MULTIWAVELET TRANSFORM AND MULTI-DIMENSION-TWO ACTIVATION FUNCTION WAVELET NETWORK USING FOR PERSON IDENTIFICATION[1]

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Abstract

The relatively new field of Multiwavelets shows promise in removing some of the limitations of wavelets. This paper introduces a new human face recognition using the combination of Multiwavelet transform (MWT) and multidimension-Two Activation Function Wavelet Network (MD-TAFWN). After taking the MWT of the image, it is required to divide the approximate quarter into four parts and rearrange them in 3D form. Next, this 3D data will be fed into a proposed MD-Two Activation Function Wavelet Network. This is for face image. For the fingerprint image,it is required to divide the approximate quarter into four parts and rearrange them in 3D form. Next, this 3D data will be fed into a proposed MD-Two Activation Function Wavelet Network.The proposed transform is considered as a feature extractor of the decomposed reference images with different frequency sub bands, and amid-range frequency sub band for data image to the representation of the given image. Evaluations have generally shown that the technique of the combination for Discrete Multi-wavelet Transform (DMWT) and the Two Activation Function Wavelet Network (MD-TAFWN) is interesting and promising. The results obtained showed that the combination technique outperformed. other conventional methods that use a given transform with neural Network (NN). It results in a perfect recognition of 100% to a data base which consists of 100 human face images.

Key Words: Biometric, Multiwavelet, Wavelet Network, Face Identification, Fingerprint Identification.

الخلاصة

نظرا لكثرة الاهتمام في الوقت الحاضر بموضوع تمييز الاشخاص والتاكد منهم وتطبيقها في المحاور الامنية والاقتصادية لذا تم في هذا البحث اقتراح طريقة جديدة في عملية التمييز هذه وذلك عن طريق تركيب هجين يتكون من محول متعدد الموجة (Multiwavelet Transform) مع الشبكة المويجية (Wavelet Network) والتي تم اقتراح طريقة جديدة هي لها (Multi-dimension Two Activation Function Wavelet Network) . تم في هذا البحث استخدام صورة الوجه وبصمة الابهام الايمن والايسر لتمييز الاشخاص و يتم ادخال صورة الوجه الى (MWT) ويتم استخدام الجزء (L2L2) فقط والتي تجزأ الى اربعة اجزاء ثم يتم ادخاله الى (MD-TAFWN) للحصول على متجه التمييز والذي يتم خزنه في قاعدة بيانات خاصة يتم استدعائه في حالة الاختبار.

بعدها يتم ادخال صورة البصمة للشخص ويتم اجراء نفس الطريقة السابقة عدى انه يتم تجزئة (L2L2) الى ستة عشر جزء ثم يتم ادخاله الى (MD-TAFWN) للحصول على متجه التمييز الخاصة بها وايضا يخزن في قاعدة بيانات خاصة.

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1. Introduction

Face and fingerprint tracking and recognition are important parts of our daily lives. Tracking an object under time varying position and orientation is a basic ability of the human visual system [1]. Studies [1] show that infants are, in some way, preprogrammed to recognize and pay attention to faces more than other objects. Throughout our lives people present their face as a form of recognition in person and through the use of photo recognition cards such as a driver's license or passport. Since face and fingerprint recognition are so pervasive in the natural world, it is reasonable to consider faces and fingerprints as a means to recognition using machines.

So far, robust algorithms to perform automated face and fingerprint tracking and recognition in unconstrained environments have not been achieved. To further complicate matters, psychology suggests that the principal means of recognition used by humans changes from a primarily feature-based method in childhood to a primarily holistic-based method in adulthood [1]. Which method, if either, will work best in an automated recognition system? A great wealth of research has been done in many fields to determine how to best track and recognize faces, how to simulate (or surpass) human face tracking and recognition performance [2], and how to overcome difficulties that hinder the development of automated face tracking and recognition. There are several imaging modalities: video, infrared, and three dimensional (3D) scanning. Although there has been tremendous research in video, other modalities deserve attention[4]. Many issues hinder research efforts in the field of face and fingerprint recognition. Variation exists in every imaging modality used, and finding fast, simple algorithms that are robust to variation is difficult (as evidenced by years of research). Categorizing the variation may be helpful in the development of effective face and fingerprint recognition algorithms. Intrinsic sources of variation include identity, facial expression, speech, gender, and age [1]. Extrinsic sources of variation include viewing geometry, illumination, imaging processes, and other objects. Viewing geometry includes pose changes, either by the observer or the object to be recognized; illumination changes include shading, color, self-shadowing, and specula highlights; imaging process variations include resolution, focus, imaging noise, sampling technique, and perspective distortion effects; variation from other objects include occlusions, shadowing, and indirect illumination. These sources of variation may or may not hinder the recognition process depending on which algorithm is used. It is possible that the variation due to factors such as facial expression, lighting, occlusions, and pose is larger than the variation due to identity [1,3]. That makes identification under such varying environments a difficult task. However, human proficiency at face recognition [5] has motivated enormous research in this area despite these challenges. (The ability of humans to recognize faces is also an actively researched field with widely varying results depending on numerous factors. Many reviews of face recognition are available [6, 7, 8, 9, 10]. Samal and Iyengar (1992) [8] describe several techniques they refer to as nonconnectionist. Most of these techniques operate on 2D images and are concerned with finding intra-feature distances, angles, and areas. A complementary survey by Valentin et al. (1994) [9] covers connectionist (statistical) methods of face processing. Connectionist methods of face processing usually take 2D image data and work with pixel values of entire face images (instead of extracting features from a subset of the total pixels for an image as is done in nonconnectionist approaches). Because full images are used in these techniques, the relationships between features within the image, texture, and shape information are preserved. Nonconnectionist and connectionist techniques are also called geometrical and statistical respectively [7,10, 11]. Chellappa et al. (1995) [6] draw the following conclusions: 1) The upper parts of the face should play a dominant role in recognition, 2) Eigenface and feature point based methods are currently the most developed and should undergo additional testing in realistic situations with thousands of faces, 3) Neural approaches should be developed further and should be tested on much larger databases. The approaches cited in this survey use between 16 and 80 faces.

2. Proposed method for Multi-biometric Identification

2.1 Training Method

1. Input seven images for each person (three face images, two right thumb fingerprint images and two left thumb fingerprint images) figure (1).
2. Take the multiwavelet transform (MWT) using (GHM) for each image.
3. Take (L2L2) only of the (MWT) for each image.
4. Segment (L2L2) to four segments for each image.
5. Take the first segment of the first person and entere it to (TAFWN) using the following algorithm (figures (2,3,4,5,6):

a) Given an initial value of ($a_{1,1}$,$a_{1,2}$,$a_{1,3}$,$b_{1,1}$,$b_{1,2}$,$b_{1,3}$,$w_{1,1}$,$w_{1,2}$,$w_{1,3}$,$a_{2,1}$,$a_{2,2}$,$a_{2,3}$,$b_{2,1}$,$b_{2,2}$,$b_{2,3}$,$w_{2,1}$,$w_{2,2}$,$w_{2,3}$) and given an accepted error (E=0.001).

b) Take the first row of the first segment and entere it to (MD-TAFWN) where the input neurons (n)are equal to the number of the rows and the column of the segments(n*n) and the hidden neurons are three and the output neuron is one where the output equals the number of person.

c) Since the images are to the first person then the output (Y=1) then find the error (E_1).

d) Update the parameters (a,b,w) using there update equations, then entere the second row of the first segment and find the error (E_2) where the output also equals one (Y=1).

e) Update the parameters (a,b,w) using there update equations, then entered the third row of the first segment and find the error (E_3) where the output also equal to one (Y=1).

f) Continue the above procedure until you reach the last row then find (E_n).

g) Find the summation of error (E_{sum}=E_1+E_2+E_3+E_4+……+E_n). then find the mean of the error where (E_{mean}=0.5*E_{sum}).

h) If (E_{mean}> E_{th}) then the above procedure returns until (E_{mean}< E_{th}). At this point finishing and take the last parameters (a,b,w) (vector 18*1) as an initial to the second segment of the same image.

i) Apply the above procedure on the second segment and then third and then fourth segment where the last value of the parameters used as an initial for the next segment until finished the fourth segment then the final parameters (a,b,w) (vector 18*1) used as an initial for irst segment of the second image of the person one (N=1 and Y=1).

6 . Take (L2L2) of the second image of person one (N=1) and apply step (5) on it then the last parameters (a,b,w) used as an initial to the third image of person and applied also step (5) to it then the last parameters ($a_{1,1}$,$a_{1,2}$,$a_{1,3}$,$b_{1,1}$,$b_{1,2}$,$b_{1,3}$,$w_{1,1}$,$w_{1,2}$,$w_{1,3}$,$a_{2,1}$,$a_{2,2}$,$a_{2,3}$,$b_{2,1}$,$b_{2,2}$,$b_{2,3}$,$w_{2,1}$,$w_{2,2}$,$w_{2,3}$) (vector 18*1) used as a representative to person one, this mean that three image of one person can be represented only by vector (18*1).

7. Apply steps (5,6) on the four images of the fingerprint of person one where also used the output (Y=1) where the result the person number one can be represented by two vectors (18*1) one for the face of the person and the other represented the fingerprint (right and left thumbs) of the person therefore person one represented by vector (36*1) then save it in database matrix.

8. Take seven images of the second person and apply steps (5,6,and 7) on it then save it's vector (36*1) where the output become (Y=2).

9. Complete the images of each persons and apply the above procedure on it where the output (Y=3,4,5….M) where (M) represented number of persons, at the end a database matrix (36*M) saved.

2.2 Testing Method

1) Input seven images (three images for face and four images for fingerprint (two for the right thumbs and two for the left thumbs)) for the person.

2) Taking (MWT) using (GHM) method for each image.

3) Taking (L2L2) only and segment it for four segment for the face image and for sixteen segments for the fingerprint images.

4) Select randomly one row from each segment and entered it to (TAWN) where used the parameters of the database matrix of training method then find the error with each person the minimum error which or less than threshold value (***t***) then the image represented this person, this result represented score one (***S1***) (for face identification), and score two (***S2***)(for fingerprint identification).

5) If (***S1***=person ***N***) and (***S2***=person ***N***) then the result is person ***N*** but if (***S1***=person ***N***) and (***S2***=person ***M***) then if the percentage of ***S1*** more than ***S2*** then the person is ***N*** but if the percentage of ***S2*** more than ***S1*** then the person is ***M.*** (figure (7)).

6) The above procedure is for identification, in case of verification the same procedure can be done but in step four used the column of parameters of the database which represented the claimed person then if (***S1***=claimed person) and (***S2***=claim person) then the result is this person but if (***S1***=claimed person) and (***S2***=unclaimed person) and used ***AND*** configuration then the result is failure.(figure (8))

3.Evaluation Tests

To perform recognition experiments we first need to create two sets of images: training and testing. Training images are used to generate a data base matrix saved to recognize the test images where in proposed method used three face images and four fingerprint image for each thimb for each person for training, test images are a set of range images of faces we wish to identify. Any subject we wish to identify must have at least one facial range image in the training data set. The faces and fingerprint in the test range images need not have the same facial expressions as those in the training data set. Each test image is then reshaped as a column vector where in proposed method used vector (18*1) to represented all the three face images of the same person and other vector (18*1) to represented the four fingerprint images of the same person therefore each person can be represent only by vector (36*1) also the database matrix will be (36*M) where (M) is the number of identification person. Any input test image applied the same procedure on it then make a correlation with the data base matrix in order to get on the maximum value of this matrix means that the test face and fingerprint images represented the person who the maximum value lied in his column where each column in the data base matrix represented one person.

Cumulative Match Characteristic (CMC) curve shown in figure (9) for identification and the receiver operating characteristic (ROC) curve shown in figure (10) for verification where the same procedure used but the comparison made with the column of the claimed person.

Table (1) and table (2) using the **OR** and **AND** configuration respectively to identification

4. Conclusions

It was shown throughout this paper that proposed combination had a great impact on the capabilities of all image techniques. The method of person identification was implemented and tested based upon the proposed combination. This paper introduced a combining of the Discrete Multi-wavelet Transform (2D-DMWT) of Repeated Row Algorithm (RRA) and the Multi-dimension Two Activation Function Wavelet Network (MD-TAFWN) .The advantage of this method can be summarized as follows:

1) The combined technique achieved an excellent result of 100%.

2) This method can give an excellent representation of the data images as well as reduce the huge information obtained as a matrix to vector one.

3) This proposed combination is important in many applications particularly when the a data rate is required and when a limited bandwidth or small memory is available.

This is achieved by the excellent combination between Multiwavelet Transform and Two Activation Function Wavelet Network where (MWT) given a good image with reduced external effect such as noise or illustration and with minimum size and without loss any information from the image. Also (TAFWN) given an excellent feature extraction vector represented the input image where an image (128*128) can be represented by (18*1) vector only. Also the segmentation of the image before we enter to the (TAFWN) reduced the effect of the facial expression.

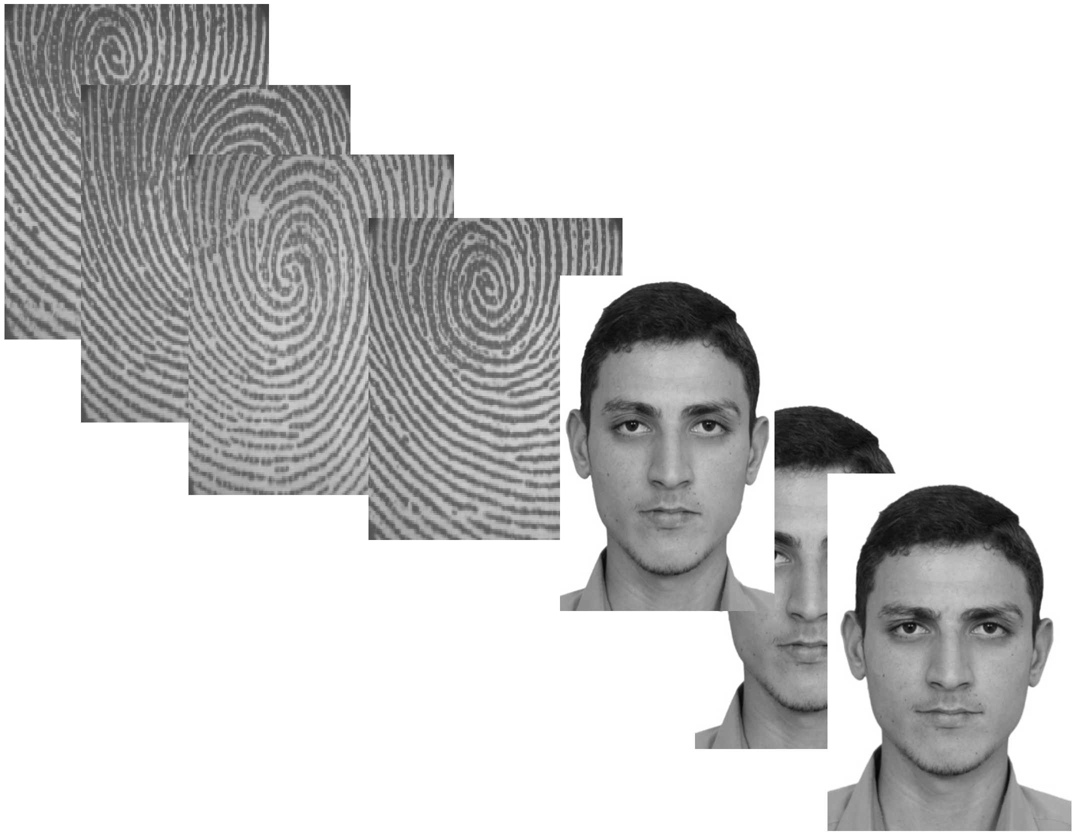

Figure (1) Seven Input images.

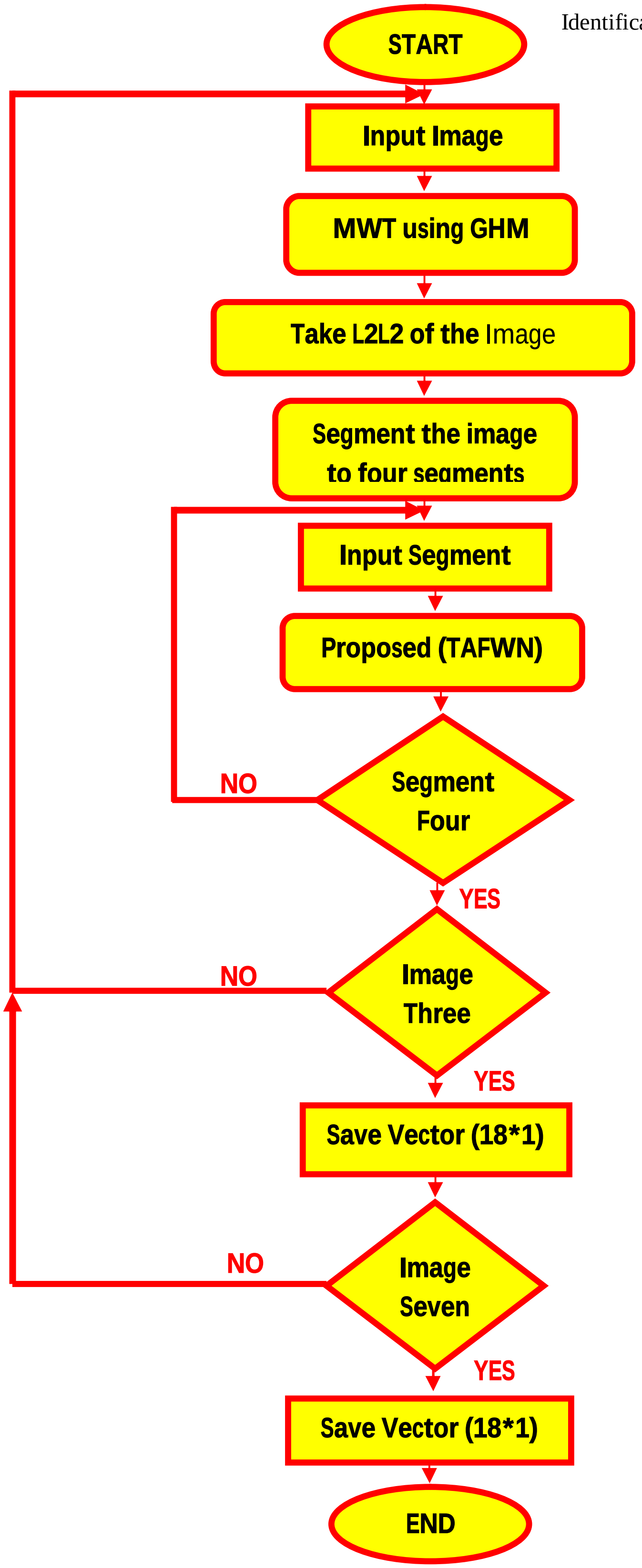

Figure (2) The Mechanization of the Proposed Algorithm for face identification.

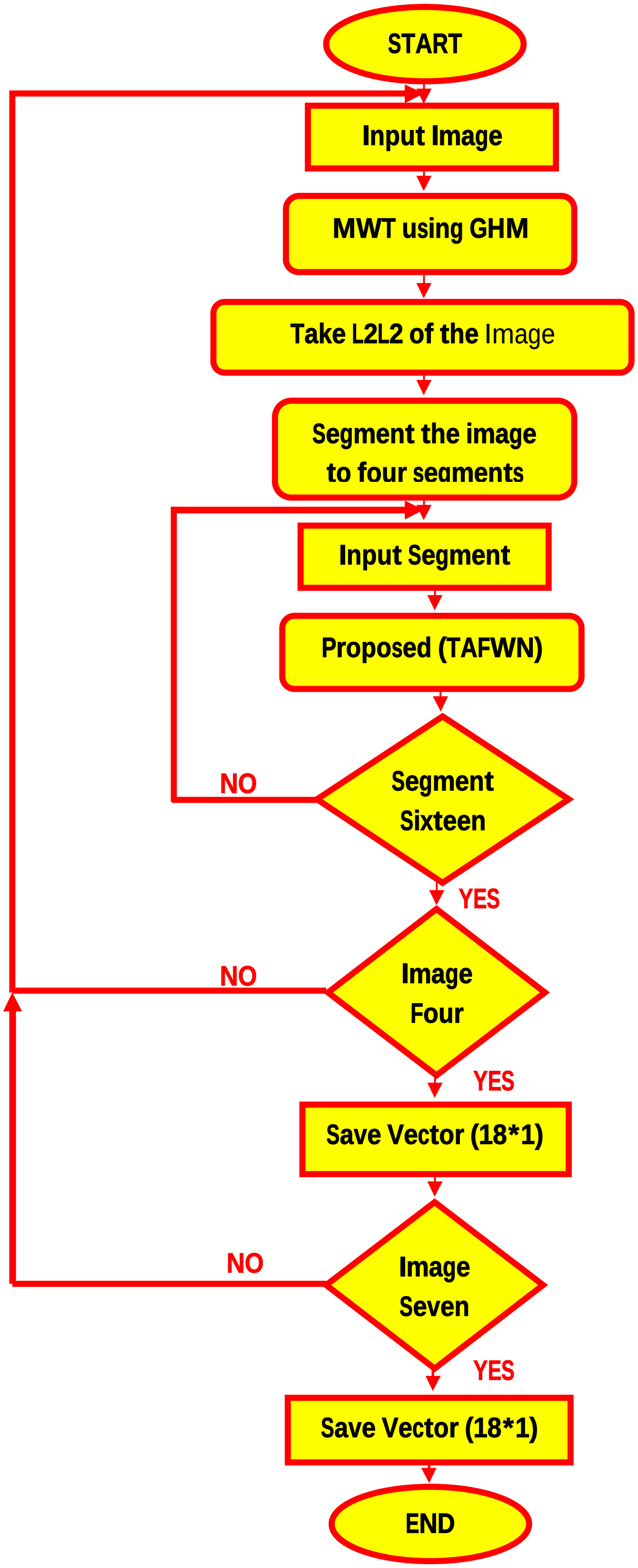

Figure (3) The Mechanization of the Proposed Algorithm for fingerprint identification.

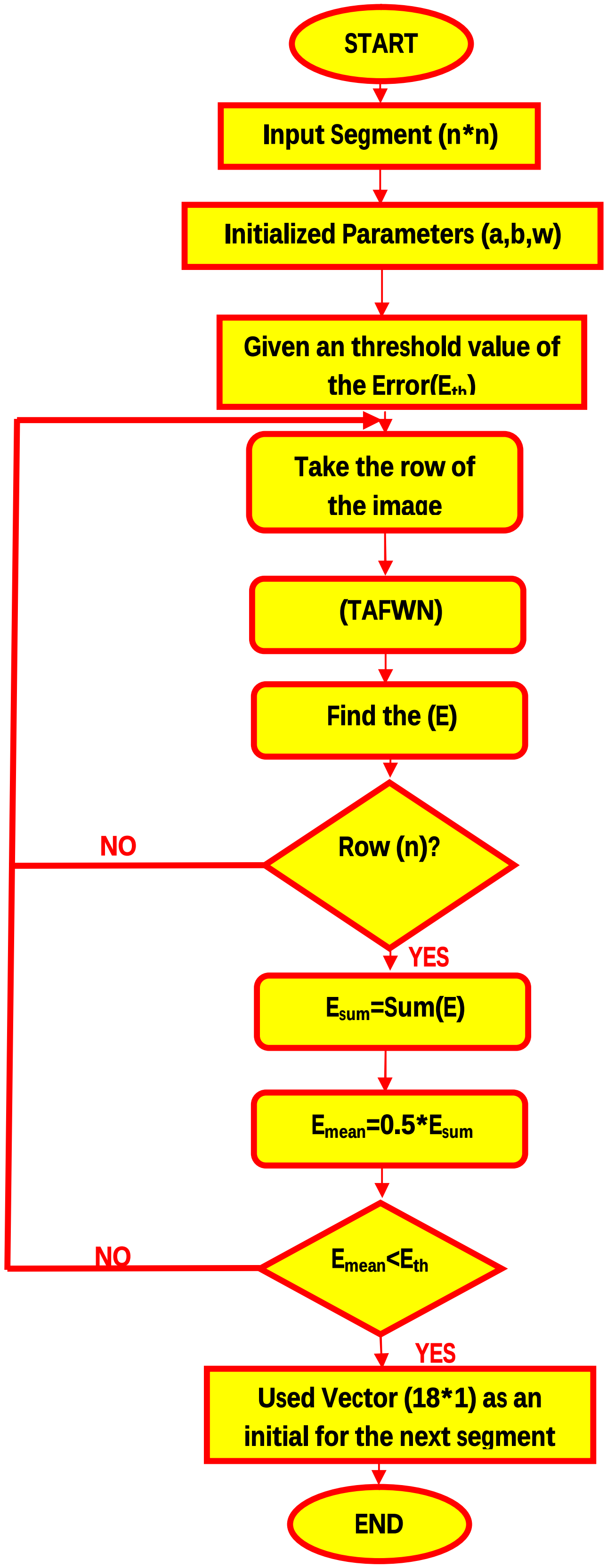

Figure (4) The Mechanization of the Proposed Algorithm of TAFWN.

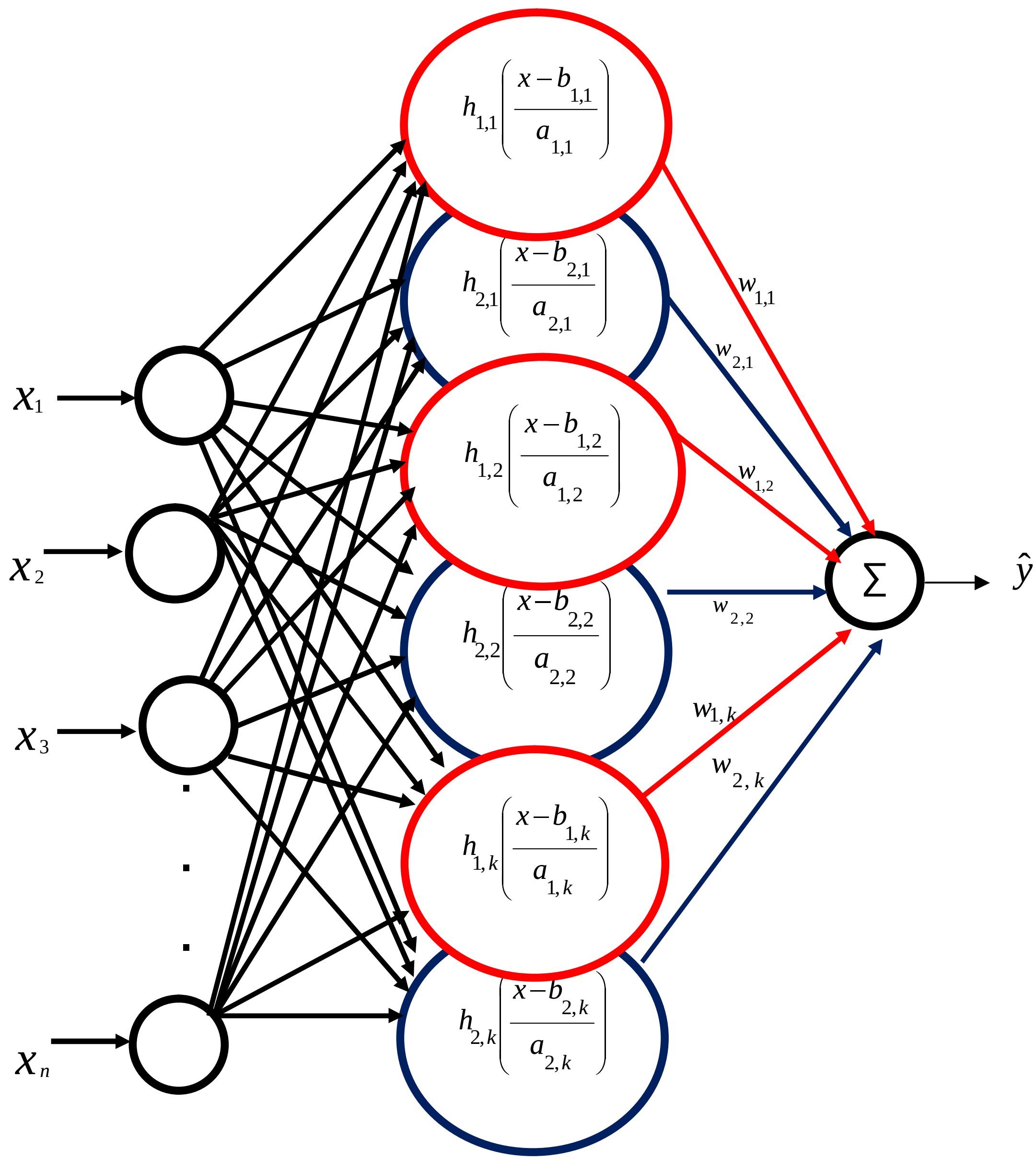

Figure (5) The block diagram of the Proposed Algorithm of TAFWN.

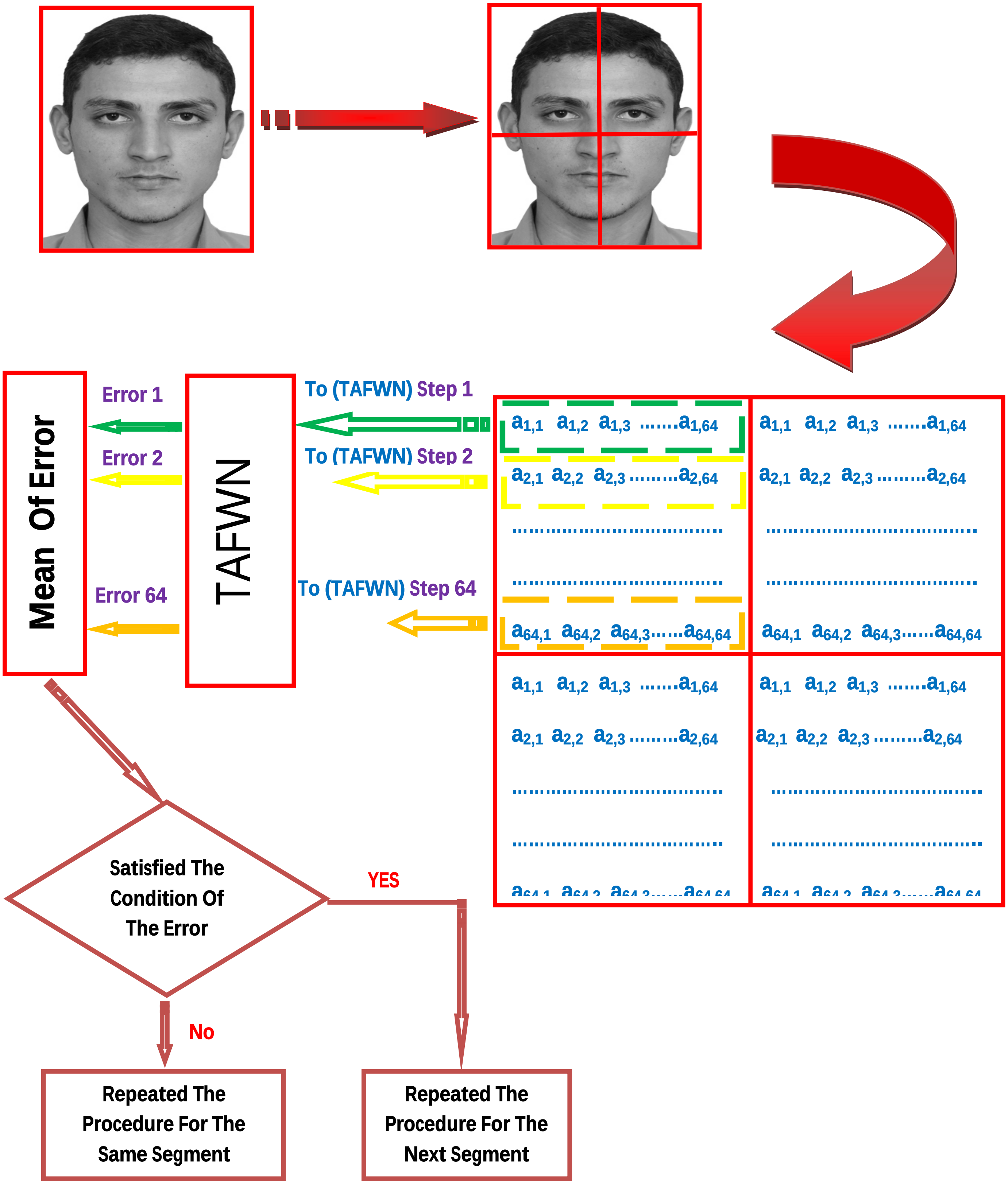

Figure (6) The block diagram of the Proposed Algorithm.

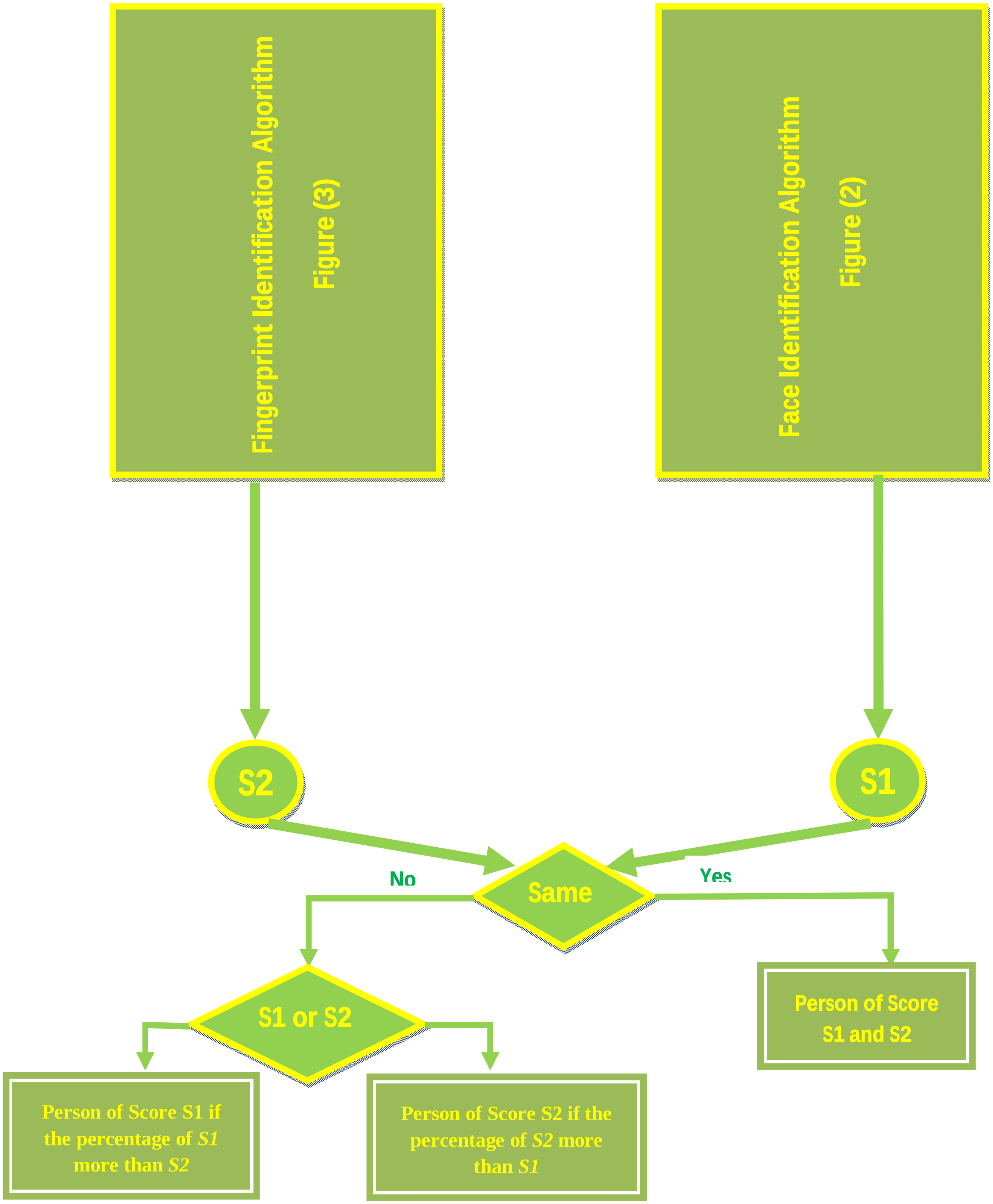

Figure (7) The block diagram of the test identification Proposed Algorithm.

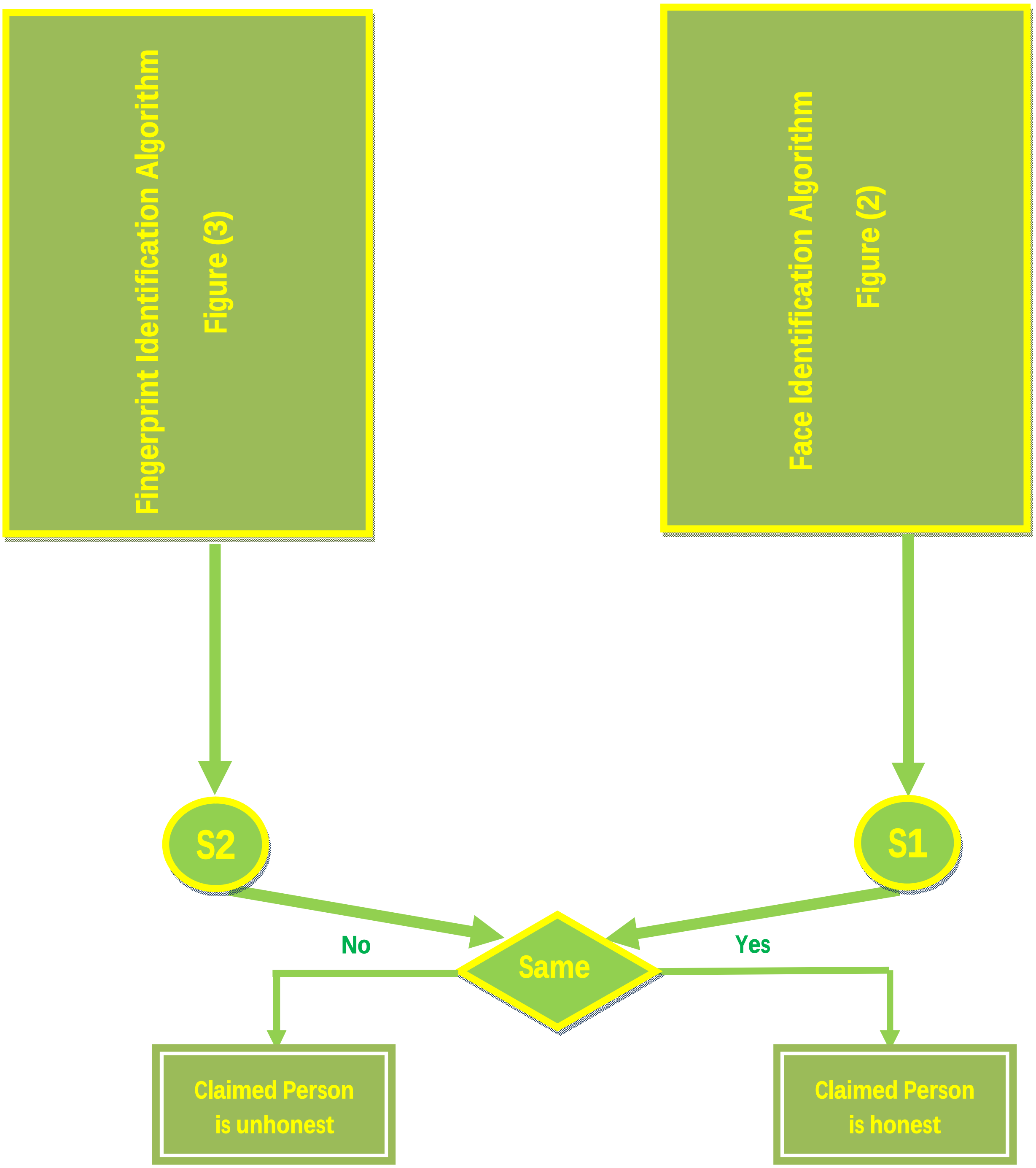

Figure (8) The block diagram of the test verification Proposed Algorithm.

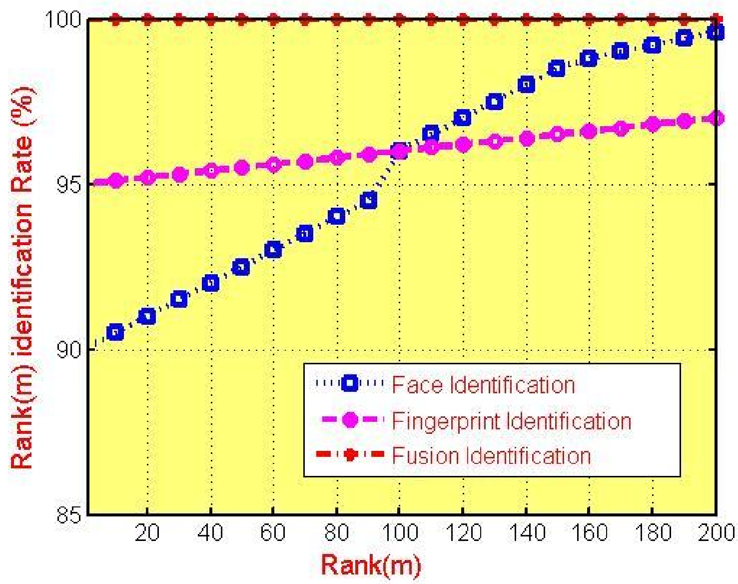

Figure (9) Cumulative Match Characteristic (CMC) curve.

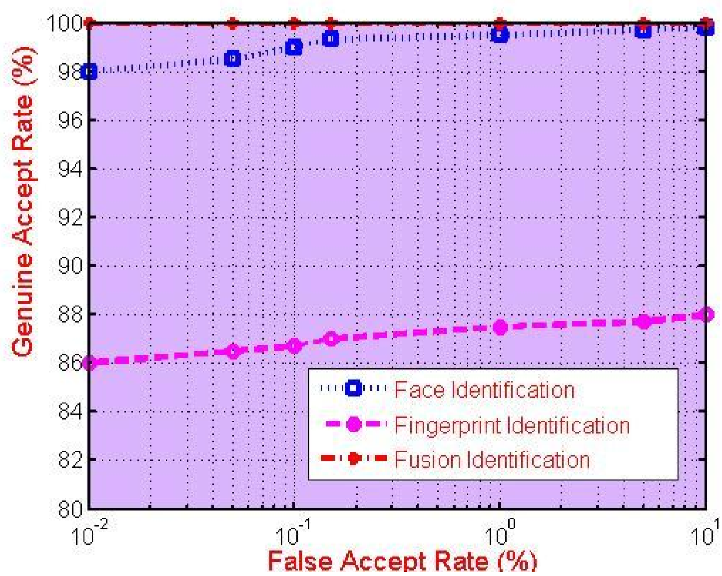

Figure (10) The receiver operating characteristic (ROC) curve.

Training Images	Test Images	Input FPI confirmation	Input FI confirmation	% Correctly identification
150	800	4	3	100%
60	480	4	3	100%
150	800	3	2	87.3%
40	200	3	2	89.2%
150	800	2	1	83.4%
60	480	2	1	84.7%
150	800	4	2	97.4%
40	200	4	1	99.1%
60	480	3	3	95.6%
40	200	3	3	96.2%

Table (1) Training and Test images with correctly identification using the OR configuration.

Training Images	Test Images	Input FPI confirmation	Input FI confirmation	% Correctly identification
150	800	4	3	100%
40	200	4	3	100%
150	800	3	2	83.6%
40	200	3	2	85.3%
150	800	2	1	80.1%
60	480	2	1	82.4%
40	200	4	2	87.4%
150	800	4	1	84.9%
40	200	4	1	86.2%
60	480	3	3	86.6%

Table(2) Training and Test images with correctly identification using the AND configuration.

References

1) Gong, Shaogang, Stephen J. McKenna, Alexandra Psarrou. Dynamic Vision: From Images to Face Recognition. Imperial College Press, 2000.

2) Zhao, W. Y., Rama Chellappa, A. Rosenfeld, P. J. Phillips. Face Recognition: A Literature Survey. UMD CfAR Technical Report, CAR-TR-948, 2000.

3) Howell, A. Jonathan, Hilary Buxton. Towards Unconstrained Face Recognition from Image Sequences. Proceedings of the International Conference on Automatic Face and Gesture Recognition, Killington, VT, pp. 224-229, 1996.

4) Daugman, John. Face and Gesture Recognition: Overview. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 19, issue 7, July 1997.

5) Srivastava, Anuj, Xiuwen Liu, Brian Thomasson, Curt Hesher. Spectral Probability Models for IR Images and their Applications to Face Recognition. Proc. of Computer Vision and Pattern Recognition workshop on Beyond Visual Spectrum, Hawaii, 2001.

6) Barrett, William A. A Survey of Face Recognition Algorithms and Testing Results Conference Record of the Thirty-First Asilomar Conference on Signals, Systems, and Computers, pp. 301-305, 1998.

7) Chellappa, Rama, Charles L. Wilson, Saad Sirohey. Human and Machine Recognition of Faces: A Survey. Proc. IEEE, vol. 83, no. 5, pp. 705 - 740, May 1995.

8) Fromherz, Thomas. Face Recognition: A Summary of 1995-1997. Technical Report ICSI TR-98-027, International Computer Science Institute, Berkeley, 1998.

9) Samal, A., P. A. Iyengar. Automatic Recognition and Analysis of Human Faces and Facial Expressions: A Survey. Pattern Recognition, vol. 25, no. 1, pp. 65-77, 1992.

10) Valentin, Dominique, Herv_e Abdi, Alice J. O'Toole, Garrison W. Cottrell. Connectionist Models of Face Processing: A Survey. Pattern Recognition, Vol. 27, no. 9, pp. 1209-1230,1994.

11) Turk, Matthew, Alex Pentland. Face Recognition using Eigenfaces. Proc. IEEE Conference on Computer Vision and Pattern Recognition, pp. 586-591, Maui, Hawaii,1991.