Fusion Framework for Multimodal Biometric Person Authentication System

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Abstract— **In recent years Biometric based Authentication systems have gained more attention due to frequent fraudulent attacks. Hence, this study aims at developing a multi-modal, multi-sensor based Person Authentication System (PAS) using Joint Directors of Laboratories (JDL) fusion model. This study investigates the need for multiple sensors, multiple recognition algorithms and multiple fusion levels and their efficiency for a Person Authentication System (PAS) with face, fingerprint and iris biometrics. The proposed system considers several environmental factors in the design. If one sensor is not functional, others contribute to the system making it fault-tolerant. Robustness has been 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 and multiplicity has been employed to establish a unanimous decision. Information fusion at various levels has been introduced. A multitude of decisions are fused locally to decide the weight for a 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'.**

Index Terms— **Biometric; Image quality; Fusion; Multi-modal; multi-sensor**

I. Introduction

BIOMETRIC is an automated authentication technique for identifying or verifying an individual based on one's physiological or behavioral characteristics [1]. The two basic tasks of biometrics are verification and identification. Verification attempts to confirm or deny a person's claimed identity whereas identification or recognition establishes a person's identity.

Biometric systems can be classified into two types namely, unimodal and multi-modal systems. A unimodal biometric system is one in which, only a single type of the constituent components is present, whereas in multi-modal system more than one type of the component is present.

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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. Unlike the process of detecting any objects, detecting human face poses many challenges due to the dynamics of skin color and facial expression. The illumination conditions, occlusion, background structure and camera positions add complexities on to the existing challenges. So the system needs multiple sensors to acquire multimodal information to authenticate a person. The multiple physiological features used for authentication are face, iris and fingerprint biometrics. 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

- Addresses the issue of non-universality encountered by uni-biometric systems.
- Spoofing multiple biometric traits of a legitimately enrolled individual is difficult.
- Addresses the problem of noisy data effectively.
- Possess fault tolerant as the system can operate even when certain biometric sources are not reliable.
- Facilitates filtering or indexing of large-scale biometric databases.
- Enables 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 users and stores the required data 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 feature extraction plays a major role in the success of the recognition system. When the quality of the input image deteriorates the performance of the recognition algorithms also get affected, which is not desirable in real time applications. To make the system performance invariant to input image quality, techniques for determining the quality of images are incorporated in the system. Quality of each of the biometrics' images (Iris, Face and Fingerprint) are determined and based on these metrics a decision level fusion strategy is proposed.

The paper is organized as follows: section II discusses related work. The proposed person authentication system is

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given in Section III and discusses on the recognition system with face, fingerprint and iris biometrics. Sensor level fusion of combining the complimentary information is discussed in section IV. Section V discusses score level fusion for multi-algorithmic face recognition system. Decision level fusion of combining the results of multi-biometric is discussed in Section VI and concludes in section VII.

II. RELATED WORK

Information fusion is necessary to arrive at unanimous decision with multiple outputs in multimodal biometric system. The individual sensors provide raw image 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 these 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 [2].

In fusion techniques the inputs from the multimodal multi-algorithm are combined based on the performance under varying conditions. With the varying quality, the performance differs raising the need for analyzing the system at each level based on quality of biometric. Various face quality estimation techniques are available in the literature. There are many approaches presented for handling varying lighting conditions, normalizing intra class variations and making use of illumination invariant features. For normalizing variations in illumination, histogram equalization technique is being widely used. However, recognition accuracy will be poor while normalizing well-lit face images.

Quality based approach for adaptive face recognition was proposed by Abboud, et.al. [3] with no-reference image quality measures in the spatial domain. In [4] Bayesian network based system is used to model the relationship between image quality, features and recognition thereby incorporating quality in decision making process. 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 by Mohamed, et.al. [5].

In literature, the quality has been determined based on various metrics such as: ridge and valley clarity, local orientation, fingerprint area, range of gray scale, dryness, wetness etc. A scheme proposed in [6] is capable of estimating orientation coherence, gray variance and coherence in spatial field and spectrum energy in frequency field. Zheng et.al., [7] proposed a time consuming scheme of using a fuzzy relation classifier to classify the fingerprint image using 10 different quality metrics. Zhao et.al [8] proposed estimation techniques for calculating effective area of fingerprint image, its mean gray-scale, wetness, dryness and deflected location. Though the proposed techniques are efficient, these involve more computation time and complexity.

Recently, a lot of research has been done in determining the iris quality. The various quality metrics for iris are: defocus, motion blur, eyelid occlusion, eyelash occlusion etc. A scheme is proposed in [9] to measure the contrast of the pupil and iris border which requires segmentation. Other techniques proposed by Kalka, et. al. [10] 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. A simple motion blur quality metric proposed by Lu, et. al., [11] is implemented in the proposed work. It is easy to implement and less time consuming.

In recent times, multimodal, multibiometric systems are emerging to overcome the drawbacks of unimodal system. Ramli and Samad [12] proposed a multibiometric approach using speech signal and the corresponding lip reading images for audio reliability estimation by Support Vector Machine (SVM). This approach analyses the quality of the incoming (claimant) speech signal to adaptively update the weighting factor for fusion of subsystems scores. The system uses SVM as a classifier for both subsystems. Principle Component Analysis (PCA) technique is executed for visual features extraction while for the audio feature extraction Linear Predictive Coding (LPC) technique has been used.

A person authentication system developed by Long and Thai [13] is multi modal and multi algorithmic. The modalities considered in the system are face and fingerprint images. The features are obtained using multiple algorithms such as Orthogonal Moments, Zernike Moment (ZM), Pseudo Zernike Moment (PZM), Polar Cosine Transform (PCT) and Radial Basis Function (RBF) Neural Networks. With such integration of multi-modal and multi-algorithms, this system minimizes the possibility of forge in authentication but the training process is very complex.

Nouyed et. al. [14] has developed multiple algorithmic approaches for facial authentication based on different Gabor phase feature representations. In the first approach, similarity score having the highest classification accuracy is used as threshold of the Gabor filter. In the second one, minimum intra-personal similarity score is used as individual subject's threshold for authentication. Both of these methods have shown high classification capability for less number of dataset. With a larger dataset the FRR and FAR increases and recognition rate is reduced.

Mohamed [15] has introduced a new criterion of good fingerprint image that could be considered as a truly good fingerprint template. In this scheme the author has concentrated more on the fingerprint enrolment process. The feature extraction was done by a simple threshold and segmentation. Another simple multimodal biometric authentication system with fingerprint, iris, face and voice biometric is proposed by Majekodunmi and Idachaba [16]

In literature, extensive study is done on multimodal biometric system with fusion at different levels such as at the match score, rank and decision levels. Table I lists the literature with different biometrics and with different levels of fusion [17], [18].

To meet the goals of information fusion, various models [32] are presented in literature like Joint Directors of Laboratories (JDL) fusion model, Dasarathy model, Boyd's control loop model etc. Information based models, activity-based models and role-based models form the major categories of fusion models. This study has developed the framework based on the JDL fusion model which is basically an information-based systematic model.

Table I. List of multimodal biometric systems with different levels of fusion

Literature	Biometrics Modalities	Level of Fusion
Marsico et al [19]	Ear, Face and Finger	Matching Score
Raghavendra et al [20]	Palm, face	Feature
Dakshina et al [21]	Face, Palm	Score Fusion
Karthik et al [22]	Face,Iris	Score Fusion
Xiao et al [23]	Palm, Face	Feature level
Hui et al [24]	Finger, Face, Speech	Matching score
Lau et al [25]	Finger, Face, voice	Matching Score
Kumar and Zhang [26]	Face, Palm	Matching Score
Kumar and Zhang [27]	Hand shape	Matching Score, Feature level
Chang et al. [28]	Face, Ear	Feature level
Shakhnarovich and Darrell [29]	Face, Gait	Matching Score
Ross and Jain [30]	Face, Hand, Fingerprint	Matching Score
Frischholz and Dieckmann [31]	Face, Voice, Lip	Matching Score

This research work is aimed at developing a framework for multi-modal biometric verification system using multiple sensors, multiple signal processing algorithms, database, 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 weights 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 [33] and the work is implemented in OpenCV.

III. BIOMETRIC AUTHENTICATION SYSTEM

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

A. *JDL Data Fusion Model*

In 1985, the data fusion work group of the Joint Directors of Laboratories (JDL) in U.S. Department of Defense, organized to define a lexicon for data fusion. Data fusion [34] 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 [35] as “Data fusion is the process of combining data to refine state estimates and predictions”.

As adapted from [32], 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 framework is shown in Fig 1.

A typical biometric system is comprised of five integrated components: Biometric sensors, Image processing algorithms, Data storage module, matching algorithm and decision module. A set of sensors acquire multiple biometric data and convert the information to a digital format [36]. The system uses three different sensors namely, image sensor (visible camera), Iris sensor (IR camera) and Fingerprint sensor. Image processing algorithms extracts meaningful information from these sensor output images and develop the biometric template. A data storage component stores the necessary data for reference. A matching algorithm compares the template with that stored and generates a match score. Finally, a decision process uses the results from the matching component to make a system-level decision.

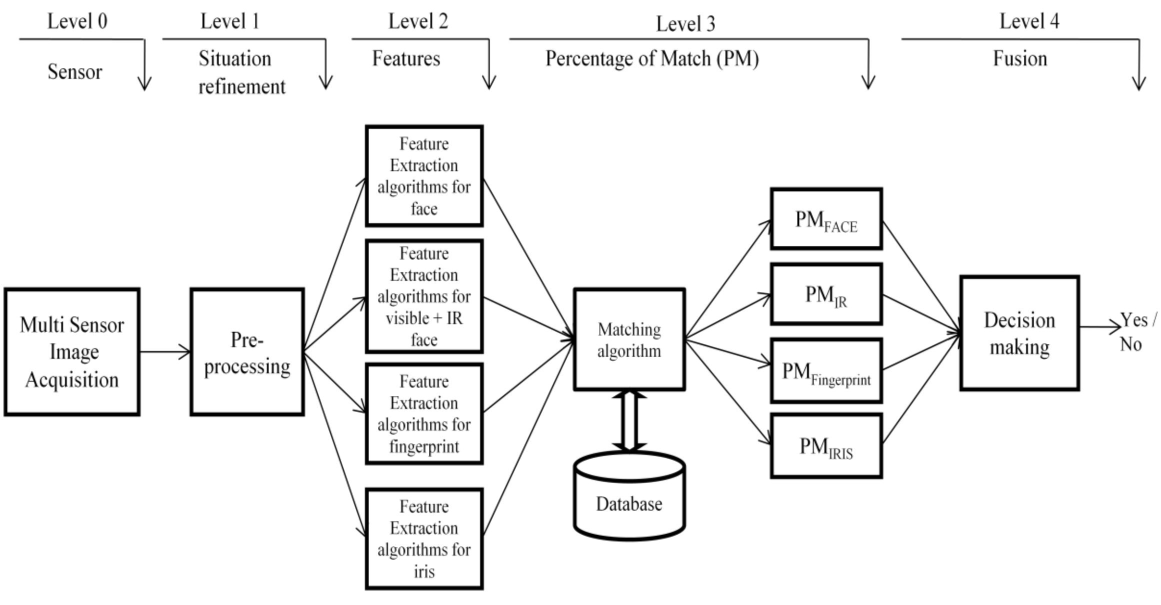


Fig. 1. JDL Fusion Frame work for Person Authentication System

B. Multi-Modal Biometric System Framework

The recognition based on face biometric is more difficult, due to the inherent variations in face with illumination and pose variations. It is a big challenge to formulate a single algorithm that works well under all conditions. In this paper, multiple sensors, multilevel fusion and multiple algorithms are taken up for face recognition. Before performing recognition, it is essential to detect the face in the image captured with the background. To crop the face, Haar feature based Adaboost classifier [37] 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. The sensors used for this purpose are visible and IR camera. 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) [38], [39] is used to improve face recognition.

To overcome the difficulties involved in face recognition like pose variations, and lighting conditions, this system employs three algorithms namely, Block Independent Component Analysis (BICA), Discrete Cosine Transform & Fishers Linear Discriminant (DCT-FLD) and Kalman Filter (KF). Kalman method gives better performance for varying poses, DCT and FLD performs well in all illumination conditions, BICA provides better features of face.

Distinct feature extraction algorithms are used in verification of a person's face which gives different match scores as output. These scores differ for every single face recognition algorithm. Hence, 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 [40]-[43]. In [44], a framework is proposed which combines match scores optimally based on the likelihood ratio test. But the major drawback of these methods is their high degree of complexity. Quality estimation can be a useful input to score level fusion.

The approach in literature [45] has 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 [5]. Based on the face quality metric weights are assigned to the different algorithms and score fusion is performed. The results of the three recognition methods are combined using weighted average score level fusion to improve the person recognition rate.

The feature extraction method used for fingerprint recognition system is Field Orientation of Cross-Correlation (FOCC). This method 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 metric since it is simple and is an indicator of other metrics like wetness, dryness etc.

For recognition using iris biometric, Hough transform is used to segment iris from the eye image and Gabor features are extracted and further match is obtained using k-NN classifier. A simple motion blur quality metric proposed in [11] is used to determine the quality. It is easy to implement and consumes less time.

The complete architecture of JDL 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 improve the system performance. To make the face recognition process robust regardless of illumination conditions and occlusion, fusion of visible and thermal images is carried out. Based on the quality of the face image, weights are assigned to each algorithm's match score computed using k-NN classifier. Then weighted-average score level fusion is performed to obtain the final score for face biometric. The quality analyses of fingerprint and iris images are also incorporated to assign appropriate weights for final decision level fusion.

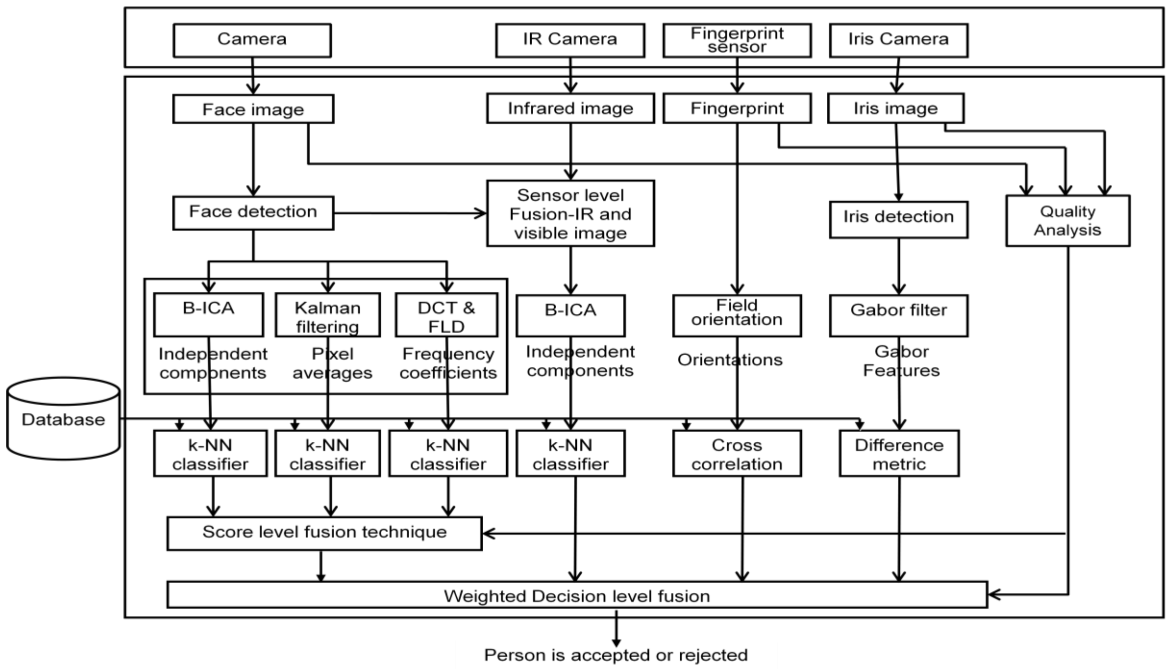


Fig. 2. Proposed Framework of multi-modal Biometric person authentication system

C. Face Recognition System

The first step in face recognition is the detection of face from the captured image. Viola-Jones Haar features based face detection algorithm has been used for face detection [37]. This approach uses Haar wavelet features and performs classification using AdaBoost classifier and is proven to be a highly robust face detection technique. The detection process is followed by the recognition phase in which three algorithms described below are used.

Block Independent Component Analysis

The Independent Component analysis (ICA) [46] is a statistical learning method that captures the sparse and independent higher order components. In ICA, the whole image is converted into a 1-D vector resulting in increased dimensionality and computational complexity. To overcome this drawback of ICA, the Block Independent Component Analysis (BICA) was introduced.

In this approach, image is subdivided into blocks of same size $[b_1,b_2,\ldots,b_n]$. Eigenvalue (ψ) and Eigenvectors (φ) of Covariance matrix for each block is computed. The whitening matrix, w_m of the block is calculated as given in Eq. 1.

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

where w_m is whitening matrix, and w_d is whitened data. The De-mixing matrix d, is obtained using kurtosis method for each column vector of whitened block and extracts the ICA features from the blocks by maximizing, kurtosis function mentioned in Eq. 2.

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

For recognition, the distance between the test image features and the stored features are computed using the k-NN approach and the percentage match (PM_{BICA}) is calculated. The Euclidean distance metric [47] is used to determine the closeness 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.

$$d(x,y) = \sqrt{((x_1-y_1)^2 + (x_2-y_2)^2 + \ldots + (x_n-y_n)^2)} \tag{3}$$

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 pertaining to the brightness of the image. Hence, robustness towards illumination variations is achieved by removing the dc component. The general expression for obtaining the DCT coefficients of an image is given by Eq. 4.

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

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.

$$P = E_{optimal}^T D \tag{5}$$

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 (PM_{DCT}).

Kalman Filter based Face Recognition

Kalman filter based face recognition shows robustness towards the pose-variations [38]. Initially, the Kalman faces are calculated and the most likely face class for set of images is identified by feature similarity. Kalman faces are calculated using the Eq. 6.

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

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 variations at the times t and $t\text{-}1$. The kalman weighting factor is determined by Eq. 7.

$$k_t = \frac{\sigma_{t-1}}{\sigma_{t-1} + \sigma_t} \tag{7}$$

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 (PM_{KF}) is computed.

D. Fingerprint Recognition

Fingerprint based person identification has been a popular method over many years [48]. 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 [49]. A pre-processing module based on Orientation Field Methodology (OFM) has been used, which is responsible for converting images into 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.

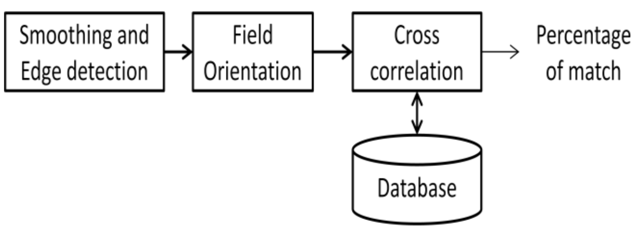


Fig. 3. Block Diagram for fingerprint identification system

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.

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

The fingerprint identification with Cross Correlation of Field Orientation images gives good recognition rate [50].

E. 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 various tasks involved in segmentation stage are: iris boundary detection, eye pupil detection, eyelash and eyelid removal. The radius and centre coordinates of the pupil and iris regions are obtained using circular Hough transform [51]. The maximum point in the Hough space which represents the radius and centre coordinates of the circle is best defined by the edge points [52].

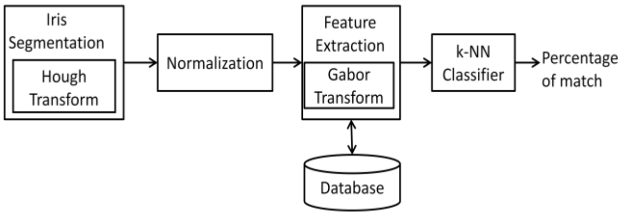


Fig. 4. Flow diagram for iris recognition system

Normalization is carried out and it negates the variable's effect on the data [53]. This allows comparison of data on different scales 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 [54]. The Eq. 9 is used to extract Gabor coefficients. These features are used for performing comparison between the test image and data base image.

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

where $x'=x\cos\theta+y\sin\theta$, $y'=-x\sin\theta+y\sin\theta$, 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.

IV. Sensor Level Fusion

Visible face images are obtained in the visible spectrum and the clarity varies according to the luminance. Thermal face images are acquired using an IR sensor camera in the far IR region (8μm -12μm). The measure of energy radiations from the object given by thermal image is less sensitive to illumination changes. In the case of thermal image, features of the face which forms the primary requisite for computing correlation with database images are indistinguishable. Hence, thermal image alone cannot provide high resolution data [55]. Hence, fusion of visible and thermal images is necessary to achieve the best feature of both the images for Face recognition system [39].

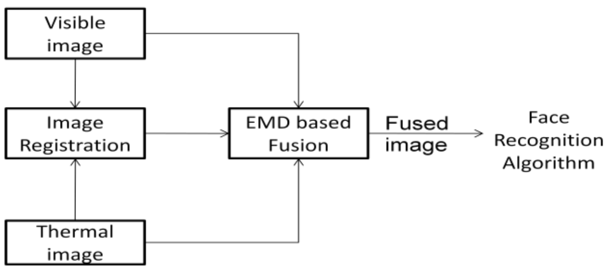
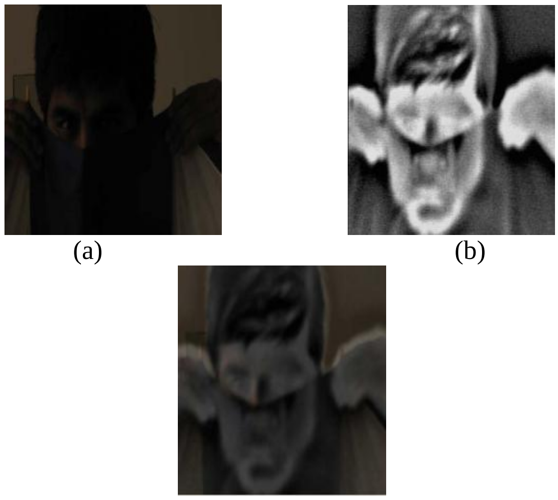


Fig. 5. Basic scheme for Sensor level fusion.



(a) (b) (c)

Fig 6. (a) Visible image (b) Thermal image (c) Fused image

The basic scheme of sensor level fusion for visible thermal image is shown in Fig 5. As given in [56], 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.

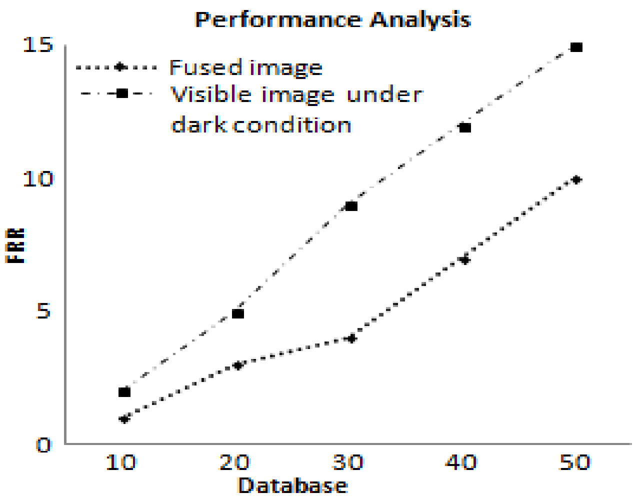


Fig 7.Comparison graph of recognition with fused and visible image.

Fig.6 shows the result of sensor level fusion in which the face covered by cloth captured in a less illuminated condition is taken as test image. From the visible image in Fig 6(a), the information about the colors and eye are extracted and from the thermal image shown in Fig 6(b) information about the outline of face is extracted. The information is integrated in the fused image shown in Fig 6(c). This shows that the fusion of the two images gives more detail on which face recognition can be performed using the feature extraction algorithms. Fig 7 shows the comparison of face recognition between the visible image alone under dark condition, and the fused image with varying database size. The False rejection ratio is obtained for both approaches with varying database size. It is found that the result with sensor level fusion outperforms the face recognition system using single sensor.

TABLE II 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

V. SCORE LEVEL FUSION

Face recognition is carried out by multi-algorithmic approach. Distinct feature extraction algorithms for face recognition, produces varying percentage of match due to varying illumination, pose and other conditions. 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) [57], Discrete Cosine Transform with Fisher Linear Discriminant Classifier [58] and Kalman filter [38]. 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 [59].

A. *Face Quality Estimation*

The quality of face image is determined with illumination analysis [5]. The quality of the face image of size MxN is determined by the Eq. 10.

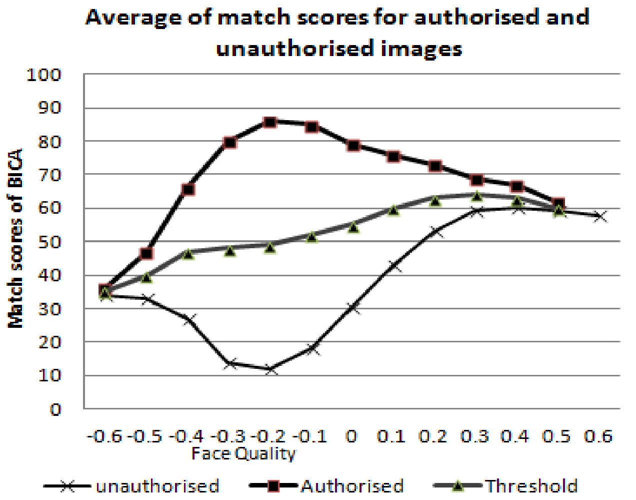
$$wmi = \sum_{i=1}^{16} w_i \times \overline{I_i} \tag{10}$$

where $\overline{I_i} = \dfrac{1}{M \times N} \sum_{x=1}^{N} \sum_{y=1}^{M} I(x, y)$

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. An illumination analysis was performed by varying the brightness of face images in the database using the tool ImageJ. The analysis was performed on images from datasets such as from WVU dataset and MIT-INDIA database. It is observed the illumination approach is able to differentiate the images based on their quality.

The performance of the face recognition using BICA algorithm for varying illumination conditions is demonstrated in Table II. First row in Table II is the images with modified brightness using ImageJ tool. Second row tabulates the match score given by the BICA algorithm and third row gives a measure for quality of face based on illumination for the respective images. BICA was found to perform well for images with quality close to 0.



(c)

Fig. 8. Final average score for Match performance vs. quality for authorised and unauthorised images

The database was created using faces of 100 different people in which each person's face shows 10 different styles. So a total of 1000 face images were available for training. Fig 8 is a plot of the average match scores obtained for the different quality levels of authorized (i.e. trained) images in the database with BICA. Fig 8 also shows a plot of average match scores obtained at various quality levels for unauthorized (untrained) face images and a non-face image. The threshold for varying face quality is also mentioned in the fig 8. It is evident that the authorized and unauthorized images can be distinguished well in the quality range from (-0.4 to +0.4). As the value falls below -0.4 or raise above +0.4, the match scores are indistinguishable for both authorized and unauthorized face images. Hence a distinct threshold could not be set. It is observed that when quality metric is closer to zero, the performance in terms of acceptance rate is high. For the quality rating falling below -0.4 or rising above +0.4, the IR image is captured and the recognition is done using the IR image. For the image in occluded condition, the IR image and visible face image of the person is fused using EMD as described in section 3.

B. *Dynamic Weighted Average Fusion*

The final match score with static weighted fusion is given by Eq. 11.

$$PM = \sum_{i=1}^{n} W_i \times P_i \tag{11}$$

where *PM is* final match score, W_i - weight assigned to individual face recognition algorithm, PM_i - match score for individual recognition algorithm, and n - the total number of algorithms. In the classical approaches fixed weights for each algorithm are set using Eq. 12.

$$W_i = \frac{(1/EER_i)}{\sum_{i=1}^{n}(1/EER_i)} \tag{12}$$

where EER_i is the 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 (BICA, Kalman and DCT) is provided in detail in [59].

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

$$PM_{face} = W_{DCT}PM_{DCT} + W_{BICA}PM_{BICA} + W_{Kalman}PM_{KF} \tag{13}$$

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

The algorithms were tested using some face images from the database and some unknown face images. The False Rejection Ratio (FRR) and False Acceptance Ratio (FAR) for each feature extraction algorithm were found with varying threshold values and shown in Fig 9 (a) and (b). Fig 9(a) shows that the overall fusion gives better FRR than the individual algorithms. Fig 9(b) clearly shows that the proposed scheme gives better FAR when the threshold is set above 65.

The performance of the proposed score level fusion is validated for illumination and pose variations and the results are presented in Table III. It is found that recognition with BICA gives very low scores for dark images compared to bright images. Kalman Filter based recognition performs well even with changes in orientation. The respective individual algorithm scores as well as the overall fusion score are computed. The score level fusion makes the system invariant to illumination and pose. It is evident from Fig.10 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 individual algorithms.

TABLE III MATCH SCORES FOR THE FEATURE EXTRACTION ALGORITHMS AND FUSION

		Dark image	Bright image	Oriented image
Match Scores	Kalman	55.43	44.98	85
	DCT	50	84	49
	BICA	98	66	55.6
	Overall	75.086	70.79	71.92

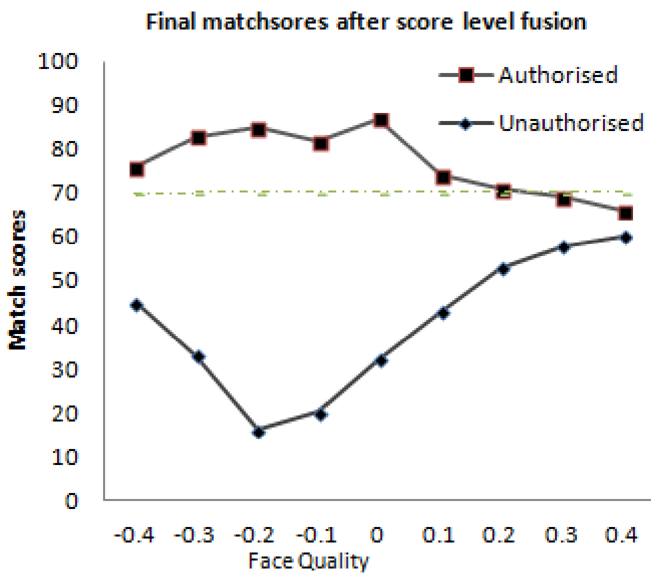
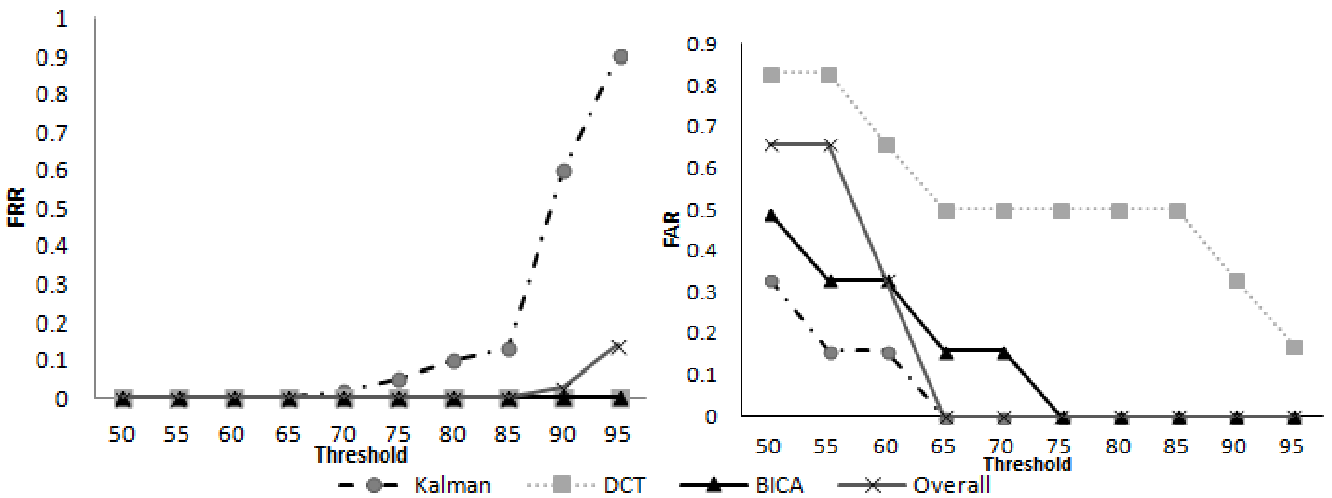


Fig. 10. Average match scores with respect to face quality after performing score level fusion



(a) (b)

Fig 9. (a) Comparison in terms of FRR (b) Comparison in terms of FAR

VI. Decision Level Fusion

Decision level fusion is the final level of fusion to determine the individual person's identity considering the score on multiple modalities. Fig 11 illustrates the decision logic. In this paper, the decision function has been constructed based on the results of analysis.

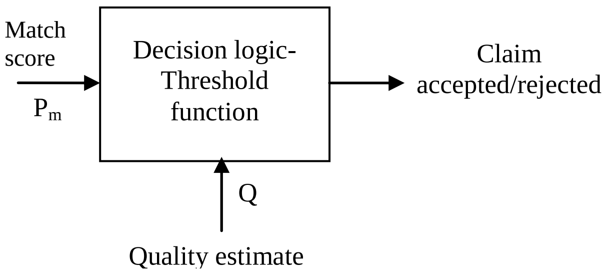


Fig. 11. Block diagram of decision logic

The match score of the independent modules are combined to give 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. For face biometric, score level fusion gives the match score based on quality as elaborated in section V. The quality analysis for fingerprint and iris biometric is performed as given in following subsections to assign weights for the individual modals based on their match score. The match scores from the recognition unit are fused to give a final score.

A. *Fingerprint Quality Estimation*

Fingerprint ridge and valley quality is the estimate used in the work. The pseudo code for the fingerprint quality estimation is given in Algorithm 1.

The pictorial description of the algorithm is shown in Fig 12. Initially, the input fingerprint image given in Fig. 12(a) is divided into blocks of fixed size 32x32. A sub-block V2 of size 32x13 is considered from the centre along the direction perpendicular to ridge direction and is shown in Fig. 12(b). Fig. 12(c) shows *V3* created as a 1-D average profile of *V2*.The equations involved in the clarity estimates are given from Eq. 14-17.

Algorithm1: Fingerprint Quality Estimation

Begin
Divided input image into blocks of fixed size
for (each block)
Consider Sub-block V2
Create V3from V2
Calculate the mean of V3;
Store ridge pixels (pixels below mean value)
Store valley pixels (pixels above mean value).
Calculate the parameters, α_t, β_t, *LCS.*
GCS=mean (LCS for each block)
end

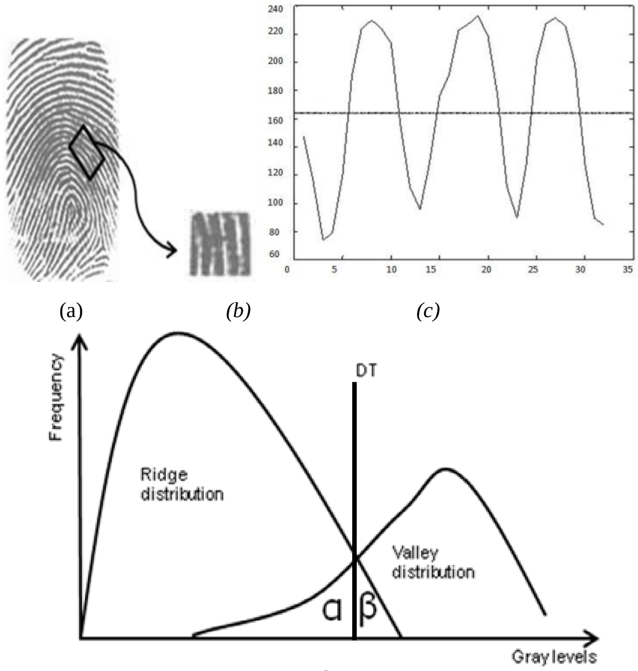
$$\alpha=v_b/v_t \tag{14}$$

$$\beta=R_b/R_t \tag{15}$$

$$LCS= (\alpha+ \beta)/2 \tag{16}$$

$$GCS=E[LCS(i,j)] \tag{17}$$

where v_b is the 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 pixels in the ridge distribution that fall in the valley region and R_t is the total number of ridge pixels. 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 decision about the fingerprint quality is given in the Table IV.



(a) (b) (c)

(d)

Fig 12. (a) Fingerprint image (b) Block V2 of size 13*32 from the fingerprint image (c) Matrix V3 (average profile of V2) (d) Ridge and Valley pixel distribution

TABLE IV. 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 V GCS FOR VARIOUS FINGERPRINT QUALITY

0.0791	0.1606	0.2089	0.2012	0.2554	0.2031	0.1865	0.2651	0.2845

The value of GCS for the fingerprints in Table V 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.

B. *Iris Quality Estimation*

Iris quality is estimated by measuring the blur caused by motion [11] in the eye image. It is a simple implementation and the pseudo code is given in Algorithm2.

The image is converted into grayscale before processing and converted to predefined size of m rows, n columns. A matrix H_{diff} is generated using Eq.18. The operator Δ is of size 3xn and given in Fig. 13. Then Q_{motion} is estimated as given in Eq. 19. It gives of the amount of motion blur in the eye image.

Algorithm2: Iris Quality Estimation

Begin
Convert the image to grayscale.
Resize to pre-defined size.
Generate a matrix H_{diff}.
Compute Q_{motion}
end

$$H_{diff} = \sum_{x,y} \left| I(x,y) \times \Delta \right| \tag{18}$$

$$Q_{motion} = mean(H_{diff}) \tag{19}$$

-1	-1	…	-1
+2	+2	…	+2
-1	-1	…	-1

Fig. 13. operator Δ

TABLE VI Q_{motion} RESULTS FOR EYE IMAGES

326.9462	126.0045	121.6637	53.5740	128.8341	147.1166

It is clear from Table VI 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.

C. Dynamic Weighted Average Fusion

Dynamic decision level fusion is performed with the biometric quality determination. As discussed, 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 conditions. The intermediate weights assigned to face recognition module and sensor fusion module (IR&face) are given by the Eq. 20 and 21.

$$W_{face}^{\text{int}} = \begin{cases} 0.9, & abs(Q_{face}) \le 0.4 \\ 0.1, & abs(Q_{face}) > 0.4 \end{cases} \tag{20}$$

$$W_{IR\&face}^{\text{int}} = \begin{cases} 0.2, & abs(Q_{face}) \le 0.4 \\ 0.8, & abs(Q_{face}) \le 0.4 \end{cases} \tag{21}$$

Based on the GCS quality measure of fingerprint, the intermediate weights for fingerprint recognition module can be set as in Eq. 22.

$$W_{finger}^{\text{int}} = \begin{cases} 1, & Q_{finger} \le 0.15 \\ 0.8, & 0.15 < Q_{finger} \le 0.35 \\ 0.3, & 0.35 < Q_{finger} \le 0.55 \\ 0, & Q_{finger} > 0.55 \end{cases} \tag{22}$$

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. 23.

$$W_{iris}^{\text{int}} = \begin{cases} 0, & Q_{iris} < 100 \\ 0.3, 100 \le Q_{iris} \le 250 \\ 0.8, 250 < Q_{iris} \le 450 \\ 1, & Q_{iris} > 450 \end{cases} \tag{23}$$

The final weights for the decision module is given by the Eq. 24.

$$W_x^{final} = \frac{W_x^{\text{int}}}{\sum_{i=1}^{n} W_i^{\text{int}}} \tag{24}$$

where *x* stands for the biometric like face, fused IR&visible 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. 25.

$$PM = \sum_{n=1}^{4} W_n^{final} \times PM_n \tag{25}$$

where PM_n-Percentage of match obtained for the nth biometric recognition module, *PM*-percentage of match based on which decision is taken.

The decision to accept or reject the person's claim is given by the Eq. 26.

$$Decision = \begin{cases} 1, PM \ge 70 \\ 0, PM < 70 \end{cases} \tag{26}$$

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

D. Case Studies

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

Case I: Good face quality (normal image Q_{face}=0, PM_{face} ranges from 75 to 100, $PM_{IR\&face}$=75 is good), good fingerprint quality (Q_{finger}=0.079, PM_{finger}=75), and good iris quality (Q_{iris}=480, PM_{iris}=75) given in Fig 14.

Case II: Face quality is poor (dark image Q_{face}=-0.85, PM_{face}=1 to 100, $PM_{IR\&face}$=75 is good), fingerprint is good (Q_{finger}=0.079, PM_{finger}=75), and iris quality is good (Q_{iris}=480, PM_{iris}=75) given in Fig 15.

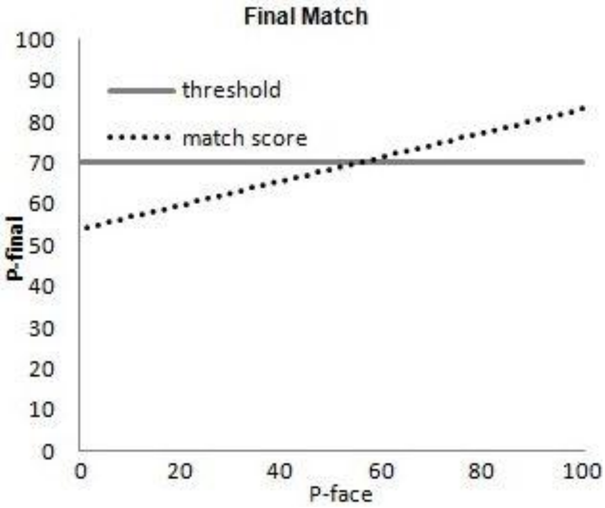


Fig 14. Case I: Good face quality

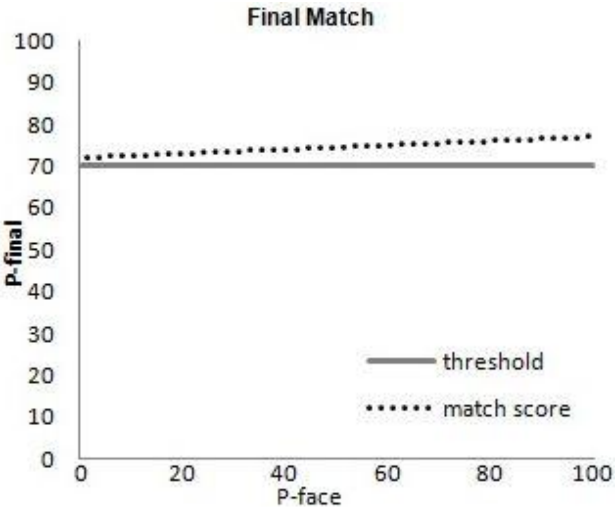


Fig 15. Case II: Poor face quality

***Case III**:* Visible face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=1 to 100), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris quality is good (Q_{iris}=480, PM_{iris}=85) shown in Fig 16.

***Case IV**:* Face quality is poor (Q_{face}=-0.89, PM_{face}=75 is good, $PM_{IR\&face}$=1 to 100), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris quality is good (Q_{iris}=480, PM_{iris}=85) shown in Fig 17.

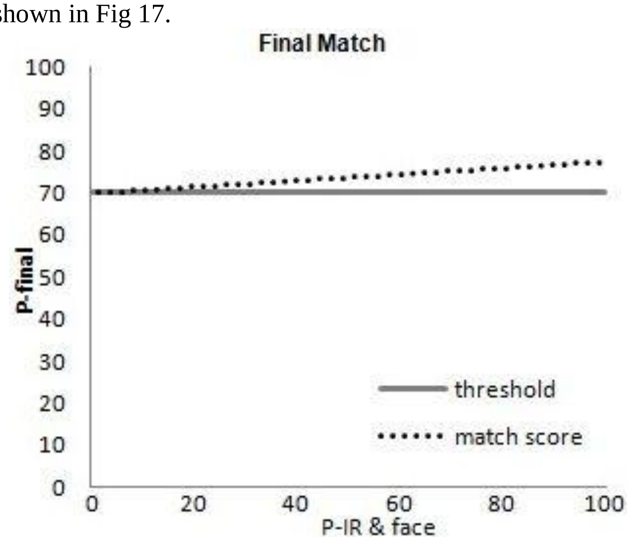


Fig 16. Case III: Good face quality with variable IR face match score

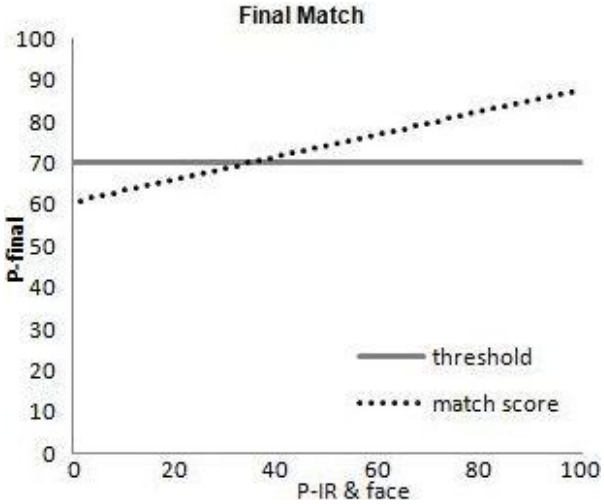


Fig 17. Case IV: Poor face quality with variable IR face match score

***Case V**:* Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint quality is good (Q_{finger}<=0.15, PM_{finger}=1 to 100), and iris quality is good (Q_{iris}=480, PM_{iris}=85) represented in Fig 18.

***Case VI**:* Face is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is intermediate (0.15<Q_{finger}<=0.35, PM_{finger}=1 to 100), and iris quality is good (Q_{iris}=480, PM_{iris}=85) given in Fig 19.

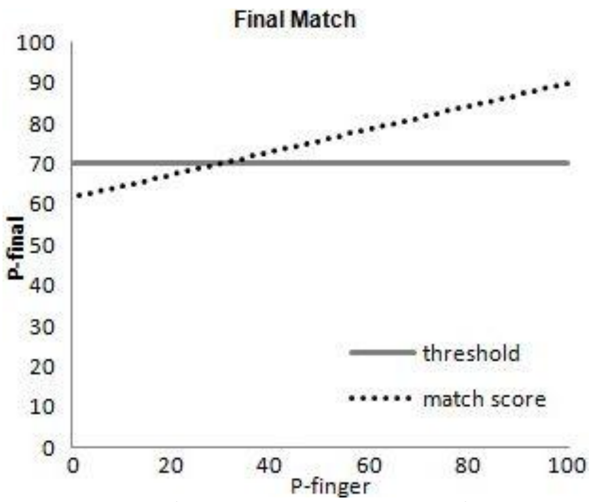


Fig 18. Case V: Good fingerprint quality with variable fingerprint match score

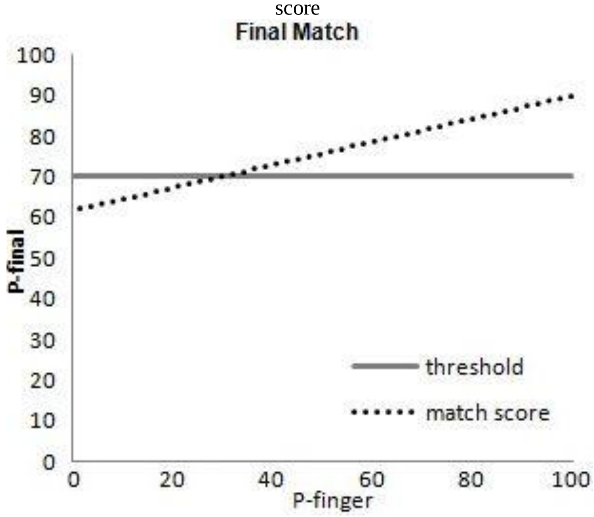


Fig 19. Case VI: Intermediate fingerprint quality with variable fingerprint match score

***Case VII**:* Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is marginal (0.35<Q_{finger}<=0.55, PM_{finger}=1 to 100), and iris is good (Q_{iris}=480, PM_{iris}=85) given in Fig 20.

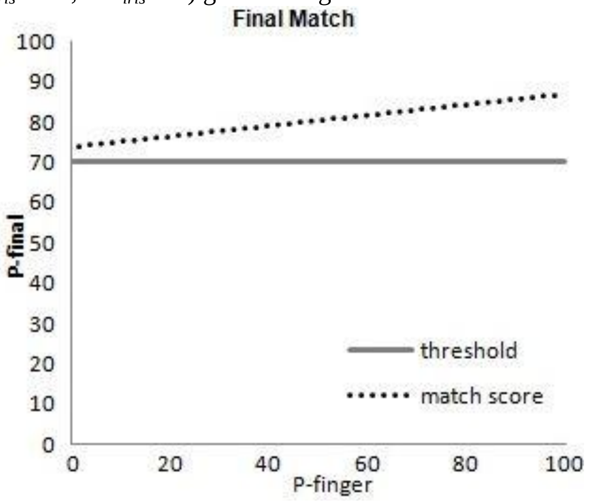


Fig 20. Case VII: Marginal fingerprint quality with variable fingerprint match score

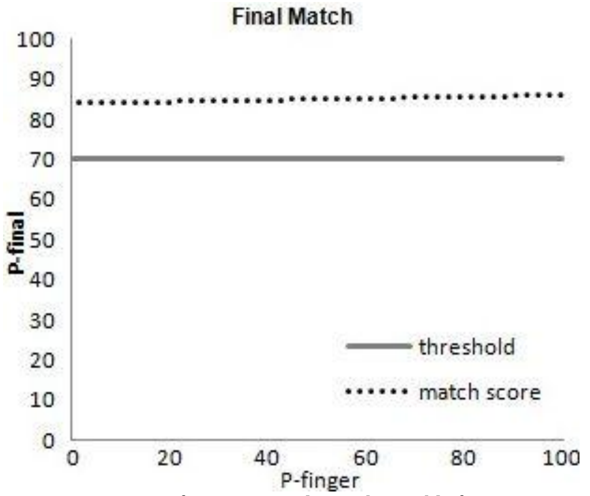


Fig 21. Case VIII: Poor fingerprint quality with variable fingerprint match score

***Case VIII**:* Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is poor (Q_{finger}>0.55, PM_{finger}=1 to 100), and iris is good (Q_{iris}=480, PM_{iris}=85) given in Fig 21.

Case IX: Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris is good (Q_{iris}>450, PM_{iris}=1 to 100) shown in Fig 22.

Case X: Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris is intermediate (250<=Q_{iris}<450, PM_{iris}=1 to 100) given in Fig 23.

***Case XI**:* Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris is marginal (100<=Q_{iris}<250, PM_{iris}=1 to 100) represented in Fig 24.

***Case XII**:* Face quality is good (Q_{face}=0, PM_{face}=85 is good, $PM_{IR\&face}$=85 is good), fingerprint is good (Q_{finger}=0.079, PM_{finger}=85), and iris is poor (Q_{iris}>100, PM_{iris}=1 to 65 & 65 to 100) represented in Fig 25.

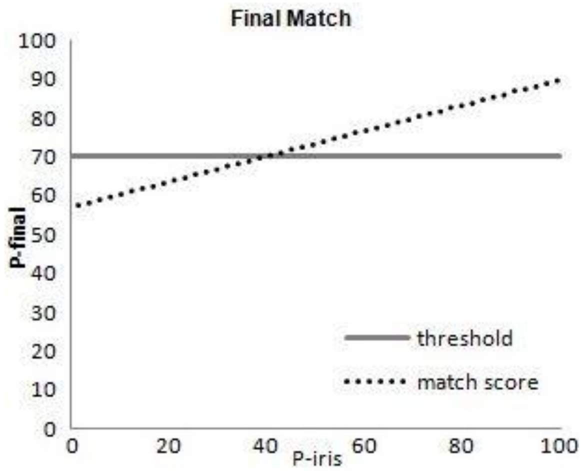


Fig 22. Case IX: Good iris quality with variable iris match score

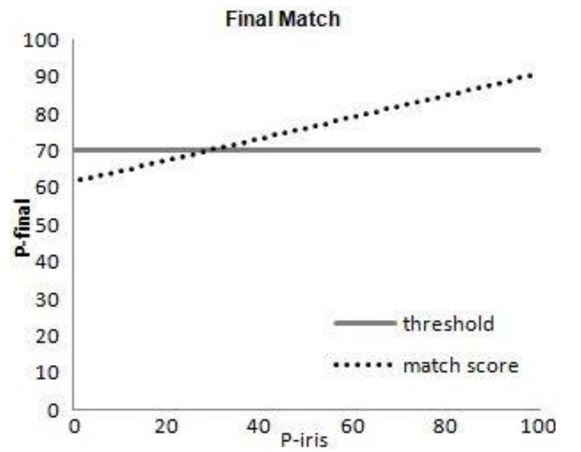


Fig 23. Case X: Intermediate iris quality with variable iris match score

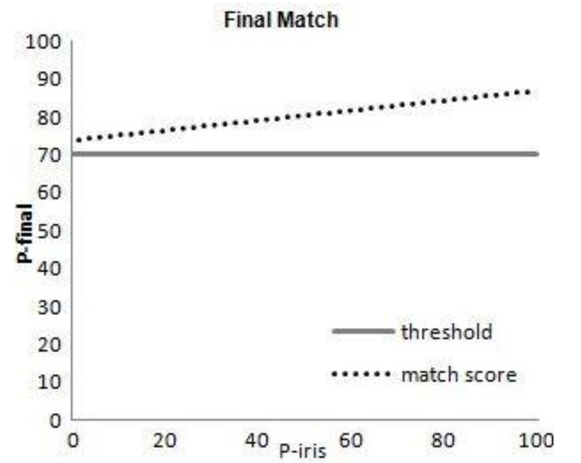


Fig 24. Case XI: Marginal iris quality with variable iris match score

Some individual cases in decision level fusion are tabulated in Table VII. 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.

VII. CONCLUSION

A JDL framework for Person Authentication System has been developed. This framework 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

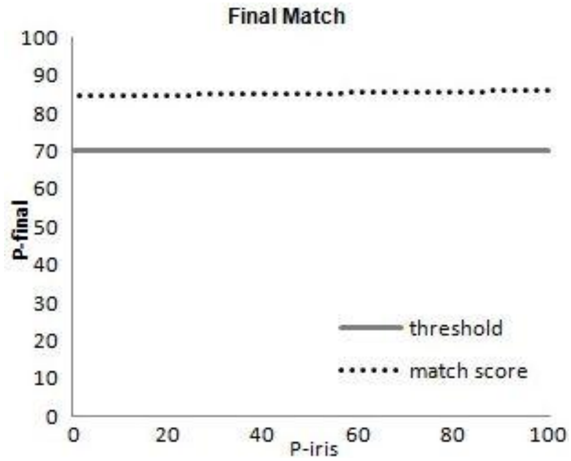


Fig 25. Case XII: Poor iris quality with variable iris match score

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 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 VII SOME INDIVIDUAL CASES

Case No.	Q_{face}	PM_{face}	$PM_{IR\&face}$	Q_{finger}	PM_{finger}	Q_{iris}	PM_{iris}	PM
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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