INFECTED REGION RECOGNITION IN HUMAN BODY MEMBERS BASED ON WAVENET WITH MINIMUM DISTANCE

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Abstract

Image identification plays a great role in industrial, remote sensing, medical and military applications. It is concerned with the generation of a signature to the image.

This work proposes a dynamic program (use Neural Network) to classify the texture of human member image then identify whether the member is infected or not. The program has the ability of determining which part of that member is infected depending on the comparison between the healthy member image stored in advance with a test image.

The first step is to make approximation to the image using wavelet network (Wavenet) technique. Through this technique we shall get an approximated image with reduced data. In addition, we shall get implicit information to that image. The second step is to subdivide the resultant image from the first step into 16 equally subparts then deal with each subpart as a unique image.

Finally, in the third step, the minimum distance (Mahalanobias Distance) approach is employed for subpart identification. All programs are written using MATLAB VER. 6.5 package.

Keywords: Wavelet Network, Wavenet, Image Recognition, Neural Network, Transformation Technique, Texture Classification.

الخلاصة

إن تحليل نسيج الصورة لغرض التعرف عليها وتشخيصها يلعب دورا كبيرا في مجالات شتى, منها الصناعة والاستشعار من بعد إضافة إلى التطبيقات الطبية والعسكرية.

هذا البحث يقترح برنامج ديناميكي يعتمد على شبكة المويجة (Wavenet) لتصنيف نسيج الصورة للعضو البشري و تشخيص فيما لو كان ذلك العضو مصاباً أم لا. كما ان لهذا البرنامج القدرة على تحديد الجزء المصاب من ذلك العضو بالاعتماد على المقارنة بين صورة العضو السليم المخزونة مسبقاً مع صورته الجديدة.

الخطوة الأولى يتم من خلالها اجراء تقريب الى الصورة (Image Approximation) باستخدام شبكة المويجة(Wavenet) والذي من خلاله نحصل على صورة تقريبية مع تقليل القيم الاصلية المكونة للصورة (Data Reduction) والحصول على قيم ضمنية تتعلق بتلك الصورة.

الخطوة الثانية يتم من خلالها تقسيم الصورة الناتجة من الخطوة الاولى الى ستة عشرجزءاً متساوياً والتعامل مع كل جزء كصورة مستقلة.

الخطوة الثالثة والاخيرة يمر خلالها كل جزء من أجزاء الصورة بمرحلة قياس أقصر مسافة بين صورتين واستخدام النتائج في عملية التشخيص النهائية.

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1-Introduction

The approximation of general continuous functions by nonlinear networks is very useful for system modeling and identification. Such approximation method can be used, for example, in black-box identification of nonlinear system. The neural networks have been established as a general approximation tool for fitting nonlinear models from input/output data.

In this paper, wavelets and neural networks (NNs) are combined and a self-recruiting wavelet NN. (Wavenet) is proposed. The combination of wavelet and NNs. have been studied and implemented. The number of hidden units was determined before learning.

Wavenet has four merits: self-construction of networks, partial retrieval of approximated function, fast convergence and escaping local minima.

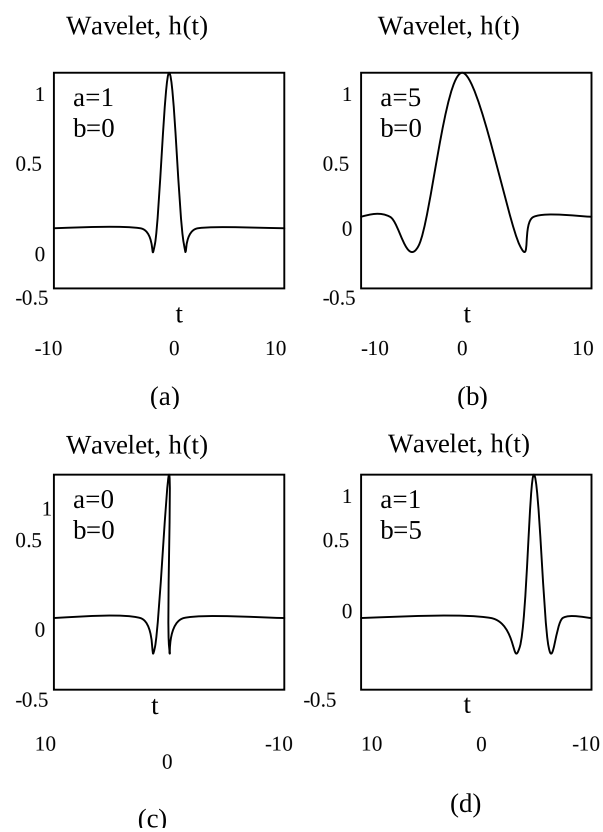
Incorporating the idea of wavelets, the output function is localized in both the time and frequency domains. Therefore each hidden unit has a square window in the time-frequency plan. Thus, wavenet can capture function-approximating problems as two tasks: optimizing the network structure and minimizing errors. In this connection, the proposed algorithm comprises two processes: construction of networks and minimization of errors.

In the first process, the network gradually recruits hidden units to effectively and sufficiently cover the time-frequency region occupied by a given target. Simultaneously, the network parameters are updated to preserve the network topology and take advantage of the later process. In the second process, the parameters of the initialized network are updated in order to minimize the errors of approximation.

Each hidden unit has a square window in the time –frequency plane. This rule is only applied to the hidden units where the selected points fall into their windows. Therefore, the learning cost can be reduced.

2-Wavelets Theory

The term “wavelet” means a little wave. This little wave must have at least a minimum oscillation and a fast decay to zero, in both the positive and negative directions, of its amplitude. Figure (1.a) is an example of a wavelet called “Morlet wavelet” named after Jean Morlet, the inventor, in1984 [1]. Sets of ” wavelets “ are employed to approximate a signal and the goal is to find set of daughter wavelets constructed by a dilated (scaled or compressed) and translated (shifted) original wavelets or mother wavelets that best represent the signal. So by traveling from the large scales toward the fine scales, one “zoom in” and arrives at more and more exact representations of the given signal. Figure (1.b-d) display various daughter wavelets where (a) is dilation and (b) is a translation corresponding to the Morlet mother wavelet. Note the constant shape of these daughter wavelets; the same number of oscillations is in each wavelet.



-2-

Figure (1): Dilated and Translated Morlet Mother Wavelet

3-Nueral Network Architecture

Artificial neural network (ANN) are networks formed of cells simulating the low level functions of neurons. ANNs are very useful for classification of input signals where the signals cannot be defined mathematically [2]. Further, ANNs have redundant networking and are very robust, providing a mathematically flexibility not available to algorithm based classifiers. There is an added advantage that these can be simulated on digital computers easily. ANNs responds to an input by producing an output. This is a result of the transmission of the input through the network of neurons linked by weights. The output of the ANN is a combination of outputs of each of the neurons in the output stages of the ANN. Figure (2) shows the model of a neuron, which is described by:

$$y = f\left(\sum_{i=1}^{N} w_i x_i - v_i\right) \quad \ldots (1)$$

where

x_i : Input signals, i =1, 2, 3, …, N .

w_i : Synaptic weights.

v_i : Threshold or bias.

$f(.)$: Activation function.

y : Output signal of the neuron.

The use of threshold v_i is to provide a bias to the activation function $f(.)$.

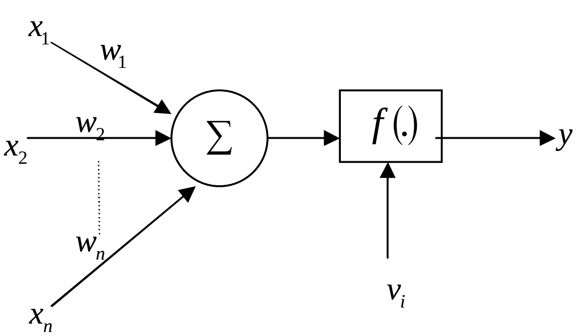


Figure (2): The McCulloch-Pitts Model of a Neuron**.**

There are a number of different ANN structures available, the choice of which is dependent on the application. Back propagation neural network (BPN) is a commonly used ANN for applications where there are predetermined targets of samples of the data along with the targets are available. Neurons in BPN are grouped in to layers, an input layer, an output layer and a hidden layer as shown in Figure (3). Each neuron in a layer is connected to every neuron in the next layer.

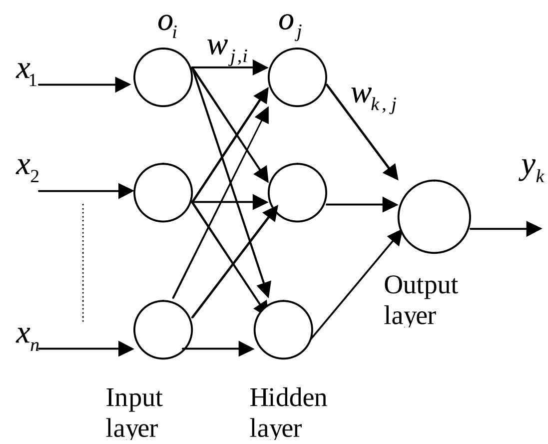


Figure (3): Back propagation neural network.

4.wavenetarchitecture&Algorithm

Combining the wavelet transforms theory with the basic concept of neural networks, a new mapping network called Wavenet is proposed as an alternative to feed forward neural networks for approximating arbitrary nonlinear functions. Wavenet uses a special mother wavelet function $h_{a,b}(t)$ as activation for ANN instead of the traditional activation function. The wavenet architecture shown in Figure (4) approximates any desired signal g(t) by generalizing a linear combination of a set of daughter wavelets, where the daughter wavelets are generated by dilation, a, and translation, b, from a mother wavelet [3]:

$$h_{a,b}(t) = h\left(\frac{t-b}{a}\right) \quad \ldots (2)$$

where

a : Dilation factor, with $a \rangle 0$.

b : Translation factor.

The approximated signal of the network g(t) can be represented by:

$$g(t) = x(t) \sum_{k=1}^{K} w_k h_{ak,bk}(t) \quad \ldots (3)$$

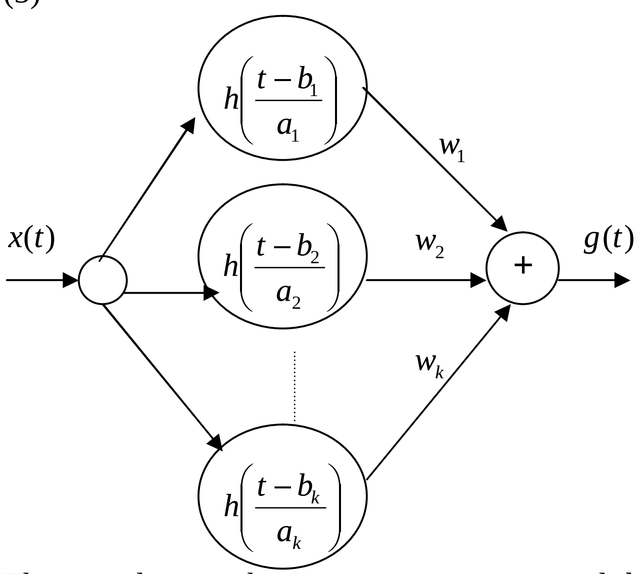


Figure (4): Adaptive Wavenet structure

The neural network parameters w_k, a_k and b_k can [illegible] Square Erro[illegible]ction or the energy function, Ef over all time t. Thus by denoting [3]:

$$e(t) = x(t) - g(t) \quad \ldots (4)$$

be a time-varying error function at time t, where $g(t)$ is the desired response and $x(t)$ is the input signal to the system .The energy function is defined by[3]:

$$Ef = \frac{1}{2}\sum_{t=1}^{T} e^2(t) \quad \ldots (5)$$

$$Ef = \frac{1}{2}\sum_{t=1}^{T} (x(t) - g(t))^2 \quad \ldots (6)$$

where T : Total interval of function

To minimize Ef, the method of steepest descent may be used, which requires the gradients $\frac{\partial Ef}{\partial w_k}$, $\frac{\partial Ef}{\partial a_k}$, and $\frac{\partial Ef}{\partial b_k}$ for updating the incremental changes to each particular parameters w_k, a_k, and b_k respectively. The gradients of Ef are:

$$\frac{\partial Ef}{\partial w_k} = -\sum_{t=1}^{T} e(t)h(\ldots \quad \ldots (7)$$

$$\frac{\partial Ef}{\partial b_k} = -\sum_{t=1}^{T} e\ldots \quad \ldots (8)$$

$$\frac{\partial Ef}{\partial a_k} = -\sum_{t=1}^{T} e(t)x(t)w_k z\frac{\partial h(z)}{\partial b_k} = z\frac{\partial Ef}{\partial b_k} \quad \ldots (9)$$

where $z = \frac{t-b_k}{a_k}$ … (10)

The incremental changes of each coefficient are simply the negative of their gradients,

$$\Delta w_k = -\frac{\partial Ef}{\partial w_k} \quad \ldots (11)$$

…

$$\Delta b_k = -\frac{\partial Ef}{\partial b_k} \quad (12)$$

…

$$\Delta a_k = -\frac{\partial Ef}{\partial a_k} \quad (13)$$

Thus each coefficient of w_k, b_k and a_k of the network is updated in accordance with the rule:

$$w(n+1) = w(n) + \mu_w \Delta w \quad \ldots (14)$$

$$b(n+1) = b(n) + \mu_b \Delta b \quad \ldots (15)$$

$$a(n+1) = a(n) + \mu_a \Delta a \quad \ldots (16)$$

Where, μ is the fixed learning rate parameter, typically between “0.01 to 0.1” [3].

In order to know the initial values of the parameter b (translation) over the domain [lower limit to upper limit] for an input function we may use the following equation [4]:

$$\text{Translation Steps} = \frac{UpperLimit - LowerLimit}{NumberOfWavelones - 1} \quad (17)$$

Where, wavelons represents the hidden layer units $h\left(\frac{t-b_k}{a_k}\right)$ in Figure (4).

-4-

Example

Make an approximation for the following given function $f(x)$ using Wavenet algorithm, with $h(z) = (1-z^2)\exp(\frac{-z^2}{2})$ as a mother function.

$$f(x) = \begin{pmatrix} -2.186x - 12.86 \ldots\ldots for -10 \le x \langle -2 \\ 4.246x \ldots\ldots\ldots\ldots\ldots\ldots for -2 \le x \langle 0 \\ 10\exp(-0.5x - 0.5x - 0.5)\sin((0.03x + 0.7)x \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots for 0 \le x \le 10 \end{pmatrix}$$

Solution

-Assume there is 4 wavelones.
-Set the parameters of Wavenet initially to:
$w_1 = 0.1$, $w_2 = 0.2$, $w_3 = 0.3$, $w_4 = 0.4$
(w is typically between "0 to 1")
$a_1 = 5$, $a_2 = 5$, $a_3 = 5$, $a_4 = 5$
While translation parameters are determining according to equation (17) as bellow:
Since, upper limit of the function=10
Lower limit of the function=-10

$$\text{Translation Step} = \frac{10-(-10)}{4-1} = 6.66667$$

Therefore:

$$b_1 = -10$$
$$b_2 = (-10 + 6.66667) = -3.33334$$
$$b_3 = (-3.33334 + 6.66667) = 3.33334$$
$$b_4 = (3.33334 + 6.66667) = 10$$

1) For $f(x) = -2.186x - 12864$, let $x = -3$
Therefore, $f(-3) = -6.306$

$$z_1 = \frac{x-b_1}{a_1} = \frac{-3-(-10)}{5} = 1.4$$
$$z_2 = \frac{x-b_2}{a_2} = \frac{-3-(-3.33334)}{5} = 0.06667$$
$$z_3 = \frac{x-b_3}{a_3} = \frac{-3-(3.33334)}{5} = -1.26667$$
$$z_4 = \frac{x-b_4}{a_4} = \frac{-3-(10)}{5} = -2.6$$

Now, the value of mother function at each wavelone is computed as follow:

Since, $h(z) = (1-z^2)\exp(\frac{-z^2}{2})$ then:

$$h_1(1.4) = (1-1.4^2)\exp(-\frac{1.4^2}{2}) = -0.3603$$
$$h_2(0.06667) = (1-0.06667^2)\exp(-\frac{0.06667^2}{2})$$
$$h_2(0.06667) = 0.9933$$
$$h_3(-1.26667) = (1+1.26667^2)\exp(\frac{1.26667^2}{2})$$
$$h_3(-1.26667) = -0.271$$
$$h_4(-2.6) = (1+2.6^2)\exp(\frac{2.6^2}{2}) = -0.196$$

Since, $g(x) = f(x)\sum_{i=1}^{4} w_i h_i(z_i)$

Therefore:

$$g(-3) = -6.306 \times (-0.3603 \times 0.1 + 0.9933 \times 0.2 - 0.271 \times 0.3 - 0.196 \times 0.4)$$
$$g(-3) = -0.01847$$

2) For $f(x) = 4.246x$, let $x = -1$

$$f(-1) = 4.264 \times (-1) = -4.264$$
$$z_1 = \frac{x-b_1}{a_1} = \frac{-1-(-10)}{5} = 1.8$$

$$z_2 = \frac{x-b_2}{a_2} = \frac{-1-(-3.33334)}{5} = 0.46667$$

$$z_3 = \frac{x-b_3}{a_3} = \frac{-1-(3.33334)}{5} = -0.86667$$

$$z_4 = \frac{x-b_4}{a_4} = \frac{-1-(10)}{5} = -2.2$$

Now, the value of mother function at each wavelone is computed as follow:

Since, $h(z) = (1-z^2)\exp(\frac{-z^2}{2})$ then:

$$h_1(1.4) = (1-1.8^2)\exp(-\frac{1.8^2}{2}) = -0.4433$$

$$h_2(0.46667) = (1-0.46667^2)\exp(-\frac{0.46667^2}{2})$$

$$h_2(0.46667) = 0.70148$$

$$h_3(-0.86667) = (1+0.86667^2)\exp(\frac{0.86667^2}{2})$$

$$h_3(-0.86667) = 0.1709$$

-5-

$$h_4(-2.2) = (1+2.2^2)\exp(\frac{2.2^2}{2}) = -0.3414$$

Since, $g(x) = f(x)\sum_{i=1}^{4} w_i h_i(z_i)$

$$g(-1) = -4.246\times(-0.4433\times 0.1 + 0.70148\times 0.2 + 0.1709\times 0.3 - 0.3414\times 0.4)$$

$$g(-1) = -0.0453$$

3) For

$f(x) = 10\exp(-0.05x-0.5)\sin((0.03x+0.7)x)$

Let $x = 3$

Therefore, $f(3) = 3.64$

$$z_1 = \frac{x-b_1}{a_1} = \frac{3-(-10)}{5} = 2.6$$

$$z_2 = \frac{x-b_2}{a_2} = \frac{3-(-3.33334)}{5} = 1.26667$$

$$z_3 = \frac{x-b_3}{a_3} = \frac{3-(3.33334)}{5} = -0.06667$$

$$z_4 = \frac{x-b_4}{a_4} = \frac{3-(10)}{5} = -1.4$$

Now, the value of mother function at each wavelone is computed as follow:

Since, $h(z) = (1-z^2)\exp(\frac{-z^2}{2})$ then:

$$h_1(1.8) = (1-2.6^2)\exp(-\frac{2.6^2}{2}) = -0.196$$

$$h_2(1.26667) = (1-1.26667^2)\exp(-\frac{1.26667^2}{2})$$

$$h_2(1.26667) = -0.271$$

$$h_3(-0.06667) = (1+0.06667^2)\exp(\frac{0.06667^2}{2})$$

$$h_3(-0.06667) = 0.9933$$

$$h_4(-1.4) = (1+1.4^2)\exp(\frac{21.4^2}{2}) = -0.36$$

Since, $g(x) = f(x)\sum_{i=1}^{4} w_i h_i(z_i)$

$$g(3) = 3.64\times(-0.196\times 0.1 - 0.271\times 0.2 + 0.9933\times 0.3 - 0.36\times 0.4)$$

$$g(3) = -0.2915$$

5-<u>Approximation Of Two-Dimension Function</u>

The previous example has been demonstrated as an approximation for one dimension function. If the signal represents a function of two dimensions like image, then it will require two variable mother functions:

$$h_{a,b}(t_1,t_2) = h\left(\frac{t_1-b}{a}, \frac{t_2-b}{a}\right) \qquad \ldots (18)$$

The Wavenet parameters w_k, a_k, and b_k in multivariable functions can be optimized in the LSM algorithm by minimizing a cost function or the energy function Ef over all dimension of function. Thus by denoting [4]:

$$e(i,j) = x(i,j) - g(i,j) \qquad \ldots (19)$$

The energy function is defined by:

$$Ef = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} e^2(i,j) \quad \dots (20)$$

$$Ef = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - g(i,j))^2 \quad \dots (21)$$

Where

N, M : Dimensions of the image in pixel.

To minimize Ef , the method of steepest descent may be used, which requires the gradients $\frac{\partial Ef}{\partial w_k}$, $\frac{\partial Ef}{\partial a_k}$, and $\frac{\partial Ef}{\partial b_k}$ for updating the incremental changes to each particular parameters w_k, a_k, and b_k respectively. The gradients of Ef are:

$$\frac{\partial Ef}{\partial w_k} = -\frac{2}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} e(i,j) x(i,j) h_k(z_1, z_2) \quad \dots (22)$$

$$\frac{\partial Ef}{\partial b_k} = -\frac{2}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} e(i,j) x(i,j) w_k \frac{\partial h_k(z_1, z_2)}{\partial b_k} \quad \dots (23)$$

$$\frac{\partial Ef}{\partial a_k} = -\frac{2}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} e(i,j) x(i,j) w_k \frac{\partial h_k(z_1, z_2)}{\partial a_k} \quad \dots (24)$$

-6-

where:

$$z_1 = \frac{i - b_k}{a_k} \quad \dots (25)$$

$$z_2 = \frac{j - b_k}{a_k} \quad \dots (26)$$

(c) (d)

Figure (5) shows the Wavenet approximation for the given (64* 64) pixels image using the following two dimensions mother function:

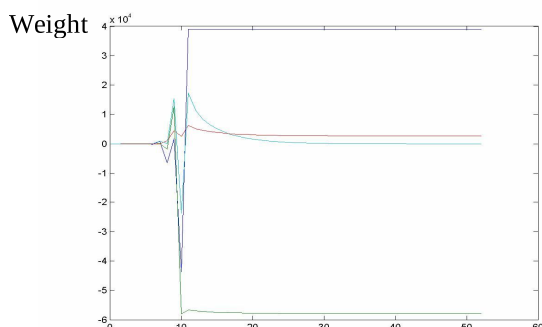
$$h(z_1 z_2) = z_1 z_2 \times e^{(-\frac{(z_1{}^2 + z_2{}^2)}{2})} \quad \dots (27)$$

The initial and final parameters are shown in table (1). Learning rate parameters for weights, dilations, and translations are fixed all at 55. A batch-mode learning of (64x 64) pixels are adapted until the desired error of 0.005 is reached. Wavenet has 4 wavelons. The total number of iterations needed was 52 iterations.

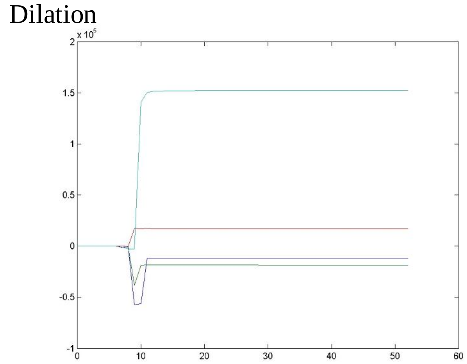
T

(a)

(b)

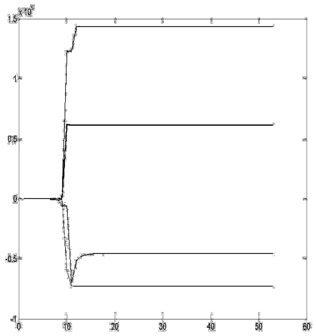


(c) Iteration



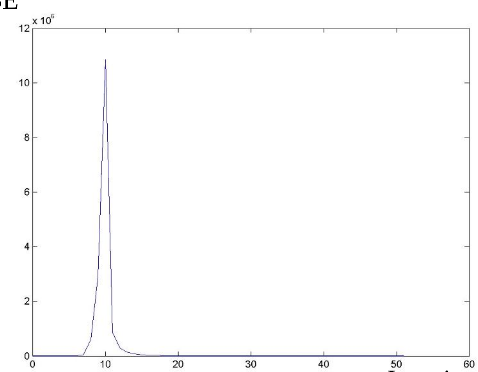
(d) Iteration

Translation



(e) Iteration

ISE



Iteration

(f)

Figure (5): Learning Process and Time Histories of Wavelet Network Parameters.

(a) Original image.
(b) Approximated image.
(c) Weight update
(d) Dilation update
(e) Translation update
(f) Integral square error (ISE).

Initial Parameters			**Final Parameters**		
w	*a*	*b*	*w*	*a*	*b*
0	4	1	38980	-12093	1.4e+005
0	4	22	-57884	-18555	-72548
0	4	43	2720	17023	61505
0	4	64	15.049	1.5e+005	-45090

Mahalanobias Distance

The Mahalanobias distance is a useful way of determining the similarity of a set of values from an "unknown" sample to a set of values measured from a collection of "known" samples. The actual mathematics of the Mahalanobias distance calculation has been known for some time. In fact, this method has been applied successfully for spectral discrimination in a number of cases. One of the main reasons why the Mahalanobias distance method is used is that it is very sensitive to inter-variable changes in the training data. In addition, since the Mahalanobias distance is measured in terms of standard deviations from the mean of the training samples, the reported matching values give a statistical measure of how well the data of the unknown sample matches (or does not match) the original training data. The Mahalanobias distance, however, does not take the sample variability into account. Instead of treating all values equally when calculating the distance from the mean point, it weighs the differences by the range of variability in the direction of the sample point. Mahalanobias distances look at not only variations (variance) between the responses at the same wavelengths, but also at the inter- wavelength variations (co-variance).

Another advantage of using the Mahalanobias measurement for discrimination is that the distances are calculated in units of standard deviation from the group mean. So, the main reason that led us for using Mahalanobias distance way among different ways of distance measure (Euclidian distance, Chess board distance and City block distance) is that the Mahalanobias distance is a weighted one, which can be expressed as follows [5]:

$$\text{Distance}=|E-E_i|\ C_i\ |E-E_i|^{T} \quad \ldots (28)$$

where C_i is the covariance matrix of the feature set of image i, E is the feature vector for the unknown image, E_i is the feature vector of

the image from the reference set, where i ranges from 1 to the total number of feature vectors in the reference set file, and T for a matrix transpose.

7- Proposed Identification System

The proposed identification system consists of two phases:

1- Construction of human body member signature

2- Identification phase

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7.1 Construction of human body member signature

The procedure of construction of human body member signatures is as follows:

1- Input a human body member color image.

2- Analyze the entered color image to three-band monochrome images (red, green, and blue).

3-Approximate each band resulting from step 2 using wavenet.

4- Subdivide each band resulting from step 3 into 16 subparts.

5- Calculate the energy En of each subpart using the following equation [6]:

$$En = \frac{1}{N} \sum x_{i,j}^{2} \qquad (29)$$

Where, En is the energy of image subpart, N is the total number of pixels, $x_{i,j}$ stands for the ith, jth individual pixels.

6- Construct a reference file that contains a three values of energy for each subpart (En_{red}, En_{green}, En_{blue}) Which represents a signature of that subpart. Figure (6) shows a block diagram of human body member signature construction.

7.2 Identification Phase

To identify whether the member is infected or not the following procedures should be followed:

1- Input the test image

2- Follow the procedures from step 2 to step 6 in suction (7.1) to construct signature of each subpart of test image.

3- Use equation (28) to calculate the distance between each subpart of test image with those in a reference file.

4-If there is no zero distance in a result (which represents a distance between the entered subpart of test image with its corresponding one in a reference file) the entered subpart will be infected, otherwise it will be a healthy subpart

8- Demonstrative Example

In order to identify whether the liver is infected or not, a new liver image to the same person should be taken then compared with the liver image stored in advance (fig. 7-A) as a features in a reference file. The following procedures should be followed:

1- Enter a new liver image as shown in figure (7-B).

2- Analyze the image into three bands image (RGB) as shown in figure (7- C, D, E).

3- Approximate each band using Wavenet structure. Figure (6-F, G, H) shows the approximated images.

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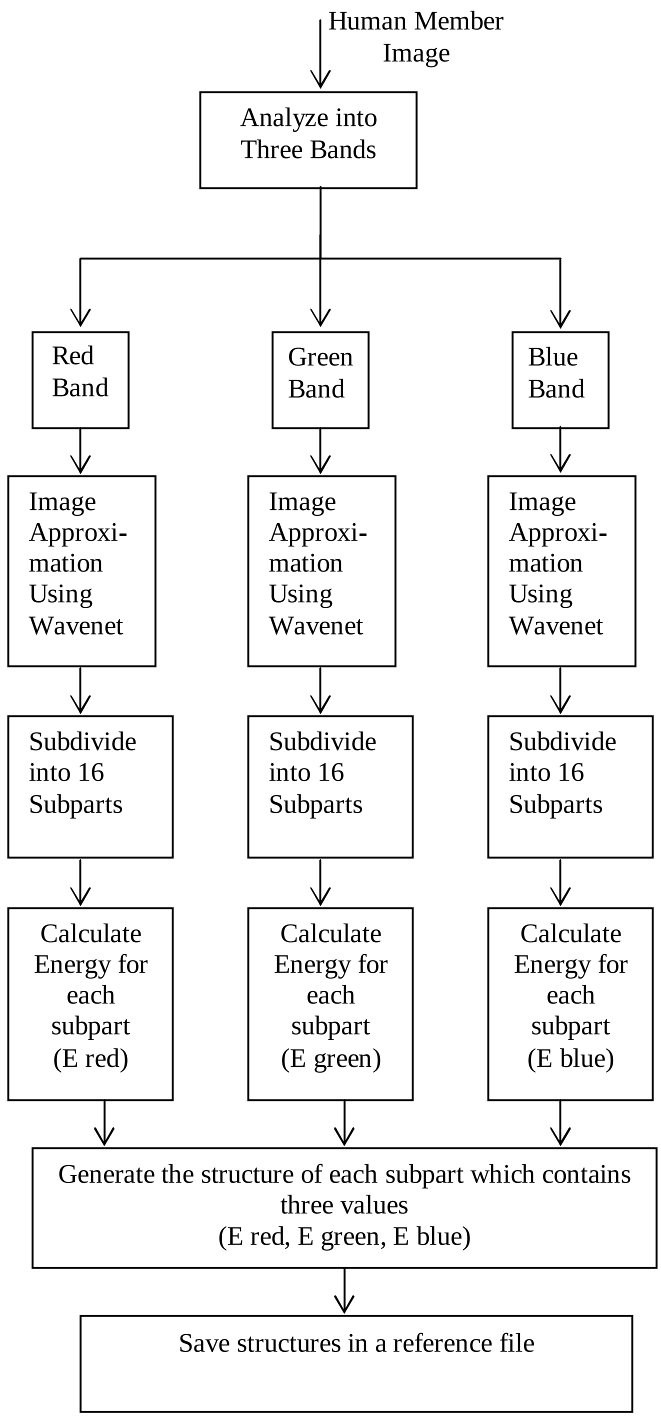

Figure (6): a block diagram of human body member signature construction.

4- Subdivide each band resulting from step 3 into 16 subparts as shown in figure (7-I, J, K).

5- Calculate the energy of each subpart for three bands using equation (29).

6- Construct the signature vector of each subpart in the main image which contains (Enx red, Enx green, Enx blue). Where, E: The energy of subpart. x: The label of subpart (from a to p) as shown in figure (7-I, J, K). for example: The vector (Ea red, Ea green, Ea blue) represents the signature vector of the first subpart in the main image and so on.

7- Using equation (28) to calculate the distance between each subpart in a new liver image with those stored in a reference set.

Table (2) shows the Mahalanobias distance between the energy vector of subpart –a- and all the feature vectors stored in a reference file. Existing of zero distance value or other value near that confirms the healthiness of this subpart.

Table (3) shows the Mahalanobias distance between the energy vector of subpart –k- and all the feature vector stored in a reference file. Because there is no zero distance value in a table (especially the value noted in a bold box), that will confirm the infection of this subpart.

9- Conclusions

In this work, wavelet network has been introduced to assist in the process of building accurate dynamic programming algorithm. It was used to extract useful image information for solving application-based problems. Both neural network and wavelet transform inspired this method. Wavelets were used as activation functions. The following points are concluded from the test of the proposed algorithm:

Distance between subpart **-a-** to all ref. set subparts (16 subparts from a to p)	Distance between subpart **-k-** to all ref. set subparts (16 subparts from a to p)
$\boxed{0.000}$	417.930
6.365	364.120
23.219	779.420
49.120	956.120
2261.100	2729.200
166.360	2.736
204.080	6.783
1.383	370.050
3.082	437.460
222.820	11.091
16.817	$\boxed{273.710}$
10.990	643.850
81.605	1113.600
65.792	66.438
6.982	603.51
80.660	1108.430

a b c d f g h i j k l m n o p

1- The integration of wavelet and neural networks has the abilities of self-learning and self-organizing which was achieved here an accurate result of classification of image textures of 100%. This is because wavelet theory is useful tool for function estimation and signal processing.

2- Wavelet networks lead to an implementation of important application in identifying sub images. So, it was noticed that it is possible to find out any given subpart that belongs to which main image in the reference set.

3- Wavelet network has some drawbacks: a) Decreasing the accuracy (cost function). b) Wavelet network may fail in a local minimum during the training; therefore, it must restart the training and change the choice of wavelet network parameters.

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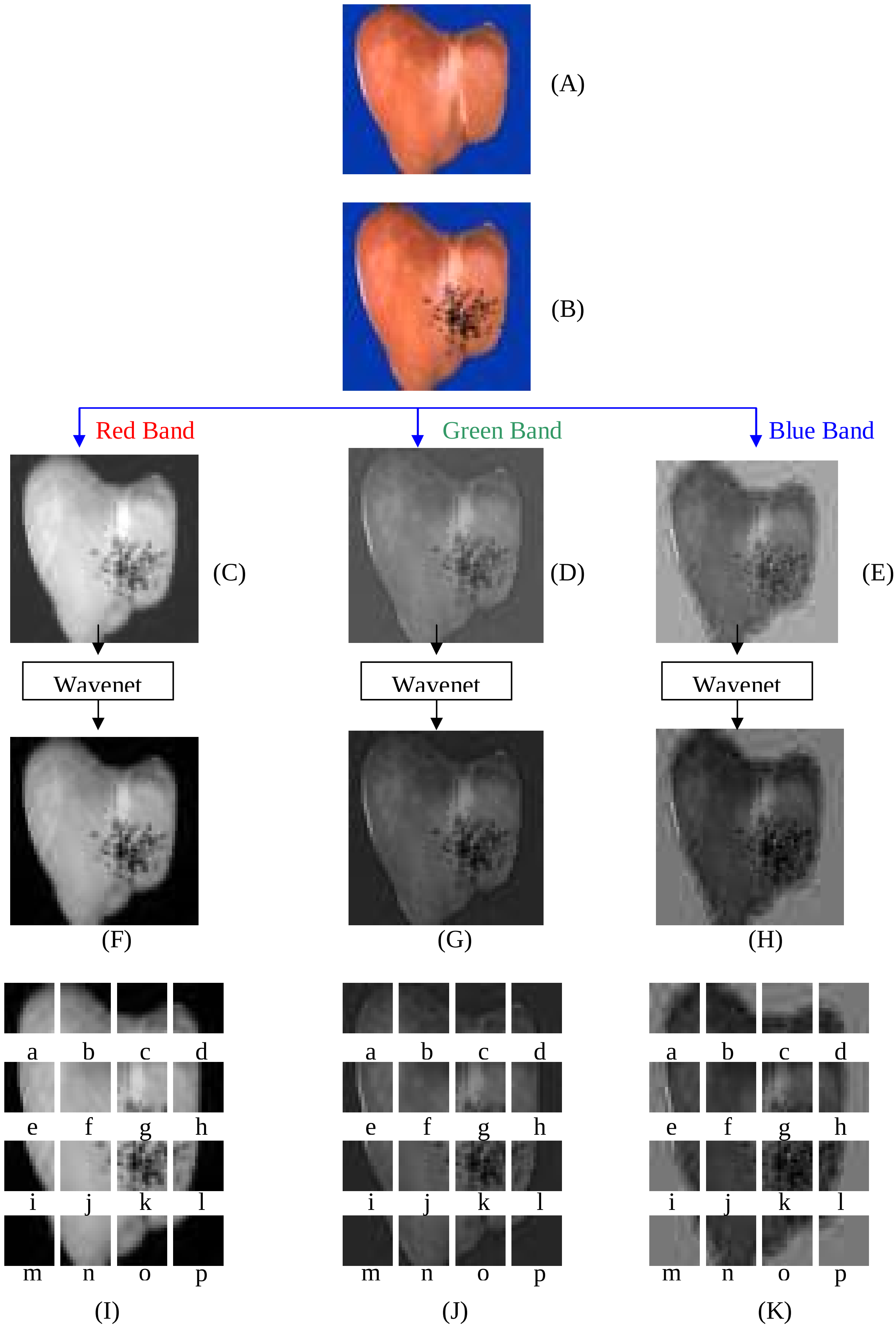

Figure (7): (A): The healthy liver image. (B): The infected liver image. (C, D, E): Three band monochrome image. (F, G, H): The approximated images. (I, J, K): Three band subparts.