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Website: http://jsci.utq.edu.iq Email: utjsci@utq.edu.iq

Image Classification System Based on Multi-wavelet and Neural Network

Ausama A. Majeed

Thi-Qar University - College of Science

Abstract:

Image classification with the generation of signature to the image. This paper propose approach of image classification based on multi-wavelet transform which has a matrix structure, and combines plays a great role in industrial, remote sensing, and military applications. It is concerned all features that a simple scalar wavelet cannot have at once. A successful classification rate of 98% was achieved with this method.
Also, the Neural Network (NN) classifier is combined with the multi-wavelet transform. The purposed neural network is a feed-forward multilayer. The learning algorithm uses is Levenberg Marquardt Algorithm. It is found that such combination is capable of performing advanced computation and approximates of a desired input-output behavior. The effect of this combination on the classification task is considered an average classification rate of 100% is achieved for Discrete Multi-wavelet with Neural Network method.

1. Introduction:

Typical image classification system includes three phases, namely the preprocessing phase, the segmentation and feature extraction phase, and the classification phase. Figure (1) gives a general block diagram for the image classification system. In the preprocessing phase, the image is first digitized by suitable sampling process. The image segmentation and the feature extraction phase are to be performed. The resulting image is segmented into many frames which are ready for the feature extraction. The classification phase assigning the image to a specific image class label, depending on a stored reference set. Then the image class entered into logical decision stage multi-wavelets can simultaneously provides perfect reconstruction while preserving length to give classification to the image depending on a database file[1].

Wavelets are a useful tool for signal processing applications such as image processing (compression, denoising, recognition, etc.). Until recently, only scalar wavelets were known: wavelets generated by one scaling function. But one can imagine a situation when there is more than one scaling function. This leads to the notion of multi-wavelets, which have several advantages in comparison to scalar wavelets[2]. On the other hand, multi-wavelets consist of several scaling functions and wavelets. It is believed that multi-wavelets are ideally suited to multichannel signals like color images which are two-dimensional three-channel signals. Multiscaling functions and (orthogonality), good performance at the boundaries (linear phase symmetry), a high order of approximation (vanishing moments) and compact support. Thus multi-wavelet offer the possibility of superior performance for image processing application, compared with scalar wavelets [3-5].

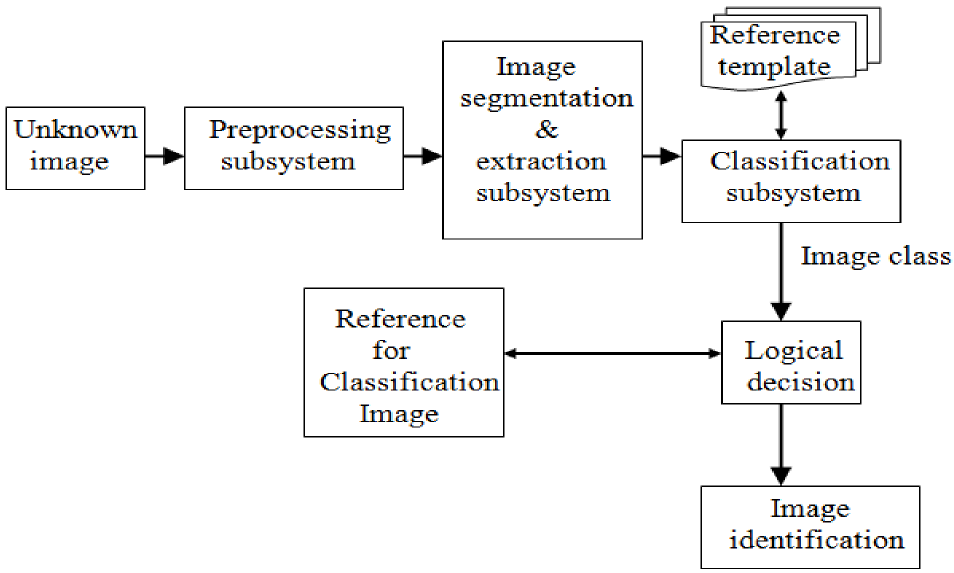


Figure (1) General block diagram of a digital image identification system[1]

One of the important differences between multi-wavelets and wavelets is that each channel in the filter bank has a vector-valued input and a vector valued output [6, 7]. A scalar valued input signal must somehow be converted into a suitable vector-valued signal. This conversion is called preprocessing.Identification is a form of pattern recognition that required the nonlinear reparation of pattern space into subsets representation the objects to be identified. Multilayer neural network can provide can provide the desired nonlinear separation. The capability of neural networks to perform nonlinear separation can be applied both to exact image feature and to identify images based on a feature set. Practical applications is distortion invariant pattern recognition have been found hybrid system utilizing neural network for identification [3, 7, 8].

The aim of this paper is to design an automatic classification of digital images based on the combination of multi-wavelet transform and neural networks. The rest is organized as follows: Section 2 presents a mathematical material of discreet multi-wavelets transform combining with neural network. Section 3 explains the proposed classification system. Section 4 presents the experiments results with examples. Finally conclusion is finishing this paper

2. The combination of multi-wavelets and neural network:

Any good transform should possess several important properties: orthogonality, symmetry and finite-length filters for computational efficiency. However, most real scalar wavelet transforms fail to possess these properties simultaneously. To circumvent these limitations, multi-wavelets have been proposed where orthogonality and symmetry are allowed to co-exist by relaxing the time-invariant constraint. Multi-wavelets may be considered as a generalization of scalar wavelets. However, some important differences exist between these two types of multiresolution transforms [2, 9].

For the purpose of this paper the Discreet Multi-Wavelet Transform (DMWT) was applied an original image to get the image features extraction that are reflect the information of an original image. Because there is no a priori knowledge and experience, only from these features that is not convenient for the image classification. So a neural network is used to fit the values extracted by the DMWT. Then a mapping relation between images can be obtained by the pattern recognition of image based on the neural networks.

2.1 Multi-Wavelet Decomposition of the Image:

Multi-wavelet offers simultaneous orthogonality, symmetry, and short support, which are not possible with scalar two-band wavelet systems. This process is divided into two parts: *preprocessing* and *decomposition*.

2.1.1 The Preprocessing Part:

Traditionally scalar signal consist of one stream but the DMWT algorithm requires multiple input streams, a method of mapping the scalar data to the multiple streams has to be developed. DMWT (for more information refer to [2, 10]) contains the two scaling functions $\varphi 1(t)$, $\varphi 2(t)$ and the two wavelets $\psi 1(t)$, $\psi 2(t)$, where L = 2, M = 4. The dilation and translation equations for system have four coefficients are as follows:

$$\varphi(t)=\begin{bmatrix}\Sigma_1(t)\\ \psi_2(t)\end{bmatrix}=H_0\varphi(2t)+H_1\varphi(2t-1)+H_2\varphi(2t-2)+H_3\varphi(2t-3) \quad \ldots\ldots\ldots\ldots.. (1)$$

$$H_0=\begin{bmatrix}\frac{3}{5} & \frac{4*\sqrt{2}}{5}\\ -\frac{1}{10*\sqrt{2}} & -\frac{3}{10}\end{bmatrix} \qquad H_1=\begin{bmatrix}\frac{3}{5} & 0\\ \frac{9}{10*\sqrt{2}} & 1\end{bmatrix}$$

$$H_2=\begin{bmatrix}0 & 0\\ \frac{9}{10*\sqrt{2}} & -\frac{3}{10}\end{bmatrix} \qquad H_3=\begin{bmatrix}0 & 0\\ -\frac{1}{10*\sqrt{2}} & 0\end{bmatrix}$$

$$G_0=\frac{1}{10}\begin{bmatrix}-\frac{1}{\sqrt{2}} & -3\\ 1 & -3*\sqrt{2}\end{bmatrix} \qquad G_1=\frac{1}{10}\begin{bmatrix}\frac{9}{\sqrt{2}} & -10\\ -9 & 0\end{bmatrix}$$

$$G_2=\frac{1}{10}\begin{bmatrix}\frac{9}{\sqrt{2}} & -3\\ 9 & -3*\sqrt{2}\end{bmatrix} \qquad G_3=\frac{1}{10}\begin{bmatrix}-\frac{1}{\sqrt{2}} & 0\\ -1 & 0\end{bmatrix}$$

$$\psi(t)=\begin{bmatrix}\psi_1(t)\\ \psi_2(t)\end{bmatrix}=G_0\psi(2t)+G_1\psi(2t-1)+G_2\psi(2t-2)+G_3\psi(2t-3) \quad \ldots\ldots\ldots\ldots (2)$$

This mapping process is called preprocessing and it is done by a prefilter Q, the minimal matrix prefilter was used where L=2, (L is the number of decomposition levels).

$$C_{0,k} = \begin{pmatrix} f_2\,(n+k)+1 \\ \psi\, Q_n \\ f_2(n+k)+2 \end{pmatrix} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Which means the data is partitioned into a sequence of L-vectors and a filter is applied defined by a sequence of L by L matrices Q_n.

2.1.2 Two Dimensional DMWT Decomposition:

Using the same idea of separable decomposition along each dimension of a two-dimension image, the above Multirate pre-filter can integrated with Mallat's pyramid algorithms, where tensor products of the one-dimensional filter banks are used to process two-dimensional (2-D) images. Figure (2) shows the multi-wavelet framework for image decomposition. The prefilter is first applied to all the rows of the given image, before the application of first level of decomposition to each of the resultant rows.

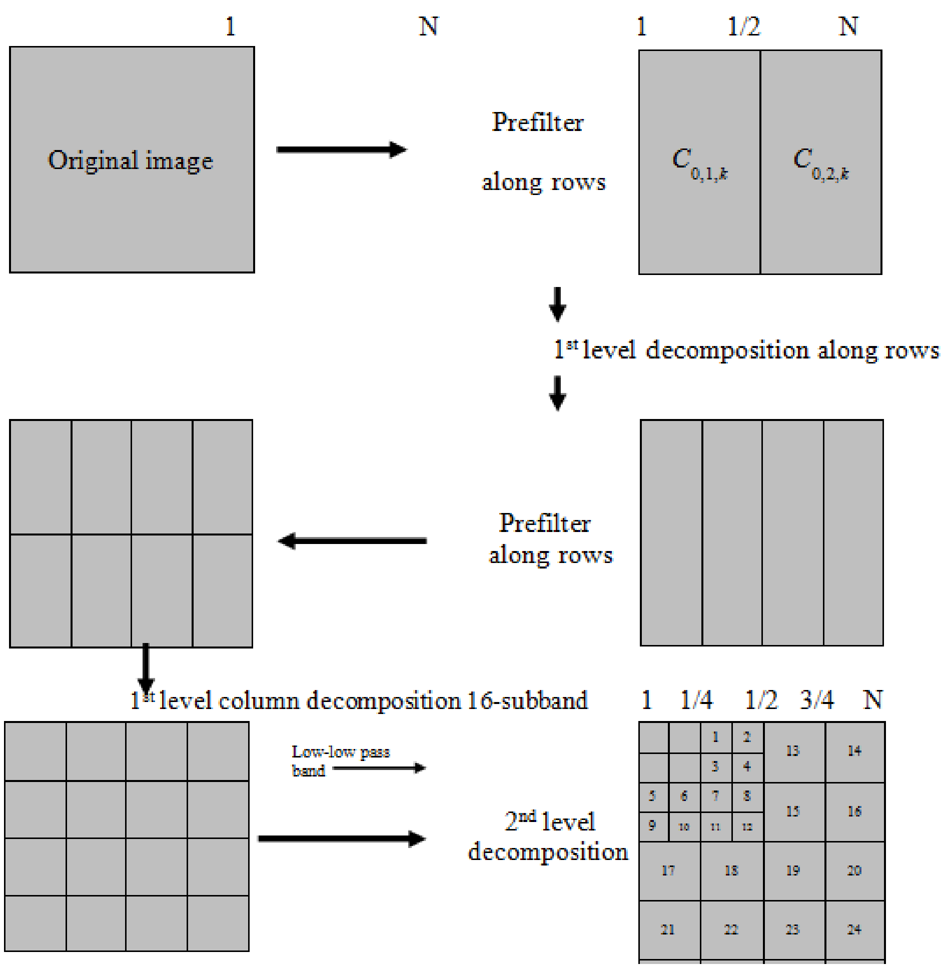


Figure 2: Two level of 2-D multi-wavelet decomposition of a 2-D image of size N×M

The first half of each row contains coefficients corresponding to the first scaling function and the second half contains coefficients corresponding to the second scaling function. Then the prefilter and decomposition operations are repeated to the columns, such that the first half of each column contains coefficients corresponding to the first scaling function and the second half of each column corresponds to the second scaling function. Then the multi-wavelet cascade starts–it consists of iterative low and high-pass filtering of the scaling coefficients in horizontal and vertical directions. At the end of the first of 2-D multi-wavelet decomposition (one cascade step), there are 16 sub-bands intermediate image as shown in figure (3-a).A typical block H_2L_1 contains low-pass coefficients corresponding to the first scaling function in the horizontal direction and high-pass coefficients corresponding to the second wavelet in the vertical direction. The next step of the cascade will decompose the "low-low pass" submatrix shown in figure (3-b) in a similar manner.

No prefiltering is performed for these 2-D decompositions where the one-dimensional (1-D) multiwavelet decomposition is applied first to the rows followed by those to the columns. In this fashion, an L-level decomposition of a 2-D image will produce 4(3L+1) subbands. The 2-D reconstruction of a 2-D image is obtained by simply performing all the steps described above for decomposition in the reverse order.

L_1L_1	L_2L_1	H_1L_1	H_2L_1
L_1L_2	L_2L_2	H_1L_2	H_2L_2
L_1H_1	L_2H_1	H_1H_1	H_2H_1
L_1H_2	L_2H_2	H_1H_2	H_2H_2

(a)

L_1L_1	L_2L_1
L_1L_2	L_2L_2

(b)

Figure 3 :(a) Two dimensional Multi-wavelet first level decomposition.
(b) The low-low-pass submatrix.

The separable product of one-dimensional "repeated row" algorithms leads to a 4:1 data expansion. This will restrict the utility of this approach to applications such as denoising by thresholding, for which critical sampling is irrelevant. The separable product of the approximation-based preprocessing methods yields a critically sampled representation which is potentially useful for both denoising and data compression.

The result of this 2-level DMWT decomposition will be 24 sub images except for the low-low pass sub images which will not be used because it loses the information through the decomposition levels.

2.2 Neural Network:

A neural network (NN) combined with multi-wavelet transform will be used in the proposed image classification system. The dynamical learning property of the neural network can be applied in system classification. The states of the neurons can represent the elements of the adjustable model, which is compared with the system to be identified. The learning rule is designed in such a way as to minimize the error between the system and the model.

The proposed NN consists of 24 nodes in the input layer which correspond to the number of features computed for the input image, and 48 nodes in the output layer which correspond to the number of image classes the application system is concerned with. Two hidden layered networks can represent an arbitrary decision boundary to arbitrary accuracy, and could approximate any smooth mapping to any accuracy with sigmoid activation functions.

Levenberg_Marquardt (LM) [11, 12] is training algorithm used to train Multi layer Feed Forward networks (MLFF), based on nonlinear optimization technique by minimizing the Sum of Squares of Error (SSE). It has better convergence properties and it is well known that, it is the best choice in many offline training of neural nets. Figure (4) the steps of illustrates the LM algorithm. The search direction for the LM algorithm is defined by:

$\Delta w = (JT*J + \eta * I)-1*(-J * \varsigma)$

Where:

JT: Jacobean matrix of proper dimension.

JT*J: covariance matrix of proper dimension.

Δw: correction matrix of proper dimension.

η: learning parameter 1> = η>0.

I: identity matrix.

ς: Difference between network output and desired output.

1-Initialize network (weights and biases).
2- For each training pair Do (3-7) UNTILL performance criterion.
3- Sums weighted input and apply activation function to compute output signal.

$$h_{qj} = \sum_{i=1} w_{ij} x_i + b_i \Rightarrow h_j = f(h_{qj})$$

4-Compute output of the network.

$$yy = b_p + \sum w_{pi} h_i \Rightarrow y = f(yy)$$

5-Calculate error term $\varsigma = y - yd$

6- Calculate correction term.

$$wb = [w_1 b_1 + w_2 b_2 + \ldots\ldots w_p b_p]$$

$$\Delta wb = (J^T * J + \eta I) * (-J^T \varsigma)$$

7- Update weights and biases.

$W_{ij}(new) = w_{ij}(old) + \Delta wb.$

Figure (4) the steps of LM algorithm

3. Tth proposed image classification system:

The input to the system is a grayscale image of size 128 × 128. The procedure of image classification system consist of three phases: *build the reference images set, neural network training,* and *classification.*

First: Build the reference set phase.

In this phase a reference set of all system images are built. Figure (5) illustrate the flow chart to generate a reference set.

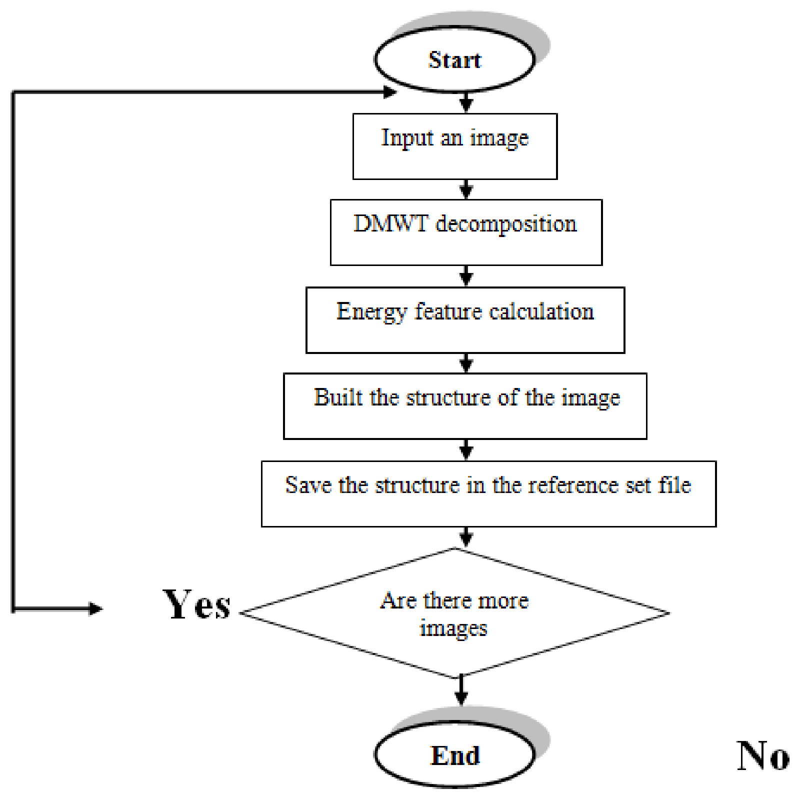


Figure (5) Generation of reference set flowchart

Second: Neural Network Training phase.

There are two phases in neural information processing: which are the learning phase and the retrieving phase. A multilayer feed-forward neural network is used with two hidden layers. The tan sigmoid function has proven to be suitable for the transfer function. The training algorithm used is the ***Levenberg Marquadt*** training algorithm. The proposed NN consists of 24 nodes in the input layer which correspond to the number of features computed for the input image, and 48 nodes in the output layer which correspond to the number of texture image classes the application system is concerned with.Learning in neural networks involves adjusting the connection weights so that the difference between the output and the desired output is deceased. Once the network weights and biases have been initialized, the network is ready for training. The training process requires a set of examples of proper network behavior. The input (training pattern) to the net will be the feature vectors stored in the reference file for all the images concerned the application we work with to make the net learn the characteristics of those images.

Third: Classification phase:

The steps of the classification phase are given below:

1- The unknown image is entered to the system.
2- Decompose the image from step (1) using multi-wavelet transformation, the result will be (24) sub images except for the low-low sub image.
3- Construct image feature vector that contains information about important features on the image, by calculating the energy feature for each one of the (24) sub images resulting from step (2) above, which describes the image.
4- Classify the unknown image using the feature vector which results from step (3), which is first normalized and then entered to the neural network trained in phase two.
5- Classification of the class label resulted from step (4) are used in this classification application system and the corresponding image classification for each class. The result of this matching process is classification for the unknown texture image entered to the system.

4. EXPERIMENTAL RESULT:

Several experiments were carried out to test the proposed image classification system. There were carried out two distinct families of samples:

- Natural images: The performance of our method on images of natural image using multiwavelets.
- *Synthetic images*: These tests are performed on several synthetic images.

To test the results of the proposed classification algorithm, this classification algorithm has been tested on 12 original and constructed images from the original images saved in a reference set file (refer to Appendix A).

Example (1): Natural image

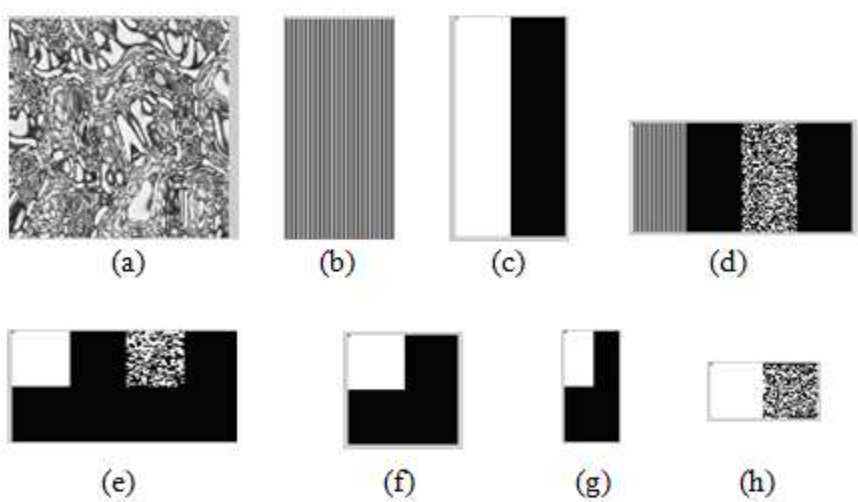


Figure (6): (a) Natural unknown image. Two-level multi-wavelet decomposition, (b) Prefilter along rows, (c) First level decomposition along rows, (d) Prefilter along columns, (e) First level decomposition along columns, (f) Low-low pass submatrix of size 64×64, (g) Second level decomposition along rows for the low-low pass submatrix, (h) Second level decomposition along columns for the low-low pass submatrix.

where,

The feature vector for the 24 sub images = (0.1376, 0.0095, 0, 0, 0, 0.1078, 0.0023, 0, 0, 0.8647, 0.2673, 0.0868, 0.0023, 0.0651, 0.0143, 0.0543, 0.0845, 0.0152 , 0.0719, 0.0543, 0, 0, 0, 0)

Example (2): Synthetic image

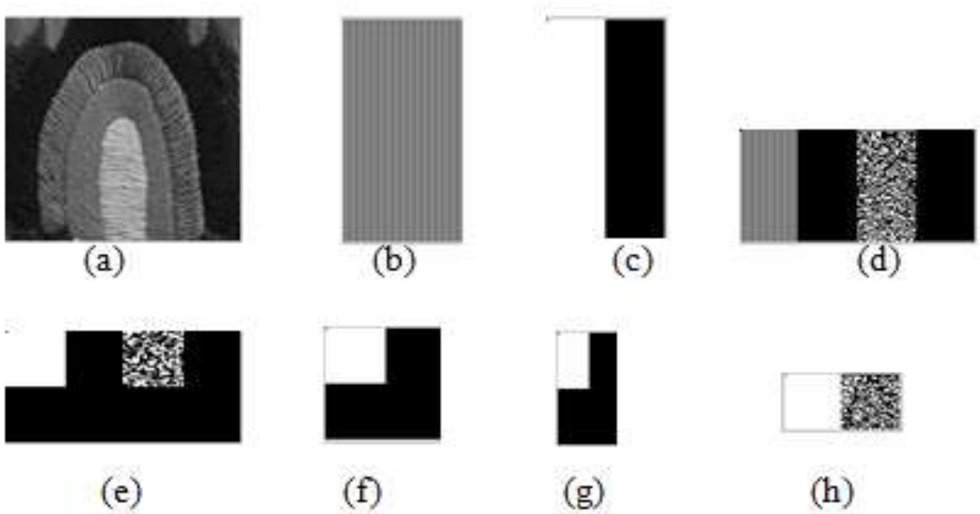


Figure (7): (a) Natural image, (b) Prefilter along rows, (c) First level decomposition along rows, (d) Prefilter along columns, (e) First level decomposition along columns, (f) low-low pass submatrix of size 64×64, (g) Second level decomposition along rows for the low-low pass submatrix, (h) Second level decomposition along columns for the low-low pass submatrix.

where,

The feature vector for the 24 sub images = (0.1376, 0.0095, 0, 0, 0, 0.1078, 0.0023, 0 , 0 , 0.8647, 0.2673, 0.0868, 0.0023, 0.0651, 0.0143, 0.0543, 0.0845, 0.0152, 0.0719, 0.0543,0 ,0 ,0 ,0)

The Classification: After decompose image, as shown in previous examples, the neural network has been trained in phase two, the net can be tested to classify images. The feature vector results (as stated in previous examples) will be first normalized and then entered to the trained neural network. The result of the adapted learned weights and the output of the net will be the entire node 1 which has an output 1.000, which means that it is the active node the class label given to the entered unknown image is 1.

4.1 Evaluation tests of the results:

A combined method between multi-wavelet and neural network is proposed and trained and the tested results show that this method gives perfect classification results. Our results show that a multilayer feed-forward network has potential for classifying image into 48 classes with high accuracy. However, the computation time required for training the network depends on the properties of the combined feature set. The number of nodes in the neural network output layer corresponds to the number of classes in our training data (i.e. 48) fixed layer. The number of nodes in the input layer varies according to how many features we use in the experiment.

On the other hand, well-known problems involved in the use of neural networks are to be faced. No general criteria for defining a suitable network architecture, dependence of classification results on training conditions (choice of the training set, initial weights, training parameters, etc.) and difficulty with interpreting the “ network behavior ’’.

5. CONCLUSION:

From the test of the proposed method concluded that Multi-wavelets are a new addition to the body of wavelet theory. Realizable as matrix-valued filter banks leading to wavelet bases, multi-wavelets offer simultaneous orthogonality, and short support, which is not possible with scalar 2-channel wavelet system. Multi-wavelets differ from scalar wavelet systems in requiring two or more input streams to the multi-wavelets filter bank. Multi-wavelets are generated by more than one scaling function. There are many degrees of freedom in the construction of multi-wavelets. These allow for more features to be built into a multi-wavelet transform, and enable one to construct multi-wavelet filters to suit one's need.

Many types of images were decomposed using different DMWT and features were computed on the decomposed sub-images. The proposed DMWT method was examined on the database under consideration. After testing all the images a correct classification rate of 98% was achieved.

A neural network approach was selected to be combined with the MWT order to develop the classification rate to be perfect. Neural networks have proven to be highly adaptable classifiers for mixed data sets where the user does not wish to describe the data by a fixed statistical model.

6. REFINANCES:

[1]J. Teuber, *Digital Image Processing*: Prentic Hall, 1989.

[2]H.-H. Wang, "Multisensor Image Fusion Using Discrete Multiwavelet Transform," *IEEE Int. Conf. on Machine Learning and Cybernetics*, vol. 7, pp. 4331-4336, 2000.

[3]A. Morimoto, R. Ashino, and R. e. Vaillancourt, "Multiwavelet Neural Network Preprocessing of Irregularly Sampled Data," vol. 19, 2006.

[4]G. G. Wilkinson, F. Frierens, and L. Kanellopoulos, "Integration of Neural and Statistical Approaches in Spatial Data Classification," *Geographical System*, vol. 2, pp. 1-20, 1995.

[5]M. Alfaouri, "Image Identification and Labeling Using Hybrid Transformation and Neural Network," *I-manager’s Journal on Future Engineering & Echnology*, vol. 2, pp. 50-61, 2007.

[6]M. Alfaouri, "Image Recognition Using Combination of Discrete Multi_Wavelet and Wavenet Transform," *American Journal of Applied Sciences*, vol. 5, pp. 418-426, 2008.

[7]V. Strela, P. N. Heller, G. Strang, P. Topiwala, and CHeil, "The Application of Multiwavelet Filterbanks to Image Processing," *IEEE Transactions on Image Processing*, vol. 8, pp. 548 - 563, 1999.

[8]B. U. Shankar, S. K. Meher, and A. Ghosh, "Neuro-Wavelet Classifier for Remote Sensing Image Classification," *Int. Conf. on Computing: Theory and Applications (ICCTA'07)*, pp. 711-715, 2007.

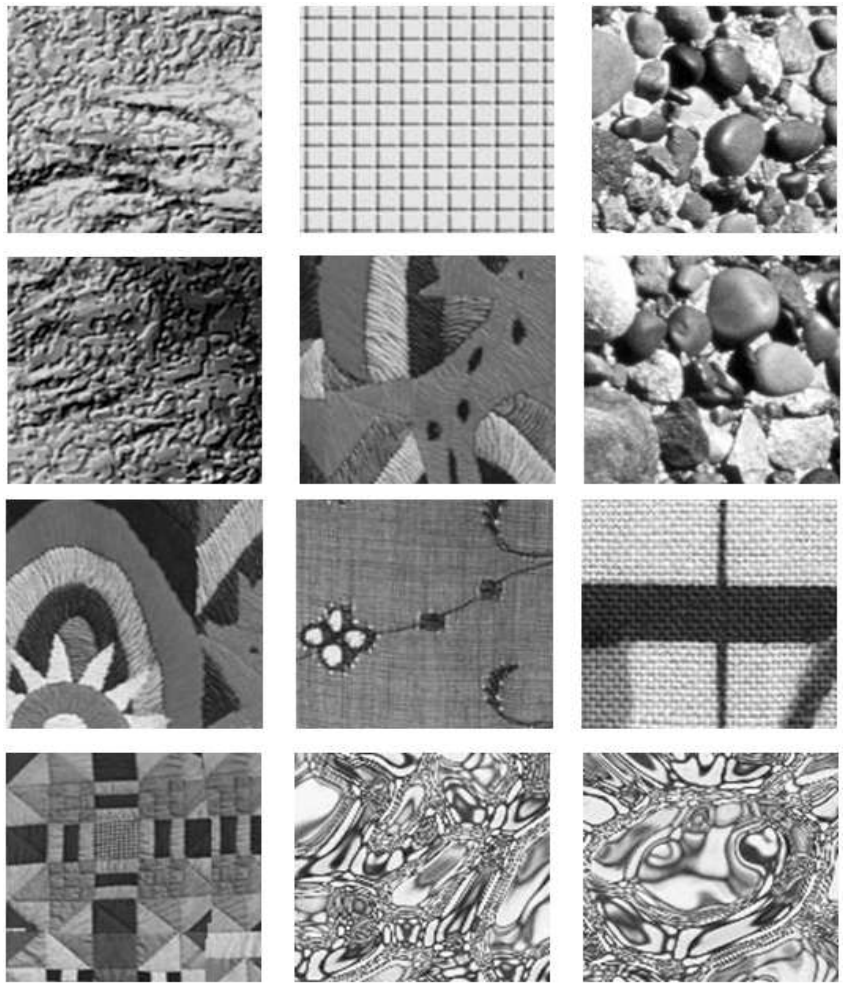
[9]C. V. Serdean, M. K. Ibrahim, A. Moemeni, and M. M. Al-Akaidi, "Wavelet and Multiwavelet Watermarking," *IET Image Process*, vol. 1, pp. 223-230, 2007.

[10] A. Dalal'ah and N. Alramahi, "A Multi-Level Identification System Using Wavelet Transform and Multi-wavelet Transform With Neural Networks," *Information Technology & National Security Conferance*, vol. 4, pp. 2047-2073, Dec. 2007.

[11] B. Soucek and M. Soucek, *Neural and Massively Parallel Computers*, 6th ed. U.S.A.: John Wiley and sons Inc., 1988.

[12] L. Rutkowski, *Computational Intelligence: Methods and Techniques*: Springer, 2008.

Appendix A: The Original Reference Set Images



نظام تصنيف الصور باستخدام المويجات المتعدده و الشبكه العصبيه

الخلاصة:

إن تصنيف الأنسجة لعب دوراً كبيراً في الصناعة والتحسس عن بعد وفي التطبيقات العسكرية. في السنوات الأخيرة تحليلات الموجة أصبحت مهمة في تحليل وتمييز الصور. اعتمد البحث على تصنيف الصور بالاعتماد على دمج التحويل متعدد المويجات مع الشبكه العصبيه.إن تحويل متعدد المويجات ذو تركيب مصفوفاتي تناظري مما يجعله مناسباً جداً لاستخلاص الصفات وبصورة أكفأ من تحويل الموجة العددي. أن تحويل متعدد المويجات حقق نجاحاً مقداره 98٪ في تصنيف الصور وبدمج الشبكة العصبية مع تحويل متعدد المويجات يكون مقدار تأثير الاتحاد على عملية التصنيف في إنجاز وتنفيذ الصور بمقدار 100٪ ، حيث تم التدريب باستخدام طريقة(Levenberg Marquardt Algorithm) .