Fingerprint and Iris Fusion for personal Identification

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Abstract

A variety of researches Dealt with the fusion of multi-biometrics for identification in different ways and Showed different results. This paper presents novel study on fusion strategies for personal identification using fingerprint and iris biometrics. The purpose of our paper is to investigate whether the integration of iris and fingerprint biometrics can achieve performance that may not be possible using a single biometric technology. We propose to use two activation function wavelet neural network for feature extraction and identification process after segments the fingerprint image into 16 blocks with (128*128) dimensions and segments the iris image into 32 blocks with (128*128) dimensions. The proposed method in this paper involves three steps. First reduced image size using wavelet packet 1-level decomposition , second feature extraction using two activation function wavelet neural network and identification using trained data and correlation for fingerprint and iris separately and finally fusion fingerprint and iris match scores to get the finally score for each person.

Keywords: fingerprint, iris, wavelet packets, wavelet networks, two activation function networks

المستخلص

تناولت العديد من الابحاث موضوع اندماج القياسات الحيوية لاستخدامها في كشف الهويةواظهرت نتائج مختلفة ,يقدم هذا البحث دراسة جديدة حول الموضوع باستخدام بصمة الاصبع وقزحية العين .الغرض من هذا البحث هو التحقق في ما اذا كان التكامل بين بصمة الاصبع والقزحية ممكن ان يحقق اداء لا يتم باستخدام تقنيةالقياس الحيوي المنفرد. تم اقتراح استخدام دالتي تفعيل لشبكات المويجات لاستخلاص المميزات بعد تجزئة صورة بصمة الاصبع الى (16) جزء وتجزئة صورة القزحية الى (32) جزء وان ابعاد الصور قبل التجزئة (128*128).ان الطريقة المقترحة في هذا البحث تتضمن ثلاث خطوات:الخطوة الاولى تقليل حجم الصورة باستخدام حزمة المويجة , الخطوة الثانية استخلاص المميزات باستخدام دالتي تفعيل لشبكات المويجات وكشف الهوية باستخدام طريقة التطابق ,والخطوة الاخيرة الاندماج بين بصمة الاصبع والقزحية للتوصل الى النتيجة النهائية لكل شخص.

Introduction

Biometric systems that utilize more than one physiological or behavioral characteristic for identification are called multimodal biometric systems. Multimodal biometric identification system is a new approach. Biometric fusion is generally classified in terms of both categories and levels. The categories define what inputs or processes are being used for fusion and the levels define how the fusion performed [1].

Categories of fusion: Multi-sample, Multi-instance, Multi-modal, and Multi-algorithm [2]. The Evidence in a multi-biometric system can be integrated in several different levels as described below [3]:

- Sensor level: The raw data acquired from multiple sensors can be processed and integrated to generate new data from which features can be extracted. For example, in the case of face biometrics, both 2D texture information and 3D depth (range) information (obtained using two different sensors) may be fused to generate a 3D texture image of the face which could then be subjected to feature extraction and matching.
- Feature level: The feature sets extracted from multiple data sources can be fused to create a new feature set to represent the individual. The geometric features of the hand, for example, may be augmented with the eigen-coefficients of the face in order to construct a new high-dimension feature vector. A feature selection/transformation procedure may be adopted to elicit a minimal feature set from the high-dimensional feature vector.
- Match score level: In this case, multiple classifiers output a set of match scores which are fused to generate a single scalar score. As an example, the match scores generated by the face and hand modalities of a user may be combined via the simple sum rule in order to obtain a new match score which is then used to make the final decision.
- Decision level: When each matcher outputs its own class label (i.e., accept or reject in a verification system, or the identity of a user in an identification system), a single class label can be obtained by employing techniques like majority voting, behavior knowledge space, etc.

Fingerprint: A fingerprint is the pattern of ridges and valleys on the surface of a fingertip. Humans have used fingerprints for personal identification for many decades and the matching accuracy using fingerprints has been shown to be very high for verification systems and small- to medium-scale identification systems involving a few hundred users. Fingerprints of identical twins are different and so are the prints on each finger of the same person [4] .we used CASIA fingerprint database.

Figure (1) samples of fingerprint and iris database

Iris: The iris is the colored ring of textured tissue between the pupil and the white ofthe eye. The formation of each iris is stabilized by the age of two, and even twins have different iris patterns. Irises can only be altered by surgery, and it is therefore very difficult to impersonate someone based on this characteristic. This textured tissue of the iris possesses a unique mesh-like structure of features forming a complex pattern .The pattern can contain some of the following features: arching ligaments, ridges, crypts, corona, freckles, pits, furrows, straights, and rings[5]. In this paper we use Palacký University iris database [6], some samples of fingerprint and iris images shown in figure (1).

2. Wavelet Packets (WP)

The wavelet packet method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis and which allows the best matched analysis to a signal as in figure(2). It provides level by level transformation of a signal from the time domain into the frequency domain [7]. It is calculated using a recursion of filter decimation operations leading to the decrease in time resolution and increase in frequency resolution. The **WP** divides not only the low, but also the high frequency sub band. In wavelet analysis, a signal is split into an approximation and a detail coefficient. The approximation coefficient is then itself split into a second level approximation coefficients and detail coefficients, and the process is repeated. In wavelet packet analysis, the details as well as the approximations can be split. When the wavelet transform (WT) is generalized to the WP, not only can the low pass filter output be iterated through further filtering, but the high pass filter can be iterated as well so it offers a more complex and flexible analysis. To computation WP We start with the two filters of length 2N.

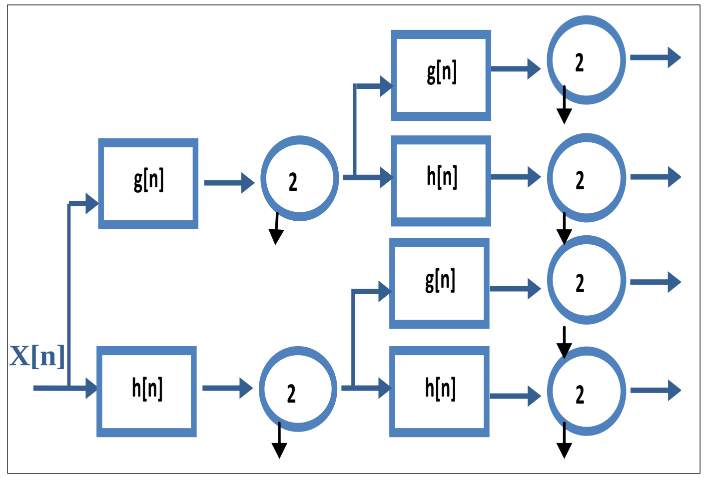


Figure (2) wavelet packet decomposition

Wn(x), n=(0,1,2,3)

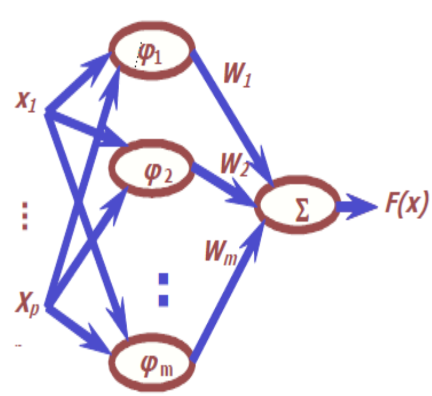
$$W2n(x) = \sqrt{2}\sum_{k=0}^{2N-1} h(k)Wn(2-k) \text{......................} (1)$$

$$W2n+1(x) = \sqrt{2}\sum_{k=0}^{2N-1} g(k)Wn(2x-k) \text{..............} (2)$$

$h(n)$ and $g(n)$, corresponding to the wavelet.

$W0(x) = \Phi(x)$ is the scaling function and $W1(x) = \Psi(x)$ is the wavelet function.

3. Wavelet neural network



Wavelet Networks attempt to combine the properties of the Wavelet decomposition, along with the

Figure (3) The WNN architecture

characteristics of neural networks [8] .Their structure relies on the aforementioned principles underlying non-linear function approximation. The idea of using wavelets in neural networks has been proposed recently by Zhang and Benveniste, Pati and Krishnaprasad [9]. The network architecture is shown in Figure (3), Wavelet Neural Networks (WNNs) has recently attracted great interest, because they are universal approximations, it's achieved faster convergence than Radial Basis Function Neural Networks (RBFNN) and are capable to deal with the problems of "curse of dimensionality". In addition, WNN are generalized RBFNN [10].The structure of the WNNs is similar to the RBFNNs, except the radial basis function is replaced with or to normal basis functions Wavelet Networks have the advantage, that the wavelet coefficients are directly related data stream through the wavelet transform. in addition ,the parameters of the wavelets in the WNs are subject to optimization wavelet networks and neural networks (in particular, Radial Basis Functions) are very often used as non-parametric estimators in the fields of function approximation and system modeling. Wavelet Networks (WNs) are an implementation of Wavelet Decomposition, a technique which has recently emerged as a powerful tool for many applications in the field of signal processing, such as data compression and function approximation. The Two Activation Function Wavelet Network (TAFWN) is very similar to wavelet Network (WN) but have some important differences, whereas wavelets has an associated scaling function ϕ(t) and wavelet function ψ(t), TAFWN has two scaling ϕ1(t), ϕ2(t) and two wavelet functions ψ1(t), ψ2(t). Accordingly, there are two scaling filters and two wavelet filters. in This paper using the combination of the wavelet packet Transform (WPT) and Two Activation Function Wavelet Network (TAFWN), figure(4) explain how TAFWN work. The result obtained by the suggested method is promising and will shed some light to encourage researchers to adopt this technique [11].

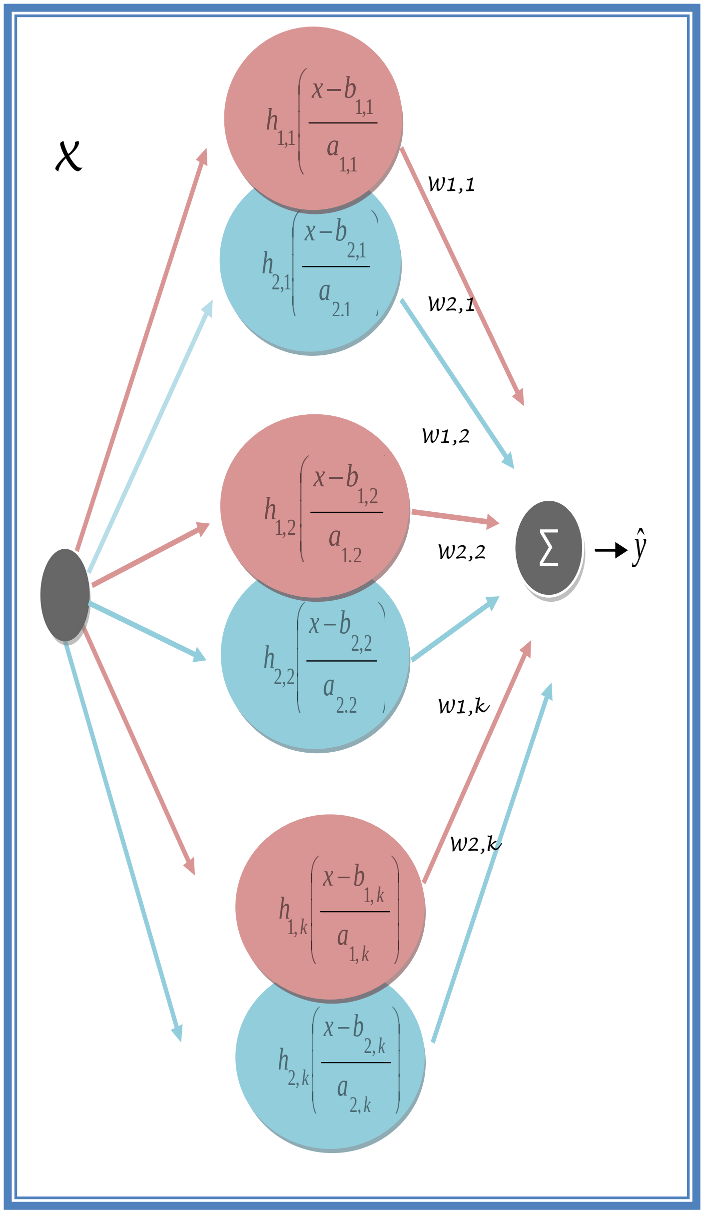


Figure (4) adaptive TAFWN structure

4. The proposed work

4.1. Two Activation Function Wavelet Networks Algorithm

The TAFWN architecture approximates any desired image y by generalizing a linear combination of two set of daughter wavelets $h_{1,a,b}(x)$ and $h_{2,a,b}(x)$, where the daughter wavelets $h_{1,a,b}(x)$ and $h_{2,a,b}(x)$ are generated by dilation, a, and translation, b [2], from two mother wavelets $h_1(\tau)$ *and* $h_2(\tau)$, where $\tau = \frac{x-b}{a}$.

$$h_{1,a,b}(x) = h_1(\frac{x-b}{a}) \text{ .... (3)}$$

$$h_{2,a,b}(x) = h_2(\frac{x-b}{a}) \text{ .... (4)}$$

where a : Dilation factor, with $a > 0$, b : Translation factor, and x : pixel value of the image.

A TAFWN is a 3-layers feed forward neural network. First the TAFWN parameters, dilation a's, translation b's, and weight w's should be initialized, and the desired sets of data, the input signal *x* is the pixel value, the desired output (target) *y*, the number of scaling functions *p* (*p*=2 in this work) and the number of wavelons *k* are given. Assuming that the network output function satisfies the admissibility condition and the network sufficiently approximates the target. The approximated signal of the network $\hat{y}$ can be represented by equation:

$$\hat{y}(x) = \sum_{j=1}^{p} \sum_{i=1}^{k} w_{j,i} h_{a_{j,i},b_{j,i}}(x) \text{ .... (5)}$$

Where x is the pixel value of the image, $w_{j,i}$ is the weight coefficients between hidden and output layers, *j*=1,2,…, *p*. *p*=2: a number of scaling functions, *i*=1,2,…, *k*. *k* is a number of wavelons, and $h_{a_{j,i},b_{j,i}}$ is a two set of daughter wavelets generated from two mother wavelets $h_1(x)$, $h_2(x)$ as in equations (3) and (4) respectively.

After constructing the initial TAFWN and after calculating output signal of the network, the training of TAFWN starts. It is further trained by the gradient descent algorithms like least mean squares (LMS) to minimize the mean-squared error. During learning, the parameters of the network are optimized [12].

The TAFWN parameters $w_{j,i}$, $a_{j,i}$, and $b_{j,i}$ can be optimized in the LMS algorithm by minimizing a cost function or the energy function, E, over all function interval using equation (14).

$$E = \frac{1}{2}\sum_{t=1}^{T} e^2 \quad \text{.........} \; (6)$$

$$E = \frac{1}{2}\sum_{t=1}^{T} (y - \hat{y})^2 \quad \text{........} \; (7)$$

The energy function is defined by equations (6) and (7), y is the desired output (target) and $\hat{y}$ is the actual output signal of TAFWN. To minimize E the method of steepest descent is used, which requires the gradients $\frac{\partial E}{\partial w_{j,i}}$, $\frac{\partial E}{\partial a_{j,i}}$, and $\frac{\partial E}{\partial b_{j,i}}$ for updating the incremental changes to each particular parameter $w_{j,i}$, $a_{j,i}$, and $b_{j,i}$, respectively.

The gradients of E are:

$$\frac{\partial E}{\partial w_{j,i}} = -\sum_{t=1}^{T} E * h(\tau) \quad \text{........................} \; (8)$$

$$\frac{\partial E}{\partial b_{j,i}} = -\sum_{t=1}^{T} E * w_{j,i} \frac{\partial h(\tau)}{\partial b_{j,i}} \quad \text{.....................} \; (9)$$

$$\frac{\partial E}{\partial a_{j,i}} = -\sum_{t=1}^{T} E * w_{j,i} \tau \frac{\partial h(\tau)}{\partial b_{j,i}} = \tau \frac{\partial E}{\partial b_{j,i}} \quad \text{.........} \; (10)$$

$$\text{Where } \tau = \frac{x - b_{j,i}}{a_{j,i}} \quad \text{........................} \quad (11)$$

The derivatives of the various wavelet filter with respect to its translation, $\frac{\partial h(\tau)}{\partial b_{j,i}}$.

The incremental changes of each coefficient are simply the negative of their gradients as in equations (12), (13), and (14). Thus each coefficient w, b, and a of the network is updated in accordance with the rule given in equations (15), (16), (17).

$$\Delta w = -\frac{\partial E}{\partial w} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (12)$$

$$\Delta b = -\frac{\partial E}{\partial b} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (13)$$

$$\Delta a = -\frac{\partial E}{\partial a} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (14)$$

$$w(t+1) = w(t) + \mu_w \Delta w \ldots\ldots \quad (15)$$

$$b(t+1) = b(t) + \mu_b \Delta b \ldots\ldots \quad (16)$$

$$a(t+1) = a(t) + \mu_a \Delta a \ldots\ldots \quad (17)$$

Where ($\mu_w = \mu_b = \mu_a$ =0.1) in proposed method.

4.2. The Proposed Method For fingerprint Identification:

In this method taken four fingerprint image for each person with different expression each one of them (256*256) in size and construct in three dimension (256*256*4):

1. Take one level of wavelet packet for each image to get reduced size image (to half dimension 128*128).

2. Segment each image into 16 blocks.

3. The next steps done For each segment:

a) Taken segment (1) for image (1) and entered to Two Activation Function Wavelet Network (TAFWN) when the error became small enough, then the training is good and the algorithm is stopped where at this point stored the vector (18*1) ($a_{1,1}$, $a_{1,2}$, $a_{1,3}$, $b_{1,1}$, $b_{1,2}$, $b_{1,3}$, $w_{1,1}$, $w_{1,2}$, $w_{1,3}$, $a_{2,1}$, $a_{2,2}$, $a_{2,3}$, $b_{2,1}$, $b_{2,2}$, $b_{2,3}$, $w_{2,1}$, $w_{2,2}$, $w_{2,3}$) which used it to represent segment (1) of image (1) and then stored it in data base to represent the first person.(in this method used three wavelons (k=3) and wavelet filters ($h_1(\tau)$ is POLYWOG4 and $h_2(\tau)$ is RASP1.

b) Taken segment(2) of image (1) and entered to Two Activation Function Wavelet Network (TAFWN) to get on vector (18*1) which represent segment (2) of image (1) and then stored it in data base to represent the first person.

c) Continue for segments (3 and 4) of image (1) of person (1), then get on (288*1) vector represent the 16 segments of the first image of person1.

d) Continue the above procedure for images(2, 3, and 4) for person (1) then get on a vector (1152*1) represent the four image of person(1).

Repeated the step (4) for (15) person images therefore the result data base matrix is (1152*15) and the main block diagram of this proposed method is shown in Figure (5).

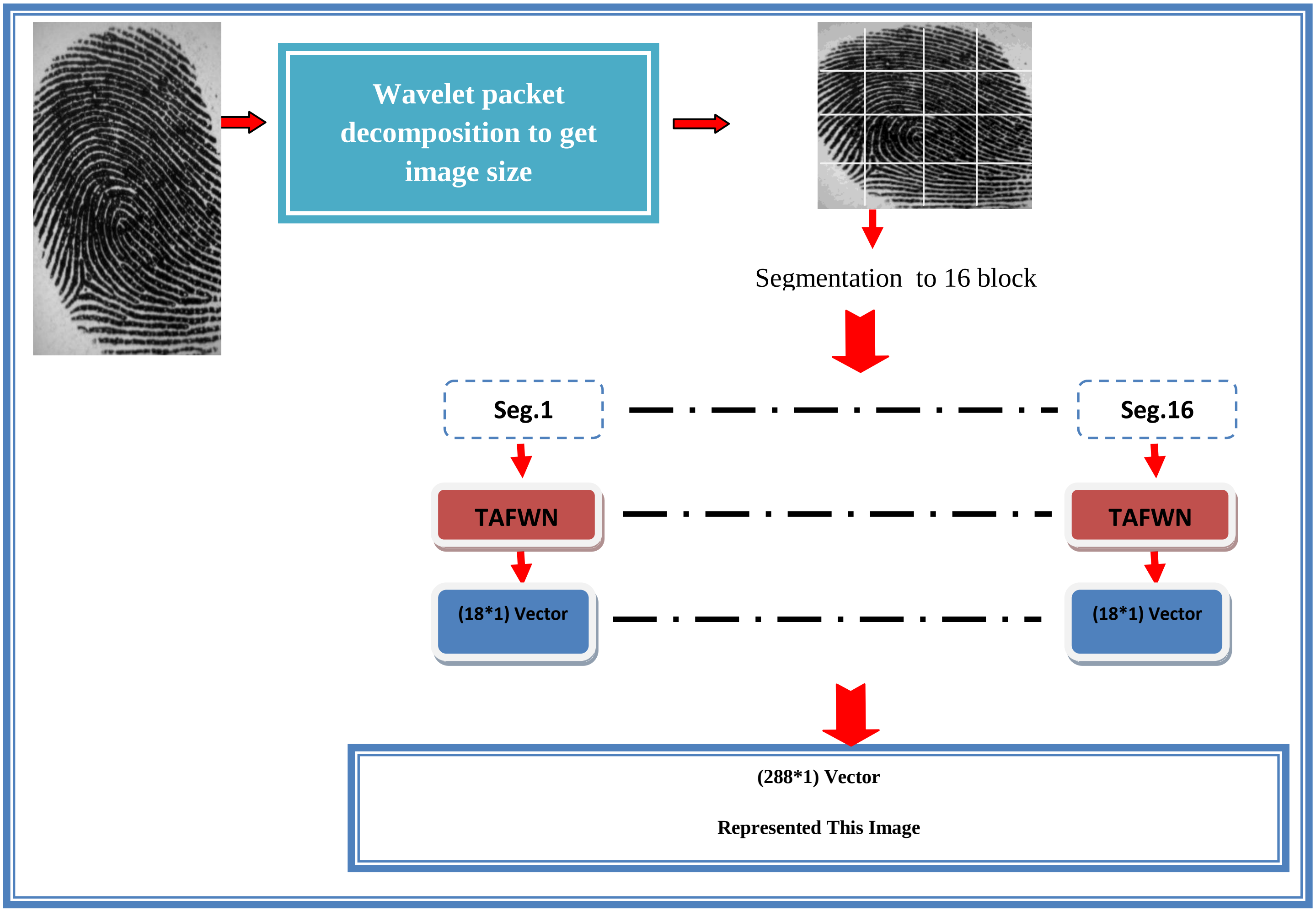


Figure (5) the proposed algorithm for fingerprint features extraction

4.3. The Proposed Method For iris Identification:

In this method taken four iris image (2 left, 2 right) for each person with different expression each one of them (256*256) in size and construct in three dimension (256*256*4):

1. Take one level of wavelet packet for each image to get reduced size image (to half dimension 128*128).
2. Segment each image into 32 blocks.
3. The next steps done for each segment:

a) a) Taken segment(1) for image (1) and entered to Two Activation Function Wavelet Network (TAFWN) when the error became small enough, then the training is good and the algorithm is stopped where at this point stored the vector (18*1) ($a_{1,1}$, $a_{1,2}$, $a_{1,3}$, $b_{1,1}$, $b_{1,2}$, $b_{1,3}$, $w_{1,1}$, $w_{1,2}$, $w_{1,3}$, $a_{2,1}$, $a_{2,2}$, $a_{2,3}$, $b_{2,1}$, $b_{2,2}$, $b_{2,3}$, $w_{2,1}$, $w_{2,2}$, $w_{2,3}$) which used it to represent segment (1) of image (1) and then stored it in data base to represent the first person.(in this method used three wavelons (k=3) and wavelet filters ($h_1(\tau)$ is POLYWOG4 and $h_2(\tau)$ is RASP1.

b) Taken segment(2) of image (1) and entered to Two Activation Function Wavelet Network (TAFWN) to get on vector (18*1) which represent segment(2) of image (1) and then stored it in data base to represent the first person.

   Continue for segments (3…32) of image (1) of person (1), then get on (576*1) vector represent the 32 segments of the first image of person1.

c) Continue the above procedure for images(2,3,4) for person (1) then get on a vector (2304*1) represent the four image of person(1).

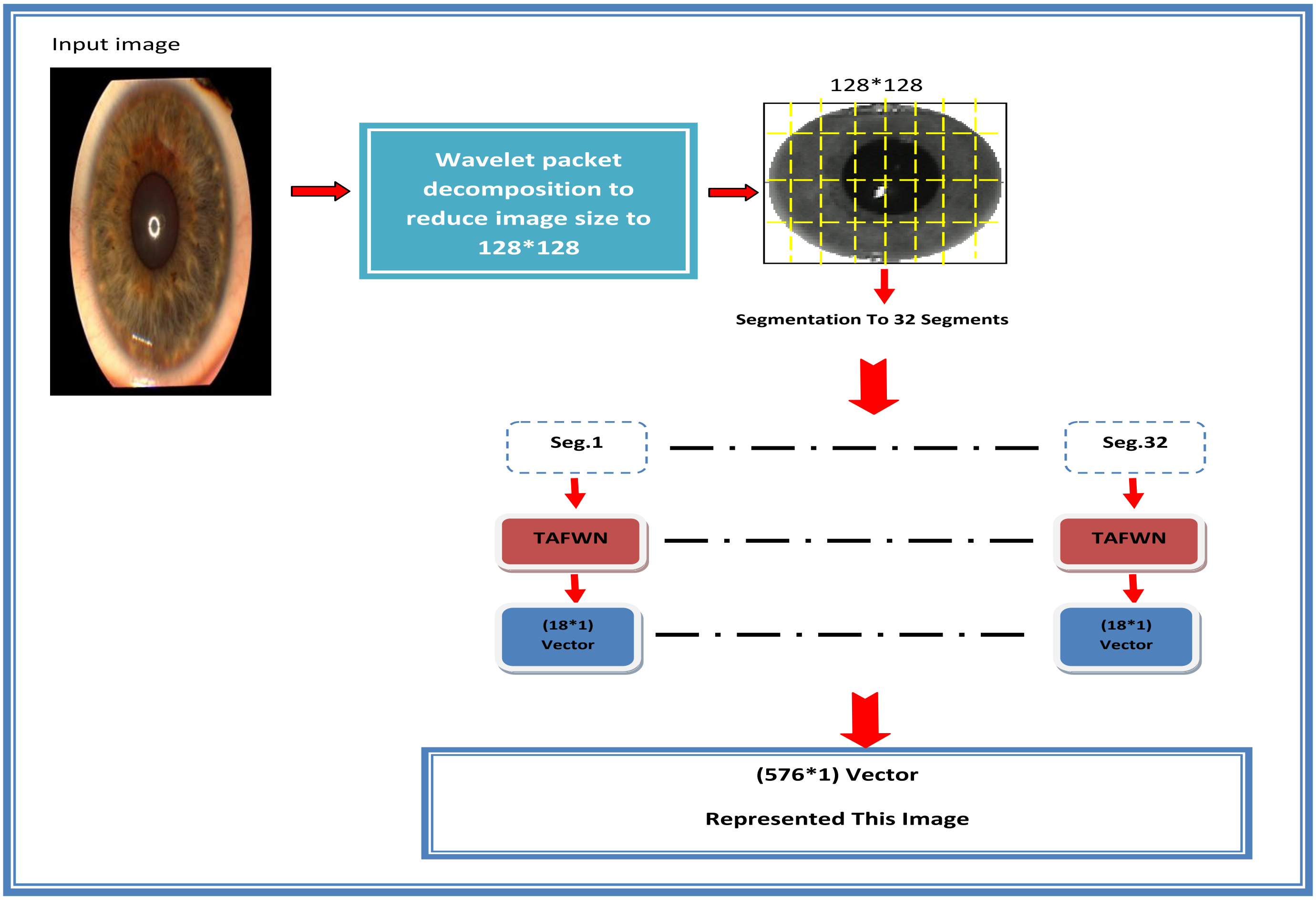
   Repeated the step (3) for (15) person images therefore the result data base matrix is (2304*15) and the main block diagram of this proposed method is shown in Figure (6).

5. Matching

The comparison is done between fingerprint or iris features generated for database and test image using correlation approach:

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \ldots . (19)$$

where x is the vector for database image and y is the vector for test image while n is the number of elements. This matching score (r) is a final result to determine if the person is genuine or imposter.



Figure(6) the proposed algorithm for iris features extraction

6. Fusion on score level

In this paper we used the Fusion at the Matching Score Level**,** feature vectors are created independently for each biometric and are then compared to the enrollment templates which are stored separately for each biometric trait. Based on the proximity of feature vector and template, each subsystem computes its own matching score. These individual scores are finally combined into a total score which is passed to the decision module.(a general diagram in figure 7)

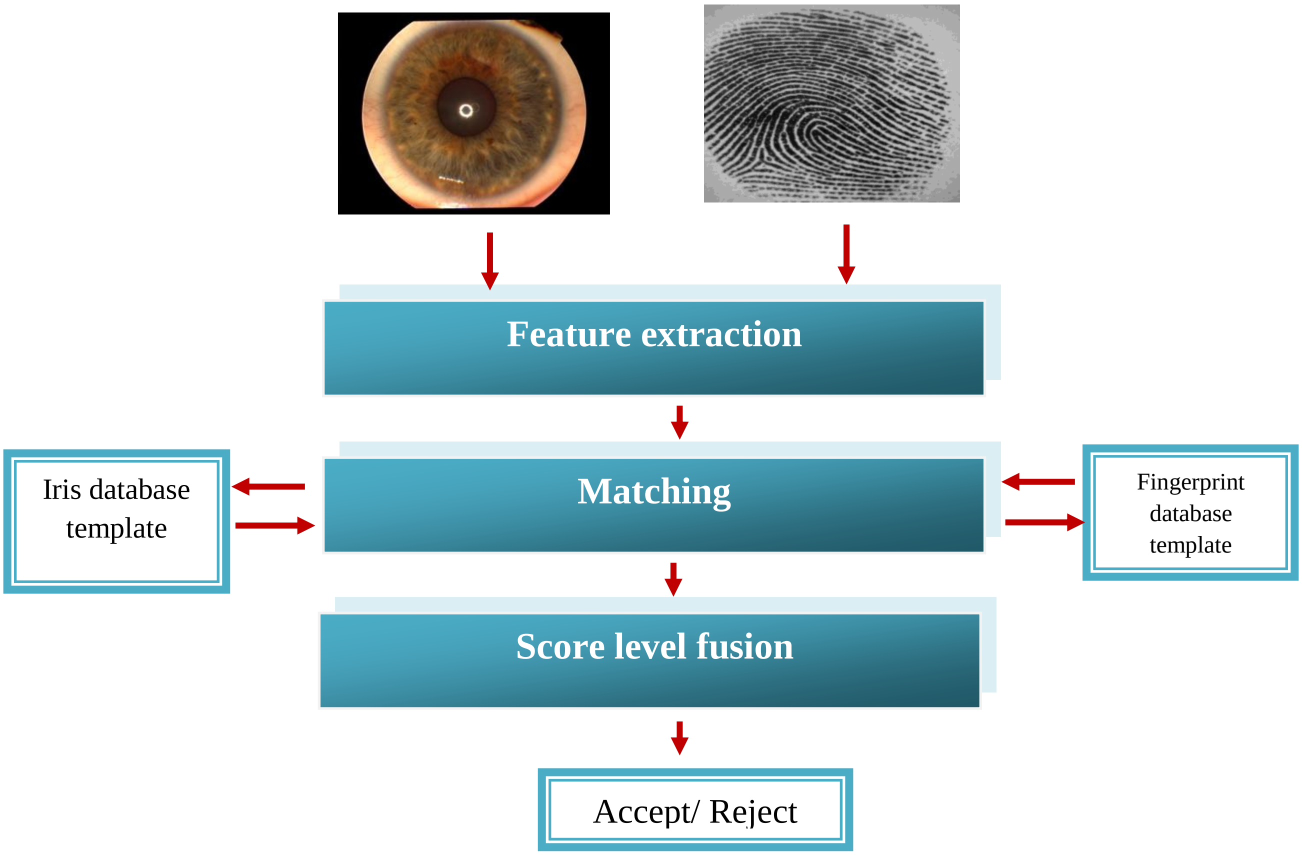


Figure (7) general diagram of fusion

6.1. Maximum Rule based fusion

The highest similarity score is selected to represent a claim:

$$y = \max_{k=1\ toj} S\,k \ldots\ldots\ldots (19)$$

We select the highest matching scores for each person for both the fingerprint and iris and then compare between them to select the highest score to make the decision if the person is imposter or genuine.

7. The Result and Conclusion

This proposed method is tested on a data base consists of 75 images for fingerprint and 75 images for iris, collected for 15 person with 10 images for each person. In the training phase for each person it is required to use 4 fingerprint and 4 iris images for each person. In the identification phase it is required two images. The identification score for the 15 person under consideration was 80.0% correctly for fingerprint identification and 86.6% correctly for iris identification when using the fusion method the accuracy optimized to 90.0% .(its mentioned in Table 1).

Wavelet packet decomposition gives good images with minimum size and (TAFWN) given a good feature extraction vector represented the input image where one segment of image can be represented by (18*1) vector only. In this method the weights and number of segments is very important because when we test it with (4&8) segments for images the accuracy was between (40-55%) So we used the segments as explanation in section (4.2) for fingerprint and section (4.3) for iris. We represent the final correlation scores of fingerprint and iris in figures (8, 9) sequentially, and the fusion of fingerprint and iris in figure (10).

Biometric trait	**Correct Match**	**Incorrect Match**	**Accuracy**
Iris	13/15	2	86.6%
fingerprint	12/15	3	80.0%
Fused	14/15	1	90.0%

8. Future work

The proposed work can work with any another biometric, It can work with different number of segments for image to increase the accuracy identification.

Table1. Raw experimental results

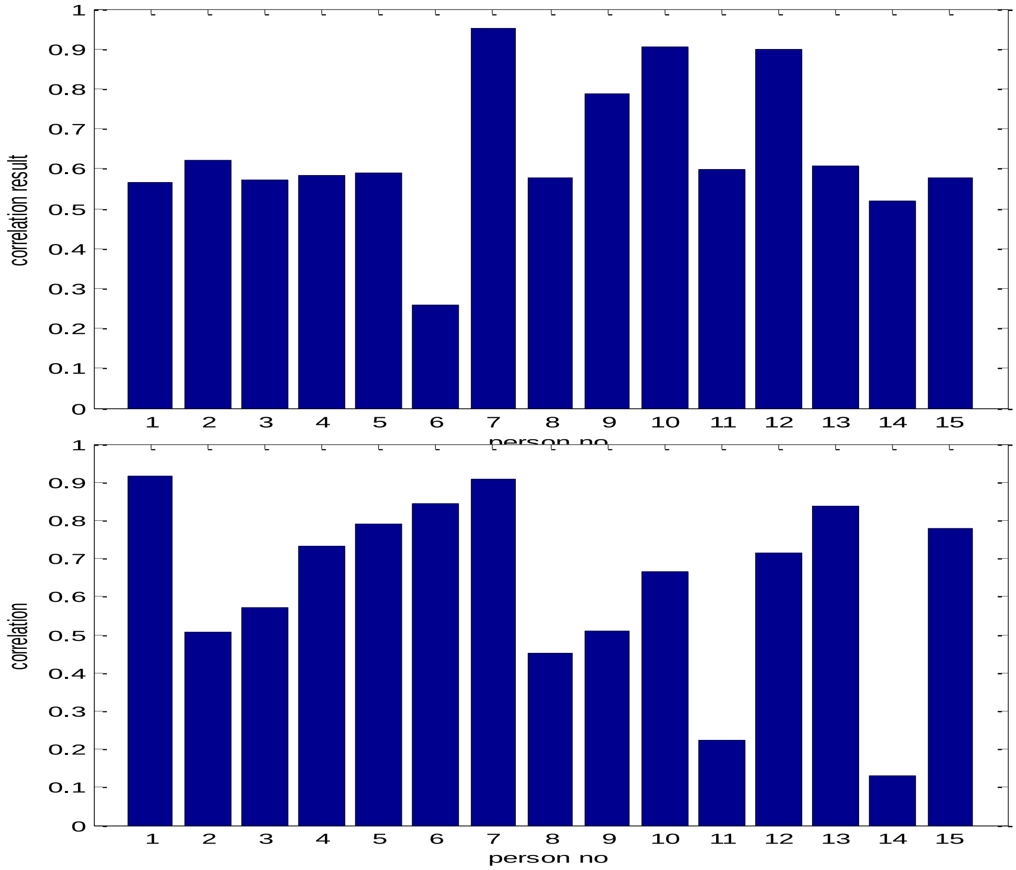


Figure (9) correlation result for the iris samples

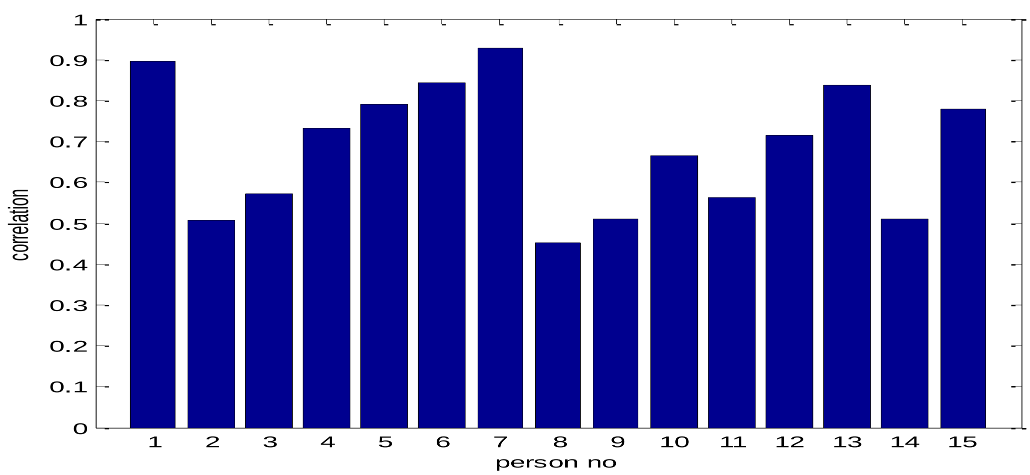


Figure (10) correlation result for the fused samples

9. References

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