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Multimodal Biometric System Fusion Using Fingerprint and Face with Fuzzy Logic

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Abstract— Biometric systems have a variety of problems such as noisy data, non-universality, spoof attacks and unacceptable error rate. These limitations can be solved by deploying multimodal biometric systems. Multimodal biometric systems utilize two or more individual traits, like face, iris, retina and fingerprint. Multimodal biometric systems improve the recognition accuracy more than uni-modal methods. In this paper, two uni-modal biometrics, fingerprint and face are used as multi-biometrics and show using this biometrics has good result with high accuracy. This paper multimodal biometric systems using fuzzy fusion of fingerprint and face recognition gives high accuracy as compare other fusion method. Different Fusion level techniques are mentioned.

Keywords— Fuzzy Fusion, Fingerprint, Face False Acceptance Rate, False Rejection Rate, Genuine Accept Rate

I. INTRODUCTION

Biometrics is the science of establishing identity of an individual based on the physical, chemical or behavioral attributes of the person. The relevance of biometrics in modern society has been reinforced by the need for large-scale identity management systems whose functionality relies on the accurate determination of an individual's identity in the context of several different applications. Examples of these applications include sharing networked computer resources, granting access to nuclear facilities, performing remote financial transactions or boarding a commercial flight. The various biometric features which include Finger prints, Ear, Face, Hand Geometry, vein pattern, voice, Keystroke Pattern, Signature, iris, palm print, gait etc. out of which Face and Ear Biometric features will be used in this project.[1]

Unimodal biometric systems have limitations like uniqueness, high spoofing rate, high error rate, non-universality and noise. For example in face recognition, it is affected by position, sadness, happiness and the amount of ambient light. It has been recently clear for most researchers that approximately two percent of the population does not have a legible fingerprint and therefore cannot be enrolled into a fingerprint biometrics system [2]. Mutibiometric systems can improve limitations faced by unimodal biometric systems. For example, the multibiometric system can address the non-universality problem encountered by biometric systems. If a person cannot be enrolled in the fingerprint system, this person can aid the problem using other biometric traits such as voice, face or iris. The multibiometric systems can also reduce the effect of noise data. If the quality biometric sample obtained from one sources is not sufficient, the other samples can provide sufficient information to enable decision-making. Another advantage of multibiometric over single biometric systems is that, they are more resistant to spoof attacks since it is difficult to simultaneously spoof multiple biometric sources. The multibiometric systems are able to incorporate a challenge-response mechanism during biometric acquisition by acquiring a subset of the trait in some random order [3]. Using multiple biometric indicators for identifying individuals, known as multimodal biometrics, has been shown to increase accuracy [4] and population coverage, while decreasing vulnerability to spoofing. The important part in multimodal biometrics is the fusion level of various biometric modalities. Four levels are proposed including sensor level, feature extraction, matching score, or decision levels [5]. In this research, decision level fusion is used. This approach has the advantage of utilizing as much information as possible from each biometric modality. Two modalities are used in these researches which are fingerprint and face. In first sections a brief review for fingerprint and face acquiring code is provided, and then the combination method of these two modalities and fusion method are introduced.

II. FINGER PRINT RECOGNITION

A fingerprint is the feature pattern of one finger and it is believed that each fingerprint is unique. Each person has his own fingerprints with the permanent uniqueness. So fingerprints have being used for identification and recognition. A fingerprint is composed of ridges and furrows which are parallel and have same width.

However, in fingerprint recognition, fingerprints are not distinguished by their ridges and furrows; they are distinguished by Minutia, which are features on the ridges. There is variety of minutia types on fingerprint image as in the below figure but two are mostly significant and in heavy usage: one is called termination, which is the immediate ending of a ridge and the other is called bifurcation, which is the point on the ridge from which two branches derive [6].

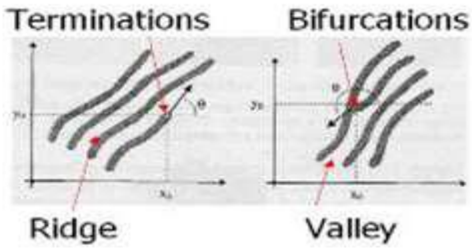

Fig. 1: Minutia on Fingers

Fingerprint identification system has three part that are image acquiring part, minutia extraction part and matching part. In image acquiring part, optical sensors are used. The main part is minutia extraction and this part has three sections: pre-processing, minutia extraction and post processing. Pre-processing section tries to enhance image quality with histogram enhancement and Fourier transformation and then convert the enhanced image to binary image and then ridges on fingerprint are making thin. Now fingerprint image is ready for minutia extraction [6].

Minutiae-based methods have been used in many commercial fingerprint matching systems. Based primarily on a point pattern matching model, these methods rely heavily on the accuracy of minutiae extraction and the detection of landmarks like core and delta for pre-alignment. Spurious and missing minutiae can both introduce errors in minutiae correspondence. Equally problematic is the inability to detect landmarks to guide pre-alignment. Taken together, these problems lead to sub-optimal matching accuracy [7].

Fortunately, the contextual information provided by ridge flow and orientation in the neighbourhood of detected minutiae can help eliminate spurious minutiae while compensating for the absence of genuinely missing minutiae both before and during matching. In addition, coupled with a core detection algorithm that can robustly handle missing or partially available landmarks for pre- alignment, significant improvement in matching accuracy can be expected. I use algorithm fingerprint matching using a hybrid shape and orientation descriptor for fingerprint recognition. Fingerprint matching using a hybrid shape and orientation descriptor that is designed to address the above problems. The hybrid descriptor can effectively filter out spurious or unnatural minutiae pairings while simultaneously using the additional ridge orientation cues in improving match score calculation. In addition, the method can handle situations where either the cores are not well defined for detection or the fingerprints have only partial overlapping [7].

III. FACE RECOGNITION

Two decades ago face recognition has become an important topic in computer vision. This is due it has potential application values [9]. A lot of approaches have been presented to solve face recognition problems. Principal Component Analysis (PCA)[10], and Linear Discriminant Analysis(LDA)[11] based methods, has significantly face recognition methods.

Face recognition algorithm is based on an eigenfaces approach which represents a PCA method in which a small set of significant features are used to describe the variation between face images. PCA is a projection technique that finds a set of projection vectors designed such that the projected data retains the most information about the original data. The most representative vectors are eigenvectors corresponding to highest eigenvalues of the covariance matrix. This method reduces the dimensionality of data space by projecting data from *M*-dimensional space to *P*-dimensional space, where $P << M$.

The training database consists of M images which is same size. The images are normalized by converting each image matrix to equivalent image vector Γ_i. The training set matrix Γ is the set of image vectors with

$$\text{Training set } \Gamma = [\Gamma_1, \Gamma_2 \ldots\ldots \Gamma_M]$$

The mean face (ψ) is the arithmetic average vector as given by:

$$\psi = (1/M) \sum_{i=0}^{M} \Gamma i$$

The deviation vector for each image Φ_i is given by:

$$\Phi_i = \psi - \psi \quad i=1, 2, ... M$$

Consider a difference matrix A= $[\Phi_1 \Phi_2 \ldots\ldots \Phi_M]$ which keeps only the distinguishing features for face images and removes the common features. Then eigen faces are calculated by find the Covariance matrix C of the training image vectors by:

$$C = AA^T$$

Due to large dimension of matrix *C*, we consider matrix *L* of size $(M_t \times M_t)$ which gives the same effect with reduces dimension. The eigenvectors of *C* (Matrix U) can be obtained by using the eigenvectors of *L* (Matrix V) as given by:

$$U_i = AV_i$$

The eifenfasecs are:

$$\text{eigenface} = [U_1, U_2, U_3, \ldots\ldots\ldots\ldots U_M]$$

Instead of using M eigenfaces, the highest m' <= M is chosen as the eigenspace. Then the weight of each eigenvector ω_i to represent the image in the eigenface space, as given by:

$$\omega_i = U_i^T (\Gamma - \Psi) \text{ , i=1,2,......} m'$$

Weight matrix $\Omega = [\omega_1\ \omega_2\ \ldots .\ \omega_{m'}]^T$

Average class projection $\Omega_\Psi = \frac{1}{x_i}\sum_{i=1}^{x_i}\Omega_i$

The euclidean distance δ_i is used to find out the distance between two face keys vectors and is given by:

$$\delta_i = \|\Omega - \Omega_{\Psi i}\| = \sum_{k=1}^{M}(\Omega_k - \Omega_{\Psi ik})$$

The smallest distance is considered to be the face match score result[12].

IV. MULTIMODAL BIOMETRICS SYSTEMS

A multibiometric system performs recognition based on the evidences obtained from multiple sources of biometric information. Multibiometric systems can be classified into six categories which are multi-sensor, multi-algorithm, multi-sample, multi-instance and multi-modal systems [13].The scenario of multibiometric systems is depicted as in Fig.2.

Multi-sensor: In multi-sensor, different sensors are used for capturing different representations of the same biometric modality to extract diverse information. For example fingerprint image with optical and ultrasound sensors.

Multi-instance: Multi-instance involved fusion of information from multiple instances within the same biometric trait. For example, evidence from the left and right irises or the left.

Multi- algorithm: In multi- algorithm use the same sensor but its input is processed by different algorithm and compares the results.

Multi-sample: In multi-sample use single senor but multiple samples of the same biometric trait. For example, multi fingerprint image from multi finger of one of person.

Multi-modal: In multi-modal use the evidence of different biometric traits which were capured from different sensors and employ them in the variety fusion strategies.

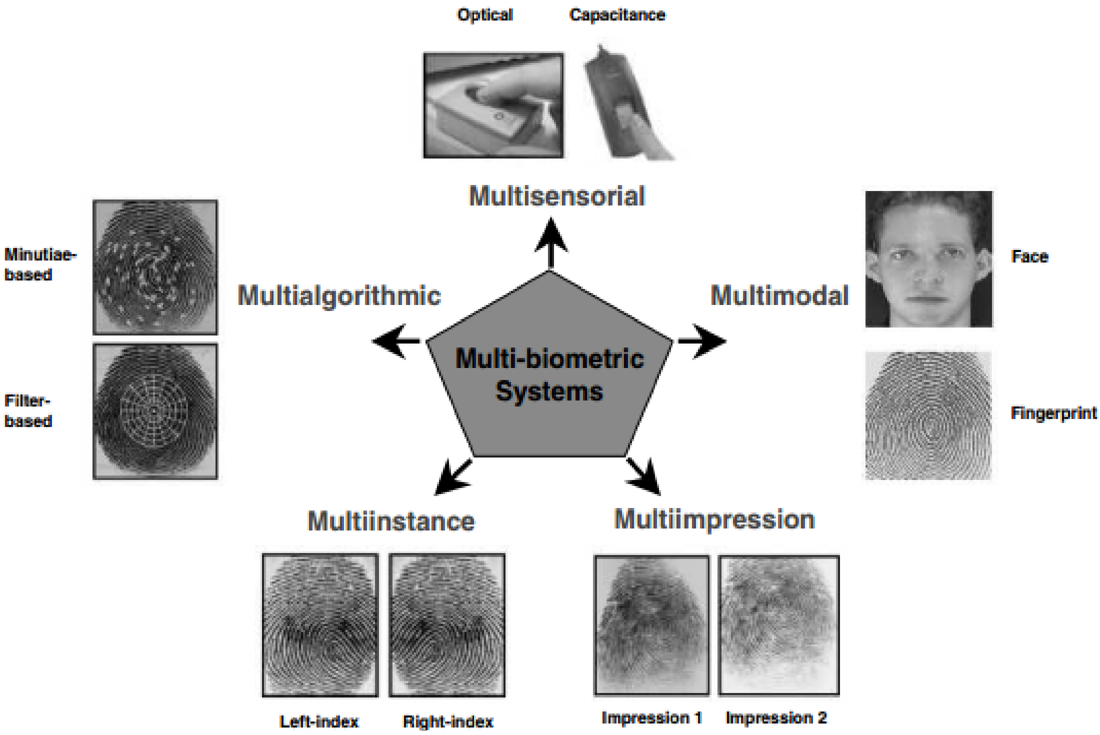

Fig.2 The different types of multibiometric system

V. FUSTION STRATEGIES

Multimodal biometric fusion combines the distinguished aspect from different biometric features to support the advantages and reduce the limitations of the unimodal biometric. The fundamental issue of information fusion is to determine the type of information that should be fused and the selection of method for fusion. The goal of fusion is to devise an appropriate function that can optimally combines the information rendered by the biometric subsystems [14].

In multimodal biometrics, the fusion scheme can be classified as sensor level, feature level, match score level, rank level, and decision level. The process can be subdivided into two main categories: prior-to-matching fusion and after matching fusion [15]. The fuzzy fusion method can be employed in both level prior-to-matching and after matching stage.

A. Prior to Matching Fusion

Fusion in this category integrates evidences before matching. Fusion prior to matching can be achieved with two methods:

Sensor Level Fusion

Sensor level fusion is defined as “the consolidation of evidence presented by multiple sources of raw data before they are subjected to feature extraction” [16]. Sensor level fusion can be performed in two conditions i.e. data of the same biometric trait is obtained using multiple sensors; or data from multiple snapshot of the same biometric traits using a single sensor [17, 18]. This level of fusion is also known as data level fusion or image level fusion.

Feature Level Fusion

Fusion at this level can be applied to the extraction of different features from the same trait or different multi traits. Feature extraction level refers to combining different feature vectors that are obtained from multiple sensors for the same biometric trait or multiple biometric traits. When feature vectors are homogeneous, a single feature vector can be calculated with "and", "or", "xor" or other operations. When the feature vectors are non-homogeneous, we can concatenate them to form a single vector [19, 20].

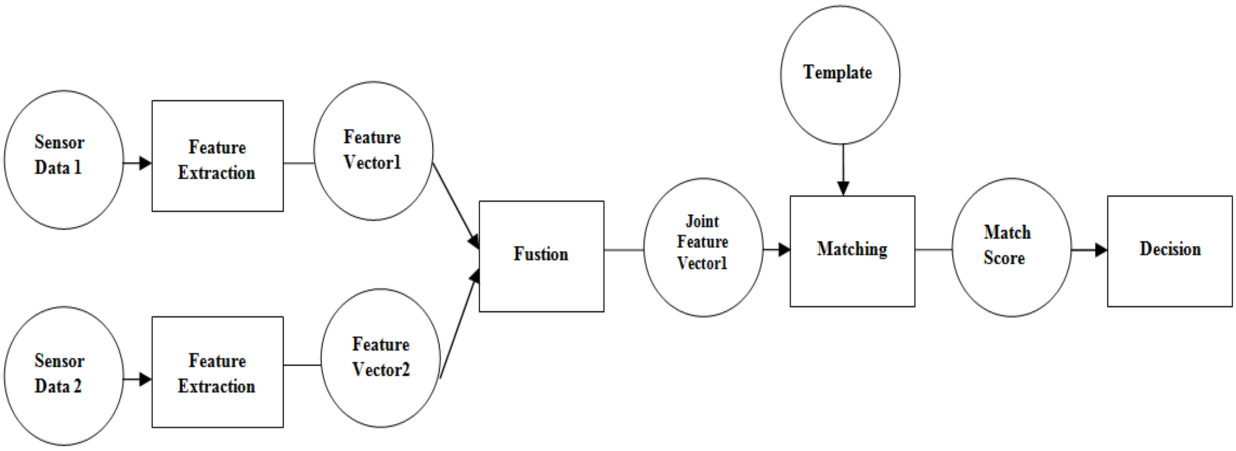

Fig 3. Fusion at the feature extraction level[6]

After Matching Fusion

Fusion in this category integrates evidences of after matching module. Most multimodal biometric systems have been developed using these fusion methods as the information needed for fusion is easily available compared to fusion prior matching methods. Fusion after matching can be achieved with three different ways:

Match Score Level Fusion

In score level fusion, different biometric matchers provide match scores indicating the degree of similarity between the input and template enrolled in the database for each biometric trait. These match scores are consolidated to reach the final recognition decision. Fusion at score level provides the best trade-off between the available information content and convenience of fusion. This is also known as fusion at measurement level or confidence level. Density, transformation, and classifier based score fusion are different methods to achieve this fusion level [21].

The matching scores cannot be used or combined directly; because these scores are from different modalities and based on different scaling methods. Score normalization is required, by converting the scores into common similar domain or scale. This can be carried out with different methods.

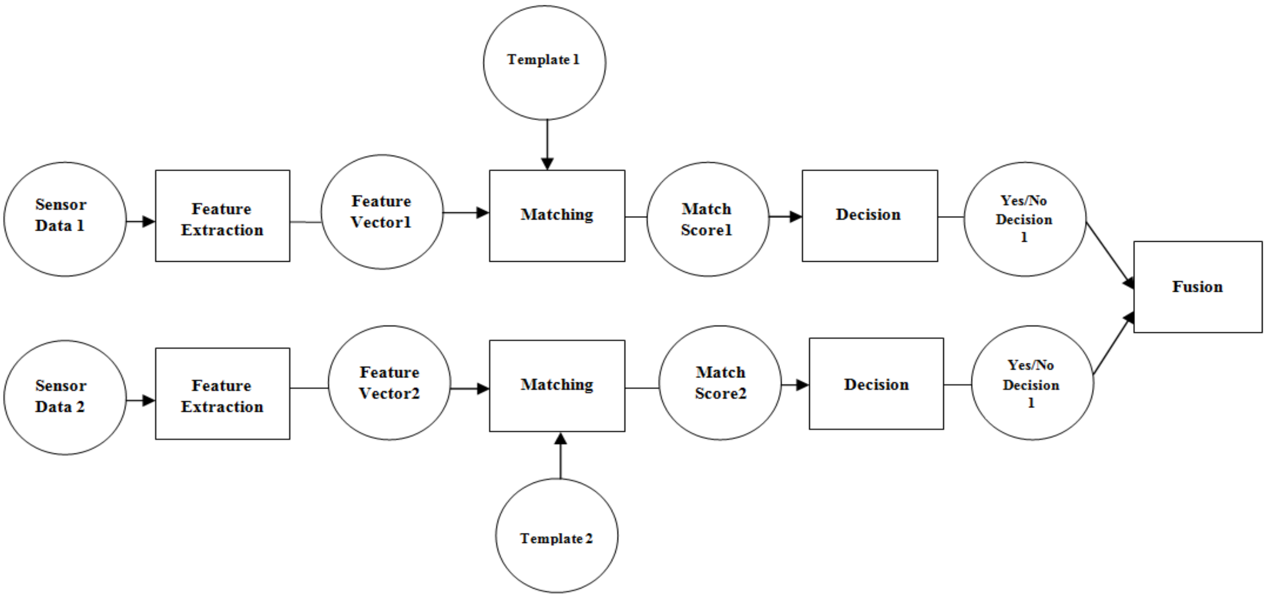

Fig 4. Fusion at the matching score level[6]

Rank Level Fusion

Rank level fusion consolidates multiple ranking lists obtained from several biometric matchers to form a final ranking list which would aid in establishing the final decision [14]. Sometimes, only the final ranked outputs from a biometric system are available. Furthermore, in some biometric systems, the matching scores from the matchers are not suitable for fusion. Thus rank level fusion is a feasible solution in such systems [22]. This type of fusion is relevant in identification systems where each classifier associates a rank with every enrolled identity.

Decision Level Fusion

Decision level fusion method consolidates the final decision of single biometric matchers to form a consolidated decision. When each matcher outputs its own class label (i.e., accept or reject in a verification system, or the identity of a user in an identification system), a single class label can be obtained by employing techniques, such as, "AND"/"OR", majority voting, weighted majority voting, decision table, Bayesian decision and Dempster-Shafer theory of evidence[14]. Many biometric systems can only output the final decision, thus decision level fusion is very appropriate for biometric systems. The available information for this fusion method is binary (yes/no in most cases), which allows very simple operations for fusion.

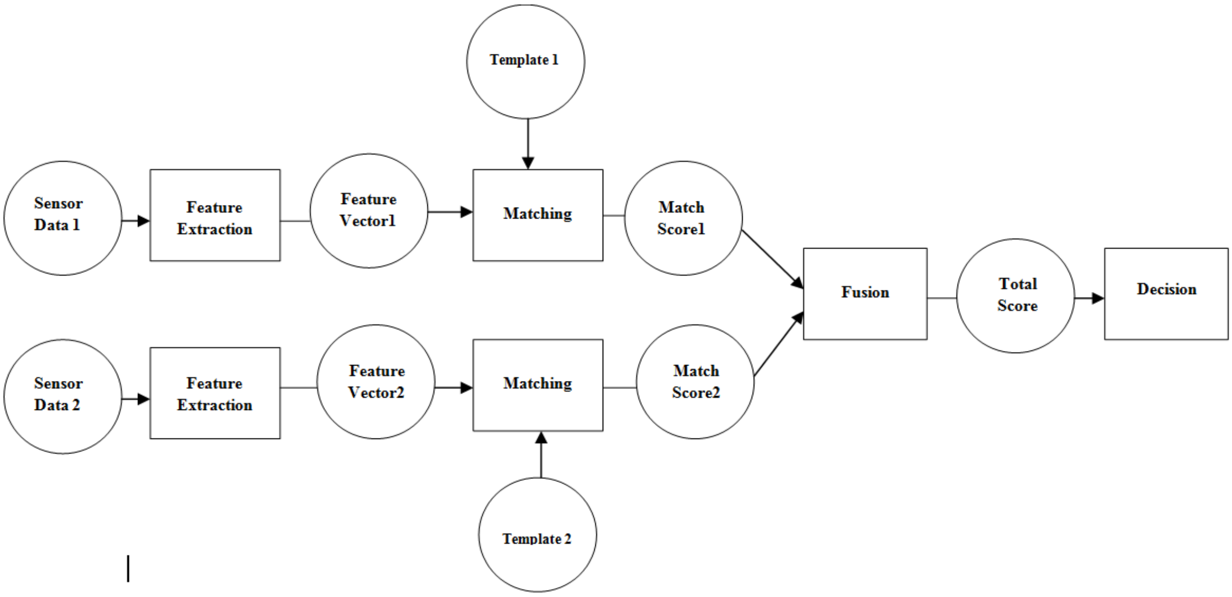

Fig 5. Fusion at the matching score level[6]

VI. RESEARCH METHODOLOGY

The different stages of our multimodal biometric system are being shown in figure (6); these stages are executed as follow:

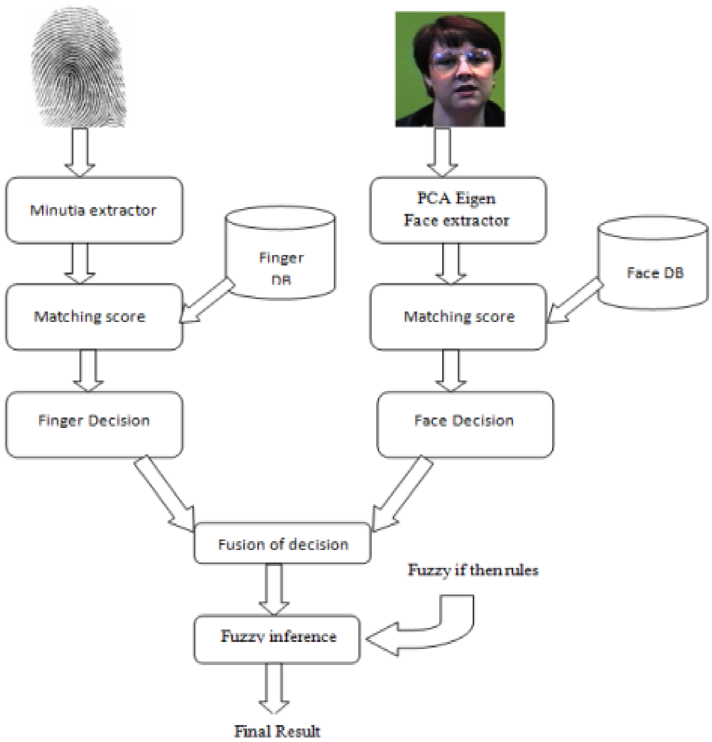

Fig 6: proposed multimodal stages

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

Feature Extraction: This is the second stage where two feature extraction algorithms are presented to extract and form the feature template. Minutia-based algorithm are applied to extract feature from finger image and Principal Component Analysis (PCA)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, Euclidean distance for face matching process which introduces the smallest distance 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 then unary decision will be out to determine the matching degree between client and individuals in database.

VII. FUZZY LOGIC

Fuzzy logic is a form of soft computing, which mimics human decision making. The general block diagram for fuzzy logic is shown in figure (7). Fuzzification is the process of each input convert to linguistic variable. One or more membership function with a degree of membership function is obtained from linguistic variables. The degrees of membership function based on predefined rules and rule weights are combined and the output is produced. Each rule can be given a weight to show the influence of the particular rule on the output.

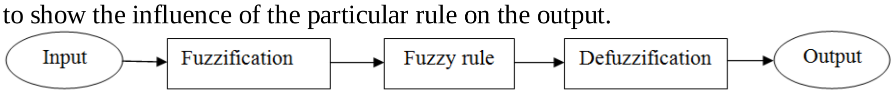

Fig 7: Fuzzy logic block diagram

In this paper, fuzzy logic is used for fusion at decision level. The fuzzy engine has two inputs, one of them named finger and the other face. Finger considered as fingerprint results in identification and face considered as face result identification.

VIII. EXPERIMENT RESULTS

Two sets of databases are used to evaluate the performance of unimodal and multimodal systems. The first is FVC2002 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.. The third database is the face database which collected from **face94** (university of Essex, UK). Every person has 20 samples and beards with different facial expressions. It contains images of JPEG files and colored. We have chosen 100 different persons with 8 samples. All these databases are independent from each other because there is no common database contains two biometrics" fingerprint and face" for the same person. In this work, two unimodal biometric systems are given" fingerprint 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 [23]. The aim is always to reduce both FAR and FRR to get better accuracy.
In table I: FVC2002 database is collected to evaluate fingerprint recognition systems by using minutia-based algorithm, the best accuracy given by the system equal 94.65 %. The experimental results on face94 (university of Essex, UK) database are presented to evaluate face recognition system which use PCA based eigenface algorithm, the system gives accuracy equal to 94%.

Table I Accuracy of the used single systems

System	Algorithm	Database	Accuracy%
fingerprint	Minutia based	FVC2002	94.65
face	PCA based eigenface	Face94(university of Essex, UK)	94

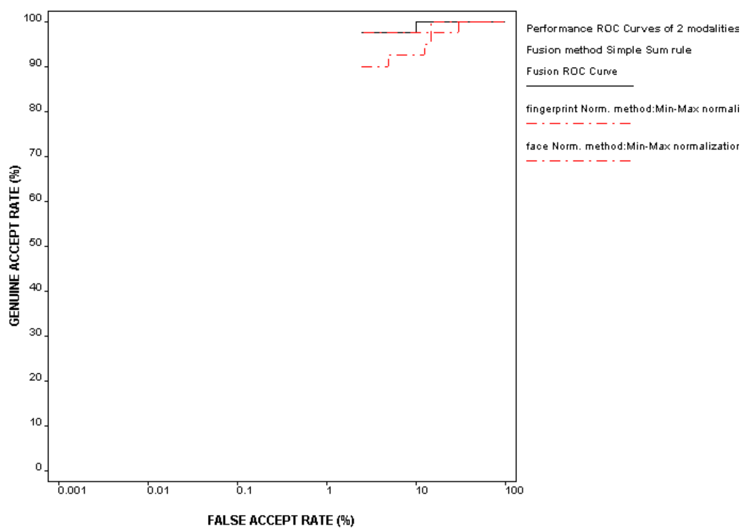

Fig 8. Fusion ROC curve simple sum rule method.

Table II presents the FAR and GAR achieved by simple sum rule fusion at decision level. The overall accuracy achieved by this system is more than 97.8 FAR & FRR of 2.4% and 2% respectively.

Table II FAR, GAR of fingerprint & face

Traits	FAR%	GAR%
fingerprint	2.4	98
Face	2.5	90
Fingerprint &face	2.4	98

Table III presents the accuracy achieved by fuzzy logic fusion at decision level. The accuracy achieved by this system is 99.5 %. And we accept the fusion decisions excellent, good and pass as genuine. This system will give accuracy equal to 99.99 %.

TableIII Accuracy of the proposed fuzzy logic fusion

Method	Database	Level of fusion	Accuracy
Fuzzy logic	FVC2002+ Face94	decision	99.5

IX. CONCLUSION

The proposed system based on decision level fusion of fingerprint and face is found to be highly accurate. The proposed work is successful in overcoming the drawbacks of individual sensors. The level of security is the most important criterion for the biometric sensor. Its threshold or match sores will be chosen high value or low FAR. Experiments show that the proposed approach for fuzzy logic authentication is feasible and effective.

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