Person Authentication System with Quality Analysis of Multimodal Biometrics

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Abstract:- This work is aimed at developing a multi-modal, multi-sensor based Person Authentication System (PAS) using JDL model. This research investigates the necessity of multiple sensors, multiple recognition algorithms and multiple levels of fusion and their efficiency for a Person Authentication System (PAS) with face, fingerprint and iris biometrics. Multiple modalities address the issues of non-universality encountered by unimodal systems. The PAS can be aptly addressed as ‘smart’ since several environmental factors have been considered in the design. If one sensor is not functional, others contribute to the system making it fault-tolerant. Smartness has been very tactfully administered to the processing module by employing different efficient algorithms for a given modality. Selection of the recognition algorithms is rooted on the attributes of the input. Multiplicity has been employed to establish a unanimous decision. Information fusion at various levels has been introduced. Sensor level fusion, local decision level fusion at algorithmic level and global decision level fusion provide the right inference. A multitude of decisions are fused locally to decide the weightage for the particular modality. Algorithms are tagged with weights based on their recognition accuracy. Weights are assigned to sensors based on their identification accuracy. Adaptability is incorporated by modifying the weights based on the environmental conditions. All local decisions are then combined to result in a global decision about the person. The final aggregation concludes whether ‘The Person is Authenticated or not’.

Key-Words:- Biometric; Image quality; Fusion; Multi-modal; Multi-sensor

1 Introduction

Biometrics is an authentication mechanism that relies on the automated identification or verification of an individual based on unique physiological or behavioral characteristics [21]. Biometric technologies offer two means to determine an individual’s identity: verification and identification. Verification confirms or denies a person’s claimed and Identification, also known as recognition, attempts to establish a person’s identity.

Biometric systems can be classified into two types namely, unimodal and multi-modal biometric systems. A unimodal biometric system is one in which, only a single type of the constituent components is present. Whereas, in *multi-modal* biometric system more than one type of the component is present. Arun Ross [2] establishes six advantages of a multi-modal system. Multiple modalities address the issues of non-universality encountered by unimodal systems. For example, a person who has lost his hands cannot be authenticated by a fingerprint authentication system. The Detection of human face also has more challenges than detecting any other object as the skin color and facial expression varies dynamically. The illumination conditions, occlusion, background structure and camera positions add complexities on to the existing challenges. So the system needs multiple sensors to acquire multiple modal to authenticate a person. The multiple physiological features used for authentication are face, iris and fingerprint biometrics. This paper deals with multi-modal multi-biometric based Person Authentication System (PAS). Multi-biometric systems helps in reducing false match and false non-match errors compared to a single biometric device.

The advantages of using multimodal biometric [2] are

a. It addresses the issue of non-universality encountered by uni-biometric systems.
b. It becomes increasingly difficult for an impostor to spoof multiple biometric traits of a legitimately enrolled individual.
c. Effectively address the problem of noisy data. If the single trait is corrupted with noise, the availability of other traits may aid in the reliable determination of identity.
d. It is a fault tolerant system and continues to operate even when certain biometric sources become unreliable due to sensor or software malfunction, or deliberate user manipulation.
e. Multi-biometric systems can facilitate the filtering or indexing of large-scale biometric databases.
f. These systems can also help in the continuous monitoring or tracking of an individual in situations when a single trait is not sufficient.

The biometric system has the following two modes of operation:

Enrollment mode: In this mode the system acquires the biometric of the user and stores required data obtained from the people in the database. These templates are tagged with the user's identity to facilitate authentication.

Authentication mode: This mode also acquires the biometric of the person and uses it to verify the claimed identity.

For recognition, features form the basic unit for processing and thus the feature extraction plays a major role towards the success of the recognition system. However, none of the feature extraction techniques have been able to extract features that are invariant to input image conditions. As the quality of the input decreases, the performance of the recognition algorithms also decreases, which is not desirable in real time applications. In order to make the system invariant to input image quality, quality estimates have also been incorporated into the fusion schemes. Quality of each of the biometrics' images (Iris, Face and Fingerprint) are estimated and based on the quality estimates a decision level fusion strategy is proposed.

To arrive at unanimous decision with multiple outputs, information fusion is incorporated. Data is provided by each component in the system; sensors provide raw data acquired from the person to be authenticated; signal processing algorithms extract the feature vectors from the raw data; matching algorithms provide the match data. All this data from multiple sources, are aggregated for the decision process. Information fusion for a multi-modal biometric verification system can be classified into sensor-level fusion, feature-level fusion, score-level fusion and decision-level fusion as discussed in [2].

Various face quality estimation techniques are available in the literature. Common approaches are available to address the effects of varying lighting conditions, to normalize intraclass variations and the use of illumination invariant. Histogram equalization is a widely used technique in to normalize variations in illumination. However, normalizing well-lit face images could lead to a decrease in recognition accuracy, also it adds to the processing complexity.

Quality based approach for adaptive face recognition was proposed by Abboud [1] with no-reference image quality measures in the spatial domain. In [14] a system is proposed to utilize quality in the decision process, employing a Bayesian network to model the relationships among qualities, image features and recognition. But all these approaches have an inherent complexity which is undesirable in real time applications. A simple and fast way of calculating illumination of a face image has been proposed in [12].

In the literature, the quality has been estimated based on various metrics such as: ridge and valley clarity, local orientation, fingerprint area, range of gray scale, dryness, wetness etc. A scheme is proposed in [18] to estimate gray variance, gray coherence, and orientation coherence in the spatial field and the dominating spectrum energy proportion in the frequency field. Zheng [10] proposed a time consuming scheme of using a fuzzy relation classifier to classify the fingerprint image using 10 different quality metrics. Zhao [19] proposed estimation techniques for calculating effective area of fingerprint image, its mean gray-scale, wetness, dryness and deflected location. Though their techniques are good, they involve a lot of computation time and complexity.

Recently a lot of research has gone into iris quality estimation. The various quality metrics for iris are: defocus, motion blur, eyelid occlusion, eyelash occlusion etc. A scheme is proposed in [11] to measure the contrast of the pupil and iris border which also requires segmentation. Other techniques [13] are based on the success of the segmentation algorithms. But the quality estimate needs to be an indicator of the input image quality for decision making otherwise some information may be lost in an improperly segmented image. A simple motion blur quality metric proposed by Lu [6] is implemented. It is easy to implement and less time consuming but at the same time solves the purpose of quality estimation.

To meet the goal of information fusion various models [3] have been presented like JDL fusion model, Dasarathy model, Boyd's control loop model etc. The fusion models can be classified as information based models, activity-based models and role-based models. This research work has developed the framework based on the Joint Directors of Laboratories (JDL, 1985) fusion model which is basically an information-based systematic model.

This research work is aimed at developing the framework for a multi-modal biometric verification system using multiple sensors, multiple signal processing algorithms, databases, multiple matching algorithms and decision processes. The main contribution of PAS is the design of decision level fusion using dynamic weighted average fusion for combined face, fingerprint and iris biometrics to authenticate and identify a person. The influence of environmental conditions and the quality of the input data have been considered for assigning dynamic weight in decision level fusion. The whole system has been implemented using JDL fusion frame work and found to give better accuracy rates. The application demands very fast execution of the image processing algorithms, so OpenCV proves to be the solution [5]. OpenCV provides dynamic memory allocation.

2 Person Authentication System

This paper deals with multi-modal multi-biometric based Person Authentication System (PAS) with JDL fusion framework. Multi-biometric systems helps in reducing false match and false non-match errors compared to a single biometric device.

2.1 JDL Data Fusion Model

In 1985, the data fusion work group of the Joint Directors of Laboratories (JDL) organized to define a lexicon [U.S. Department of Defense, 1985] for data fusion. Data fusion [17] is defined as a "multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources". This definition was revised [15] as "Data fusion is the process of combining data to refine state estimates and predictions."

As adapted from Nakamura [3], JDL is comprised of 4 components: sources, database management, Human-Computer Interaction (HCI) and processing component. The processing component is further divided into 5 levels namely Sub-Object Data Assessment, Object Assessment, Situation Assessment, Impact Assessment, and Process Refinement. The adoption of JDL model for person authentication is shown in Fig. 1.

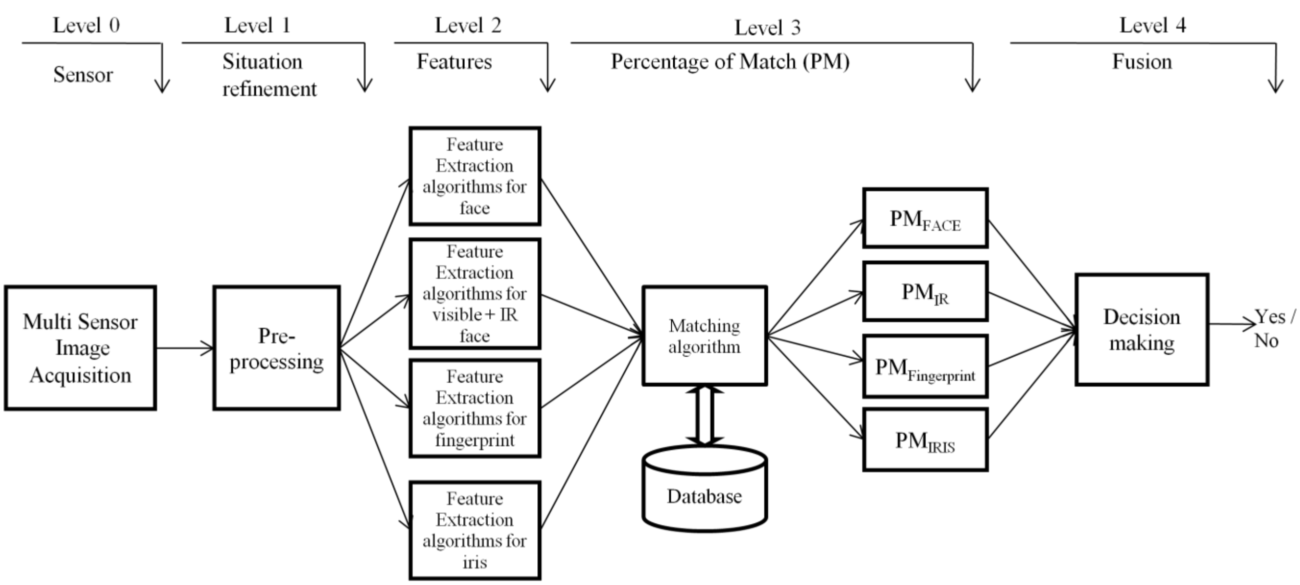


Fig. 1. JDL Frame work for Person Authentication System

A typical biometric system is comprised of five integrated components: A sensor to acquire multiple biometric data and convert the information to a digital format [22]. The system uses three different sensors namely, image sensor (visible camera), Iris sensor (IR camera) and Fingerprint sensor. Image processing algorithms extracts meaningful information and develop the biometric template. A data storage component stores the necessary data for reference. A matching algorithm compares the template with that stores and gets match score. Finally, a decision process uses the results from the matching component to make a system-level decision.

2.2 Multi-Modal System Framework

The recognition based on face biometric is more difficult, due to the inherent variations in face with illumination and pose variations; hence it is a big challenge to formulate a single algorithm that works well under all variations. In this paper, multiple sensors, multilevel fusion and multiple algorithms are taken up for recognition based on face. Before performing recognition, it is essential to detect the face in the captured image amidst the background. To crop the face, Haar feature based Adaboost classifier [24] is used and the cropped face image is taken for further processing.

For varying brightness conditions, fusion of visible and thermal images is performed to enhance the recognition rate and efficiency. Registration of visible and thermal face images is performed using Fourier based method and fusion is performed using Empirical Mode Decomposition (EMD). An image fusion technique, utilizing Empirical Mode Decomposition (EMD) [20] is used for improved face recognition. The sensors used are visible camera and IR camera.

To overcome more challenges involved in face recognition like pose variations, lightning conditions, this research addresses three algorithms namely, Block Independent Component Analysis (B-ICA), Discrete Cosine Transform & Fishers Linear Discriminant (DCT-FLD) and Kalman Filter (KF). The multiple algorithms: Kalman method gives better performance for varying pose of the face, DCT and FLD performs well for all illumination conditions, BICA provides better features of face.

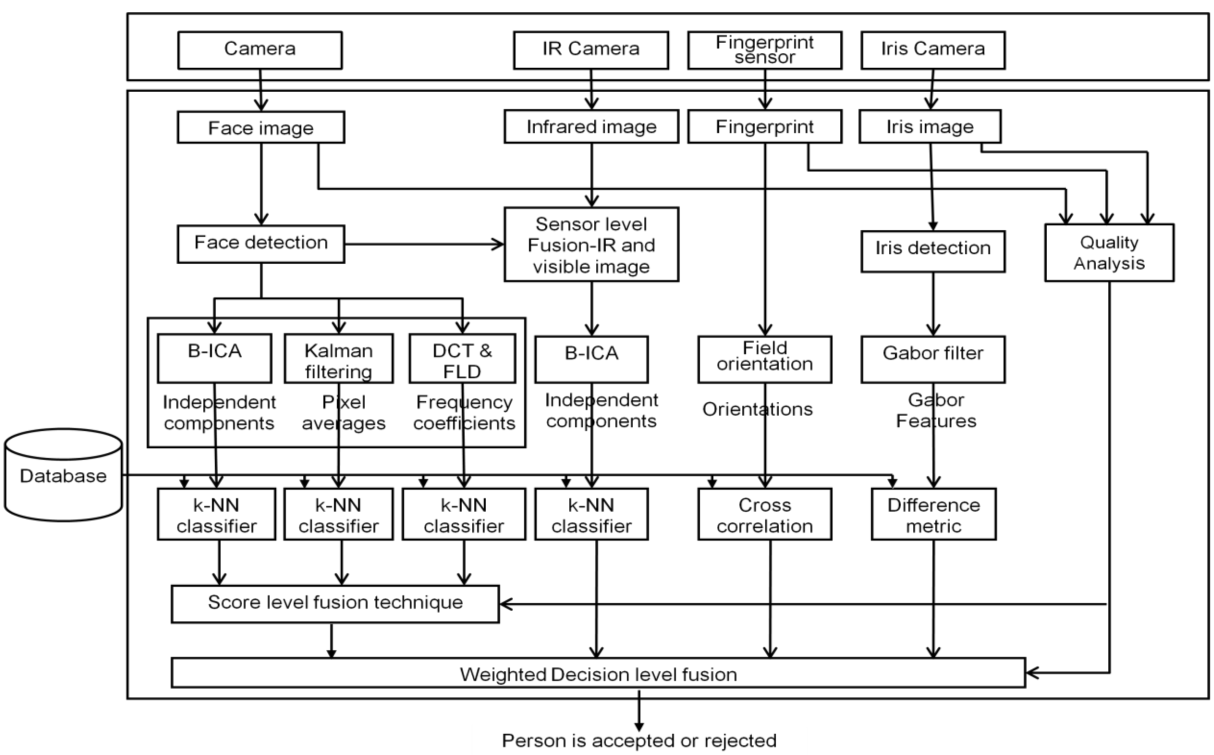


Fig. 2. Overall architecture of multi-modal Biometric person authentication system

Distinct feature extraction algorithms are used in verification of a person's face which gives different match scores as output. The scores are different for every single face recognition system. Thus there is a need to implement score level fusion to give a unanimous match score to decide the identity of the person based on the face biometric. Score level data fusion can be done using classic data fusion approaches [4, 8, 9, 16]. In [7], a framework for optimal combination of match scores that is based on the likelihood ratio test is proposed. But the major drawback of the bulk of these methods is their rather high degree of complexity. Quality estimation can be a useful input to score level fusion.

The approaches from literature have an inherent complexity for evaluating the quality of image, which is undesirable in real time applications. A simple and fast way of calculating illumination of a face image has been proposed in [12]. Based on the face quality the weights to the different algorithms are given and score fusion is performed. The results of the three recognition methods are combined using weighted average based score level fusion to improve the person recognition rate.

The recognition with another biometric Fingerprint, uses Field Orientation of Cross-Correlation (FOCC) method which combines field orientation with cross correlation to get better accuracy even in case of damaged or partial fingerprint. In this work the ridge and valley clarity are taken up as a quality estimate since it is simple and is an indicator of other metrics like wetness, dryness etc.

For recognition with iris biometric, Hough transform is used to segment iris from the eye image and Gabor features are extracted for further obtaining the match with k-NN classifier. A simple motion blur quality metric proposed in [6] is implemented. It is easy to implement and less time consuming but at the same time solves the purpose of quality estimation.

The complete architecture of Fusion framework for PAS using multi-modal, multi-sensor and multi-algorithmic approach is shown in Fig. 2. Sensor level fusion combines information from complementary sources to increase the amount of information in the input. Visible and thermal IR sensors capture complementary information of reflectance and radiation from the face. Fusion of visible and thermal images is done for robust face recognition regardless of illumination conditions and occlusion. Depending on the quality of the face image, the weights are assigned to each algorithm's matching result computed using k-NN classifier. And the final result for face biometric is obtained with weighted-average score level fusion. The quality analyses of fingerprint and iris images are also incorporated to assign appropriate weights for final decision level fusion.

2.2.1 Face Recognition System

The first step in Face recognition is the detection of face part from the captured image. Viola-Jones Haar features based face detection algorithm has been used for face detection [24]. This approach uses Haar wavelet features and classifies the features using AdaBoost classifier and is proven to be a highly robust face detection technique. Further after detection, proceeds with recognition algorithms to extract primitives and to conclude the authentication based on face biometric.

A Block–Independent Component Analysis

The Independent Component analysis (ICA) [28] is a statistical learning method; it captures sparse and independent higher order components. In ICA, the whole image is stretched into 1D vector resulting in increase in dimensionality and computational complexity. To overcome these difficulties, BICA was devised.

In this approach, the image is subdivided into blocks of same size b1, b2, … bn. Eigen value (ψ) and Eigenvectors (φ) of Covariance matrix for each block is computed. The whitening matrix, w_m of the block is acquired using the Eq. 1.

$$w_d = \left(\varphi\psi^{-\frac{1}{2}}\right)\vec{b}_i = \left(w_m{}^T b_i\right) \tag{1}$$

where w_m is whitening matrix, and w_d is whitened data. The Demixing matrix d, is attained using kurtosis method for each column vector of whitened block and extracts the ICA features from the blocks by maximizing the Eq. 2.

$$kurt\left(d^T w_d\right) = E\left[\left(d^T w_d\right)^4\right] - 3\left(E\left[\left(d^T w_d\right)^2\right]\right)^2 \tag{2}$$

For recognition, the distance between the test image features and the stored features are computed using the k-NN classifier and the percentage match (P_{BICA}) is calculated. The Euclidean distance metric [29] is used to determine the nearness between the data points in k-NN. The distance between any two vectors x and y is given by standard form given in Eq.3.

$$d(x,y)=\sqrt{\left((x_1-y_1)^2+(x_2-y_2)^2+...+(x_n-y_n)^2\right)} \quad (3)$$

B Discrete Cosine Transform (DCT) with Fisher Linear Discriminant (FLD) Classifier

DCT has many advantages such as data independency and illumination invariant when compared with the other face recognition algorithms. The first DCT coefficient represents the dc components of an image which is solely related to the brightness of the image. By removing the first coefficients it shows the robustness towards the illumination variations. The general expression for obtaining the DCT coefficients of an image is given by Eq. 4.

$$F(u,v)=\alpha(u)\alpha(v)\sum_{x=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\frac{(2x+1)u\pi}{2N}\cos\frac{(2y+1)v\pi}{2N} \quad (4)$$

After obtaining the DCT coefficients, FLD is employed on to obtain the most salient and invariant feature of the human faces. The discriminating feature vector P from the DCT domain to optimal subspace is obtained by Eq. 5.

$$P=E_{optimal}^{T}.D \quad (5)$$

where D is DCT coefficient vectors and $E_{optimal}$ is the FLD optimal projection matrix. For recognition, the minimum distance is calculated using the K-NN classifier to obtain the percentage match (P_{DCT}).

C Kalman Filter based Face Recognition

Kalman filter based face recognition shows robustness towards the pose-variations [27]. Initially, the Kalman faces are calculated and identify most likely face class for a set of images by feature similarity. Kalman faces are calculated using the Eq. 6.

$$x_t = x_{t-1}+k_t(x_{t-1}-l_t) \quad (6)$$

where, x_t is the estimate of the pixel average at time t, l_t is the luminance value and k_t is the kalman weighting factor which varies with respect to the luminance variances at the times t and t-1. The kalman weighting factor is determined by Eq. 7.

$$k_t=\frac{\sigma_{t-1}}{\sigma_{t-1}+\sigma_t} \quad (7)$$

where, σ_t is the standard deviation of the considered face region at time t. From the averaged Kalman face, the feature vector is extracted by fixing a threshold which eliminates the most variant pixel and retains the invariant pixels in the image. For recognition, the minimum distance is calculated using the K-NN classifier and the percentage match (P_{KF}) is computed.

2.2.2 Fingerprint Recognition

Fingerprint has been widely used for person identification in several centuries [30]. The fingerprint recognition system uses orientation of the input image and cross correlation of the field orientation images Field orientation extracts the directional properties of the image [31]. Orientation Field Methodology (OFM) has been used as a pre-processing module, and it converts the images into a field pattern based on the direction of ridges, loops and bifurcations in the image of finger print. The input image is then Cross Correlated (CC) with all the images in the cluster and the highest correlated image is taken as the output. The block diagram of the fingerprint identification system is shown in Fig. 3.

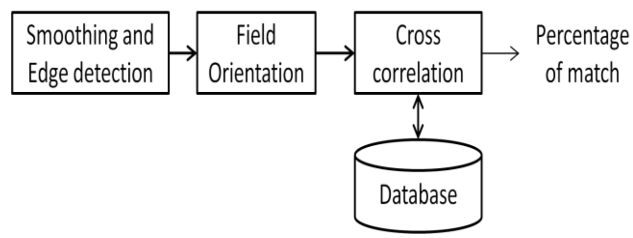


Fig. 3. Block Diagram for fingerprint recognition system

The cross-correlation computation of Template (T) and Input (I) images is determined with the Eq. 8, where both T and I are field orientation images.

$$CC(T,I)=\sum_{i=0}^{n-1}\sum_{j=0}^{m-1}T(i,j)I(i,j) \quad (8)$$

The fingerprint identification with Cross Correlation of Field Orientation images gives good recognition rate [38].

2.2.3 Iris Recognition

The recognition with iris biometric uses Hough transform for detection of Region of Interest (ROI), and Gabor transform for feature extraction. Fig.4 shows the block diagram of the proposed feature extraction scheme. The tasks in segmentation stage are iris boundary detection, eye pupil detection, eyelash and eyelid removal. The circular Hough transform is employed to deduce the radius and centre coordinates of the pupil and iris regions [35]. A maximum point in the Hough space corresponds to the radius and centre coordinates of the circle is best defined by the edge points [33].

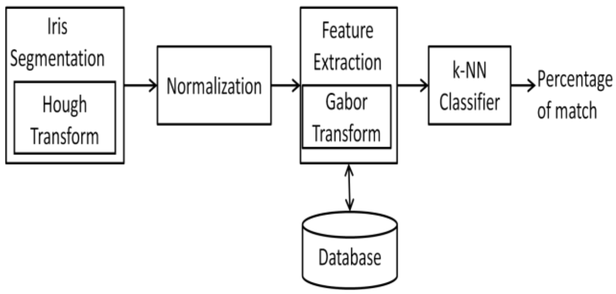


Fig.4. Flow diagram for iris recognition system

Normalization is carried on, it is a linear process and it negates the variable's effect on the data [32]. This allows the data on different scales to be compared, by bringing them to a common scale. During normalization the circular IRIS coordinates are converted to rectangular coordinates. Finally features are extracted using Gabor filter [34]. The Eq. 9 is used to extract Gabor coefficients. These features are used for performing comparison between the test image and data base image.

$$g(x,y;\lambda,\theta,\psi,\sigma,\gamma)=\exp(-\frac{x'^2+\gamma^2 y'^2}{2\sigma^2})\cos(2\pi\frac{x'}{\lambda}+\psi) \quad (9)$$

where, $x' = x\cos\theta + y\sin\theta$, $y' = -x\sin\theta + y\sin\theta$, and λ represents the wavelength of the cosine factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function, ψ is the phase offset, and γ is the spatial aspect ratio, and σ specifies the ellipticity of the support of the Gabor function.

3 Sensor Level Fusion

Visible face images are obtained in the visible spectrum and the clarity varies according to the luminance under which the images have been taken. Thermal face images are acquired using an IR sensor camera in the far IR region (8μm -12μm). Thermal Image gives the measure of energy radiations from the object, which is less sensitive to illumination changes. The features of the face that are the primary requisite for acquiring the correlation with the database images are indistinguishable in case of thermal image. In addition, thermal image as a standalone does not provide high-resolution data [23]. Hence, fusion of visible and thermal images is necessary to achieve the best feature of both the images for Face recognition system [20].

The basic scheme of sensor level fusion for visible thermal image is shown in Fig.5. As given in [37], registration is performed using Fourier based method while fusion of visible and thermal images is performed using Empirical Mode Decomposition. The feature extraction and face recognition on the fused images is implemented using Block Independent Component Analysis with k-NN classifier. It is found that this method out performs the face recognition system using single sensor.

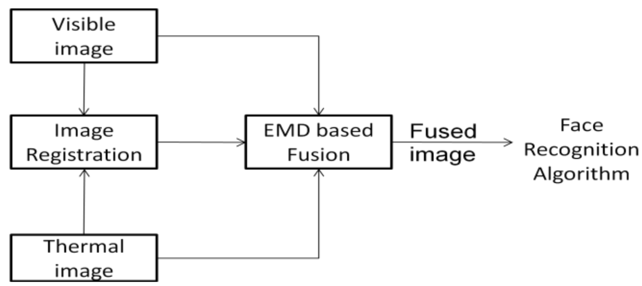


Fig. 5. Basic scheme for Sensor level fusion.

4 Score Level Fusion

Distinct feature extraction algorithms for face recognition, produces varying percentage of match due to varying illumination, pose and other conditions. Face recognition is carried out by multi-algorithmic approach. This system identifies a person by a fusion methodology using weighted average approach from the percentile obtained from three face recognition algorithms, Block - Independent Component Analysis (BICA) [25], Discrete Cosine Transform with Fisher Linear Discriminant Classifier [26] and Kalman filter [27]. It is observed from the individual algorithms, Kalman method gives better performance for varying pose of the face, DCT and FLD performs well for all illumination conditions, BICA provides better features of face. The score level fusion is implemented to give a unanimous match score to decide the identity. The complete procedural analysis of the score level fusion with multi algorithm face recognition algorithm is provided in [36].

4.1 Face Quality Estimation

The quality of face image is determined with illumination analysis [12]. The quality of the face image of size MxN is determined by the Eq.10.

$$wmi = \sum_{i=1}^{16} w_i * \overline{I_i} \qquad (10)$$

where $\overline{I_i} = \frac{1}{M*N}\sum_{x=1}^{N}\sum_{y=1}^{M} I(x,y)$ and w_i is the Gaussian weight factor.

The value of *wmi* determines the illumination of the face image. The measure *wmi* spans a range of values from -1 to +1, where -1 implies a very dark image and +1 for a very bright image.

Table 1. Face quality analyses of images taken from WVU dataset

				
-0.5529	-0.4648	-0.1574	-0.0732	0.0241

The analysis was performed on images from the WVU dataset as well as images taken in the lab and the values obtained are depicted in Table 1. The value of *wmi* for face quality ranges from -1 to +1. The value for dark images fall close to -1 and those for bright images comes near +1.

4.2 Dynamic Weighted Average Fusion

The formula for static weighted fusion scheme is given by Eq. 11.

$$P_f = \sum_{i=1}^{n} W_i * P_i \qquad (11)$$

where P_f =final match score, W_i =weight assigned to individual face recognition algorithm, P_i=match score for individual recognition algorithm, and n=total number of algorithms.In the classical approaches fixed weights for each algorithm are set using the formula given in the Eq. 12.

$$W_i = (1/EER_i)/(\sum_{j=1}^{n}(1/EER_j)) \qquad (12)$$

where EER_i=Equal Error Rate of each recognition algorithm. The Equal Error Rate is defined as the operating point (threshold) at which the False Acceptance Rate (FAR) and False Rejection Rate (FRR) of the algorithm are equal.

To make the fusion scheme dynamic, weights are computed during run-time depending on the input quality of the image. The performance of the three different face recognition schemes (B-ICA, Kalman and DCT) is provided in detail in [36].

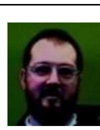
The final score after score level fusion is given by the Eq.13.

$$P_{face} = W_{DCT} * P_{DCT} + W_{BICA} * P_{BICA} + W_{Kalman} * P_{Kalman} \qquad (13)$$

where P_{face} =final match score for the visible face recognition, P_{DCT}, P_{BICA}, P_{Kalman} are the individual match scores of the respective algorithms and W_{DCT}, W_{BICA}, W_{Kalman} are the weights computed for the respective algorithms.

An illumination analysis was performed by varying the brightness of face images in the database using the tool ImageJ. First row in Table 2 is the images with modified brightness. Second row tabulates the match score given by the B-ICA algorithm and third row gives a measure for quality of face based on illumination for the respective images. B-ICA was found to perform well for images with quality close to 0. It is evident from Fig. 6 that score level fusion takes the best from each of the recognition algorithms thereby leading to a better match score with smaller FAR and smaller FRR compared to the algorithms taken individually in the range of quality from -0.4 to +0.4.

Table 2 Image vs. Match Score vs. Quality Score

								
42.7	35.7	52.4	89.3	100	93.9	82.2	69.7	58.7
0.597	0.448	0.290	0.122	-0.062	-0.251	-0.420	-0.568	-0.696

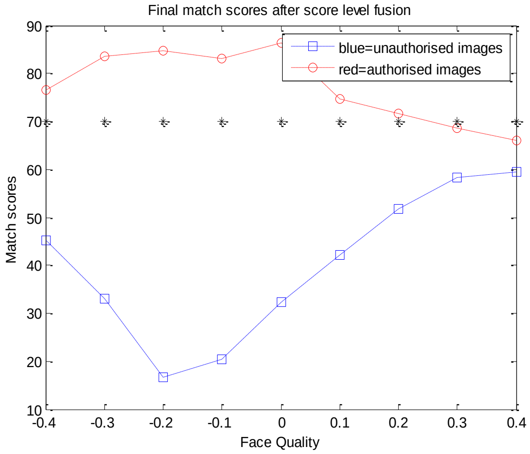


Fig. 6. Average match scores with respect to face quality after performing score level fusion

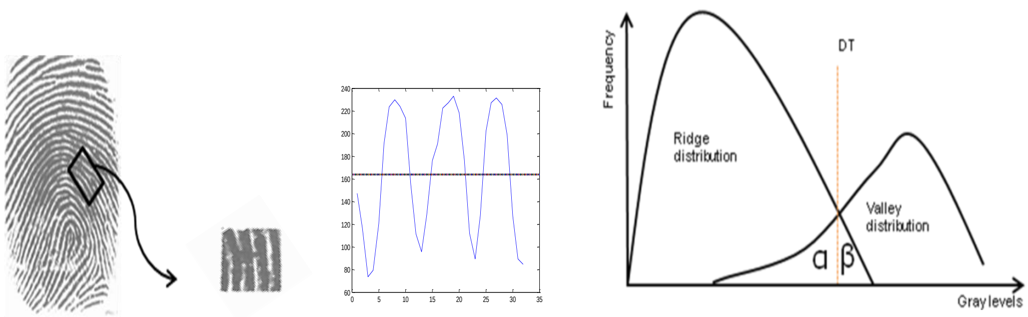
5 Decision Level Fusion

In decision level fusion, the match score of the independent modules are combined to give a unanimous decision on the person's identity. A dynamic weighted average fusion technique is formulated that adjusts its weights to the recognition units based on the input image quality. The match scores from the face recognition unit, iris recognition unit and fingerprint recognition unit are fused to give a final score based on which the decision about the person's authenticity is taken.

5.1 Fingerprint Quality Estimation

The pseudo code for the fingerprint ridge and valley clarity estimate follows:

Start
{
*Divide the fingerprint image into blocks of size 32*32;*
for (each block in image)
{
*Remove a 32*13 block V2 from the centre along the direction perpendicular to ridge direction;*
Create V3, a 1-D average profile of V2;
Calculate the mean (DT) of V3;
Store the ridge pixels (pixels below DT) in one matrix and the valley pixels (pixels above DT) in another matrix;
Calculate the area of the overlapping regions,
$\alpha = v_b / v_t$, $\beta = R_b / R_t$, $LCS = (\alpha + \beta)/2$;
}
GCS=mean (LCS for each block)
}
Stop



(a) **(b)** **(c)** **(d)**

Fig. 7. (a) Fingerprint image (b) 13*32 block of the fingerprint image (c) Matrix V3 (average profile of V2) (d) Ridge and Valley pixel distribution

Table 3. LCS scores and corresponding decision on quality

Clarity Score	Quality
LCS<0.5	Good
0.15<LCS<0.35	Intermediate
0.35<LCS<0.55	Marginal
LCS>0.55	Bad

Table 4. GCS for various fingerprint quality

0.0791	0.1606	0.2089	0.2012	0.2554	0.2031	0.1865	0.2651	0.2845

LCS (Local Clarity Score) is the value of clarity observed for each block in the fingerprint. GCS (Global Clarity Score) is the mean of the local clarity scores. The pictorial description of the algorithm is shown in Fig. 7. The equations involved in the clarity estimates are: $\alpha = v_b / v_t$, $\beta = R_b / R_t$, $LCS = (\alpha + \beta)/2$, $GCS = E(LCS(i, j))$, where v_b is the poor pixels of the valley distribution that lie in the ridge region, v_t is the total number of pixels in the valley distribution, R_b is the poor pixels in the ridge distribution that fall in the valley region and R_t is the total number of ridge pixels. The decision about the fingerprint quality is given in the Table 3.

The value of GCS for the fingerprints in Table 4 is found to range from 0 to 3. Those with values close to 0 have very good clarity while those close to 3 have very poor clarity.

5.2 Iris Quality Estimation

Iris quality is estimated by measuring the blur caused by motion [6] in the eye image. It is a simple implementation and the pseudo code follows:

Start
{
Convert the image to grayscale;
Resize to pre-defined size (m rows, n columns);
*Generate a matrix H_{diff} by multiplying the gray image with an 3*n operator;*
Take the mean (Q_{motion}) of the absolute value of the matrix H_{diff};
}
Stop

Q_{motion} is the estimate of the amount of motion blur in the eye image. The equations involved are:

$$H_{diff} = \sum_{y} |I(x,y) * \Delta|, \; Q_{motion} = mean(H_{diff})$$

where the operator Δ is given in Table 5.

Table 5. Δ operator

-1	-1	…	-1
+2	+2	…	+2
-1	-1	…	-1

Table 6. Q_{motion} results for eye images

326.946188	126.004484	121.663677	53.5740	128.8341	147.1166

It is clear from Table 6 that motion blurred eye images show very small values of Q_{motion}. From the results of analysis over the eye images from the CASIA dataset and images captured in lab, the values of Q_{motion} were found to span a range from 40 to 602. Very blurred images give values of quality below 100.

5.3 Dynamic Weighted Average Fusion

Dynamic decision level fusion is performed with the face, fingerprint and iris quality estimates. As discussed earlier, the multi-algorithmic face recognition module has been made approximately illumination invariant for a range of face illumination quality from -0.4 to +0.4 by performing score level fusion. For absolute values of quality greater than 0.4, the match scores of authorised as well as unauthorised images tend to merge leading to larger values for FRR and FAR, above 0.8 the images are either very dark or very bright and so identification is also unreliable. Therefore, the IR sensor images are utilised to give a better performance in such quality conditions. The intermediate weights assigned to face recognition module and sensor fusion module (IR&face) are given by the Eq. 14 and 15.

$$W_{face}^{\text{int}} = \begin{cases} 0.9, abs(Q_{face}) \le 0.4 \\ 0.1, abs(Q_{face}) > 0.4 \end{cases} \quad (14)$$

$$W_{IR\&face}^{\text{int}} = \begin{cases} 0.2, abs(Q_{face}) \le 0.4 \\ 0.8, abs(Q_{face}) > 0.4 \end{cases} \quad (15)$$

Based on the GCS quality measure of fingerprint, the intermediate weights for fingerprint recognition module can be set as in Eq. 16.

$$W_{finger}^{\text{int}} = \begin{cases} 1, Q_{finger} \le 0.15 \\ 0.8, 0.15 < Q_{finger} \le 0.35 \\ 0.3, 0.35 < Q_{finger} \le 0.55 \\ 0, Q_{finger} > 0.55 \end{cases} \quad (16)$$

After the study of performance of the iris recognition algorithm with respect to the quality (motion blur), the weights are assigned as given in Eq. 17.

$$W_{iris}^{\text{int}} = \begin{cases} 0, Q_{iris} < 100 \\ 0.3, 100 \le Q_{iris} \le 250 \\ 0.8, 250 < Q_{iris} \le 450 \\ 1, Q_{iris} > 450 \end{cases} \quad (17)$$

The final weights for the decision module is given by the Eq. 18

$$W_x^{final} = \frac{W_x^{\text{int}}}{\sum_{i=1}^{n} W_i^{\text{int}}} \quad (18)$$

where x stands for the biometric like face, IR&face, finger or iris, n=total number of biometrics (in this case 3), W_x^{int} =intermediate weight for the biometric x, and W_x^{final} =final weight assigned to the biometric x. The final score for decision making is given by Eq.19.

$$P = \sum_{n=1}^{4} W_n^{final} * P_n \quad (19)$$

where P_n=Percentage of match obtained for the n[th] biometric recognition module, P=percentage of match based on which decision is taken.

The decision to accept or reject the person's claim can be given by the Eq. 20.

$$Decision = \begin{cases} 1, P \ge 70 \\ 0, P < 70 \end{cases} \quad (20)$$

If the decision is 1, the person's claim is accepted and if the decision is 0, the person's claim is rejected.

5.4 Case Studies

The analysis of the decision fusion module is done by studying various cases:

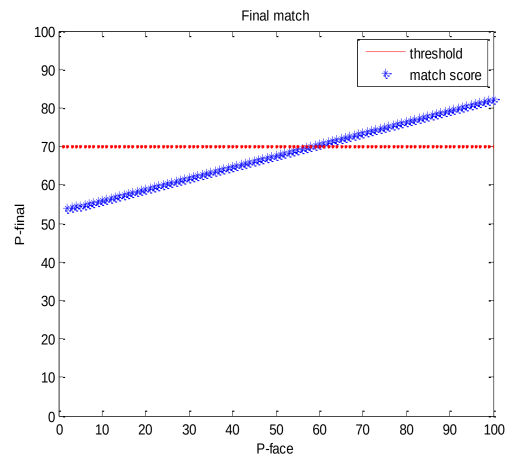


Fig. 8. Case I: Good face quality

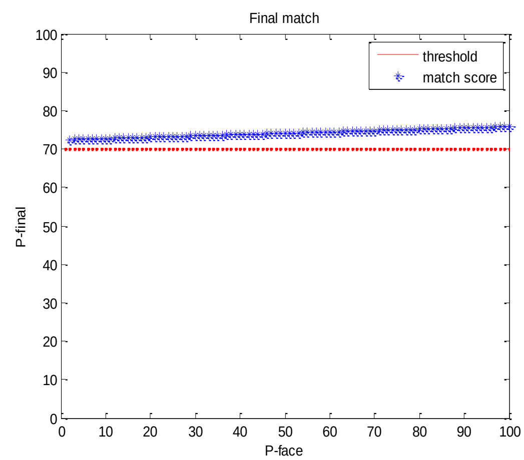


Fig. 9. Case II: Poor face quality

Case I: Good face quality (normal image Q_{face}=0, P_{face} ranges from 75 to 100, $P_{IR\&face}$=75 is good), good fingerprint quality (Q_{finger}=0.079, P_{finger}=75), and good iris quality (Q_{iris}=480, P_{iris}=75)

Case II: Face quality is poor (dark image Q_{face}=-0.85, P_{face}=1 to 100, $P_{IR\&face}$=75 is good), fingerprint is good (Q_{finger}=0.079, P_{finger}=75), and iris quality is good (Q_{iris}=480, P_{iris}=75)

Case III: Visible face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=1 to 100), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris quality is good (Q_{iris}=480, P_{iris}=85)

Case IV: Face quality is poor (Q_{face}=-0.89, P_{face}=75 is good, $P_{IR\&face}$=1 to 100), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris quality is good (Q_{iris}=480, P_{iris}=85)

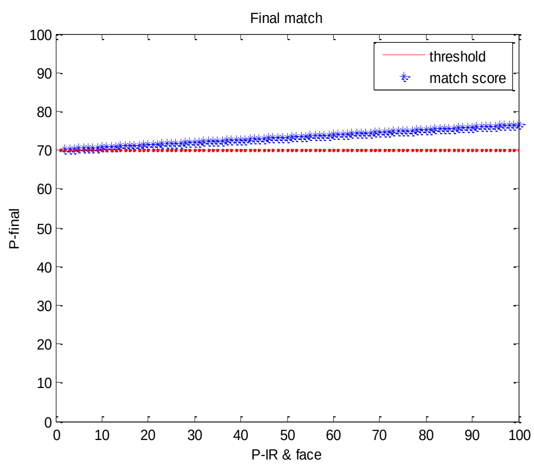


Fig.10. Case III: Good face quality with variable IR face match score

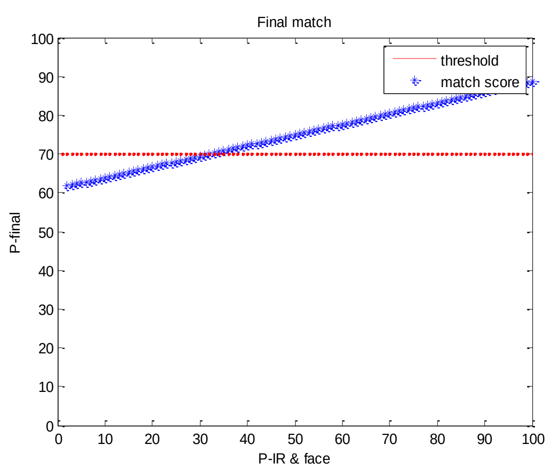


Fig. 11. Case IV: Poor face quality with variable IR face match score

Case V: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint quality is good (Q_{finger}<=0.15, P_{finger}=1 to 100), and iris quality is good (Q_{iris}=480, P_{iris}=85).

Case VI: Face is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is intermediate (0.15<Q_{finger}<=0.35, P_{finger}=1 to 100), and iris quality is good (Q_{iris}=480, P_{iris}=85)

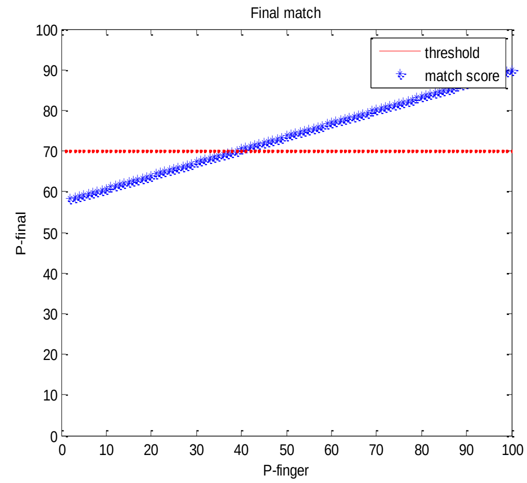


Fig. 12. Case V: Good fingerprint quality with variable fingerprint match score

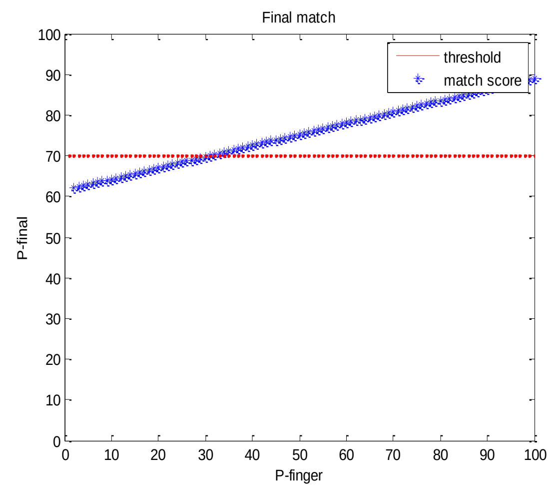


Fig. 13. Case VI: Intermediate fingerprint quality with variable fingerprint match score

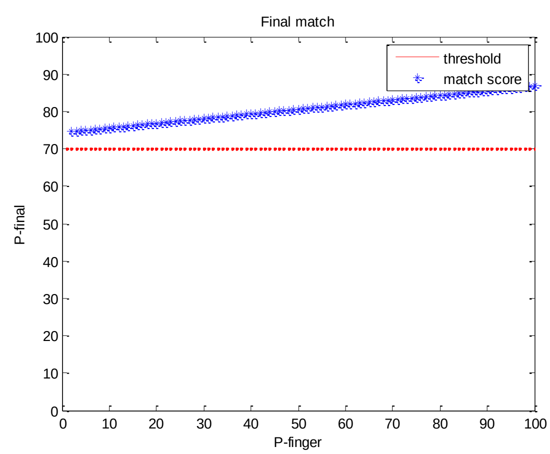


Fig. 14. Case VII: Marginal fingerprint quality with variable fingerprint match score

Case VII: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is marginal (0.35<Q_{finger}<=0.55, P_{finger}=1 to 100), and iris is good (Q_{iris}=480, P_{iris}=85)

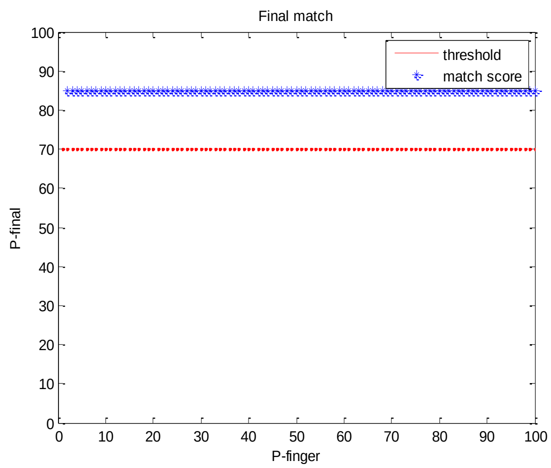


Fig. 15. Case VIII: Poor fingerprint quality with variable fingerprint match score

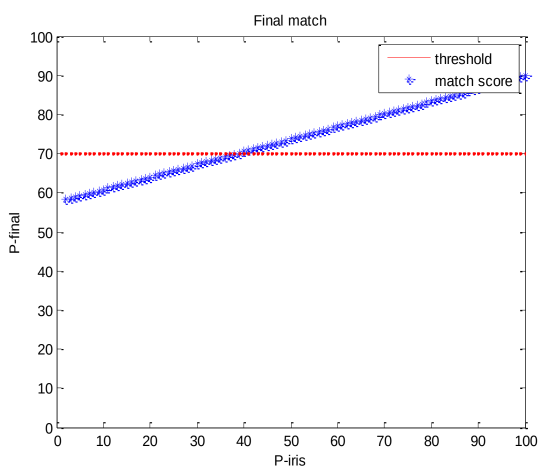


Fig. 16. Case IX: Good iris quality with variable iris match score

Case VIII: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is poor (Q_{finger}>0.55, P_{finger}=1 to 100), and iris is good (Q_{iris}=480, P_{iris}=85)

Case IX: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris is good (Q_{iris}>450, P_{iris}=1 to 100)

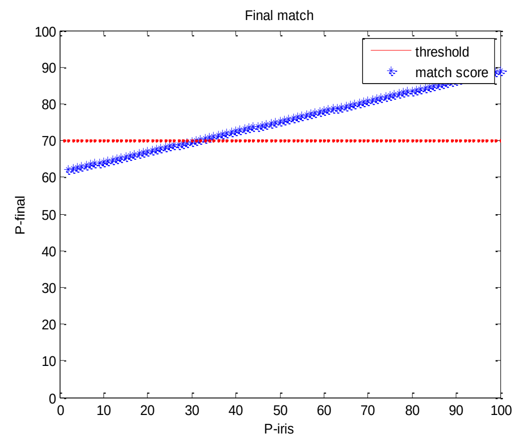


Fig. 17. Case X: Intermediate iris quality with variable iris match score

Case X: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris is intermediate (250<=Q_{iris}<450, P_{iris}=1 to 100)

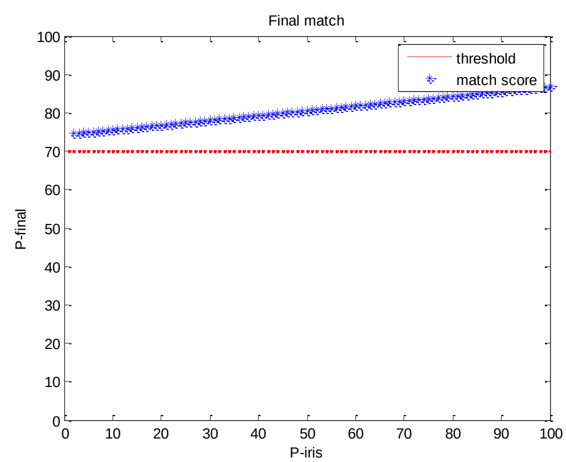


Fig. 18. Case XI: Marginal iris quality with variable iris match score

Case XI: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris is marginal (100<=Q_{iris}<250, P_{iris}=1 to 100).

Case XII: Face quality is good (Q_{face}=0, P_{face}=85 is good, $P_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, P_{finger}=85), and iris is poor (Q_{iris}>100, P_{iris}=1 to 65 & 65 to 100).

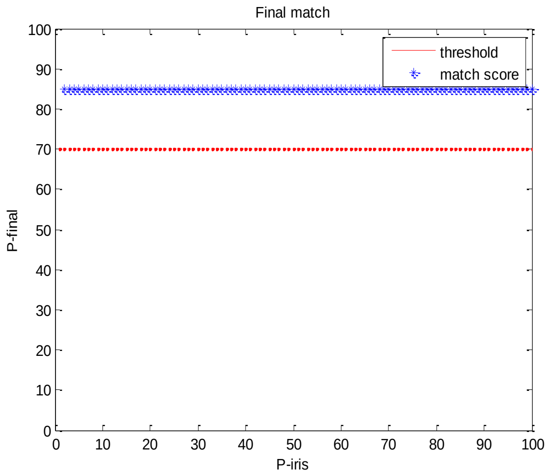


Fig. 19. Case XII: Poor iris quality with variable iris match score

Some individual cases in decision level fusion are tabulated in Table 7. The study of the above cases shows that the weighted average decision fusion technique performs well with a small FRR and FAR as can be concluded from the case studies.

6 Conclusion

A JDL frame work for Person Authentication System has been developed. This frame work consists of sensing different biometrics (face, fingerprint, iris) using multiple sensors, multiple algorithms, multiple classifiers and multiple fusion level. The work has formulated a dynamic score level fusion scheme for a multi-algorithmic face recognition module by incorporating quality as an input for fusion. Score level fusion has been implemented to make use of the complementarities of the algorithms thereby making the system approximately illumination independent for the range of face quality from -0.4 to +0.4. This increases the accuracy of the match scores and provides a unanimous match score. The Face recognition module of PAS handles illumination, occlusion, background structure, camera position complexities and gives better performance. The work has also implemented a dynamic decision level fusion scheme using a fingerprint and iris image quality estimation along with the face quality estimate as an input for fusion. The unanimous decision about an identity claim is arrived on the basis of the final match obtained by the weighted average fusion. The advantage of using multiple modalities for authentication has been justified by the analysis of the decision fusion scheme. The multisensor PAS overcomes the drawbacks of each of the individual sensor and gives better detection rate.

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Table 7. Some individual cases

Case No.	Q_{face}	P_{face}	$P_{IR\&face}$	Q_{finger}	P_{finger}	Q_{iris}	P_{iris}	P
XIII	0	50	50	0.079	85	480	85	72.5806
XIV	0	50	50	0.079	65	480	85	66.1290
XV	0	50	50	0.079	65	480	65	59.6774
XVI	0	85	85	0.079	65	480	65	72.0968
XVII	0	85	85	0.079	85	480	65	78.5484
XIX	-0.89	65	65	0.079	85	480	65	71.8966

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