value has one neighbour with 1 value in its 8 neighbors, it is terminate and if it has three neighbors with 1 value it is bifurcation [6], [18].

0	1	0
0	1	0
1	0	1

0	0	0
0	1	0
0	0	1

Fig 2: The left form is bifurcation and the right is termination

E. Post- processing
This phase is to remove false minutia to reduce the complexity of computation and enhance the accuracy of the system. The false minutia are defined as seven types, most of them can be removed by proposing a threshold D, if the distance between minutiae less than D, these minutiae will be removed [18].

F. Fingerprint matching
An alignment-based match algorithm includes two consecutive phases: first is alignment phase and the second is match phase. In alignment phase each set of minutia is transformed to a new coordination system with the referenced points to coincident with the direction of the referenced points. For each fingerprint, translate and rotate all other minutia with respect to the references minutiae.
The last phase is the matching process itself, where we use elastic match algorithm to count the matched minutia pairs of two fingerprint images. In this method bounding box around each template minutia is assumed. If the minutia to be matched is within the rectangle box and the direction discrepancy between them is very small, then the two minutiae are regarded as a matched minutia pair. Each minutia in the template image either has no matched minutia or has only one corresponding minutia [18].

IV. IRIS RECOGNITION
The iris system composes of a number of subsystems, which correspond to each stage of iris recognition. The stages include segmentation for locating the iris region in an eye image, normalization for creating a dimensionally consistent representation of the iris region, enhancement by histogram equalization of normalized iris region, feature encoding for creating an iris code containing only the most discriminating features of the iris and finally matching by hamming distance to make a decision of acceptance or rejection.

A. Iris Segmentation
Segmentation is the first stage in iris pre-processing to isolate the required iris region from the whole eye image by separating the part of an image between the inner boundary and outer boundary. Canny method used to detect edges by searching about local maxima of the gradient of iris image. The gradient is computed using the derivative of a Gaussian filter. It determines two values as thresholds to reveal strong and weak edges. This method is more robust to noise and more likely to detect true weak edges. The output of the canny edge detector is the edge strength image and the orientation image. The image intensity value has to be increased by adjusting the gamma correction factor. With the orientation image and the adjusted gamma image as the input, the local maxima are suppressed. Then Circular Hough Transform is used to detect the iris and pupil boundaries and reveal both radius and centre coordinates [10].

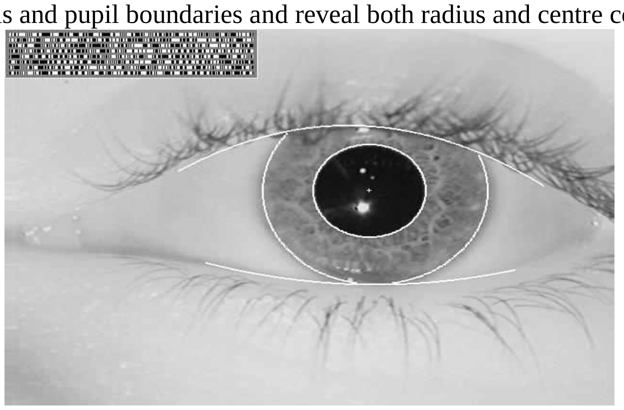

Fig 3: iris segmentation

B. Iris normalization
Normalization is a process of transforming the segmented iris region into fixed dimension. However, dimensional inconsistencies arise between eye images due to the stretching of iris, caused by pupil dilation from varying levels of illumination. Such elastic distortion in iris texture will affect the result of iris matching. Therefore, normalization is done to recover the iris deformation caused by illumination variations. The normalization process uses Daugman's rubber sheet model and this method remaps the annular iris image I(x, y) from original Cartesian coordinates (x, y) to a dimensionless pseudo polar coordinate system I(r, Ɵ). Rubber sheet model takes into account the pupil dilation and size inconsistencies in order to produce a normalized representation with constant dimension. Normalization produces a 2D array with horizontal dimensions of angular resolution and vertical dimensions of radial resolution. A template of dimension 20 x 240 is produced, where 20 are the radial resolution and 240 is the angular resolution [19], [20].

C. Iris Enhancement
Applying histogram equalization (HE) improves the contrast of the image by enhancing the normalized pattern. Equalization implies mapping one distribution (the given histogram) to another distribution. HE enhances the global contrast of image, when the pixel values of the image are represented by Convergent contrast values. In this process, the intensity values can be better distributed on the histogram by redistributing the most frequent intensity values. This action pushes the areas of lower local contrast to gain a higher contrast without affecting the global contrast.

D. Feature encoding

Feature encoding extracts the underlying information from the iris pattern and generates the binary iris template that is used in matching. Convolving the normalized iris pattern with 1D Log-Gabor filter generates the iris feature set. The filter is Gaussian on a logarithmic scale and used to produce zero DC components for any bandwidth. It is given by:

$$G(f) = exp\left(\frac{-\log\left(\frac{f}{f_o}\right)^2}{2\log\left(\frac{\sigma}{f_o}\right)}\right)$$

Where (f_o) represents the centre frequency, and gives the bandwidth of the filter. By applying 1D Log-Gabor filter, the 2D normalized pattern is divided into a number of 1D signals and these are convolved with 1D Gabor wavelets. The rows of the 2D normalized pattern are taken as the 1D signal; each row corresponds to a circular ring on the iris region. The angular direction is taken, which corresponds to columns of the normalized pattern, since maximum independence occurs in the angular direction. The filter is constructed by calculating the radial filter component such as center frequency of filter and normalized radius from the center of frequency plan. The resultant complex features are phase quantized and encoded into binary iris templates [21], [24].

E. Iris matching

Matching is a process to determine whether two iris templates are from the same individual or not. Hamming distance is applied for bit-wise comparisons of images. Noise in the iris image is masked and only significant bits generated from the true iris region are used in the Hamming distance calculation between two iris templates [22] ,[23].

$$HD=\frac{\left\|(code\mathrm{A}\otimes code\mathrm{B})\cap(mask\mathrm{A}\cap mask\mathrm{B})\right\|}{\left\|mask\mathrm{A}\cap mask\mathrm{B}\right\|}$$

where *HD* is the Hamming distance, A and B are two normalized iris images, code A and code B are the bit-codes of A and B, mask A and mask B are respectively the masks of noise of A and B which produced by eyelashes or eyelids. The hamming distance between the templates, which have deployed the best bits is reduced comparing with the use of full iris code. If two irises are identical then *HD* will give 0 results.

V. FACE RECOGNITION

Two decades ago face recognition has became an important topic in computer vision. This is due it has potential application values [25]. A lot of approaches have been presented to solve face recognition problems. Principal Component Analysis (PCA) [26], and Linear Discriminant Analysis (LDA) [27] based methods, has significantly face recognition methods. In PCA, a face subspace is formed to represent optimally only the face; by using LDA, a discriminant subspace is formed to discriminate faces of different subjects. Gabor wavelet based and Local features analysis are other approaches which build a local appearance-based feature space, these approaches are more robust against various changes by using appropriate image filters[28]. Local Binary Patterns (LBP) is presented as a Strong local descriptor for microstructures of images [29]. In this work local binary pattern are used for face recognition.

Face recognition with LBP:

The original LBP operator was introduced by Ojala et al. [30]. It is a powerful means of texture description. The face area is first divided into small regions from which Local Binary Pattern (LBP) histograms are extracted and concatenated into a single vector see fig (6)

Fig 4: facial image divided into 5x5 regions

In each region the operator labels the pixels of an image by threshold the 3x3-neighbourhood of each pixel with the center value and considering the result as a binary number or a decimal number**.**

$$\textbf{LBP} = \sum_{p=0}^{p-1} s\big(f(x,y) - f(x_p, y_p)\big)2^p$$

$$S(Z) = \begin{cases} 1 & \text{if} \quad z \geq 0 \\ 0 & \text{if} \quad z < 0 \end{cases}$$

Then the histogram of the labels can be used as a texture descriptor. Figure (5) illustrate the original LBP operator. Later the operator was extended to use neighborhoods of different sizes .Using circular neighborhoods and bilinearly interpolating the pixel values allow any radius and number of pixels in the neighborhood. For neighborhoods the notation (P, R) are used which means P sampling points on a circle of radius of R. See Figure (6) as an example of the circular (8, 2) neighborhood.

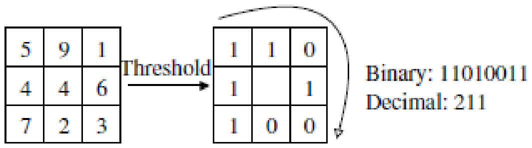

Fig 5: Basic LBP operator

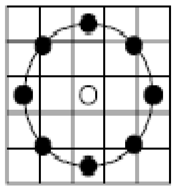

Fig 6: Circular (8, 2) neighborhood

Another modification to the original operator uses so called uniform patterns [30], [31]. A Local Binary Pattern is called uniform if it contains at most two bitwise transitions from 0 to 1 or vice versa when the binary chain is considered circular. For example, 11100000, 00011110 and 11000001 are uniform patterns. Ojala et al. noticed that in their experimental results with texture images, uniform patterns account for a bit less than 90 % of all patterns when using the (8, 1) neighborhood and for around 70 % in the (16, 2) neighborhood. Shengcai Liao et al. proposed an improved method over the basic LBP in which multi-scale block LBP are used. Multiscale LBP is an extension to the basic LBP, with respect to neighborhoods of different sizes. In MB-LBP, the comparison operator between individual pixels in LBP is simply replaced with comparison between average gray-values of sub-regions. Each sub-region is a square block containing neighboring pixels (or just one pixel particularly). The whole filter is composed of 9 blocks. We take the size s of the filter as a parameter, and s x s denoting the scale of the MB-LBP operator (particularly, 3x3 MB-LBP is in fact the original LBP). Note that the scalar values of averages over blocks can be computed very efficiently from the summed-area table or integral image [25]. For this reason, MB-LBP feature extraction can be very fast, and it only incurs a little more cost than the original 3x3 LBP operator [14]. Other different version of LBP which outperform the original LBP are proposed by researches like completed LBP (CLBP), dominant LBP (DLBP) and LBP Histogram Fourier (LBP-HF). For matching two facial images, there are several possible dissimilarity measures have been proposed for histograms [32].in this work Chi square statistic is used as follow:

$$\chi^2(S,M) = \sum_i \frac{(S_i - M_i)^2}{S_i + M_i}$$

Where S and M represent the matched face images

VI. MULTIMODAL BIOMETRICS SYSTEMS

Multibiometric systems have five different methods to address problems associated with single biometric systems [6]. Figure (7) show these types

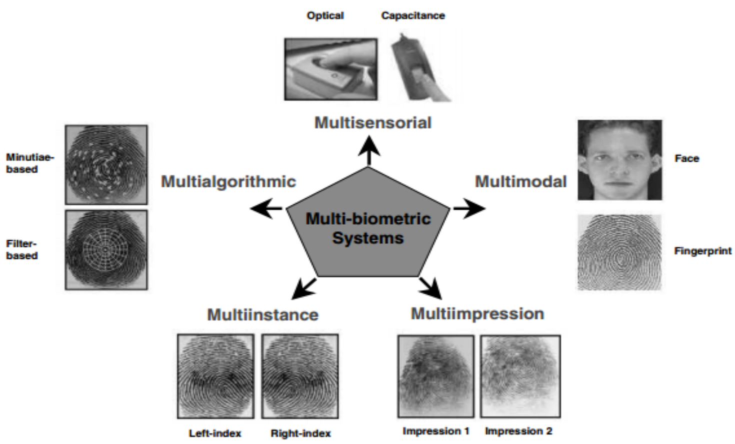

Fig 7: Multimodal types

a) *Multi sensor:* Two or more sensors are used to obtain data from one biometric trait such as fingerprint image with optical and ultrasound sensors and facial image by visible light camera or infrared camera**.**

b) *Multi representation:* Several sensors capturing several similar body parts(multi fingerprint image from multi finger but from one person).

c) *Multi instance:* The same sensor captures several instances of the same body part. For example, system capturing images from multiple fingers are considered to be multi-instance**.**

d) *Multi algorithm***:** Two or more of different algorithms are used for the same trait. Maximum benefit would be derived from algorithms that are based on different and independent principles.

e) *Multi modal:* It is method that use two or more of different biometric traits which were captured from different sensors and employ them in the variety fusion strategies**.**

VII. FUSION STRATEGIES

Many fusion strategies can be executed at different levels as follow:

Feature level: The data obtained from sensor is used to extract the feature vector from one biometric trait which is independent from those extracted from the other; these feature vectors are concatenated to produce a single new vector. This process is difficult when feature vectors are heterogeneous.

Matching score level: Each system provides a matching score indicating the nearness of the feature vector with the template vector. These scores can be combined to assert the veracity of the claimed identity [33]. While the information contained in matching scores is not as rich as in images or features, it is much richer than ranks and decisions. Further, it is easier to study and implement than image-level and feature-level fusion. It can also be used in all types of biometric fusion scenarios.

Decision level: Each individual biometric system gives its own binary result. The fusion process fuses them together to outputs single binary decision accepts or reject.

VIII. RESEARCH MEYHODOLOGY

The different stages of our multimodal biometric system are being shown in figure (8); these stages are executed as follow:

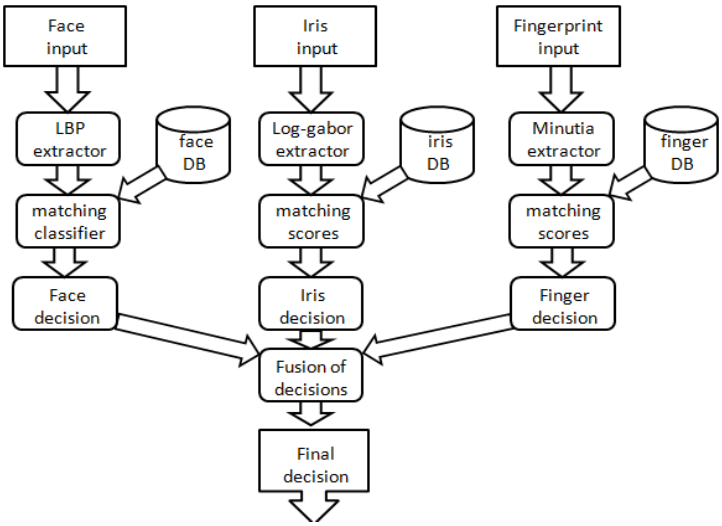

Fig 8: Proposed multimodal stages

Acquisition Images**:** In this stage fingerprint, iris and face image are captured by appropriate sensor for each trait then the three images are saved to be the input in next step.

Feature Extraction: This is the second stage where three feature extraction algorithms are presented to extract and form the feature template. Minutia-based algorithm are applied to extract feature from finger image, Daugman algorithm with 1D log-Gabor filter for iris template extraction and Local Binary Pattern (LBP) to extract feature from face image.

Matching scores: Each extracted template is matched with the corresponding templates in the database. An alignment-based match algorithm is used as fingerprint matcher who determines the similarity between fingerprint templates, Hamming distance HD is applied for iris matching stage to give the dissimilarity between iris images and Chi square for face matching process which introduces the dissimilarity between face images.

Decision: Each subsystem will produce two decision values low or high based on predefined threshold.

Fusion: In this stage the resulting decisions from the previous stage are fused by Fuzzy logic and weighted fuzzy logic, and then unary decision will be out to determine the matching degree between client and individuals in database.

IX. FUZZY LOGIC

Fuzzy logic is kind of soft computing which mimics human thinking [4], [34]. This concept was introduced as proposal of fuzzy set theory by lotfi A. Zadeh[35].the main stages of fuzzy logic are shown in figure(9)

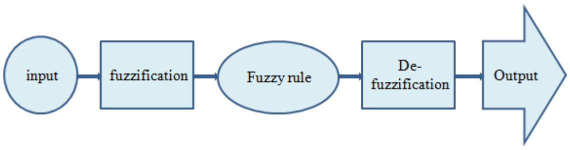

Fig 9: main stages of fuzzy logic

The fuzzy if-then rules are used to produce decisions based on the matching distance computed for every individual biometric trait. The following figure (10) shows the two decision values that result by each subsystem.

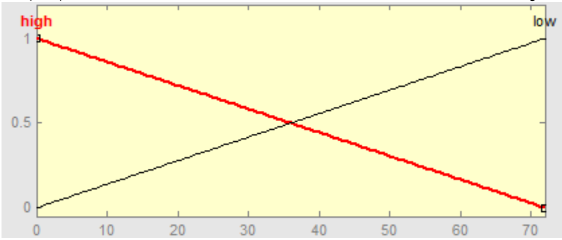

Fig 10: high and low decision values

To execute fusion by fuzzy logic we follow these steps: (1) we define three fuzzy variables for the input: “finger” for the fingerprint biometric, face for the face biometric, “iris” for the iris biometric and the output fuzzy variable is: “fusion,” (2) each variable is represented by a trapezoidal fuzzy set, (3) for the inputs, we define two fuzzy sets according to the matching distance: low and high (4) the output is either very low or low or high or very high.
The fuzzy if – then rules proposed by our system are as follow:
If (finger is low) and (face is low) and (iris is low) then (fusion is very bad).
If (finger is low) and (face is low) and (iris is high) then (fusion is pass).
If (finger is low) and (face is high) and (iris is low) then (fusion is pass).
If (finger is low) and (face is high) and (iris is high) then (fusion is good).
If (finger is high) and (face is low) and (iris is low) then (fusion is bad).
If (finger is high) and (face is low) and (iris is high) then (fusion is good).
If (finger is high) and (face is high) and (iris is low) then (fusion is good).
If (finger is high) and (face is high) and (iris is high) then (fusion is excellent).

X. EXPEREMINTAL RESULTTS

Three sets of databases are used to evaluate the performance of unimodal and multimodal systems. The first is FVC2004 DB3_A database for fingerprint recognition which contains grey scale images and TIF files, it contains 100 different subject each of them has 8 samples, three samples are selected for training and the rest samples are used for testing. CASIA database are prepared for iris recognition which is gray scale images and JPEG file, three samples are used for training and the remaining five images served as testing images. The recognition was done on 100 subject picked randomly from database. The third database is the face database which collected from **face94** (university of Essex, UK). Every person has 20 samples and some individuals are wearing glasses and beards with different facial expressions. It contains images of JPEG files and colored. We have chosen 100 different persons with 8 samples; the first 3 samples are used for training and 5 for testing. All these databases are independent from each other because there is no common database contains three biometrics" fingerprint, iris and face" for the same person. In this work, three unimodal biometric systems are given" fingerprint, iris and face", to determine the accuracy of the systems. Two measures are selected: false accept rate (FAR) and false reject rate (FRR) which they are computed on the given databases. Where false accept rate (FAR) is the probability that the system incorrectly matches the input pattern to a non-matching template in the database. It measures the percent of invalid inputs which are incorrectly accepted. False reject rate (FRR) is the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs which are incorrectly rejected [35]. The aim is always to reduce both FAR and FRR to get better accuracy. In table 1: FVC2004 DB3_A database is collected to evaluate fingerprint recognition systems by using minutia-based algorithm, the best accuracy given by the system equal 82.5 %. The experimental results on CASIA database evaluate iris recognition system which use log-Gabor filter algorithm; the best accuracy achieved by the system is 95.15%. the experimental results on face94 (university of Essex, UK) database are presented to evaluate face recognition system which use local binary pattern algorithm, the system gives accuracy equal to 97.58 %.

Table 1 Accuracy of the used single systems

System	Algorithm	Database	Accuracy%
fingerprint	Minutia based	FVC2004 DB3_A	82.3
iris	1D-Log Gabor filter	CASIA	95.15
face	LBP	Face94(university of Essex, UK)	97.58

Table 2 presents the accuracy achieved by fuzzy logic and weighted fuzzy logic fusion at decision level. When the fuzzy logic used, there are not weights given to any trait, so all have the same weight. At the same time we accept the person as genuine if the decision fusion was excellent or good only. The accuracy achieved by this system is 99.69 %. In weighted fuzzy logic, different weights were given for each trait. And we accept the fusion decisions excellent, good and pass as genuine. This system will give accuracy equal to 99.99 %.

Table 2 Accuracy of the proposed fuzzy logic fusion

method	**databases**	**Fusion level**	**Accuracy%**
Fuzzy logic	FVC2004 + CASIA + Face94	decision	99.69
Weighted Fuzzy logic	FVC2004 + CASIA + Face94	decision	99.990

In tables 3 some related systems and their results were presented. Both Abdollahi 2013 and Houda 2014 [35] used minutia based as fingerprint feature extractor and 1D-log Gabor filter as feature extractor for iris and making fusion by weighted fuzzy logic at decision level. The proposed system outperforms both systems in accuracy.

Table 3 Comparison among some related works

Authors	**Databases**	**Level of fusion**	**Accuracy %**
Abdolahi et al 2013	Not given	decision	99.4
Houda et al 2014	Fvc2004 CASIA	decision	99.975
Our proposed weighted fuzzy logic	Fvc2004 CASIA Face94	decision	99.990

Figure 11 show the Receiver Operating Characteristic (ROC) curves for the proposed system. ROC curves are obtained by plotting the FAR probability versus the FRR probability with different values of the decision threshold. Equal Error Rate (EER) is the position on the ROC curve where FAR and FRR are equal. The ROC curve reveals that the weighted fuzzy logic which has 0.011 % EER is more reliable than fuzzy logic with (0.29 % EER).

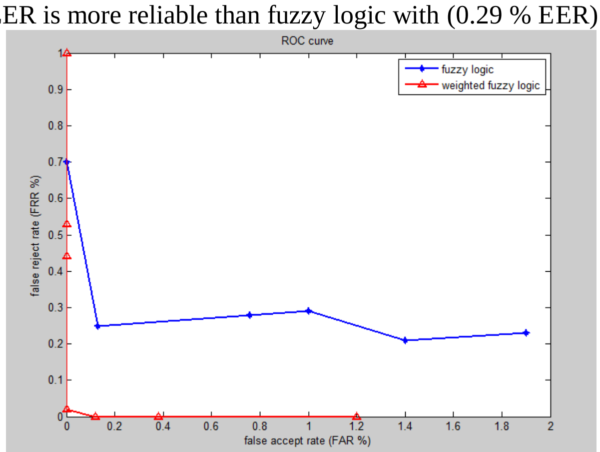

Fig 11: ROC curves of proposed fuzzy and weighted fuzzy logic fusion

XI. TIME EXECUTION

Our system are implemented by MATLAB R2012b program on HP laptop device with processor Intel® core(TM) i5-2400U CPU 2.30 GHz and RAM 4.00 GB. The time consumed for matching one sample in fuzzy logic is 1.41 microseconds and 3.12 microseconds by weighted fuzzy logic. These times were computed for one loop or for one sample because of most databases are different in the number of persons and number of samples associated per person.

XII. CONCLUSION

Fusion of fingerprint, face and iris systems at decision level was proposed. This platform is necessary if we have treat huge databases that contain hundreds millions of users. The scores don't be needed to normalize. Each subsystem gives its individual decision, and then these decisions will be fused by fuzzy logic which gives excellent accuracy.

In the future we will use other methods to fuse the decisions and comparing them with fuzzy logic to determine who will present less computation time and highest accuracy.

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