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Research Article

IRIS RECOGNITION BASED ON WEIGHTING SELECTION AND FUSION FUZZY MODEL OF IRIS FEATURES TO IMPROVE RECOGNITION RATE

[1,*]Ali Mahmoud Mayya and [2]Mariam Mohammad Saii, D.

[1]PhD Student, Department of Engineering Computer and Automatic Control
[2]Professor Assistance Department of Engineering Computer and Automatic ControlTishreen University

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ABSTRACT

The study suggests designing a weighting model for iris features and selection of the best ones to show the effect of weighting and selection process on system performance. The search introduces a new weighting and fusion algorithm depends on the inter and intra class differences and the fuzzy logic. The output of the algorithm is the feature's weight of the selected features. The designed system consists of four stages which are iris segmentation, feature extraction, feature weighting_selection_fusion model implementation and recognition. System suggests using region descriptors for defining the center and radius of iris region, then the iris is cropped and transformed into the polar coordinates via rotation and selection of radius-size pixels of fixed window from center to circumference. Feature extraction stage is done by wavelet vertical details and the statistical metrics of 1st and 2nd derivative of normalized iris image. At weighting and fusion step the best features are selected and fused for classification stage which is done by distance classifier. The algorithm is applied on CASIA database which consists of iris images related to 250 persons. It achieved 100% segmentation precision and 98.7% recognition rate. The results show that segmentation algorithm is robust against illumination and rotation variations and occlusion by eye lash and lid, and the weighting_selection_fusion algorithm will increase the system performance.

INTRODUCTION

Iris is one of the best biometrics that has been recently used in recognition systems. It considers as the most accurate biometric that recognize people. Daugman [1993] is the pioneer in the scope of iris recognition; he developed his first algorithm in 1993. Hesegmented iris and transformed it from Cartesian into polar coordinates (r, θ). Gabor filter is used to extract features and the hamming distance classifier is used in the recognition phase. The system achieved 99.73% recognition on local iris database consists of 323 persons. In 1997, whildes [1997] segmented the iris image by using gray level derivative and the Hough transform. The features were extracted by means of LOG transform and the normalized correlation. He achieved 99.9% recognition rate on a local iris database consists of 40 individuals. Boles and Boashash [1998] depends on the edge detection for segmentation phase, and wavelet transform for feature extraction phase. Dissimilarity function is used for the recognition phase but the research didn't take in account the iris problems which may affect the recognition rate. However, the system got 92.6% recognition rate. Avila et al. [2002] applied the edge detection algorithm to get the iris region, they used Gabor filter for feature extraction and hamming distance for classification step. They got 97.89% recognition rate on a database consists of 100 image obtained from 10 persons.
In 2003, Li ma [2003] developed his algorithm for iris recognition which depends on canny edge detector for segmentation phase. Multichannel even symmetric Gabor wavelet and the multichannel spatial filters were used to extract features from iris. In the recognition phase, the linear discriminant classification method is applied. Partial occlusion by eye lash wasn't taken in account. The system achieved 94.33% rate on 2252 images taken from 213 individuals from CASIA database. In 2011, Ayra and Noel [2011] used wavelet transform for the extraction of features of the iris images which have been segmented via Circular Hough Transform which detect the circles in iris images.

Corresponding author: Ali Mahmoud Mayya ,
PhD Student, Department of Engineering Computer and Automatic Control.

Iris features code was used. The algorithm is applied on images of 100 individuals form iris CASIA database. The system suggests using wavelet transform from level 1 and level 4 to obtain feature vector of length 480 for level-1 and 120 for level-4. The recognition rate was 93.6% for level 1 and 98.2% for level 4. Elgamal et al. [2013] introduces his iris recognition research in 2013 which depended on the wavelet transform for feature extraction and the principle component analysis (PCA) for dimension minimizing. The K-NN classifier is used in the classification step on database consists of 2240 iris image obtained form 224 individuals. The system achieved 0.13% FAR and 0.06% FRR. Saminathah et al. [2015] used the adequate unique features of iris such as correlate, crypts, certain degree of furrows and ridges in 1 to 10 rows of 240 columns. The result feature vector consisted of 2400 elements. At the classification phase the SVM, neural networks and distance classifiers were used to obtain 98.5%, 87% and 76.8% consequently. The suggested database was obtained from 40 persons (3 iris images for training and 3 for testing). The system didn't take in account the partial occlusion by eye lash. Some of recent researches in iris recognition scope didn't take in account the illumination or pose variation problems, and the others didn't treat the partial occlusion by eye lash. The nature of used database wasn't clarifiedsufficiently in some studies, while in other ones the database was small or easy to recognize. This study treats all these problems in addition to introduce a novel feature weighting and selection model that could improve the iris recognition performance.

System Description

The proposed system consists of the following stages:

- Preprocessing.
- Segmentation.
- 3-Normalization.
- Feature extraction.
- Feature Weighting, Selection and Fusion.
- Classification.

Figure (1) illustrates those stages graphically.

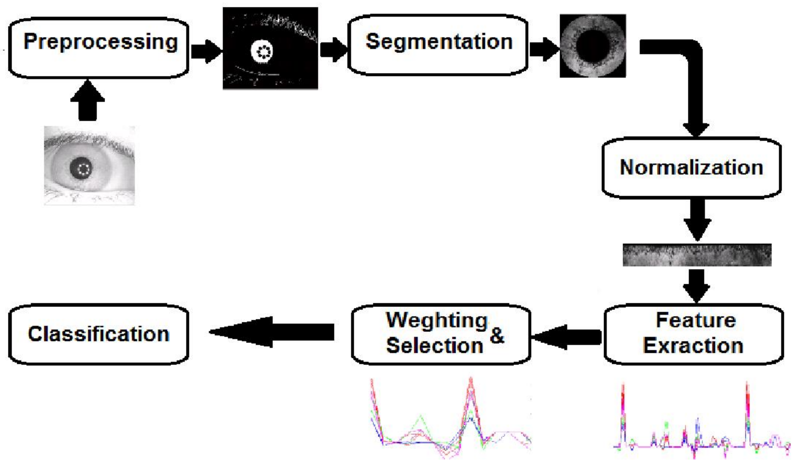


Fig.1. Block diagram of the proposed Iris recognition Stages

2.1 Preprocessing:

The system suggests using the following morphological preprocessing algorithm.

Input: Iris image f(x,y), structural element h of 20x20 square ones matrix.

Output: Thinned iris image $Bw_{thin}(x,y)$.

Steps:

1. Apply close operation via h mask (20x20 elements) to obtain the mask image ($image_{mask}$) which will be used later in the subtraction step, the following equation illustrates the operation [10]:

$$\mathrm{Image}_{mask} = (f \bullet h)(s) = (f \oplus h)\Theta\, h \quad (1)$$

$(f \oplus h)$ and $(f \ominus h)$ are the dilation and erosion operations which given as follows [10]:

$$(f \oplus h)(s) = \max\left(f(s - x) + b(x) \mid (s - x) \in D_f \text{ and } x \in D_b\right) \quad (2)$$

$$(f \ominus h)(s) = \min\left(f(s + x) - b(x) \mid (s + x) \in D_f \text{ and } x \in D_b\right) \quad (3)$$

D_f ‘D_b: are the domains of f and h, and there’s a condition that (s-x) and (s+x) have to be in the domain of f and that x and y have to be in the domain of h. figure (2-A) includes the closed iris image.

2. Subtract the mask image of step1 from the original image to obtain the difference image:

$$Diff(x,y)= Image(x,y)-Image_{mask}(x,y) \quad (4)$$

3. Magnify the subtraction image to clarify the dark points as follows:

$$Diff(x,y)=Diff(x,y)*2 \quad (5)$$

Figure (2-C) shows the magnified subtraction image.

4. Threshold the magnified subtraction image by using 0.5 threshold to get the binary image which is easier to process and segment as figure (2-D) illustrates. The process is done using the following equation:

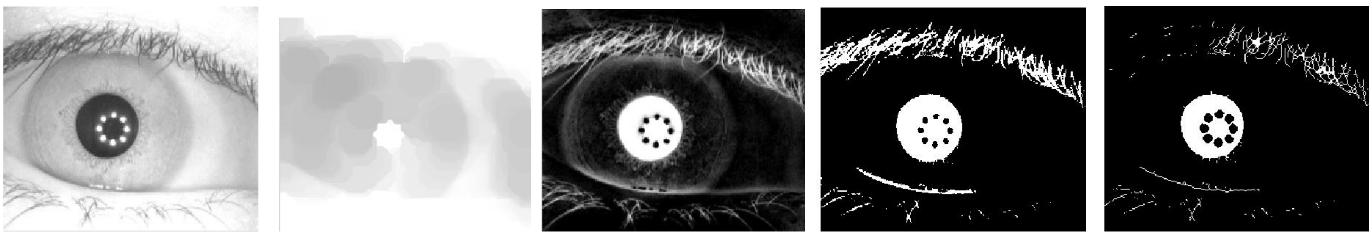
$$BW(x,y) = \begin{Bmatrix} 1 & if\ Diff(x,y) \geq 127 \\ 0 & otherwise \end{Bmatrix} \quad (6)$$

5- Apply thinning operation to minimize the eyelash region significantly. So, most of the noise and non-interest region will be eliminated. This operation won’t affect the iris circular region as shown in figure (2-E).The thinning operation is done by means of equation7 [10]:

$$BW_{thin} = BW \otimes B = BW - (BW \circledast B) \quad (7)$$

Where B is the structural element and BW $\circledast$ B is the hit-miss operation.

6- Remove the outlier pixels that stuck with the image’s boundary. The figure (2-E) illustrates the preprocessed iris image.



(A) (B) (C) (D) (E)

Fig.2. Morphological Preprocessing Stage: (A) Original image (B) closed image (C) Magnified subtraction image (D) Thresholded image (E) Thinned FilteredImage

2.2Iris Segmentation

2.2.1Iris Localizing

This stage segments the iris and extracts the iris region by applying the following algorithm:

Input: preprocessed image BW_{thin} (x,y).

Output: $Iris_{radius}$ (r), $Iris_{center}$ =[x,y].

Steps

1- Detect the center and radius of pupil: Here the preprocessed image is divided into some connected regions depending on the connectivity and adjacency principles.

The maximum connected region is the pupil as equation (8) says:

$$Pupil=max(eye\_areas) \tag{8}$$

2- Center is detected and radius of the pupil region is calculated using the MJA and MNA as follows:

$$Pupil_{radius}=(MJA+MNA)/4 \tag{9}$$

Where MJA is the major pupil axes which defined by calculating the distance between the two horizontal farthest points, while MNA is the minor axes which is defined by calculating distance between the two vertical farthest points.

3- Calculate the radius of iris region as follows:

$$Iris_{radius}=2*Pupil_{radius} \tag{10}$$

So, the iris radius is got and the pupil center is the same as iris center. Figure (3) illustrates these measurements.

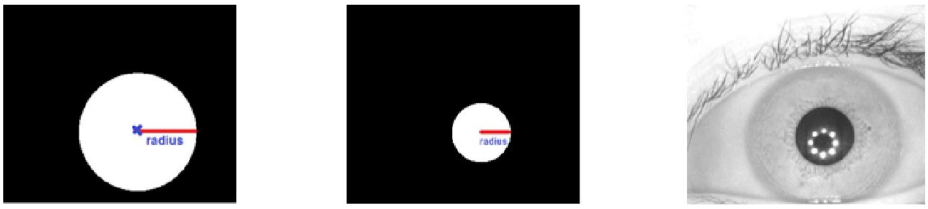


Fig.3.Radius and Center of Iris and Pupil

(A): The original image (B) Center and Radius of the Pupil (C) Center and Radius of the Iris

2.2.2 Iris Region Extraction:

The iris extraction algorithm:

Input:original image f(x,y), $Iris_{radius}(r)$, $Iris_{center}=[x,y]$

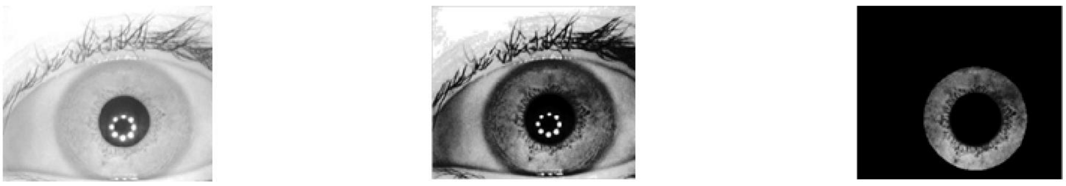
Output: Iris Segmented RegionS(x,y).

Steps:

1- Enhance the iris image by applying the histogram equalization. Figure (4-b) illustrates the enhancement effect.
2- Crop circular region (C) from enhanced image which is defined via equation (11):

$$\mathrm{C} = \mathrm{C}_1 - \mathrm{C}_2 \text{ where; } \left\{ \begin{matrix} C_1 = (\mathrm{y} - \mathrm{CentY})^2 - (\mathrm{x} - \mathrm{CentX})^2 = \mathrm{Iris_{radius}}^2 \\ C_2 = (\mathrm{y} - \mathrm{CentY})^2 - (\mathrm{x} - \mathrm{CentX})^2 = \left(\frac{\mathrm{Iris_{radius}}}{2}\right)^2 \end{matrix} \right\} \tag{11}$$

Where (CentX,CentY) are the center of iris and pupil, while $\mathrm{Iris_{radius}}$ is the radius of iris. C_1 is the circular region of Iris, while C_2 is the circular region of pupil, and C is the desired region of interest (ROI). Figure (4-c) shows the



(A) (B) (C)

Fig.4. Iris localization (A) original image (B) Enhanced image (C) Localized iris

3- Apply translation of localized iris image to locate it at the left upper corner of image by using equation (12):

$$S(x_{new}, y_{new}) = C(radius - x_{old}, radius - y_{old}) \tag{12}$$

The application of the previous steps is illustrated in figure 5.

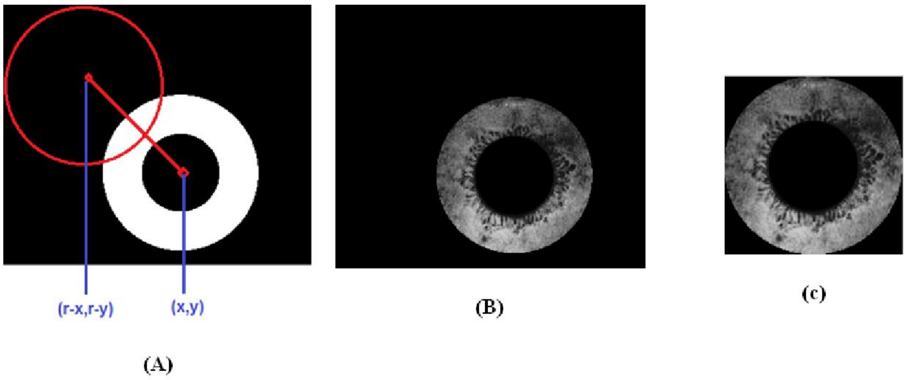


Fig. 5. Translation process of iris location

2.3 Iris Normalization:

Our proposed normalization algorithm is driven from view of Daugman's one [4],which is described below.

Input: segmented iris image S(x,y), (x,y): center of iris,r: radius of iris.

Output: Normalized Iris in the polar coordinates (r,θ).

Steps:

1- Suppose the initial values: angle of rotation θ=0, number of sampling processes frq=1,coordinates of output image (row,column)=(0,0).

2- Fix the row number, and move across columns starting from point (x,y+0.5*r) which is illustrated on figure (6) with red color until you reach the point (x,y+r), repeat the following steps from a to c:

- For each coordinates (i,j) get the pixel value from segmented image S.
- store this value S(i,j) in the location (row,column) of output image.
- Increase row by one.

3. Increase column by one.

4. Rotate the segmented image (S) on center (x,y) by angle θ using the following equation:

$$\theta = \frac{frq}{0.001*k*n} \times \frac{\pi}{4} \tag{13}$$

Where k is the number of S' rows and n is the number of columns of S.

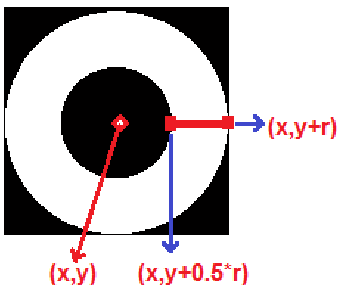
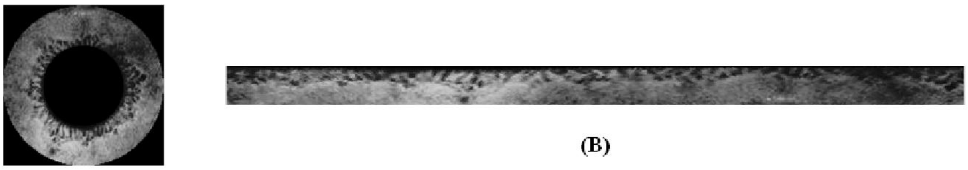


Fig.6 Sampling the iris method

Figure (7) illustrates the normalization process.

2.4 Feature extraction:

The research suggests fusion of two different feature types. The first is the vertical wavelet coefficients of image, while the second is the statistical features of iris' derivatives.



(A)

Fig. 7. Normalization Process (A) Segmented image (B) Normalized (r,θ) image

2.4.1 Wavelet coefficients feature:

The system suggests using the vertical coefficients of wavelet transform of level 2 because the normalized iris image contains vertical edges which are the ROI in iris image.

To get the vertical coefficients, the following equation is performed on normalized image [10]:

$$W_{\varphi} W_{\varphi}^{v}(j0,k1,k2) = \frac{1}{\sqrt{M*N}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) {\psi^{v}}_{j0,k1,k2}(x,y) \tag{14}$$

Where (j_0) is the initial scale of the mother wavelet which is commonly set to 0. M,N number of rows and columns of normalized image. Symbol (v) is abbreviation of 'Vertical', and $\varphi_{j0,k1,k2}$ is the approximation coefficient which is given as follows [10]:

$$\varphi(x,y) = \varphi(x) * \varphi(y) \tag{15}$$

While ${\psi^{V}}_{j0,k1,k2}$ is the vertical details coefficient which is given as follows [10]:

$$\psi^{v}(x,y) = \varphi(x) * \psi(y) \tag{16}$$

$\varphi(x)$ is the high pass filter which is applied on image's rows and the result is down_sampled by 2. On the other hand,$\psi(y)$ is the low pass filter which is applied on image's columns and the result is down_sampled by 2. The wavelet transform applies high pass followed by low pass filter to get the desired vertical details coefficient. Figure (8) illustrates the result of applying the wavelet filters on the normalized segmented iris image.

(A)

(B)

Fig. 8. Iris Wavelet Features matrix (A) normalized iris (B) Wavelet Vertical coefficients

Figure (9) shows the result of changing the feature matrix into vector by using the mean value of its columns.

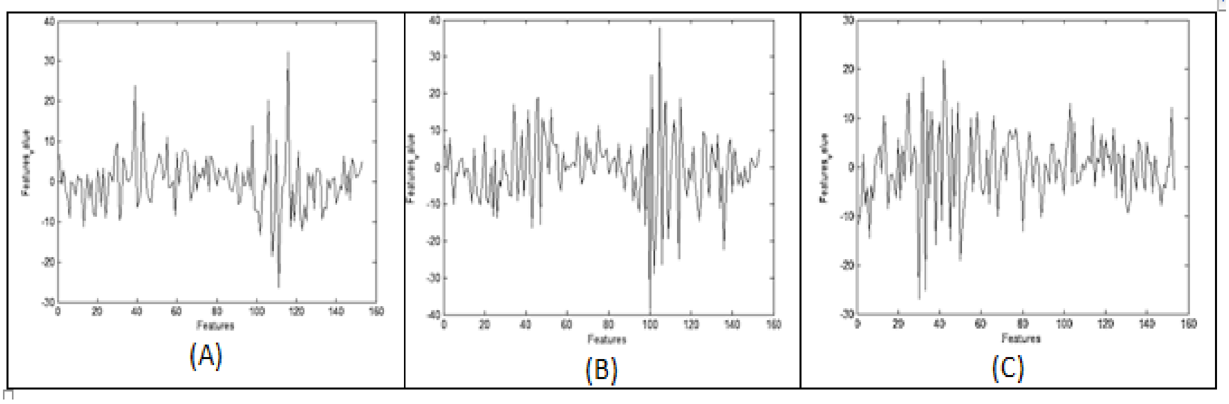


Fig. 9 Iris Wavelet Features Vector (A) Feature vector of 1st person in database (B) Another feature vector of 1st person in database (C) Feature vector of 2nd person in database

It can be noticed that the feature vectors of the same persons are similar (fig 9-A and 9-B), while they differ from the second person's feature vector (fig 9-C).

2.4.2 The Statistical Features:

The study suggests using the statistical features on 6 different copies of the image. The images are:

- The Laplacian image that result from applying Laplacian edge detector on the segmented iris.
- The first derivative of the segmented image.
- The second derivative of the segmented image.
- The double copy of the segmented image.
- The complement Laplacian image.
- The binary copy of the segmented image.

The proposed statistical that applied on the previous images are the following:

White color pixels rate which is calculated via equation (17):

$$White_{rate} = \frac{white_{num}}{M*N};\ white_{num} = \left\{\begin{matrix} (white_{num}+1) & if\ f(i,j)=1 \\ white_{num} & otherwise \end{matrix}\ for\ all\ i,j\right\} \tag{17}$$

Standard Deviation (SD):

The standard deviation is calculated as follows [5]:

$$Var(x,y) = \frac{1}{M*N}\sum_{i=1}^{m}\sum_{j=1}^{N}\left(f(i,j) - \overline{f(x,y)}\right)^2 \tag{18}$$

F(x,y) is the normalized image for which the SD will be calculated.

M*N is the number of elements of image.

$\overline{f(x,y)}$ is the mean value of image.

The variance is the sum of squared differences between the mean value and the pixels of image, while the standard deviation is the squared root of the variance [5]:

$$\sigma = \sqrt{Var} \tag{19}$$

Interquartile Range:

The interquartile rangeis the difference between the upper and lower quartile. The lower quartile is the value that25% of elements exist before and The lower quartile is the value that 75% of elements exist before [5].

Mode:

The mode is the most frequency value of image [5]. If there are two values, take the smaller one.

Range:

Range calculates the difference between the maximum and minimum values of image [5]:

$$Range = \max\left(f(x,y) - \min\left(f(x,y)\right.\right. \tag{20}$$

Mean Absolute Deviation:

This statistics calculates the variance between pixels by equation21 [5]:

$$\delta = \frac{1}{M*N}\sum_{i=1}^{m}\sum_{j=1}^{n}\left|f(i,j) - \overline{f(x,y)}\right| \tag{21}$$

Skewness

Skewness is a measure of the asymmetry of the data around the sample mean [5]. If skewness is negative, the data are spread out more to the left of the mean than to the right [5]. If skewness is positive, the data are spread out more to the right [5]. The skewness of the normal distribution (or any perfectly symmetric distribution) is zero [5].The skewness of a distribution is defined as:

$$skew = \frac{1}{M*N}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[\frac{f(i,j)-\overline{f(x,y)}}{\sigma}\right]^3 \tag{22}$$

Entropy:

Entropy describes the randomness of image' pixels so, it can define the shape of image. It depends on the binary logarithm of image pixels [5]:

$$E(x,y) = -\sum_{i=1}^{m}\sum_{j=1}^{n} \mathrm{f(i,j).*\,log2(f(i,j))} \tag{23}$$

Energy:

It calculates the sum of squares of image pixels as follows [5]:

$$Energy = \sum_{i=1}^{m}\sum_{j=1}^{n} f(i,j)^2 \tag{24}$$

Contrast:

The contrast is used to calculate the difference between pixels and its neighbors as equation (25) shows [5]:

$$contrast = \sum_{i=1}^{m}\sum_{j=1}^{n}|i-j|^2 f(i,j) \tag{25}$$

The extracted features are then fused via concatenation to get the statistical vector which consists of 60 features (10*6), number 10 is related to the statistics that described above, while number 6 is related to the derivative images that the statistics are done.

2.4.2.1 Statistical Feature Normalization

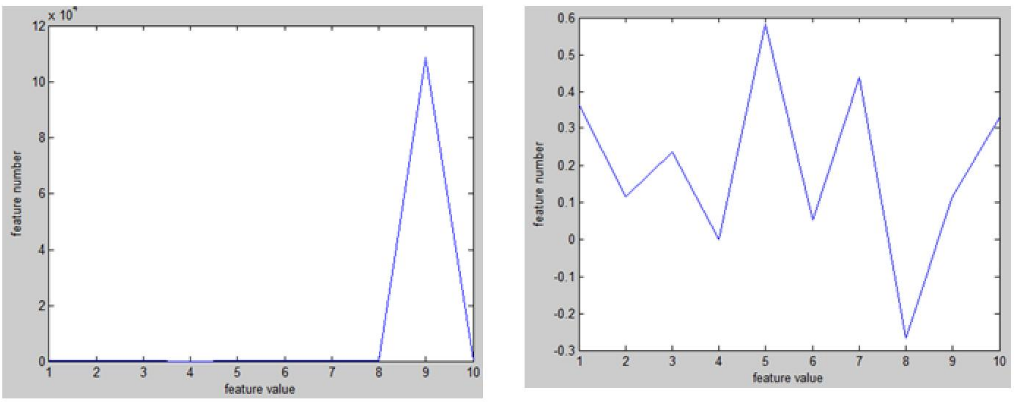
Some of the extracted features have high values while the others have low ones. To solve this problem, normalization process is done to achieve the consistence of the features. The following features are the ten features of the laplacian image of one of the iris database, it can be noticed that the first and tenth features are too low while the fifth and seventh features are very high.

0.0000363	0.1149	0.2348	0	5.8275	0.0515	4.380	-0.2678	11339	0.000331

The suggested solution is to scale the features that they lay from -1 to +1. The 1st feature is multiplied by 10^4, the 10th feature is multiplied by 10^3, the 5th feature is divided by 5, and the 10th feature is divided by 10^5. The result vector is shown below:

0.363	0.1149	0.2348	0	0.5825	0.0515	0.4380	-0.2678	0.11339	0.331

Figure (10) illustrates the difference between the two feature vectors:



(A) (B)

Fig. 10Statistical Feature example (A) Before Scaling (B) After scaling

The following figure (11) shows the entire feature vector of different 4 samples of iris database.

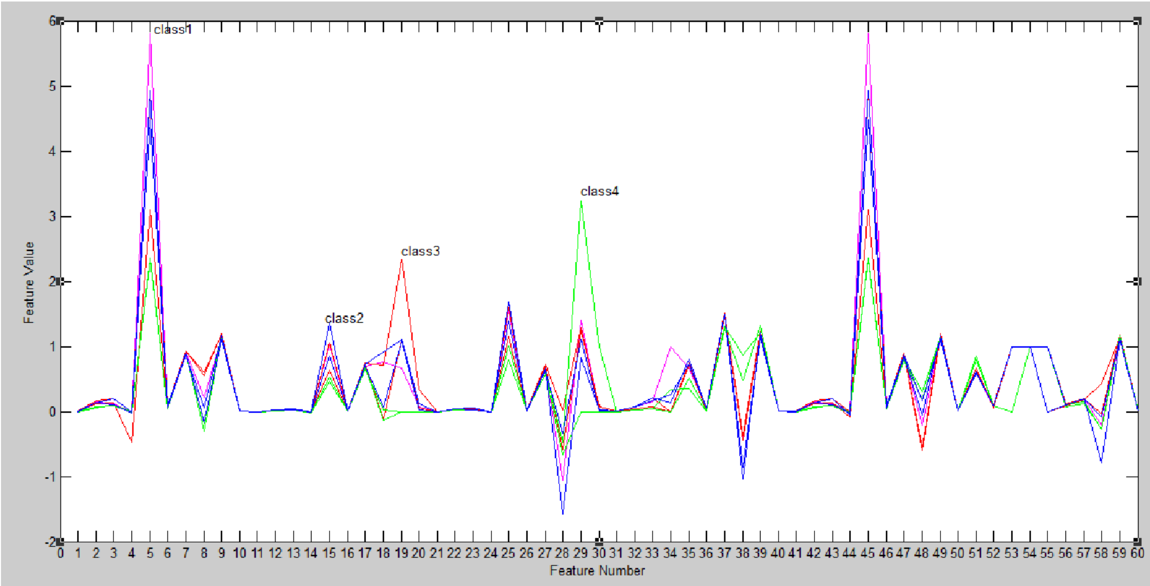


Fig. 11. Statistical Feature Vector of Four Different Individuals

It can be noticed that the features (5,8,15,19,38,45,48,58) are the best features that differentiate the individuals. To automate the selection of the best features, we proposed our weighting and selection algorithm.

2.5 Feature Weighting and Selection Algorithm:

Input: Feature Vector.

Output: Weighted Selected Feature Vector.

Steps:

Step1. Pick 4 random classes of the feature vector; let's assume them $class_1$, class2, class4 which includes the following different features X^1,X^2,X^3,X^4. For the same class, 16 features is resulted from 4 classes (sample $X^1_{3,3}$ is the 3rd feature of $class_1$).

Step2. Calculate the inner difference at the same class which is called the convergence. This will result in 4 values as follows:

$$diffin^{k}_{i,j} = \left|X^k_{i,j} - X^k_{i,j+m}\right| \quad where\ k = 1,2,,3,4\ , (j+m) \leq 4 \tag{26}$$

Where k is the number of classes, (i,j)are the coordinates of the feature in class k.

Step3. Calculate the outer difference of the features between the 4 different classes (Divergence) as follows:

$$diffout^{k}_{i,j} = \left|X^k_{i,j} - X^{k+1}_{i,j}\right| \quad where\ k = 1,2,,3,4\ , (j+m) \leq 4 \tag{27}$$

Step4. Calculate the mean value of the convergence values:

$$diffin^{k}_{i,1} = \frac{1}{6}\sum_{j=1}^{6} diffin^{k}_{i,j} \tag{28}$$

Step5. Calculate the mean value of the divergence values:

$$diffout^{k}_{i,1} = \frac{1}{4}\sum_{j=1}^{4} diffout^{k}_{i,j} \tag{29}$$

Step6. Construct fuzzy inference system with two inputs and one output; the first input is the $diffin^{k}_{i,1}$and the second input is $diffout^{k}_{i,j}$ while the output is number of values represents the feature weights (values from 1 to 15).

Step 6.1. Input function in proposed fuzzy system:

Input (1) convergence:

The member functions for the first input are 5 trim functions whose value range from 0 to 50 as figure 12 illustrates:

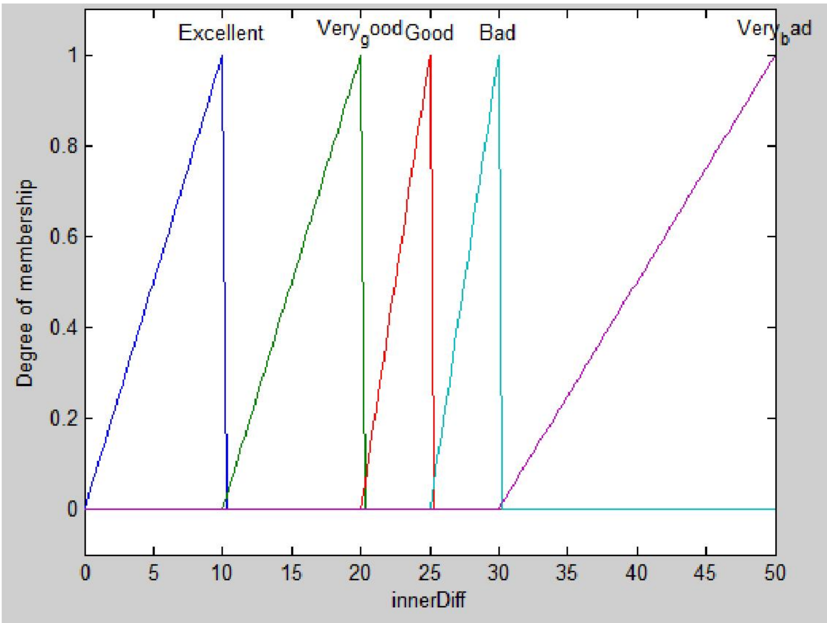


Fig. 12 Proposed Member function of the first fuzzy input

Input (2) Divergence:

The member functions for the second input are 14 trim functions whose value range from 0 to 50 as figure 13 illustrates:

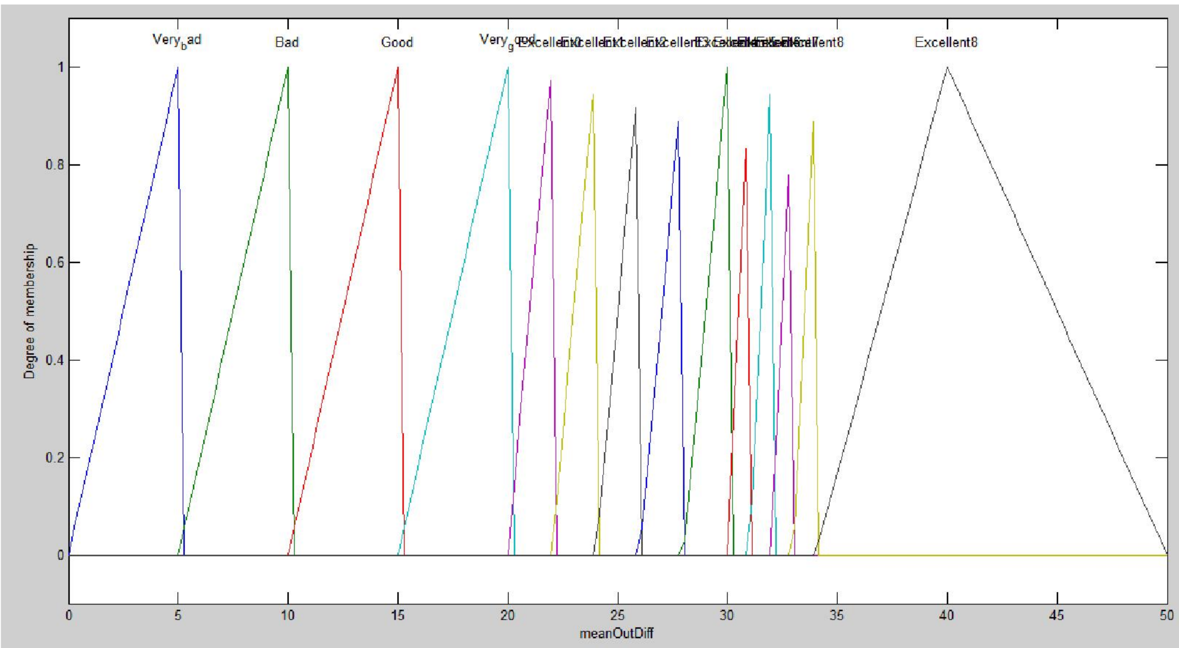


Fig. 13Proposed Member function of the Second fuzzy input

Step 6.2. Output function in proposed fuzzy system:

The output member function represents the scale value ranging from 0 to 15.

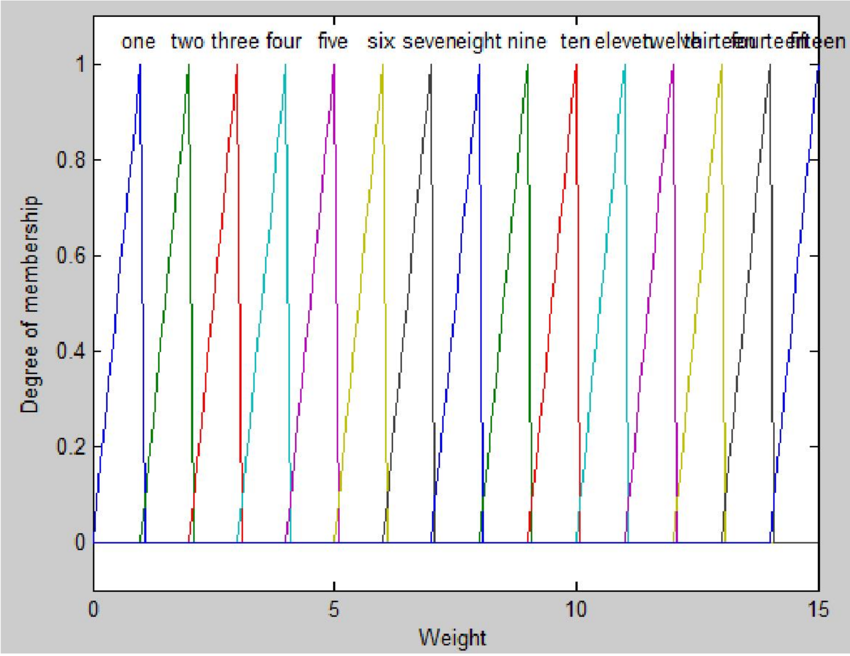


Fig. 14 Proposed OutputMember functions

Step 6.3. Fuzzy Rules Design:

70 fuzzy rules are done of the previous suggested fuzzy system. In the follows one of that rules:

If (innerDiff is Excellent) and (meanOutDiff is Excellent8) then (Weight is fifteen)

Step 6.4. De-fuzzification:

After getting the fuzzy output, a process of de-fuzzification is required to get the real value of output of the result fuzzy output. We suggest using the 'centroid' method. Figure 15 illustrates the de-fuzzification of one of the fuzzy output value (weighting value). So, low convergence and high divergence result in high weight value.

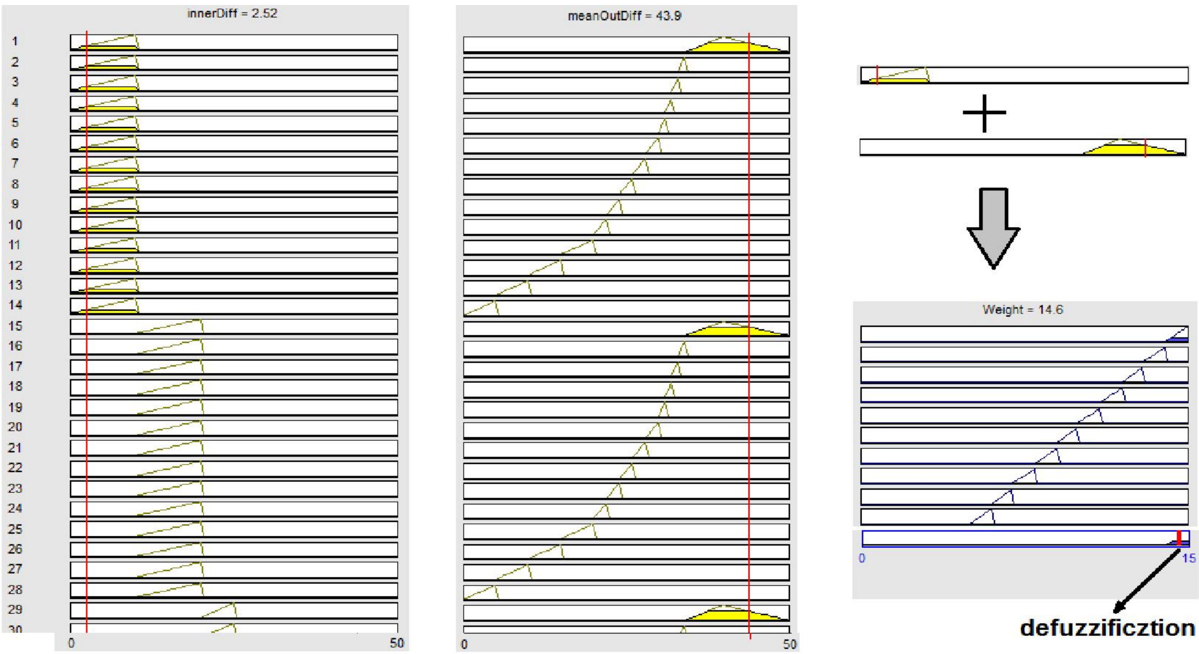


Fig. 15 De-fuzzification of one fuzzy output

The fuzzy operation is done by means of AND method, the aggregation operation is done via OR method, while the MEAN method is performed to get the final fuzzy output.

Step 7. Select the features whose value exceed threshold T.

Step 8. Multiply the selected feature vector by corresponding weight values.

Figure 16 clarifies the result of applying the weighting and selection algorithm on statistical feature vector with T={3.5,7.5}.

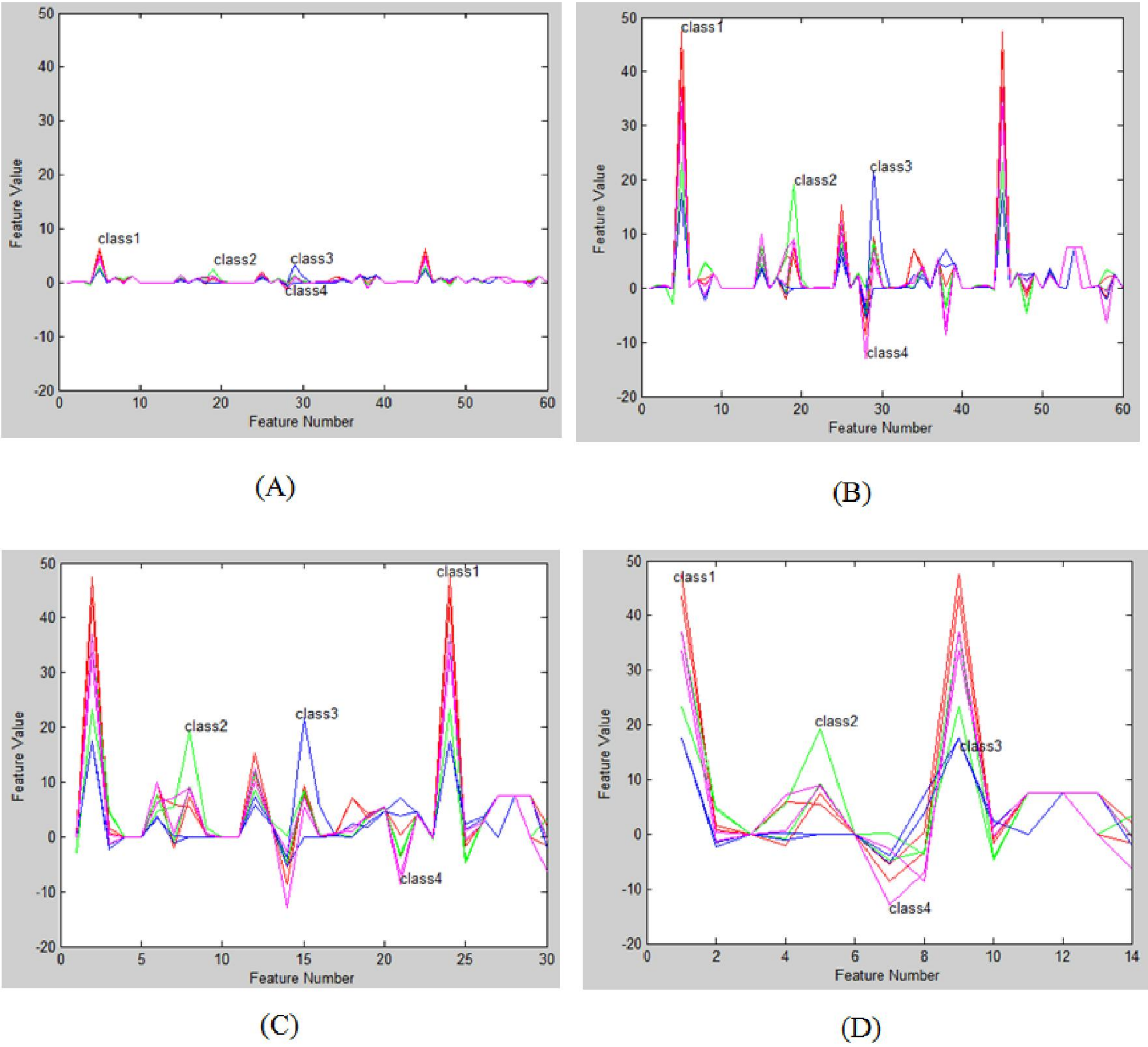


Fig. 16 Results of Applying the Weighting and Selection algorithm on Statistical Feature Vector (A): The Original Statistical Feature Vector (B): The Weighted Feature Vector (C):The Weighted Selected Feature Vector With Threshold T=3.5 (D) The Weighted Selected Feature Vector With Threshold T=7.5

By comparing figure (16-A and B), It can be noticed that the weighting process make the important features have bigger effect comparing to the rest features in the feature vector (we can see that by a glance on features (5,8,15,19,28,38,45,48,58) which are magnified significantly. This means that the weighting algorithm is promising at magnifying the best features. The next operation is the selection process, and by selecting the features whose weight value exceeds threshold T=3.5, the number of feature vector became only 30.

This reduces the feature vector length by half with reduction rate 50%.Again, by selecting the features whose weight value exceeds threshold T=7.5, the number of feature vector became only 14. This almost reduces the feature vector length by factor of 4 and result in 76.6% reduction rate. Figure (16-A and B) shows that the most promising features still existentwhile the others are eliminated. Identically, figure 17 illustrates application of the weighting and selection algorithm on the wavelet vertical feature vector. Again, the same previous notes are true on the figure (17-B) which represents the weighting process and figure(17-C) which represents the selection proce ss with T=3, and figure (17-D)represents the selection process with T=8. We can notice that T=3 yields in 100 features and 40% reduction rate. When T=8 the feature vector becomes 35 with reduction rate 75.66 reduction rate.

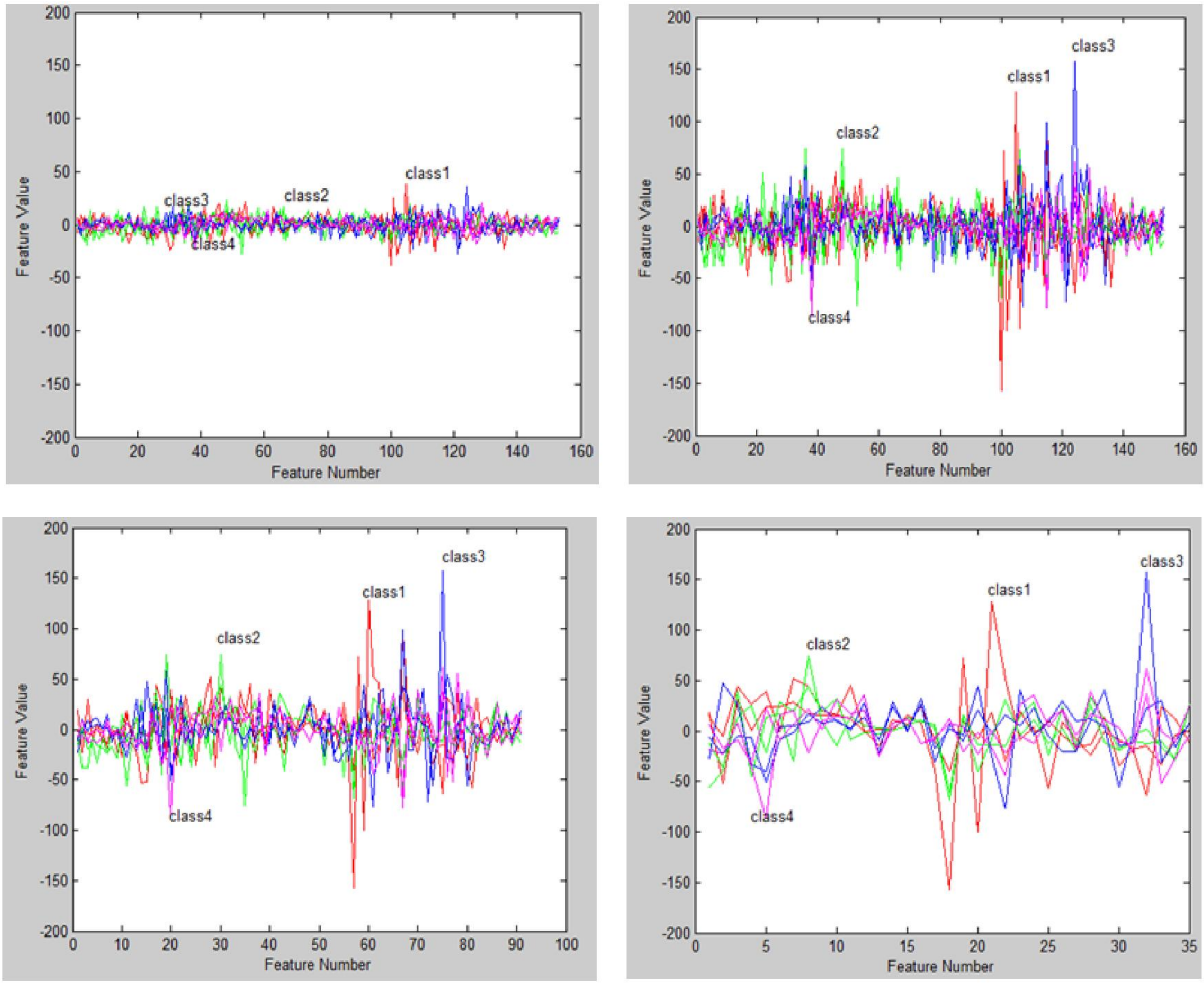


Fig. 17 Results of Applying the Weighting and Selection algorithm on Statistical Feature Vector (A): The Original Statistical Feature Vector (B): The Weighted Feature Vector (C):The Weighted Selected Feature Vector With Threshold T=3 (D) The Weighted Selected Feature Vector With Threshold T=8

2.6. Classification:

The final step of any recognition system is the classification process. The study suggests using the distance classifier which is very easy and simple to apply and is given as follows:

$$dist(i,j) = \frac{1}{M}\sum_{i=1}^{M}|F(i,j) - T(i,1)| \quad (30)$$

The equation (30) calculates the mean value of the distances. The distances is calculated between feature vector of testing sample and feature vector of the training database. The minimum difference value detects the number of recognized sample as follows:

$$Num=min(dist(x,y)) \quad (31)$$

RESULTS AND DISCUSSION

The experiments are done on two phases; the first is the segmentaion and the other is the recognition.

3.1 Segmentaion Results

The experiments are done on the CASIA iris database [2], the selected database consists of 250 individulas and 6 iris images for each one. the selected iris database includes different situations such as different illumination, different pose, different camera-distance and partial occlusion via eyelash and eyelid.The segmentaion algorithm succeeced in segmenting all the iris images and achieving 100% sesgentaion rate. Figure 18 includes examples of iris images segmentaion results.

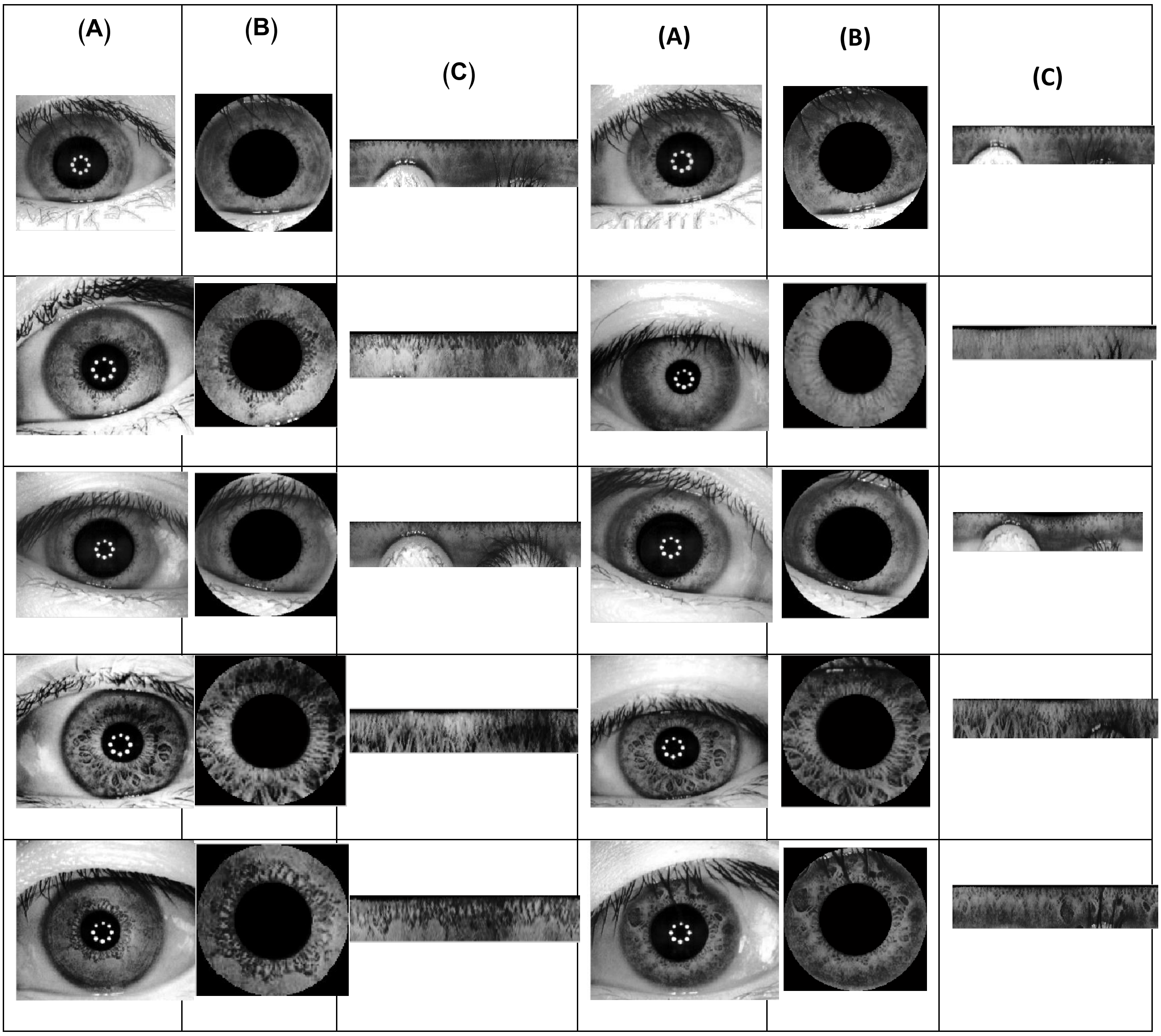


Fig. 18. Examples of proposed segmentaion and normalization algorithm on CASIA iris database (A) Enhanced Iris Image (B) Segmentaion Result (C) Normalization Result

Table (1) Results of Recognition in Different Feature Vectors:

Feature Vector Nature	Number of Features	Recognition Rate
Entire statistical feature vector	60	%76.4
Entire weighted statistical feature vector	60	%74.35
Selected weighted statistical feature vector	30	%74.35
Vertical coeificient of wavelet feature vector (CV)	150	%95.6
Weighted CV	150	%96.4
Selected weighted CV	100	%94.87
Weighted vertical coeificient of wavelet feature vector (CH)	150	%73.9
CV + CH	300	%96.4
Weighted CV + Weighted CH	300	%97.9
Selected weighted CV + Selected Weighted CH	130	%93
Weighted CV + Weighted CH + Weighted statistical vector	360	%98.2
Selected weighted CV + Selected weighted CH + Selected weighted statistical vector	160	%94.87
weighted CV + Selected weighted CH + Selected weighted statistical vector	210	%98.7

3.2 Recognition Results

The recognition stage is performed on 240 iris segmented images related to 60 individuals. These database is considered as the training database whose feature vectors are extracted and stored. The experiments are done on a test database consists of 150 sample. The original feature vectors, the weighted feature vectors and the selected weighted feature vectors are used. The results are arranged in Table (1).

In the following examples of the classification results on some iris test databaseimages

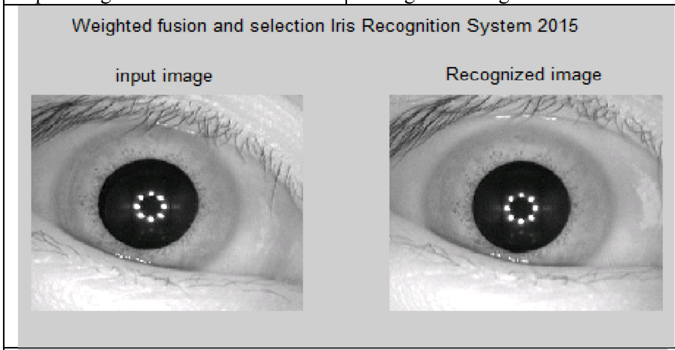
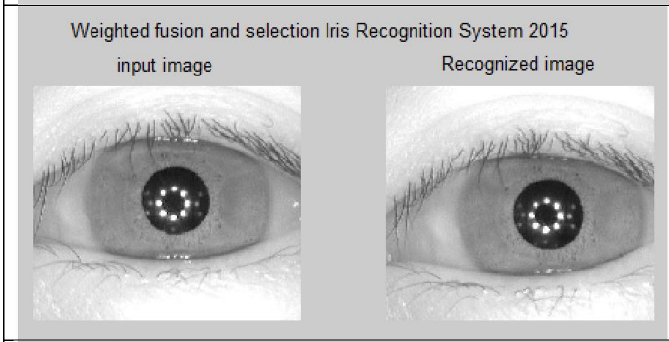
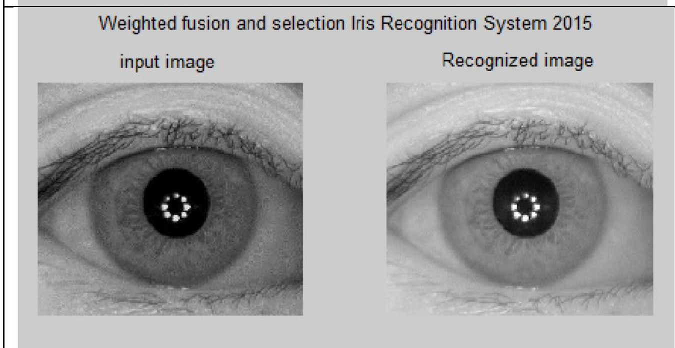
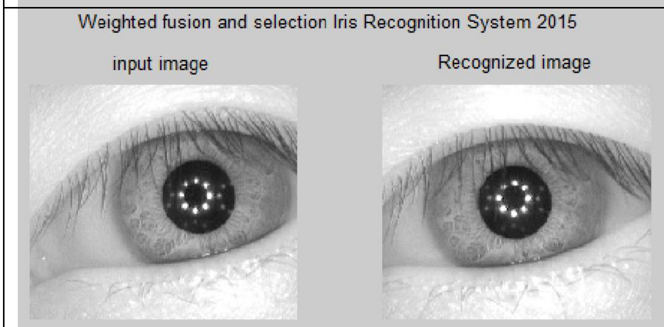
Input image	Recognized image	Remarks	Result of recognition
		Different rotate angle of test image	True
		Partial occlusion via eyelid	True
		Different illumination	True
		Partial occlusion via eyelid and eyelash	True

Fig. 19 some of recognition results

DISCUSSION

The results show that the vertical coeificients of wavelet features are the best features for regonition because they achieved the best rates when using them purely (95.6%), weighted (96.4%) and selected (94.87%). On the other hand, the statistical features and the horizontal wavelet component give low recognition rates. By using the weighting algorithm, the recognition rate increases from 95.6% to 96.4%. By applying the selection process the feature vector decreases from 150 to 100 samples (which will decrease the recognition time) and the recognition rate decreases only by 0.73%, this means that the training time will decrease significanltly while the recognition rate will not affect by that data reduction. The best recognition rate 98.7% is achieved when fusing the weighted vertical component, the selected features of horizontal component and the selected statistical features.

4. Comparative Study:

In order to view the differents between our study and the other studies in the same scope, we made the following two comparative studies.

Table (2) Comparing the current study with previous studies in scope of iris detection

Researcher	Segmentation Method	Time of Detection Process (seconds)	Segmentaion Rate	Database nature
Daugman [4]	Differential Integral Operator	6.56	98.6%	323 individuals, 592 images
Wildes [11]	First Derivative of image	8.28	99.9%	Local database depends on special imaging device
Camus [12]	Multi resolution to detect iris contour	1.98	98%	670 images (640 normal images, 30 different illumination images)
Li Ma [8]	Texture-Based methods	0.2426	99.54%	213 individuals, 2252 images from CASIA database
Current Study	Morphological Operations and Region properties	0.5	100%	250 individuals (6 images for each one) from CASIA database

Table 3. Comparing the current study with previous studies in scope of iris recognition

Researcher	Feature Extraction Method	Feature Selection Method	Feature Extraction Time	Classification Method	Classification Time	Recognition Rate	Database Nature
Daugman [4]	Gabor filter	Not exist	682.5	Hamming Distance (HD)	Not mensioned	%99.37	323 individuals from undefined database
Boles [13]	LOG filter	Not exist	170.3	Differential Function	Not mensioned	%92.6	Not mensioned
Li Ma [8]	Fisher's Analysis	Not exist	244.2	Linear Discriminant Classification Method	Not mensioned	%94.33	213 individuals from CASIA
Jong [6]	Accumulator sum of partial images	Not exist	182.0	Hamming Distance (HD)	Not mensioned	%98.21	108 individuals from CASIA
Noel [1]	Wavelet transform	Not exist	Not mensioned	Hamming Distance (HD)	Not mensioned	%98.2	100 individuals from CASIA
Elgamal [9]	Wavelet + PCA	Not exist	Not mensioned	Nearest Neighbor	3 seconds	%99.5	224 individuals from local database
Saminathan[7]	Correlation + lines + edges	Not exist	Not mensioned	HD	Not mensioned	%76.8	40 individuals from CASIA
				Neural Network		%87	
				SVM		%98.5	
Current Study	Wavelet CV and statistical features of derivatives	Not exist	15	Distance Classifier	0.5 seconds	100%	240 images from 60 individuals from CASIA

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