extraction is the reshaping of approximation matrixes of face and ear into vectors of one row and M/4*N/4 columns.

The second feature of face are geometrics features, which are illustrated in figure 5.

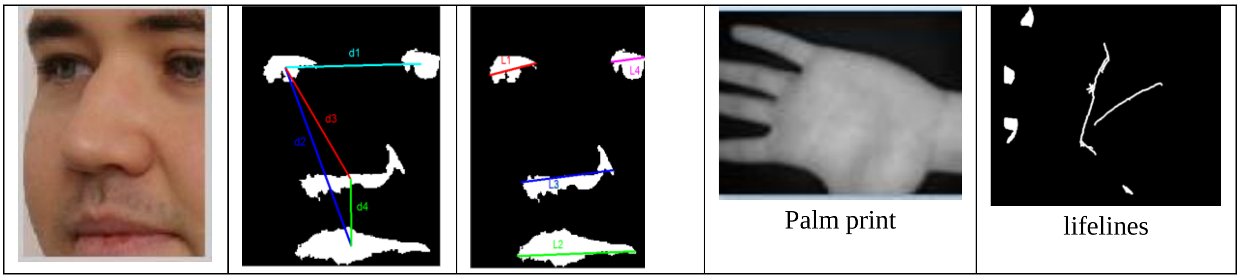

Fig 5. Face Feature Extraction Method

The features of wavelet approximation and the geometric features are fused to consist the face features. While the palm print wavelet features are fused with lifelines feature to consist the palmprint features.

2.5 Feature Selection:

Until now, the feature vector is still big (for our system 83000 samples) and will require more time for next processing steps and more size for storage. So, we introduce an improved approach from [7] for feature selection to minimize features by choose the most promised features. Figure 6 describes our modified suggested system. Our modification in the output of fuzzy system and inner coefficients.

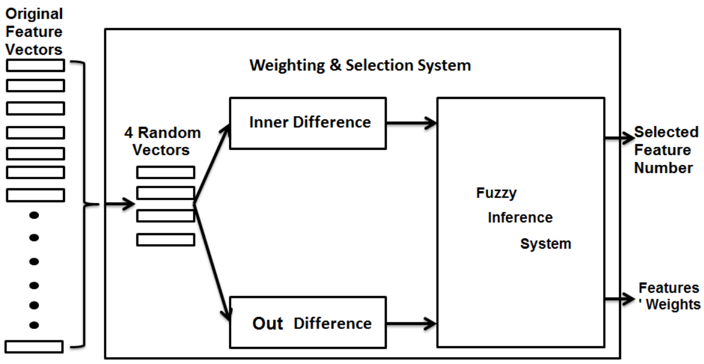

Fig 6. Suggested Weighting and Selection Model

The Weighting and selection algorithm is described below:

1- Choose N random vectors of 4 different persons (Class1, Class2, Class3, Class4) each of them contains 4 different samples F1, F2, F3,F4 for the same vector. So, we have 4*N samples of N classes. (i.e $F1_{3,3}$ is the 3rd sample of class1 where i is the class id, and j is the sample id into class).

2- Calculate the inner difference at the same class to obtain N difference value described in equation 5.

$$InDiff f^{k}_{i,j} = \sum_{i=1}^{N} \sum_{j=1}^{4} \left| F^{k}_{i,j} - F^{k}_{i,j+m} \right| \qquad (5)$$

$where\ k = 1,2,,3,4, \ldots .N\ , (j+m) \le N$

3- Calculate the difference between each two classes to obtain out difference values (Divergence) described in equation 6.

$$OutDiff f^{k}_{i,j} = \sum_{i=1}^{N} \sum_{j=1}^{K} \left| F^{k}_{i,j} - F^{k+1}_{i,j} \right| \qquad (6)$$

$where\ k = 1,2,,3, \ldots, N\ , (j+m) \le N$

4- Calculate the minimum inner difference average defined in equation 7.

$$InDiff f^{k}_{i,1} = \min\left(\frac{1}{N} \sum_{j=1}^{N} InDiff f^{k}_{i,j}\right) \qquad (7)$$

5- Calculate the maximum out difference average defined in equation 8.

$$OutDiff f^{k}_{i,1} = \max\left(\frac{1}{N} \sum_{j=1}^{N} OutDiff f^{k}_{i,j}\right) \qquad (8)$$

6- Build a fuzzy inference system with two inputs which are inner and out difference ($diff_{in}{}^{k}_{i,j}$ and $diff_{out}{}^{k}_{i,j}$), and one output which is the weights of features. Fig 6 illustrates an original and selected feature vector.

7- Choose Features, which achieve the Threshold described in equation (9).

$$Threshold = \max(Weight) - \left(\frac{800}{Num}\right) * \left(\max(Weight) - \frac{1}{Num}\sum_{i=1}^{\max(weight)} Weight_i\right) \quad (9)$$

Where Weight is the weight vectors resulting from fuzzy model, 800 is the required number of weights, Num is the number of original features.

2.5.1 Fuzzy Inference System Specifications:

Input1 is the inner difference (Similarity). The membership functions here are 5 triangular functions with values between 0 and 50. While, Input2 is the out difference (Divergence). The membership functions here are 14 triangular functions with values between 0 and 50, and here the functions have opposite effects of the previous functions. The output is the weight score of each feature which will be on a scale from 1 to 15 and each number represents the importance of the feature. We used the triangular functions because the inner and out difference are linear values range from 0 to 50.

2.5.2 Fuzzy Rules:

We configure a lot of fuzzy rules to build the fuzzy system. The rules take in account different situations in which the inner difference and outer difference changes widely from bad to excellent member values. In the following there is an example of the built rules. If (innerDiff is VeryBad) and (meanOutDiff is VeryBad) then (Weight is one).

2.5.3 De-fuzzification:

we applied the “AND” rule to perform the fuzzy operation, and the MAX way to unify the fuzzy outputs. Finally, calculating the output fuzzy of the system is done by “the centroid of area” method.

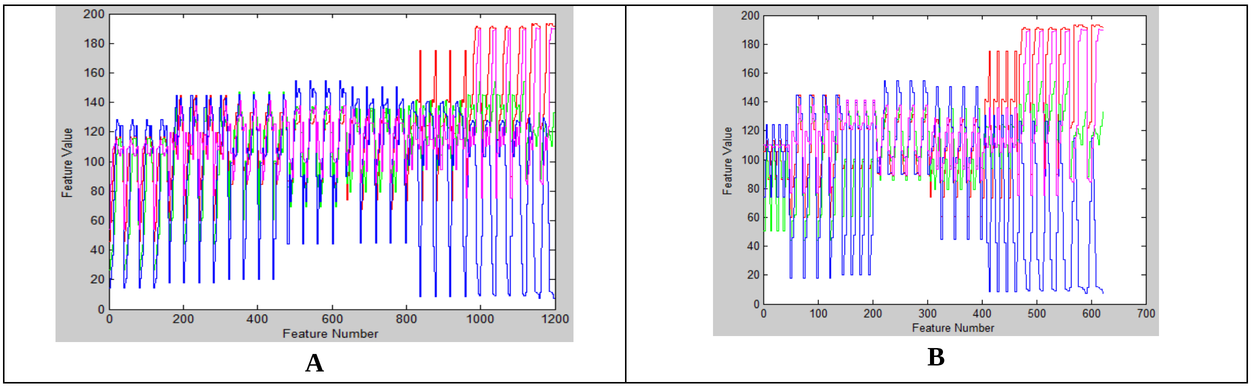

Fig 7. Feature Vector: A. Original, B. Weighted and selected

2.6 Feature Fusion:

The selected features of face and ear are fused together to configure a unified feature vector consists of 16000 face features instead of 60000, and 2000 ear features instead of 8000, and 6900 palm features instead of 15000 . The unified feature vector contains 24900 samples instead of 83000 samples which constitute almost 30% from the original feature vector. This will reduce the required time for the next steps.

2.7 Classification and Recognition:

We suggest using the feed forwarding back propagation neural networks which has the following specifications:

Number of layers:2

Number of neurons in each layer:

- 24900 for input layer which are the number of feature vector samples, 1000 for hidden layer,10 for output.
- Hidden layer function: tansig.
- Output layer function: tansig.
- Training Function: trainlm
- Performance function: Mean Squared Error MSE.

We trained the network using the selected and extracted feature vectors for all individuals in database.

The distances between the NN simulations results of test vector sample and training samples are computed as equation 10 illustrates.

$$d(\vec{x},\vec{y}) = \sqrt{\sum_{i=1}^{N} \frac{(x_i - y_i)^2}{s_i^2}}, \qquad (10)$$

The mahalanobis distance of the subtraction indicates to the individual id that the test sample is the closest to and represents the recognized person.

3. Results:

We used ScFace dataset [6] which contains faces and profile images for each individual with different poses (0^0,30^0, 45^0, 60^0,90^0,120^0,135^0, 150^0, 180^0). We selected 1440 images related to 60 individuals (8 images per one) for face, ear and palm training database. We apply tests on face and ear images separately, then we test the fused features. In order to illustrate the effect of nature and size of testing dataset on the performance rate, we decompose the test dataset into 5 different dataset. Table 1 and fig8 illustrate the nature of each dataset.

Table 1. The four different test datasets used in this search.

Dataset	Size	Nature of images
Dataset01	200 (90 ear, 110 face)	Normal images with different pose variations (30^0, 45^0, 60^0,90^0,120^0,135^0, 150^0, 180^0)
Dataset02	290 (120 ear, 170 face)	Pose Variations, Occlusion with hair and earrings for ear, Partial cutting of face or ear.
Dataset03	616 (216 ear, 400 face)	Adding the frontal images (0^0 pose)
Dataset04	806 (296 ear, 510 face).	Same as Dataset03
Dataset05	1136 (200 ear,468 face, 468 palm print)	Add Palm print to DB 4

Figure 7 includes samples of ear and face images of the four datasets.

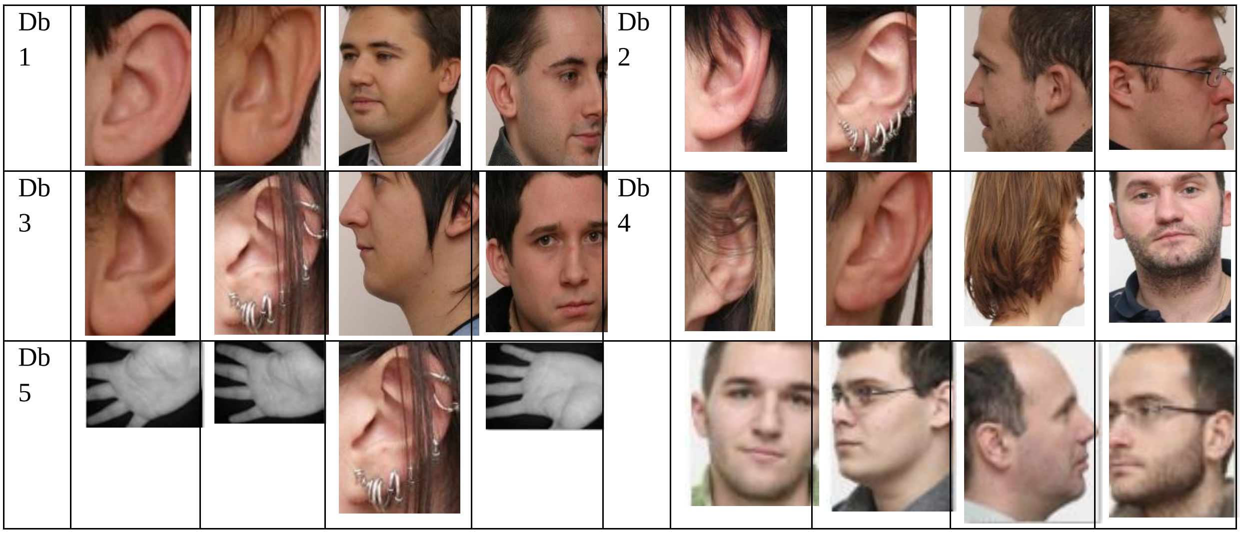

Fig 8. Samples of ear and face images of the four datasets

The recognition rate for ear and face testing datasets separately and fused are shown in table 2.

Table 2. Recognition rate for each dataset.

Type	Dataset01	Dataset02	Dataset03	Dataset04	Database05
Face	%92.38	%89.3	%89.38	%92.08	%92.08
Ear	%84.5	%80.32	%82.87	%86.04	%86.04
Palm	-	-	-	-	%93.75
(Face +Ear) Fusion	%95.5	%91.46	%93.33	%94.33	-
Fusion (Face + Ear + Palm)	-	-	-	-	%97.4

The recognition rate drops from 92.38% to 89.3% in dataset02 under effect of partial occlusion by hair and earrings in ear images. However, it rises again in dataset03 and dataset04 under effect of adding the frontal face images which are easier to be recognized than other poses. The best result is the fusion result of face, ear and palm, which is 97.4%.

From table 2, we can also see that recognition rate do not degrade under rising up the size of test dataset (i.e. dataset04 is bigger than dataset03 1.3 times but the recognition rate of set04 is bigger than set03) which means that the selected features are independent of datasets size. Also, by adding another biometric, the recognition result is improved.

3.2 Classification Time Comparative:

Table 3 includes comparative results of the classification rate and time at different situations of feature vector for dataset 4.

Table 3 Classification rate and time comparative.

Feature Vector Size	Time (in seconds)	Recognition rate (%)
Hall Feature Vector	0.18	95.3%
First 500 samples	0.042	79.9%
512 selected samples	0.032	82%
16200 selected samples (face+ear)	0.1	94.33%
24900 (face+iris+palm)	0.21	97.4%

Discussion

The result shows the following significances:

- The classification time of the selected features is lower than the hall ones.
- The recognition rate of the selected features decreases between 0.01% to -1.5% in comparing to the original hall features although that the selected features constitute only 26% from the original. In other words, the selected promised features, which constitute only 30% from feature vector, preserved a high performance and decreased the classification time (goal of our research).
- By adding a third biometric (palm), the recognition rate increases by almost 3%.
-

IV. CONCLUSION

The suggested study introduces a new algorithm to select the best features from feature vector of face, ear and palm images in order to preserve a high performance and decrease the classification time. The algorithm can deal with illumination problem by a new technique correcting the illumination by studying the histogram. The segmentation part can take any face image with different poses (frontal or profile) and extract the correct biometric (face or ear), and the classification method depends on training neural network.

The experimental tests show that the selected and weighted features always preserve high performance and low classification time and they are independent off the nature of database, and the system achieved 94.33% and 97.5% recognition rates (face+ear, face+ear+palm) in presence of pose and illumination variations, partial occlusion by hair or earrings and some deforming in test samples.

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