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Fingerprint Recognition Using Discrete Wavelet Transform And Neural Network For Estimation Rotation Region

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Abstract:

Fingerprint-based recognition is one of the most important biometric technologies which have drawn a substantial amount of attention recently. This paper proposed a fingerprint recognition adopting a multilayer back propagation neural network as decision stage and using high pass filters (horizontal and vertical sub band the out from 2-D DWT) as estimation rotation region is first stage. The output of this stage is used as input to 1-D DWT (multi-order of low pass decomposition) as feature extraction for fingerprint. Next the normalization for each feature vector is performed to reduce the size of storage and increased the learning speed for the neural network. The evaluation tests were carried out on the proposed algorithm using a database of fingerprint images. A perfect results of recognition (99%) results was achieved by using correlation measurement. we identify the fingerprint by comparing the other fingerprint features with shift position and changed angle to the measurement of performances.

Keywords: Fingerprint, discrete wavelet transforms (DWT), extracted features, estimation rotation region, and multilayer neural network

تمييز البصمات الأصابع باستخدام المحول إلموجي والشبكات العصبية لتخمين مناطق التدوير

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الخلاصة:

بصمات الأصابع على أساس التصنيف هي واحدة من تقنيات Biometric المهمة التي أثارت قدرا كبيرا من الاهتمام في الآونة الأخيرة. هذه البحث اقترح طريقة لتميز البصمات باختيار الشبكة العصبية متعددة الطبقات كمرحلة للتميز وكذلك استخدم مرشحات عالية التمرير (الأفقي والعمودية الخارجة من 2D- DWT) لتخمين منطقة التدوير كمرحلة الأولى. الناتج من هذه المرحلة يستخدم كمدخل إلى 1D- DWT (التحليل ألموجي المتكرر لمرشح الترددات

المنخفضة) وذلك لاستخلاص الميزات من البصمة وعندها يتم تنفيذ Normalization لكل ميزة لتقليل حجم التخزين وزيادة سرعة التعلم للشبكة العصبية. تم اجراء الاختبارات على الخوارزمية المقترحة باستخدام قاعدة بيانات لصور من بصمات الأصابع وتم تمييز النتائج بنسبة (99%) باستخدام مقياس Correlation وتمت المطابقة مع بصمات مع التغير بزوايا ومواقع مختلفة للبصمات.

1. Introduction

Fingerprint recognition is a method of biometric authentication that uses pattern recognition techniques based on high resolution fingerprints images of the individual. Fingerprints are imprints formed by friction ridges of the skin and thumbs. They have long been used for identification because of their immutability and individuality. Immutability refers to the permanent and unchanging character of the pattern on each finger. Individuality refers to the uniqueness of ridge details across individuals; the probability that two fingerprints are like is about 1 in $1.9\text{x}10^{15}$ [1]. Automated fingerprint identification system involves three main steps: pre-processing, feature extraction and classification. In a general way, pre-processing of fingerprint such as detection of core point, binarization, smoothing and thinning is needed to identify fingerprint. Extraction of appropriate features is one of the most important tasks for a recognition system. The accuracy is totally dependent on the identification of features extraction for fingerprints.

In this paper, our proposal is presented as follow: Given the gray image of a fingerprint from the device, firstly a 2-D wavelet transform as high pass filters (horizontal and vertical sub band the out from 2-D DWT) is used to estimate rotation region. Next a one dimensional DWT (discrete wavelet transform only low pass filter) is perform for each row of the image until we get a column vector, normalized the vector of the wavelet output, finally the classification of rotation and translation fingerprint is done by using multilayer back propagation neural network.

2. Related Work

A number of methods have been proposed for estimate the values of local orientation .To determine the location of the core point we first need to calculate the orientation field of the fingerprint. Two approaches available in the literature, ones is directional using gray image (special domain) to calculate the values of orientation field as introduced in [2] which used a Hierarchical method based on fingerprint gradient and its consistency level. H.Szuand C.Hsu is intended to report the improved reliable core and delta detection, aiming to achieve both of higher detection rate and fast computation by the candidate analysis [3]. Another are used frequency domain to found the global local as can be seen in these approach for reliable core-point detection which exploits the directional properties of Discrete Wavelet Transform (DWT) and is applied directly on the image acquired from a fingerprint scanner [4,13] use the same method in which instead of scanning the orientation image, wavelet coefficients of the orientation image in the horizontal, vertical and diagonal direction have been used to locate the core-point for fingerprint.

Some fingerprint identification algorithm using Gabor filter as feature extraction when the ink-scan fingerprint acquisitions [5, 9]. In S.Iranmanesh proposes a more general feature extraction scheme for fingerprint images using a discrete wavelet transform and presents design suitability for neural network classifiers [6]. The fingerprint recognition methods in wavelet domain converts the fingerprint images directly to the feature vector form, and then verify it. It preserves a potential of developing a lost cost, and small design fingerprint recognition system. H.Vieira suggested the use of neural networks as a possible solution for the case of fingerprint matching [7]. While K.Thaiyalnayaki introduced an applicable method of back–propagation algorithm, because the network learning speed has highly increased [8].

3. Proposed Algorithm

Most methods for fingerprint recognition use minutiae as the fingerprint features. For small scale fingerprint recognition system, it would not be efficient to undergo all the preprocessing steps (edge detection, smoothing, thinning ...etc), instead of these steps, we suggest to use one dimensional discrete wavelet system to extract features directly from the output of the 2D discrete wavelet to find the estimation rotation region and conversion for 1D to obtain extraction features for fingerprint. The block diagram for the proposed algorithm is shown **Figure(1).**

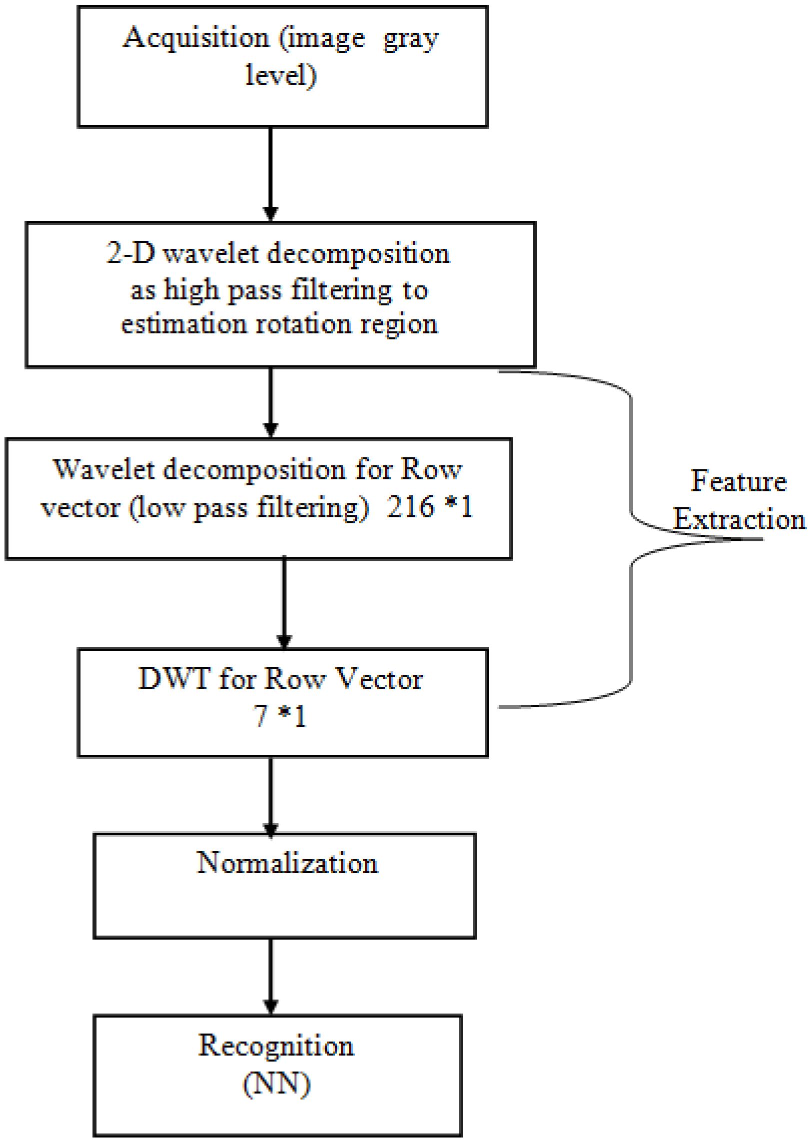


Fig .(1): Block diagram of fingerprint recognition algorithm

As shown from the block diagram, the proposed algorithm is consist from five steps: image acquisition, 2D wavelet transform to estimated maximum rotation and feature extraction, normalization and classification. Each of these steps will be further described in details in the following sections.

3.1 Image Acquisition

A number of methods are used to acquire fingerprints. Among them, the ink impression method remains the most popular one. A special device for the collection of fingerprint images was built based on a simple principle, which is employed in most of the commercial devices. Diagonal side of the prism interact with the touching finger ridges, forming the correspondent image on the other square side of the prism. The formed image is then focused on the CCD camera by means of a lens. The device that illustrates the entire process is shown in [8]. Thumbs images are taken to be less susceptible to rotation problems because the sizes of thumbs are close to the size of the window on the acquisition device that provides a physical limitation for the degree of freedom of rotation.

3.2 Wavelet Transform

Wavelet transform is used to convert a spatial domain into frequency domain. The use of wavelet in image feature extraction lies in the fact that the wavelet transform clearly separates the high frequency and low frequency information on a pixel by pixel basis. In two dimensional transform, first apply one step of the one dimensional transform to all rows and then repeat to all columns. This decomposition results into four classes or band coefficients [12]. The Haar Wavelet Transform is the simplest of all wavelet transform. In this the low frequency wavelet coefficient are generated by averaging the two pixel values and high frequency coefficients are generated by taking half of the difference of the same two pixels. The four bands obtained are approximate band (LL), Vertical Band (HV), Horizontal band (HH), and diagonal detail band (HD) as shown in **Figure(2).** The approximation band consists of low frequency wavelet coefficients, which contain significant part of the spatial domain image. The other bands also called as detail bands consists of high frequency coefficients, which contain the edge details of the spatial domain image [9].

(a) **(b)** **(c)** **(d)** **(e)**

Fig.(2): (a) Original Image (b) approximate band (LL), (c) Horizontal Subimage(HH), (d) Vertical Subimage (HV), (e) Diagonal Subimage (HD).

3.3 Feature Extraction

During the wavelet transformation, low frequency components in the image will be filtered out as approximations and high frequency components will be filtered out as details [9].In this paper we used haar wavelet transform in two stage, first is used 2-D wavelet decomposition as high pass filtering to estimation rotation region ,second is applied used 1-D wavelet decomposition as low pass filtering for multi-order to find feature same for any variable of the fingerprint for person.

3.4 Estimation Rotation Region Algorithm (ERRA)

With used 2-D wavelet transform of the fingerprint, the algorithm below explains steps to estimate the local orientation.

1. Compute the single level wavelet decomposition on the gray image G(x,y) to obtain the three wavelet coefficient sub images $I_H(x,y)$, $I_V(x,y)$ and $I_D(x,y)$.

2. Divide the $I_H(x,y)$, $I_V(x,y)$ sub band image into non-overlapping blocks of size W x W . In our paper W choose to be W=3.

3. Compute the gradients $G_x(i,j)$ and $G_y(i,j)$ from high pass filter(horizontal subimage, vertical subimage).

4. Estimate the values of local orientation by finding:

$$G_{xx} = \sum_{(x,y)\in w} I_H^2(x,y) \qquad \text{.... (1)}$$

$$G_{yy} = \sum_{(x,y)\in w} I_V^2(x,y) \qquad \text{.... (2)}$$

$$G_{xy} = \sum_{(x,y)\in w} I_H(x,y).I_V(x,y) \qquad \text{......(3)}$$

$$\theta(x,y) = \frac{1}{2}\tan^{-1}\left(\frac{2G_{xy}}{G_{xx}-G_{yy}}\right) \qquad \text{.....(4)}$$

Eq.(4) is illustrated in [10].

5. Find maximum orientation value using:

max= maximum(θ(x,y)) …(5)

6. Compare the max obtained in step 3 with all values of the matrix θ(x,y), if the value is equal or less then 0.8* max then values location will be added to the sum of old location (in order to include the maximum value of rotation and the neighbor of it) and counts the number of repeated coordinates.

7. Find center of rotation region coordinate by divide the sum of locations by its counts from step 6.

8. Take window neighbor the center of rotation region by R. where R is a region centered at the average of rotation. In our paper R choose to be 20*20.

9. Construct the new low sub band coefficient (obtained from step 8).

Low frequency coefficients outcome from step 9, we extract the fingerprint features of the size that we want to be. Using the Haar, one-dimensional DWT for each row of the out of 2-D wavelet is perform (via the low filtering and down sampling) continuously until a single point for that row is get. For this row vector the size will be 216 x 1. The same operation is perform until we get the feature vector of the appropriate size (here we use the size of 7 x 1). In order to use large of data for the vector, normalization is used by each value of vector divided by maximum value of the vector as defined in Equation (6). These vectors are used as inputs for the neural network.

$$P= P/\max (P) \qquad ......(6)$$

where P: pattern vector

3.5 Recognition

Multilayer Neural Network classifier can be used to distinguish one from the other features .The neural networks are a class of computational architectures that are composed of interconnected nodes (neurons). Their name reflects their initial derivation from biological neural systems, though the functioning of artificial neural networks may be quite different from those of the biological ones [11].

A classifier depends on neural networks. In our proposal paper, the neural network classifier for fingerprint recognition is back propagation neural network composed of 7 input nodes (corresponding to the dimension of the feature vectors, 20 hidden nodes and 10 output nodes (corresponding to the number of concerned fingerprint classes).

4. Experimental Results

In this section we have presented the experimental analysis of our proposed scheme. Our scheme is programmed in (Matlab version9). The database consists of fingerprint images of ten individuals and four different orientations and three shift positions. All images in the database were 216×216 in size and had been captured with 256 gray levels using an inkless fingerprint scanner as in Figure(2). DWT is used as the analysis tool. Haar wavelet is used as the mother wavelet. One level is used as it gives high compression and removes random additive noise. Figure (3) shows some fingerprints with their own wavelet transformed minutiae. In this test, each person takes two images for the same fingerprint with different size and rotation, so one of them that is the original fingerprint(without rotation and shift position) is used in training phase and all fingerprints are used to test phase of the recognition. The result of this recognition is using correlation measurements as defined [9]:

$$Corr. = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(o(i,j)-\bar{o})(T(i,j)-\bar{T})}{\sqrt{\left[\sum_{i=1}^{M}\sum_{j=1}^{N}(o(i,j)-\bar{o})^2\right]\left[\sum_{i=1}^{M}\sum_{j=1}^{N}(T(i,j)-\bar{T})^2\right]}} \quad .....(7)$$

where $o(i,j)$ is the output of neural

$\bar{o}$ is the mean of the output.

$T(i,j)$ is the target.

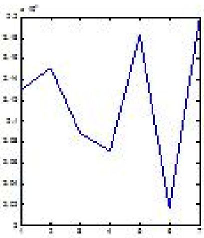
$\bar{T}$ is the mean of the target.

The results of these tests are given in **Table(1)**. We can see from testing the NN by using wavelet for feature extraction without estimate rotation region that the NN unrecognized the fingerprint rotation with angle 10, 20, 30 but recognized other patterns shown in **Table(2)**. The proposed algorithm that estimate the rotation region are improved the recognition. In Table 5 the recognition rate is computed by the correlation measurement. Our proporsal is compared with two methods (Gabor and FBI) for same number of the fingerprint and different feature extraction methods with same NN classifiers. In Gabor method, the core point of the fingerprint image is detected, then the magnitude Gabor features are extracted from a small subimage centered at the core point. The test of this method is shown in **Table(3)**. In the Wavelet Scalar Quantization (WSQ) compression algorithm of FBI standard Haar wavelet is used to find feature extraction that consist from 63 subimages, which is a low resolution approximation of the original image, and dj =1,2,...,63 j are the wavelet subimages containing the image details at different scales and orientations. The test of FBI is shown in **Table(4).** The correlation measurement achieved 99% as shown in Table 5 when the fingerprint shifted or rotated we can see that the result will be the same as shown in **Finger (11-17)** correspond to **Finger (1).**

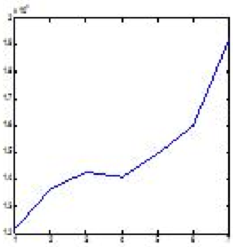
5. Conclusions

In this paper, we proposed an algorithm for fingerprint recognition based on 2D and 1Dwavelet domain to estimation rotation region and features extraction. The estimation rotation region is directly extracted from sub band vertical and horizontal 2D wavelet domain with orientation equation, with no preprocessing. Recognition procedure has shown to be quite sensitive to translation rotation for fingerprint images with estimation rotation region.

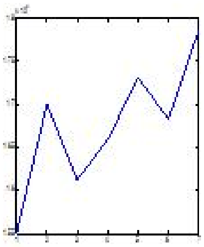

Finger1



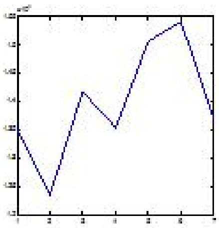

Finger2



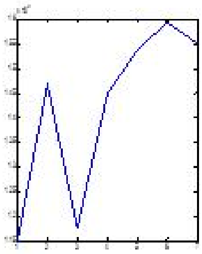

Finger3



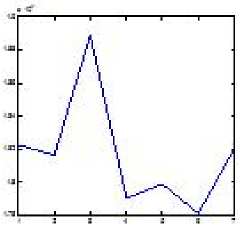

Finger4



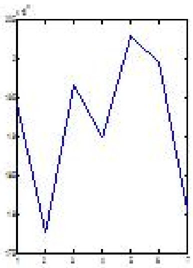

Finger5



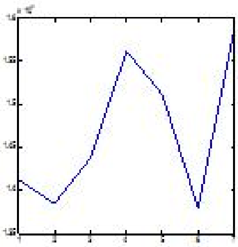

Finger6



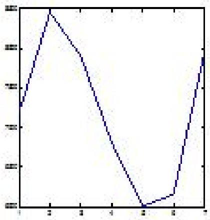

Finger7



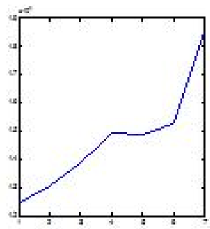

Finger8

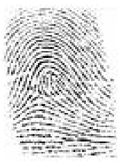


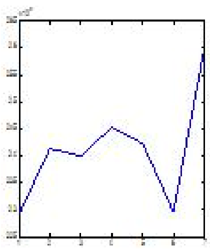

Finger9



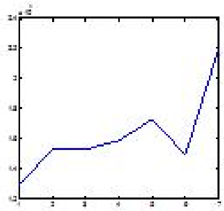

Finger10




Finger11




Finger12



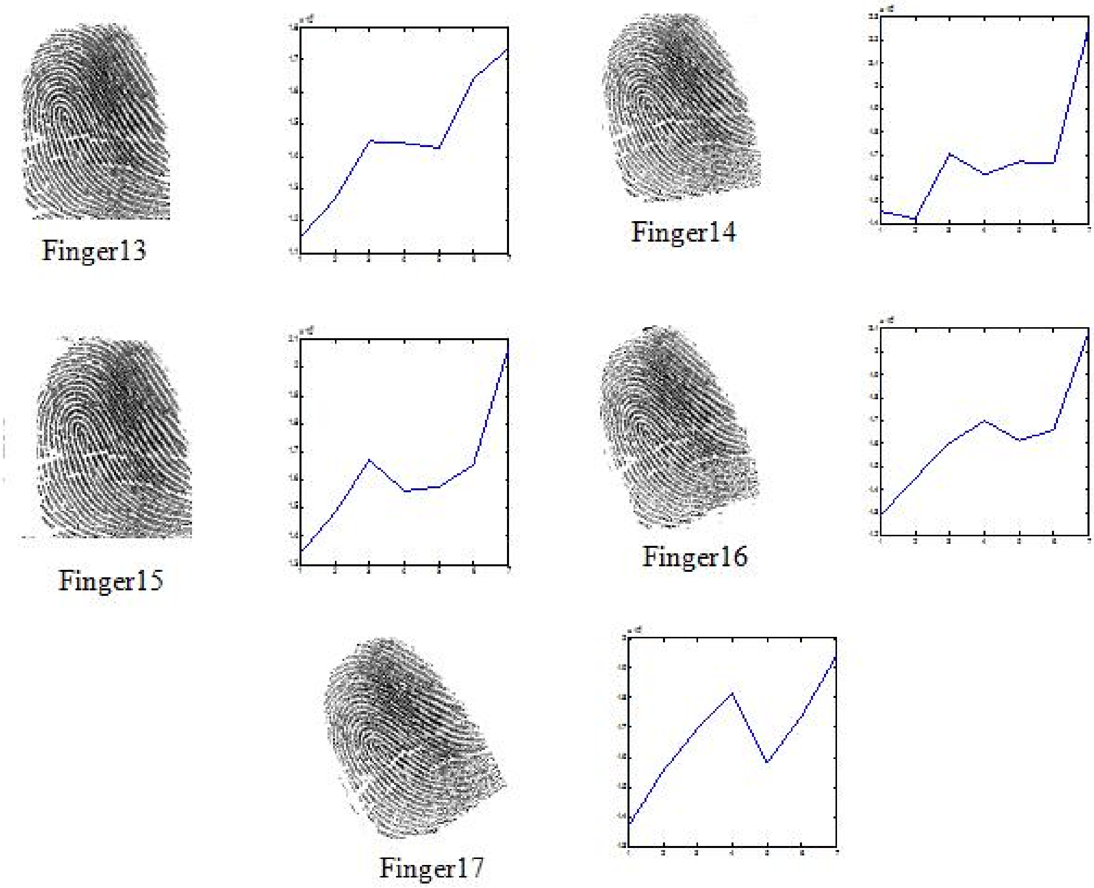


Fig .(3) Feature examples of the various fingerprints

Table .(1): Output of the Neural Network in the testing phase without using Estimation Rotation Region Wavelet Domain Algorithm

Out	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F1s 1	F1s 2	F1s 3	F1-5°	F1-10°	F1-20°	F1-30°
O1	0.99	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.97	0.96	0.95	0.00	0.01	0.00	0.02
O2	0.01	0.98	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.01	0.00
O3	0.00	0.01	0.97	0.01	0.01	0.01	0.01	0.00	0.00	0.0	0.0	0.0	0.0	0.10	0.10	0.20	0.90
O4	0.01	0.00	0.00	0.98	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
O5	0.02	0.02	0.00	0.00	0.98	0.00	0.00	0.02	0.09	0.00	0.00	0.00	0.00	0.98	0.00	0.00	0.00
O6	0.00	0.00	0.00	0.02	0.01	0.99	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O7	0.02	0.01	0.01	0.01	0.02	0.00	0.98	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
O8	0.03	0.00	0.00	0.04	0.00	0.01	0.00	0.98	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02
O9	0.01	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.96	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
O10	0.00	0.01	0.02	0.00	0.01	0.00	0.03	0.00	0.00	0.98	0.01	0.01	0.01	0.01	0.00	0.01	0.03

Table .(2): Output of the Neural Network in the testing phase with using Estimation Rotation Region Wavelet Domain Algorithm

Out	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F1s1	F1s2	F1s3	F1-5⁰	F1-10⁰	F1-20⁰	F1-30⁰
O1	0.99	0.00	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.97	0.96	0.95	0.99	0.99	0.98	0.62
O2	0.01	0.98	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.01	0.01	0.01	0.00	0.01	0.00
O3	0.00	0.01	0.97	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.02	0.01	0.03	0.10	0.10	0.00	0.10
O4	0.01	0.00	0.00	0.98	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00
O5	0.02	0.02	0.00	0.00	0.98	0.00	0.00	0.02	0.09	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O6	0.00	0.00	0.00	0.02	0.01	0.99	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
O7	0.02	0.01	0.01	0.01	0.02	0.00	0.98	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.01
O8	0.03	0.00	0.00	0.04	0.00	0.01	0.00	0.98	0.00	0.01	0.01	0.02	0.01	0.01	0.02	0.02	0.00
O9	0.01	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.96	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
O10	0.00	0.01	0.02	0.00	0.01	0.00	0.03	0.00	0.00	0.98	0.01	0.01	0.01	0.01	0.00	0.03	0.20

Table .(3) : Output of the Neural Network in the testing phase using Gabor filter

Out	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F1s1	F1s2	F1s3	F1-5⁰	F1-10⁰	F1-20⁰	F1-30⁰
O1	0.99	0.0	0.01	0.01	0.00	0.01	0.02	0.01	0.01	0.05	0.76	0.98	0.76	0.9	0.79	0.20	0.05
O2	0.01	0.98	0.00	0.02	0.01	0.04	0.00	0.00	0.01	0.02	0.01	0.01	0.00	0.01	0.00	0.01	0.00
O3	0.02	0.01	0.97	0.01	0.01	0.05	0.01	0.00	0.00	0.0	0.06	0.00	0.03	0.10	0.12	0.20	0.90
O4	0.01	0.03	0.00	0.98	0.02	0.00	0.04	0.01	0.05	0.00	0.02	0.00	0.00	0.11	0.02	0.00	0.02
O5	0.02	0.02	0.00	0.00	0.98	0.00	0.06	0.02	0.09	0.00	0.10	0.01	0.00	0.98	0.01	0.01	0.00
O6	0.01	0.05	0.00	0.02	0.01	0.99	0.02	0.03	0.00	0.00	0.03	0.15	0.00	0.11	0.21	0.02	0.01
O7	0.03	0.01	0.01	0.01	0.12	0.00	0.98	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01	0.03	0.03
O8	0.03	0.00	0.00	0.04	0.00	0.01	0.00	0.98	0.00	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02
O9	0.01	0.00	0.01	0.00	0.00	0.02	0.01	0.01	0.96	0.01	0.01	0.01	0.01	0.01	0.00	0.00	0.01
O10	0.00	0.01	0.02	0.00	0.01	0.00	0.03	0.00	0.00	0.98	0.01	0.01	0.01	0.01	0.00	0.01	0.03

Table .(4): Output of the Neural Network in the testing phase with using FBI Wavelet Domain Algorithm

Out	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F1s1	F1s2	F1s3	F1-5⁰	F1-10⁰	F1-20⁰	F1-30⁰
O1	0.99	0.00	0.02	0.03	0.01	0.01	0.02	0.01	0.05	0.01	0.00	0.01	0.95	0.00	0.001	0.01	0.001
O2	.001	0.99	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.01	0.01	0.01	0.00	0.907	0.000
O3	0.00	0.01	0.98	0.01	0.01	0.01	0.01	0.00	0.00	0.01	0.02	0.01	0.03	0.12	0.30	0.00	0.30
O4	0.01	0.00	0.00	0.99	0.02	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.00	0.03
O5	0.02	0.02	0.00	0.00	0.97	0.00	0.00	0.02	0.09	0.00	0.00	0.00	0.18	0.00	0.001	0.00	0.009
O6	.003	0.00	0.00	0.02	0.01	0.98	0.02	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.59	0.00	0.001
O7	0.02	0.01	0.01	0.01	0.02	0.00	0.98	0.01	0.00	0.01	0.01	0.48	0.10	0.01	0.01	0.02	0.012
O8	0.03	.002	0.06	0.04	0.00	0.01	0.00	0.99	0.00	0.01	0.01	0.02	0.02	0.01	0.02	0.02	0.004
O9	0.01	0.01	0.01	0.00	0.00	0.02	0.01	0.01	0.98	0.01	0.01	0.01	0.3	0.01	0.00	0.00	0.028
O10	.003	0.01	0.02	0.01	0.01	0.00	0.03	0.01	0.00	0.99	0.01	0.01	0.01	0.01	0.00	0.03	0.003

Table (5): Comparison of the results on correlation ,epoch and length feature.

Method	Correlation %	Epoch	Length of feature
Proposal	**99**	**390**	**7**
Gabor filter	**91**	**581**	**64**
FBI	**71**	**418**	**63**

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