

PERSON AUTHENTICATION USING MULTIPLE SENSOR DATA FUSION

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Abstract

This paper proposes a real-time system for face authentication, obtained through fusion of Infra Red (IR) and visible images. In order to identify the unknown person authentication in highly secured areas, multiple algorithms are needed. The four well known algorithms for face recognition, Block Independent Component Analysis(BICA), Kalman Filtering(KF) method, Discrete Cosine Transform(DCT) and Orthogonal Locality Preserving Projections (OLPP) are used to extract the features. If the data base size is very large and the features are not distinct then ambiguity will exist in face recognition. Hence more than one sensor is needed for critical and/or highly secured areas. This paper deals with multiple fusion methodology using weighted average and Fuzzy Logic. The visible sensor output depends on the environmental condition namely lighting conditions, illumination etc., to overcome this problem use histogram technique to choose appropriate algorithm. DCT and Kalman filtering are holistic approaches, BICA follows feature based approach and OLPP preserves the Euclidean structure of face space. These recognizers are capable of considering the problem of dimensionality reduction by eliminating redundant features and reducing the feature space. The system can handle variations like illumination, pose, orientation, occlusion, etc. up to a significant level. The integrated system overcomes the drawbacks of individual recognizers. The proposed system is aimed at increasing the accuracy of the person authentication system and at the same time reducing the limitations of individual algorithms. It is tested on real time database and the results are found to be 96% accurate.

Keywords:

Face Recognition, Combined Classifier, Weighted Average, Matching Score Level, Fuzzy Fusion

1. INTRODUCTION

Human Verification is a rapidly growing research area due to increasing demands for security in commercial and law enforcement applications. Person authentication involves verification of a person's identity based on his/her physiological or behavioral characteristics. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

In practice face recognition systems are exposed to numerous challenges, although there exist several holistic and feature based face recognition algorithms such as Principal Component Analysis (PCA) [1], Fisher Linear Discriminant analysis [2], Image Principal Component Analysis (ImPCA) [3], Independent Component Analysis(ICA), Orthogonal Locality Preserving Projections (OLPP) [4] and various other methods [5], the theoretical concept of face recognition is not satisfied by the existing systems. It is observed that these recognition algorithms

work well in constrained environment and therefore face recognition is still an open and very challenging problem in real world applications [5]. The holistic approach to face recognition has the advantage of distinctively capturing the most prominent features within the face image. However, disadvantages of holistic approaches are that the recognition performance could be significantly affected by illumination, orientation and scale.

On the other hand, feature based approaches have the advantage of automatic selection of facial features to uniquely identify individuals. These exhibit robustness in recognition performance despite variations in lighting conditions, facial expressions, orientation and occlusion by another object. The disadvantage lies in inaccurate extraction of features. To reduce/remove the limitations of the individual recognizers, there is a growing research to boost the field of multi-biometrics system [5, 6] in the form of multiple classifiers for face recognition system. The Block Diagram of a general biometric system is shown in Fig.1 and it has the following five important levels: a) Image acquisition b) Situation refinement c) Feature extraction d) Percentage of Match (PM) and e) Decision level.

In the level 0, the face image is acquired using Digital and IR camera. The level 1 is situation refinement, in which the Histogram technique is used to classify the captured visible images based on illumination and corresponding weightage is assigned for each algorithm. In the 2nd level, the features are extracted using the proposed methodologies. The database contains features of all the trained images. In the level 3, features of the query image is compared with trained data base features and the percentage of matching is obtained using Euclidian distance metric. Then matching scores are computed for each algorithm. If the given image is dark, more weightage is given to BICA algorithm, else weightage is given to DCT. If the intensity is moderate, weightage is given to Kalman algorithm. The decision is taken based on weighted average method, which is done at level 4. The final fusion methodology can be done at the same level using Fuzzy logic.

This paper proposes a system which combines the results of Block Independent Component Analysis (BICA) [8], Kalman Filtering method (KF) [9], Discrete Cosine Transform (DCT) [10] and Orthogonal Locality Preserving Projections (OLPP) [4] algorithms. These four algorithms are capable of considering the problem of dimensionality by eliminating redundant features and reducing the feature space based on histogram output. The system can handle variations (illumination, pose, etc.) up to a significant level. KF and DCT cannot extract the exact features when a big accidental or emotional change occurs in the face image but BICA can work in these cases.

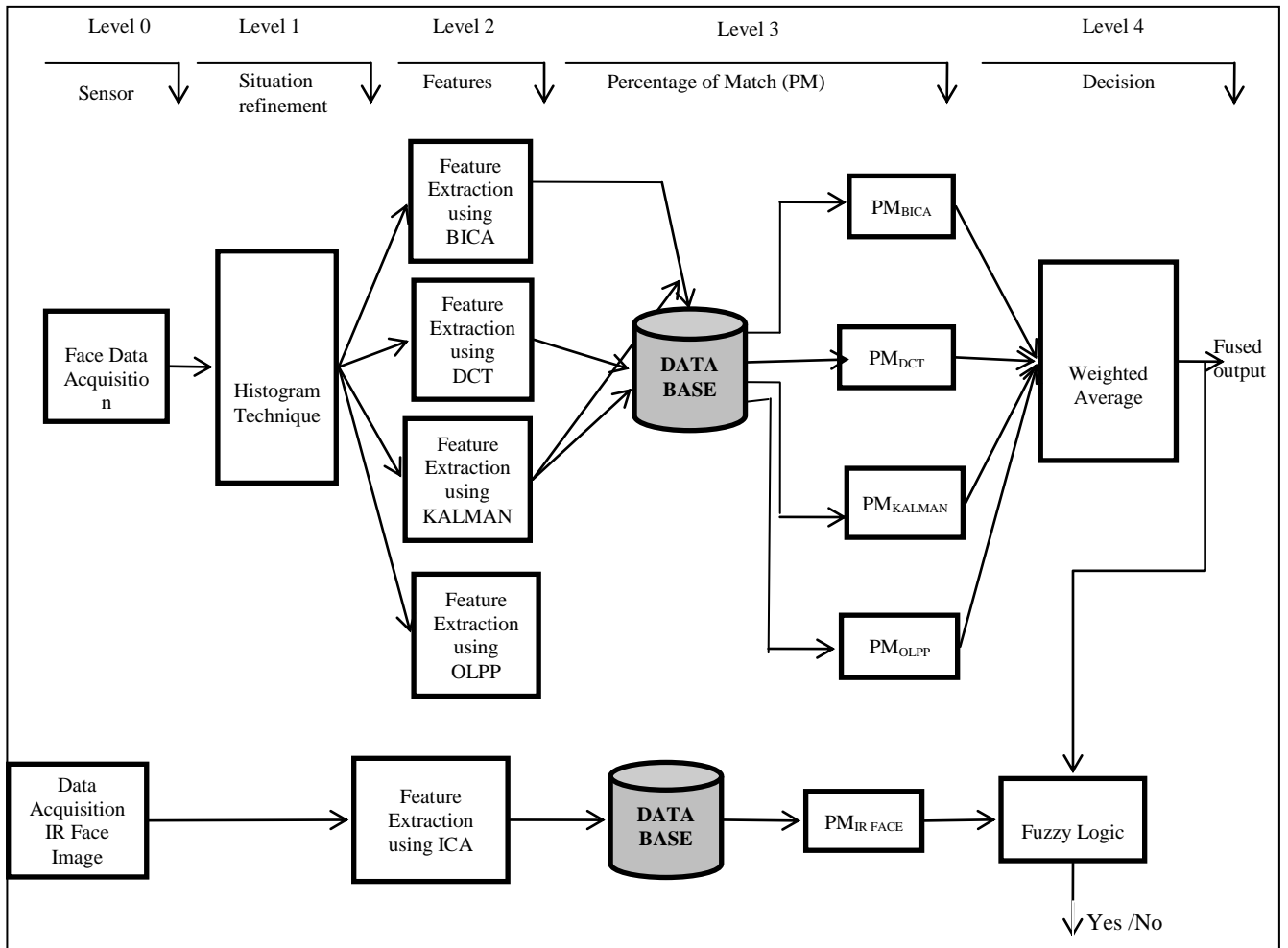


Fig.1. Block Diagram of a General Biometric system

The features extracted from all the four algorithms are fused together by using weighted average approach. KNN classifier is best suited for classifying persons based on their images due to its less execution time and better accuracy than other methods such as Hidden Markov Model and Kernel method [5][7]. The percentage of match for every individual algorithm has been calculated and the weights are determined based on lightning and illumination conditions. The sum of product of percentage match and weights from the algorithm has been calculated. If the maximum value of the result is greater than the threshold, then the corresponding person is validated.

The similar procedure is followed for IR image and single algorithm is used to extract the features. To Increase the accuracy of the person authentication, both visible and IR algorithm outputs are applied to the Fuzzy Logic Controller to take the final decision.

This paper is organized as follows: Section 2 describes the feature extraction process using the individual recognizers BICA, KF, DCT and OLPP. In Section 3 the fusion classifier is presented and discussed in detail. In Section-4 the simulation results are presented.

2. FEATURE EXTRACTION (BICA, KF, DCT, OLPP)

The image captured by visible camera is given as training input images, the BICA, KF, DCT, and OLPP algorithms extract significant features and store it in their respective databases. In case of BICA the optimal discriminant features are calculated. DCT extracts the required facial features. Kalman features are extracted from Kalman averaged images and stored in the database. In OLPP approach, it builds an adjacency graph which best reflects the geometry of the face manifold and the class relationship between various points. The projection is then obtained by preserving such graph structure which forms the Orthogonal Laplacianface. In this way, the unwanted variations resulting from changes in lighting, facial expression and poses are reduced. Orthogonal Laplacianfaces are calculated for each training image.

For any test image, given as input, all the four algorithms extract the features and compute the matching scores. Following subsections discuss the algorithms for extracting features and matching score computation.

2.1 BICA METHOD

Face recognition using BICA [8] is based on computation of feature space F (from training set). The whole image is portioned into many sub-images, i.e. blocks, of the same size, and a common demixing matrix for all the blocks is calculated. Compared with ICA, whose training vector is stretched from the whole image, B-ICA stretches only part of the face image as the training vector. B-ICA greatly dilutes the dimensionality reduction of ICA because the dimension of the training vector is much smaller.

2.1.1 Algorithm:

Step 1: Split the training face (t) images into four blocks where each block of face image (like x_1, x_2, x_3, x_4) is represented as same size.

Step 2: Calculate the whitening matrix (wm), eigenfaces, and eigenvectors for any one of the block.

$$wd = (v \wedge^{-1/2})^T \bar{x}_i = (wm)^T \bar{x}_i \quad (1)$$

where $wm = v \wedge^{-1/2}$ is called the whitened matrix, and wd is the whitened data.

Step 3: Calculate the Demixing matrix (d) using kurtosis method for the whitened block and extract the ICA features from the blocks.

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

Step 4: By using the same demixing matrix extract the ICA features of the entire facial image(x).

Step 5: Store the feature vector y in the database (D). Repeat the step one to five for all the images in the data base.

Similarly for each test image optimal discriminant features can be calculated by BICA. For recognition, the minimum distance is calculated using K-NN classifier.

2.1.2 KNN Classifier:

The simplest classification scheme is a nearest neighbor classification in the image space. Under this scheme an image in the test set is recognized by assigning to it the label of the closest point in the learning set, where distance are measured in image space. If all images have been normalized to zero mean and have unit variance, then this procedure is equivalent to choosing the image in learning set that best correlates with the test image. Because of normalization process, the result is independent of light source intensity and the effects of a digital camera's automatic gain control.

The Euclidean distance metric [11] is often chosen to determine the closeness between the data points in KNN. A distance is assigned between all pixels in a dataset. Distance is defined as the Euclidean distance between two pixels. The Euclidean metric is the function $d: \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$ that assigns to any two vectors in Euclidean n -space $X=(x_1, \dots, x_n)$ and $Y = (y_1, \dots, y_n)$ the number,

$$d(x, y) = \sqrt{((x_1 - y_1)^2 + \dots + (x_n - y_n)^2)} \quad (3)$$

The Eq. (3) gives the standard distance between any two vectors in \mathbb{R}^n . From these distances, a distance matrix is constructed between all possible pairings of points (x, y) .

2.1.3 KNN Algorithm:

Step 1: Each data pixel value within the data set has a class label in the set, $class = \{c_1 \dots c_n\}$.

Step 2: The data points, k -closest neighbors (k being the number of neighbors) are then found by analyzing the distance matrix.

Step 3: The k -closest data points are analyzed, to determine which class label is the most common among the set.

Step 4: The most common class label is then assigned to the data point being analyzed.

Then the percentage of matching (PM) is determined with respect to distance between the database and the test image.

2.2 KALMAN FILTERING METHOD

The Kalmanface approach identifies the most likely face class for an image by feature similarity and is shown in Fig.2. It expects every face class (person) to be represented by a sequence of image samples. The number of inputs should not be smaller than 3-5 poses for reasonable application of the Kalman filter. Each face class is represented by a single feature vector that is extracted using the following algorithm:

2.2.1 Algorithm:

Step 1: Image normalization:

All face images are transformed to Luminance (grayscale) matrices of the same size. Every pixel (x_i) represents one face region.

Step 2: Averaging:

An average face is computed form normalized by Kalman filtering ("Kalmanface"), using Eq. (4).

$$x_t = x_{t-1} + k_t(x_{t-1} - l_t) \quad (4)$$

where, x_t - estimate of the pixel average at time t ,

l_t - luminance value and

k_t - Kalman weighting factor, which is given by Eq. (5),

$$k_t = \frac{\sigma_{t-1}}{\sigma_{t-1} + \sigma_t} \quad (5)$$

where σ_t and σ_{t-1} - Standard Deviation of face region at time t and $t - 1$

Step 3: Feature Extraction:

The regions of the Kalmanface are considered as features that are sufficient.

Step 4: Repeat step 1 to step 3 for all database

In the third step, features are extracted form the Kalman averaged face. Here the pixel values are selected as face features. For recognition, the minimum distance is calculated using K-NN classifier, which was discussed in the previous section (2.1).



Detected faces Kalman face

Fig.2. Generation of Kalman Face

2.3 DISCRETE TIME COSINE TRANSFORM (DCT)

The DCT is often used in signal and image processing, because it has a strong energy compaction property. Most of the signal information tends to be concentrated in a few low-frequency components of the DCT. High amplitude DCT coefficients do concentrate more energy than others, which is located in the lower part of the spectrum. The test image and its corresponding DCT image are shown in Fig.3.

2.3.1 Algorithm:

Step 1: $f(x,y) \rightarrow$ database pixel values.

Step 2: Calculation of DCT:

The low frequency components are computed using Eq.(6),

$$F(u,v) = \alpha(u)\alpha(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos \frac{(2x+1)u\pi}{2N} \cos \frac{(2y+1)v\pi}{2N} \quad (6)$$

where,

$$\alpha(u)\alpha(v) = \sqrt{\frac{1}{2N}}, u, v = 1$$

$$\sqrt{\frac{1}{2N}}, \text{otherwise}$$

Step 3: Feature selection stage:

The selected features are located in the lower part of the spectrum.

Step 4: Repeat step 1 to step 3 for all database

In the second step, features are extracted form the DCT. For recognition, the minimum distance is calculated using K-NN classifier.



Test image DCT image

Fig.3. Generation of DCT image

2.4 ORTHOGONAL LOCALITY PRESERVING PROJECTIONS (OLPP)

The algorithmic procedure for Orthogonal Laplacianfaces is performed by following steps. The Eigenfaces and Orthogonal Laplacianfaces are shown in Fig.4(a) and (b) respectively.

2.4.1 Algorithm:

Step 1: PCA Projection:

Calculate the empirical mean along each dimension $M=1 \dots m$ and place the mean values into an empirical mean vector u of dimensions $m \times 1$.

$$u[m] = (1/n) \sum_{N=1}^n X[M, N] \quad (7)$$

Calculate the deviations of the data matrix X from the mean vector u ,

$$B = X - u.h \quad (8)$$

where $h [N] = 1$, for $N = 1 \dots n$.

Calculate the $m \times m$ covariance matrix C from the outer product of matrix B ,

$$C = E[BxB] = E[B.B^*] = (1/n)B.B^* \quad (9)$$

Compute the matrix V of eigenvectors of the covariance matrix C ,

$$V^{-1}CV = D \quad (10)$$

where, D is the diagonal matrix of eigen values of C

Step 2: Constructing the Adjacency Graph:

The adjacency graph is determined by classifying each data pixel value within the data set to a class label in the set, $C = \{c_1, \dots, c_n\}$. The data points', k -closest neighbors (k being the number of neighbors) are then found by analyzing the distance matrix. The k -closest data points are then analyzed to determine which class label is the most common among the set. The most common class label is then assigned to the data point being analyzed.

Step 3: Choosing the Weights:

If node i and j are connected, put

$$S_{ij} = \exp(-\|x_i - x_j\|^2/t) \quad (11)$$

$S_{ij} = 0$. Otherwise,

where, S_{ij} - similarity matrix,

t - is a constant.

If nodes i and j are connected, then the weight is given by,

$$W_{ij} = \exp(-\text{norm}(x_i - x_j)/2t^2) \quad (12)$$

where, W_{ij} - Weight matrix

This weight mode can only be used under Euclidean distance metric.

Step 4: Computing the Orthogonal Basis Functions:

Compute a_1 as the eigenvector of $(XDX^T)^{-1}XLX^T$ associated with the smallest eigenvalue and Compute a_k as the eigenvector of associated with the smallest eigenvalue of $M^{(k)}$.

$$M^{(K)} = \{I - (XDX^T)A^{(k-1)}[B^{(k-1)}]^{-1}[A^{(k-1)}]^T\} (XDX^T)^{-1}XLX^T \quad (13)$$

Step 5: OLPP Embedding:

Let $W_{olpp} = [a_1, \dots, a_m]$, the embedding is as follows

$$x \rightarrow y = W^T X \tag{14}$$

$$W = W_{pca} W_{lpp} \tag{15}$$

where y is a 1-dimensional representation of the face image x , and W is the transformation matrix.

3. PERCENTAGE OF MATCH

A fusion technique deals with the integration and correlation of data from various sources to arrive at an overall assessment of the situation. Fusion is necessary to integrate the data from the different sensors and extract the relevant information on the specified target. The motivations behind using multiple sensors are many folds, to reduce error, uncertainty in the measurements and to obtain results that could not be accessible using a single sensor.

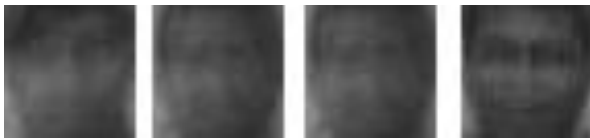


Fig.4(a). Eigenfaces

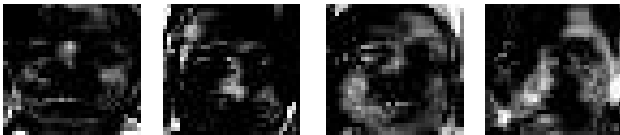


Fig.4(b). Orthogonal Laplacianfaces

For the database images (training database) all the features are extracted using the four algorithms. Each recognizer compares the set of features and calculates the percentage of matching corresponding to each recognizer. Then The Percentage of Matching (PM) scores are normalized.

The procedure begins with the normalization of the scores. The min-max normalization scheme is used to normalize the score to a common range i.e., between 0 and 1. In order to give all the recognizer's equal weightage at their corresponding threshold value, the matching scores are further rescaled, so that, the threshold value becomes same for all the algorithms. Then these four different algorithms are combined using weighted sum rule.

4. DECISION LEVEL FUSION

Numerous functions / combination of functions have been tested to assign weightage to the matching scores, so that the matching score lower than threshold should get lower value and the matching scores higher than the threshold should get higher value. In case of combination function, one function has been applied for values below threshold and another function for values above threshold. i.e. a linear function is used for values below threshold, and an exponential function is used for values above threshold. After applying these functions, the weighted scores are obtained from the BICA, KF, DCT, and OLPP

algorithms are PM_{BICA} , PM_{KF} , PM_{DCT} , and PM_{OLPP} respectively. Then, these weighted score corresponding to each algorithm are combined using sum of scores technique.

$$PM_{comb} = \frac{(PM_{BICA} + PM_{KF} + PM_{DCT} + PM_{OLPP})}{4} \tag{16}$$

A person is accepted, only if the PM_{Comb} is within some threshold T . Experimental results show that a combination of linear plus exponential functions, it is giving the best accuracy for wide range of threshold values.

The final decision will be taken by using Fuzzy Logic Controller for visible image and IR image.

5. EXPERIMENTAL RESULTS

The data bases are created for both visible and IR images. The four algorithms are tested on real time database consisting of 500 images with ten images per person. These images comprises of variation in facial expressions, lightning conditions, tilt on either side as shown in Fig.7(a). The images are acquired in dim light background using a digital camera.

5.1 RESULTS FOR VISIBLE IMAGE

Initially, the individual face algorithms are tested for any test image and the accuracy of each algorithm is computed independently. The accuracy versus threshold graph is shown in Fig.5. This shows that the maximum performance of BICA, KF, DCT and OLPP can be obtained at the thresholds of 0.6, 0.4, 0.7 and 0.5 respectively. Finally the hybrid fusion of the three classifiers at percentage matching score level is performed and the accuracy of the individual and combined recognizers are computed and displayed in Table.1.

Table.1. Accuracy of individuals and combined recognizer

Algorithm	BICA	KF	DCT	OLPP	COMB
Threshold (max)	0.6	0.4	0.7	0.5	0.5
Accuracy (%)	85	89	87	86	96

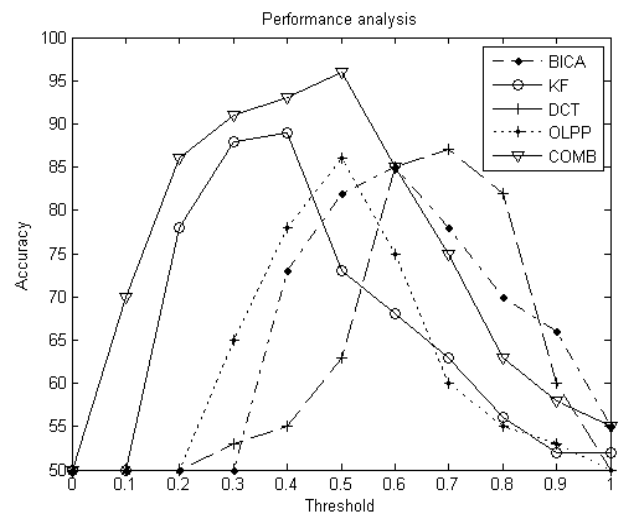


Fig.5. Accuracy vs. Threshold plots for the algorithms

The Fig.5 shows that at threshold 0.5, the maximum performance (96%) of the combined recognizers can be obtained. Thus combined recognizers perform better than each of the individual recognizers. Fig.6. (a) shows some of the accepted images which are rejected by the individual algorithms. Fig.6 (b) shows some images rejected by the combined classifier.

5.2 RESULTS FOR IR IMAGE

Obtain the training set images store it in the database. The Fig.7(b) shows some of the data base images for IR images. Based on ICA, the features are extracted for each image in database and test image.

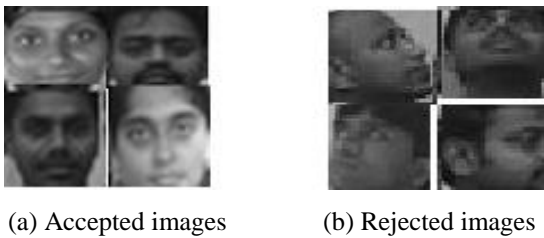


Fig.6. Performance of combined classifier



Fig.7(a). Some real time visible database images

5.2.1 Algorithm:

- Step 1:** Calculate the eigen value and eigen values by diagonalizing matrix B.
- Step 2:** Select k eigen values from those eigen values, obtain the eigen face.
- Step 3:** Calculate the weights of the each of the eigen image.
- Step 4:** Obtain the input image from the user.
- Step 5:** Calculate the deviation of the input image from the mean image stored in the database. Calculate the weights.
- Step 6:** Calculate the Euclidean mean distance.

If the distance is less than the selected threshold, then we say that the person is authenticated.

6. FUZZY LOGIC CONTROLLER

Fuzzy logic has rapidly become one of the most successful of today’s technologies for developing sophisticated classification systems. Fuzzy logic is a method of easily representing analog processes on a digital computer [12]. These processes are concerned with continuous phenomena that are not easily broken down into discrete segments, and the concepts involved are difficult to model-sometimes extraordinarily so-along mathematical or rule-based lines. Major advantage of this theory is that it allows the natural description, in linguistic terms, of problems that should be solved rather than in terms of relationships between precise numerical values. This advantage, dealing with the complicated systems in simple way, is the main reason why fuzzy logic theory is widely applied in technique.



Fig.7(b). Some real time IR database images

The general Fuzzy Logic Controller is shown in Fig.8 and it consists of four modules.

1. Fuzzification
2. Fuzzy inference engine
3. Fuzzy rule base
4. Defuzzification

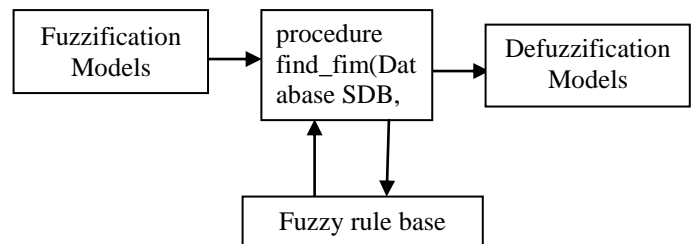


Fig.8. Fuzzy Logic Controller

6.1 FUZZIFICATION

Fuzzification can be considered as a mapping form an observed input space to fuzzy sets. The fuzzyfier measures the value of the input variable at every instant, normalizes the measured variables and converts the input data into linguistic variables. In the context of fuzzy reasoning, members if a fuzzy subset are assigned degree of compatibility or membership. The degree of membership characteristic the confidence measure assigned to a given assertion. The input linguistic variables are

Small (S), Medium (M), and Large (L). Similarly the output linguistic variables are Poor (P), Moderate (M), and Good (G).

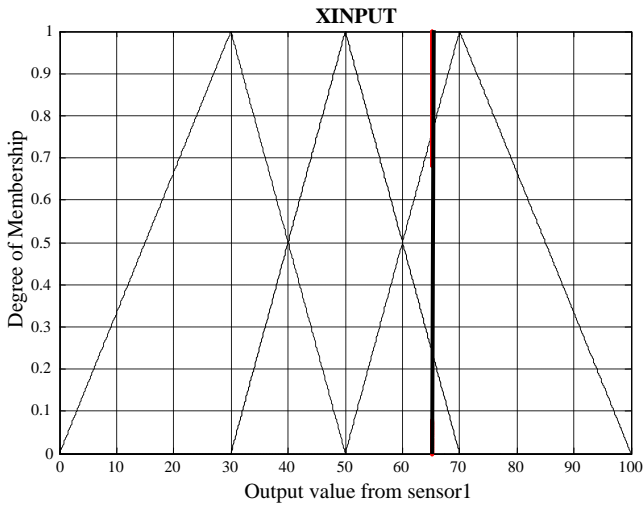


Fig.9(a). Input linguistic variable for sensor 1

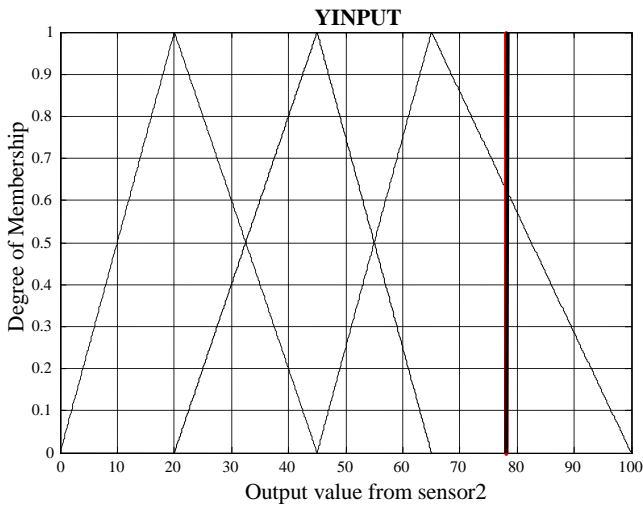


Fig.9(b). Input linguistic variable for sensor 2

The Fig.9(a) and (b) shows the Input linguistic variable for sensor 1 and sensor 2 respectively.

The concept of membership function provides a means to characterize vagueness where the “belongingness” of a subset to a set can take a degree of membership within the interval [0, 1] where the degree $\mu = 1$ represent a full belongingness, degree $0 < \mu < 1$ represent intermediate belongingness and degree $\mu = 0$ represents a full non-belongingness. For a given fuzzy tem, the membership function can have different shapes such as triangular, trapezoidal and Gaussian.

In Fig.9(a), the dark line shows that the output value of the sensor1 (Face), the value of the percentage of match is 65%. Similarly the Fig.9(b), shows that the output value of the sensor2, (IR sensor). The percentage of match is 78%. Based on the above values, DOM (Degree of Membership) is calculated.

6.2 FUZZY RULE BASES

Fuzzy rule [13] is actually the simple combination of two linguistic variables. The fuzzy system has a characteristic to

represent human knowledge or experiences using fuzzy rules. The learning ability and accuracy of approximation are related to the number or shape of membership functions. Fuzzy inference with more membership functions and fuzzy rules have higher learning ability, however, these may include some redundant or unlearned rules. The fuzzy rule has been framed and as shown in Table.2.

Table.2. Fuzzy Rule Table

Rule 1:	IF ED_{face} is small AND ED_{IRface} is small THEN Decision is poor
Rule 2:	IF ED_{face} is small AND ED_{IRface} is Medium THEN Decision is poor
Rule 3:	IF ED_{face} is small AND ED_{IRface} is large THEN Decision is moderate
.....
Rule 4:	IF ED_{face} is large AND ED_{IRface} is large THEN Decision is good

Based on the fuzzy rule, construct the Fuzzy Associate Memory (FAM) [14] table for each sensor outputs.

Defuzzification is the process of producing a quantisable result in fuzzy logic. Typically, a fuzzy system will have a number of rules that transform a number of variables into a "fuzzy" result, that is, the result is described in terms of membership in fuzzy sets. A useful defuzzification technique must add the results of the rules together in some way. The most typical fuzzy set membership function has the graph of a triangle. Now, if this triangle were to be cut in a straight horizontal line somewhere between the top and the bottom, and the top portion were to be removed, the remaining portion forms a trapezoid. The first step of defuzzification typically "chops off" parts of the graphs to form trapezoids (or other shapes if the initial shapes were not triangles). The centroid of this shape, called the fuzzy centroid, is calculated. The x coordinate of the centroid is the defuzzified value.

Table.3. FAM Table for face Vs IR face

		Euclidean Distance (ED_{face})		
		S	M	L
Euclidean Distance (ED_{IRface})	S	P	P	M
	M	P	M	G
	L	M	G	G

There are many different methods of defuzzification [12] available, including the following

1. Center of area method
2. Center of Maxima method
3. Mean of Maxima method

It is defined as Eq. (17) as below,

$$FD = \frac{\sum \mu D}{\sum \mu} = \frac{\mu_U D_U + \mu_{LH} D_{LH} + \dots}{\mu_U + \mu_{LH} + \dots} \quad (17)$$

where, μ – Membership value from each sensor
 D – Decision value from fuzzy function (from x-axis value)

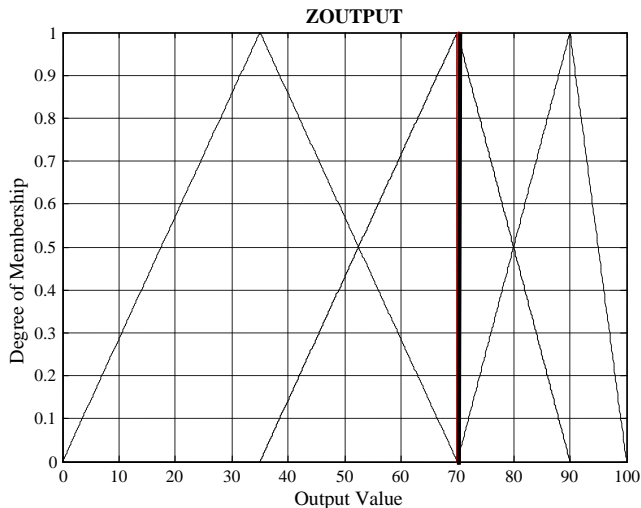


Fig.10. Output linguistic variable for Fusion

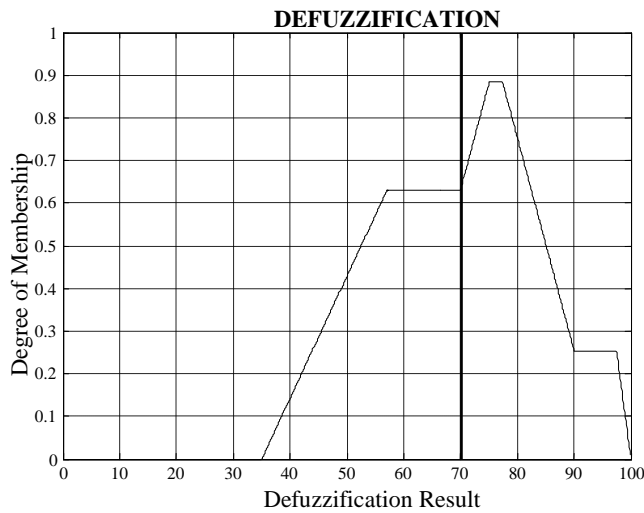


Fig.11. Defuzzification Output

The Fig.10 shows that the output linguistic variable for final fusion. According to FAM table the output linguistic variable is calculated and the defuzzification output is calculated by using Eq. (17) and the defuzzification value is 70, which is shown in Fig.11 if the threshold is set to 50, the defuzzification value is greater than the threshold and the person is authenticated.

7. CONCLUSION

The proposed system based on fusion of BICA, KF DCT and OLPP algorithm is found to be 96% accurate. The combined algorithm is successful by overcoming the drawbacks of individual algorithm. These algorithms are efficient as it can be integrated with the output from multi-modal sensors and thus can be used as part of multi-sensor data fusion.

The results presented here express that decision fusion methods based Fuzzy Logic Controller can be exact wanted alternatives to conventional classification methods. However, these schemes are potentially very useful since they combine different output.

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