Image Recognition Using Combination of Multiwavelet and Radon Transforms with Neural Network

Ahmed Q. AL-Thahab
Babylon University, College of Engineering

Abstract

In many of the digital image processing application, observing image is modeled to be corrupted by different type of noise that result in a noisy version. Hence, image classification is an important problem that aim to find an estimate version from image have a noise that is close to the original image as possible. In the last few years, for image classification, accuracy of previous methods like Fourier transform, wavelet transform, and other methods are not so high, so they neglect some particular characters of image data. In this paper, classification method based on multiwavelet transform and radon transform that proposed, and these two transforms combine together to extract useful information from image, and then forward these features extraction for classification by using robust method of artificial neural network. The aim of this paper is that how the noisy image can be classified properly into original image via high recognition rate. A successful recognition rate of 99.3% was achieved.

Keywords: Multiwavelet Transform, Radon Transform, Type of Noise, Artificial Neural Network

الخلاصة:

في عديد من تطبيقات معالجة الصورة الرقمية، الصورة المرئية صممت لكي تكون مشوشة عن طريق أنواع مختلفة من الضوضاء التي نتجت من صورة صاخبة. لذالك، تصنيف الصور يكون من المشاكل المهمة التي تهدف إلى إيجاد نسخة مخمنة من صورة تمتلك ضوضاء والتي تكون مقاربة الى الصورة الأصلية بقدر الإمكان. في السنوات القليلة الماضية، لتصنيف الصور، دقة الطرق السابقة مثل تحويل فورير، تحويل المويجة، وطرق أخرى ليست عالية جدا، بحيث إنها تهمل بعض الصفات الخصوصية المتعلقة ببيانات الصورة. في هذا البحث، طريقة التصنيف المعتمدة على أساس تحويل متعدد المويجة وتحويل الرادون قد اقترحا، وكلا هذين التحويلين جمعا معا لاستخلاص المعلومات المفيدة من الصورة، وبعد ذلك إرسال هذه الخواص المستخلصة إلى الإمام للتصنيف عن طريق استخدام طريقة قوية في الشبكات العصبية. إن الهدف من هذا البحث هو الحصول على نسبة تمييز عالية للصورة الحاوية على ضوضاء واستخلاص صورة أصلية لها. وقد تم تحقيق نسبة تمييز ناجحة قدرها 99,3%.

1. Introduction

Unlike human beings who have the excellent capability to recognize different faces, machines are still lacking this aptitude due to variation in image illuminations, complex backgrounds, visual angles and facial expressions. Therefore face recognition has become a complex and challenging task. Research on this issue as a part of computer vision is nearly 20 years old [Almas Anjum, et al, 2006].

The various applications of image processing on image content representation has drawn much attention in the past decade. A set of keywords is used to represent image contents in most of the systems. However, keyword-based taxonomy reduces the system complexity while increasing the requirements of users knowledge. On the other hand, much research has been conducted on representing image contents with visual features. Most of the applications represent images using low level visual features, such as color, texture, shape and spatial layout in a very high dimensional feature space, either globally or locally. However, the most popular distance metrics, for example, Euclidean distance, cannot guarantee that the contents are similar even their visual features are very close in the high dimensional feature space[Zou, et al, 2007]. Image is a visual impression of something, so the images are a vital and integral part of every day life. On an individual, or person-to-person basis, images are used to reason, interpret, illustrate, represent, memorize, educate, communicate, evaluate, navigate, survey, entertain, etc [Tayel, et al, 2006]. There are different kinds of images, but what is a color image? A color image is a representation of what can capture a human eye. Color images can be of different types such as RGB, multichannel, or raster images[Diaz, et al, 2000].

Image classification has been an interesting task for the computer vision and image processing community. The basic problem of image classification is to find an appropriate category for an image given a predefined set of categories. Many problems can be treated as a variant of the image classification problem. For example, the problem of object detection can be viewed as a special case of image classification where each type of object is treated as a different image category. Recently, some machine learning techniques have been applied in order to solve the problem of image classification. The basic idea is that, by looking at positive and negative examples for an image category, the machine learning algorithm will learn a model from those examples and apply the learned model to predict the category for an unseen image. To accomplish it, we need to solve two issues: the first one is the representation issue, i.e. how to represent an image with a set of features and the second issue is the issue of classification, i.e. how to learn a model from the examples for an image category and then use the learned model to determine the appropriate category for an image [Jin, et al, 2003].

Image classification, especially face image classification, attracts much attention recently as a result of the increasing demand for developing real-world vision systems. Face recognition using appearance-based learning algorithms, a particular open topic in such areas, brings out a great deal of research and discussion due to its promising applications. However, improving the face recognition performance is still difficult because of the large variability in the facial appearance. In general, there are four main factors that mostly affect the recognition accuracy: discriminate subspace (dimensionality reduction), similarity metric, data structure, and classifier[Fu, et al, 2008]. Image classification from a database is particularly difficult for traditional machine learning algorithms because of the high number of images and many details that describe an image. For these reasons, traditional machine are unstable to classify images from a database. Furthermore, these machines take long time for classification[Lotfi, et al, 2009].

2. Related Work

In this section, describe a bout previous work for image classification using combination of wavelet transforms and neural networks. In [park, et al, 2004] Haar and a bank of perceptrons applied to image classification from data base of 600 images (300 for training and 300 for testing). They obtain 81.7% correct classification for training set and 76.7% for testing set. In [Tayel, et al, 2006] combination of wavelet transform and neural network for ECG(Electrocardiogram) image classification they report performance up to 92%. In [Gonzalez, et al, 2006] Daubechies wavelet transform are used to classification, 120 color images of airplanes were used for training and 240 for testing the best efficiency of 88% was obtained. Our proposed method in this paper also is based on the combination between two dimensional discrete multiwavelet transform, radon transform, and neural network, 15 different types of color image was used. Each one of color image have 60 version in different environment, 40 of them used for training set. The total number of images that used in training set are 600, and 300 of color images are used for testing set. The best efficiency of 100% was obtained for training set, and 99.3% for the testing set.

3. The Effect of Noise on Digital Image

Noise can be defined as an unwanted signal that interferes with the communication or measurement of another signal. A noise itself is an information-bearing signal that conveys information regarding the sources of the noise and the environment in which it propagates[Vaseghi, 2008]. The digital image acquisition process, which converts an optical image into a continuous electrical signal that is then sampled, is the primary process by which noise appears in digital images [Umbangh, 1998].

4. Types of Noise That Used in This Work

4-1 White noise

This is noise with a constant power spectrum, i.e. its power spectral density, often referred to as its noise power spectrum (NPS), is constant with frequency. Theoretically, the spectrum would extend to infinite frequency and therefore the total noise power would be infinite; in practice, the spectrum of any naturally occurring white noise falls off at sufficiently high frequencies. The terminology is derived from an analogy with white light, which contains nearly all the frequencies in the visible spectrum in equal proportions **[**Dougherty, 2009]**.**

4-2 The Gaussian Noise

Gaussian noise takes the bell-shaped curve distribution which can be analytically described by [Umbangh, 1998]:

$$f(G) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(G-m)^2}{2\sigma^2}} \qquad \ldots\ldots \quad (1)$$

Where:

G : is the gray level.

m : is the mean (average).

σ : is the standard deviation.

σ^2 : is the variance.

About 70% of all the values fall within the range from one standard deviation (σ) below the mean (m) to one above, and about 95% fall within two standard deviations. The Guassian model is most often used to model natural noise process, such as those occurring from electronic noise in the image acquisition system.

4-3 The Uniform Noise

With the uniform distribution, the gray level values of the noise are evenly distributed across a specific range, which may range (0 to 255 for 8-bits), or a smaller portion of the entire range, which can be modeled as :

$$f(G) = \begin{cases} 1/(t-y) & \text{for } y \le G \ge t \\ 0 & \text{Otherwise} \end{cases} \qquad \ldots\ldots \quad (2)$$

Where:

G : is the gray level.

t : is the ending range.

y : is the starting range.

The Mean = (y + t)/2

The Variance = $(t - y)^2/12$

Uniform noise is useful because it can be used to generate any other type of noise distribution and is often used to degrade images for the evaluation of image denoising and restoration algorithms because it provides the most unbiased or neural noise model [Umbangh, 1998].

4-4 The Salt and Pepper Noise

In the salt-and-pepper noise model, there are only two possible values, a and b, and the probability of each is typically less than (0.1) with numbers greater than (0.1) values, the noise will dominate the image. For an 8-bit image, the typical value for pepper-noise is (0) and for salt-noise is (255):

$$f(G) = \begin{cases} A & \text{for} \quad G=a \\ B & \text{for} \quad G=b \end{cases} \qquad \ldots\ldots \quad (3)$$

Where:

G : is the gray level.
a : is the starting range.
b : is the ending range.
A : is the salt-and-pepper value for $G=a$.
B : is the salt-and-pepper value for $G=b$.

Malfunctioning pixel elements in the camera sensors, faulty memory location, or timing errors typically cause the salt-and-pepper type noise. Usually, the speckle noise image appears similar to that of Gaussian noise images but darker. Salt-and-pepper type noise appears in the images as dots contaminate the image [Umbangh, 1998].

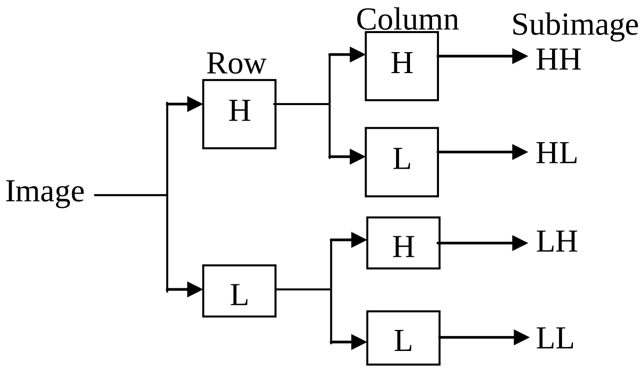
5. Multiwavelet Transform

Wavelet transforms nowadays in the most popular method to analysis images and gives information from an image such as a shape and texture[Lotfi, et al, 2009]. Wavelet transform has been widely used in image processing and shows tremendous advantages over Fourier transform. Wavelet transform is a multiresolution analysis that represents image variations at different scales. According to the definition of wavelet, a wavelet is an oscillating and attenuated function and its integrals equal to zero. It is a mathematical function useful in digital signal and image processing. Given f(x) is a one-dimensional input signal, a 1-D discrete wavelet transform is defined as:

$$\varphi_{jk}(x)=2^{-j/2}\,\varphi(2^{-j}x-k) \qquad \ldots\ldots \quad (4)$$

$$\psi_{jk}(x)=2^{-j/2}\,\psi(2^{-j}x-k) \qquad \ldots\ldots \quad (5)$$

A two-dimensional (2-D) wavelet transform, which is a separable filter bank of row and column directions, decomposes an image into four sub images, are shown in figure (1)[Zhang, et al,, 2005].



Figure(1): Tree Wavelet Decomposition of an Image into Four Subimages LL, LH, HL, and HH

The multiwavelet decompositions produce two lowpass subbands and two highpass subbands in each dimension, the organization and statistics of multiwavelet subbands differ from the scalar wavelet case. During a single level of decomposition using a scalar wavelet transform, the 2-D image data is replaced with four blocks corresponding to the subbands representing either lowpass or highpass in both dimensions. These subbands are illustrated in figure (2-a). The subband labels in this figure indicate how the subband data is generated. For example, the data in subband HL is obtained from highpass filtering of the rows and then lowpass filtering of the columns. The multiwavelets used here have two channels, so there will be two sets of scaling coefficients and two sets of wavelet coefficients. Since multiple iterations over the lowpass data are desired, the scaling coefficients for the two channels are stored together. Likewise, the wavelet coefficients for the two channels are also stored together. The multiwavelet decomposition subbands are shown in figure (2-b).

For multiwavelets, the L and H labels have subscripts denoting the channel to which the data corresponds. For example, the subband labeled L1H2 corresponds to data from the second channel highpass filter in the horizontal direction and the first channel lowpass filter in the vertical direction. Figure(2) shows how a single level of decomposition is done.

LL	LH
HL	HH

(a)

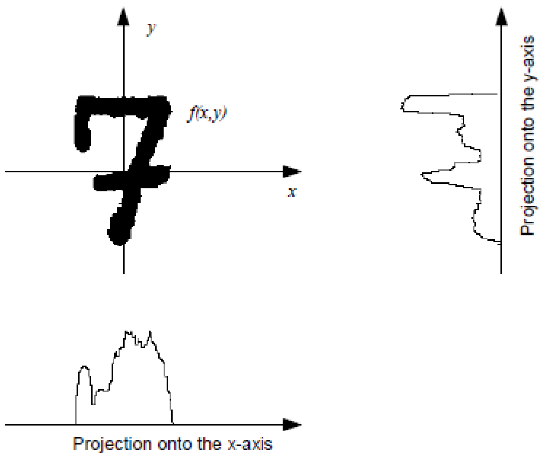
L_1L_1	L_1L_2	L_1H_1	L_1H_2
L_2L_1	L_2L_2	L_2H_1	L_2H_2
H_1L_1	H_1L_2	H_1H_1	H_1H_2
H_2L_1	H_2L_2	H_2H_1	H_2H_2

(b)

Figure (2): Image Subbands After A Single-Level Decomposition, For (a) Scalar Wavelets and (b) Multiwavelets.

6. Radon transform

The radon transform is the projection of the image intensity along a radial line oriented at a specific angle. The radial coordinates are the values along the x' -axis, which is oriented at θ degrees counter clockwise from the x -axis. The origin of both axes is the center pixel of the image . Figure(3) shows horizontal and vertical projections for a simple two-dimensional function.



Figure(3): Horizontal and Vertical Projection

Projections can be computed along any angle θ, by use general equation of the Radon transformation [Kupce, et al, 2004] :

$$R_\theta(x') = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x,y)\delta(x\cos\theta + y\sin\theta - x').dydy \qquad \ldots\ldots\ (6)$$

where $\delta\ (\cdot)$ is the *delta* function with value not equal zero only for argument equal 0, and:

$$x' = x\cos\theta + y\sin\theta \qquad \ldots\ldots\ (7)$$

x' is the perpendicular distance of the beam from the origin and θ is the angle of incidence of the beams. Figure(4) illustrates the geometry of the radon Transformation.

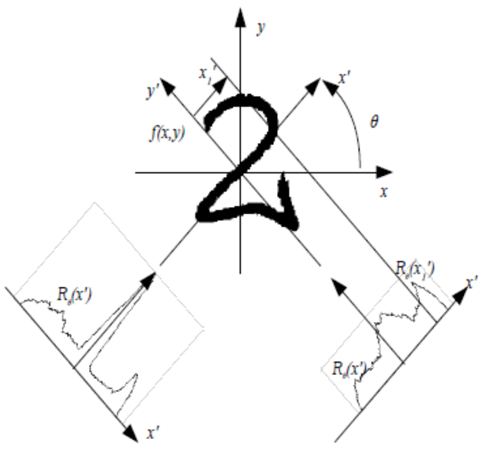
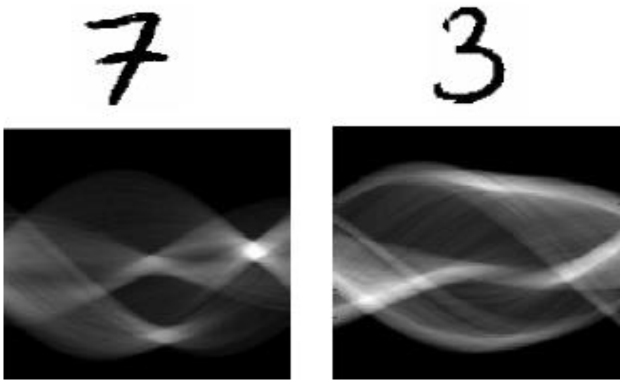


Figure (4): The Geometry of The Radon Transformation.

The very strong property of the radon transform is the ability to extract lines (curves in general) from very noise images. Radon transform has some interesting properties relating to the application of affine transformations. We can compute the radon transform of any translated, rotated or scaled image knowing the radon transform of the original image and the parameters of the affine transformation applied to it. This is a very interesting property for symbol representation because it permits to distinguish between transformed objects, but one can also know if two objects are related by an affine transformation by analyzing their radon transforms [Ramos, et al, 2003]. It is also possible to generalize the radon transform in order to detect parameterized curves with non-linear behavior [Bracewell, 1995]. Figure(5) show the cumulative of radon transform.



Figure(5): Sample of Accumulator Data of Radon Transformation

7. Neural Network

The artificial neural network (ANN) is an information processing system mimicking the biological neural network of the brain by interconnection many artificial neurons[Lee, et al, 2006].

An ANN works as a solid massive parallel processor, which is constituted by several simple units and has a natural propensity to store experimental knowledge and use it to create non-linear relationships between inputs and outputs. In other words, an ANN is a highly interconnected network made of many simple processors. Each processor in the network maintains only one piece of dynamic information and is capable of only a few simple computations. An ANN performs computations by propagating changes in activation between the processors. Using the ANN, one can acquire, store and use the knowledge extracted from experts or experiments. The knowledge is kept in a steady state net of relationships between individual neurons and can be updated automatically using some kind of learning algorithm[Lorenzi, et al, 2003].

An ANN are very useful for analyzing complex problems where the relationships between input and output data are not very well known, such as pattern and speech recognition, machine vision, robotics, signal processing and optimization. They are also useful in fields where there is a high degree of uncertainty, such as market analysis, analysis and control of industrial processes and medical diagnosis [Lorenzi, et al, 2003].

7-1 Back Propagation Training Algorithm:

Back Propagation was created by generalizing the Widrow-Hoff learning rule to multiple layer neural networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors[Moghadas, et al, 2008]. The back propagation algorithm is a generalization of the least mean square algorithm that modifies network weights to minimize the mean squared error between the desired and actual outputs of the network. Back propagation uses supervised learning in which the network is trained using data for which inputs as well as desired outputs are known[Sapkal, et al, 2006].

Back-propagation algorithm is a widely used learning algorithm in ANN. The Feed-Forward Neural Network architecture figure(6) is capable of approximating most problems with high accuracy and generalization ability. This algorithm is based on the error correction learning rule. Error propagation consists of two passes through the different layers of the network, a forward pass and a backward pass. In the forward pass the input vector is applied to the sensory nodes of the network and its effect propagates through the network layer by layer. Finally a set of outputs is produced as the actual response of the network. During the forward pass the synaptic weight of the networks are all fixed. During the back pass the synaptic weights are all adjusted in accordance with an error-correction rule. The actual response of the network is subtracted from the desired response to produce an error signal. This error signal is then propagated backward through the network against the direction of synaptic conditions. The synaptic weights are adjusted to make the actual response of the network move closer to the desired response [Durai, et al, 2007].

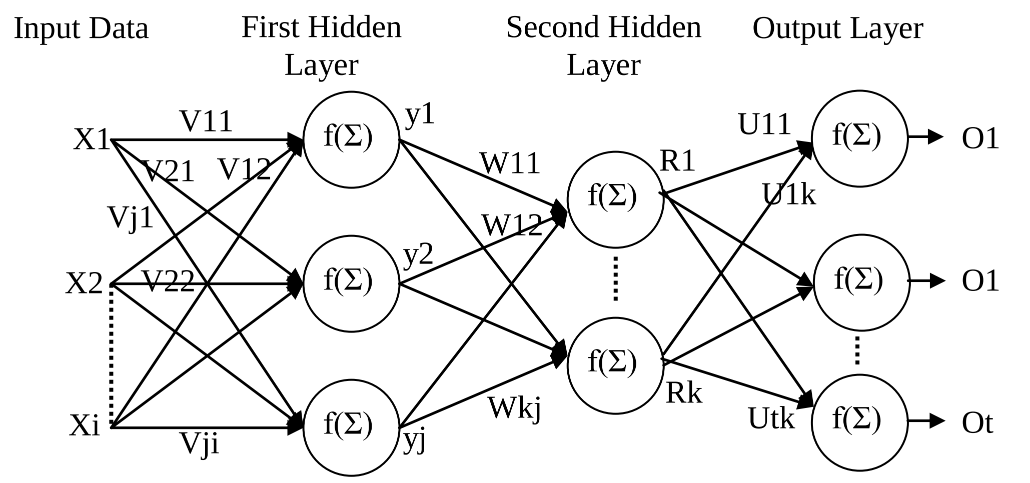


Figure (6): The Feed Forward Neural Network

8. The Proposed Technique

This paper present two method that combine together to give best performance in the system. Our goal is classification of large number of images based on the color and shape information. Therefore, one can used the combination of two methods in the first order and then used the neural network. These combination of two methods are very important in image processing (image recognition). So, the proposed technique contain two part:

1. Feature Extraction.
2. Recognition.

The following discussion for each part:

1. Feature Extraction:

A feature extraction algorithms used to get best information from images via combining two-dimensional discrete multiwavelet transform (2-D DMWT) and radon transform (RT). Before applying these transforms upon the images, some processing must be done:

a) After reading the images, the size of all images must be calculated. Some of them have the size (8003600 pixels), the other have (10243768 pixels), the other have (5003700 pixels), and all the images that getting for the internet have different size (X3Y pixels).
b) In the first must convert these sizes into general size for all images, and this size is (2563256 pixels). This conversion must be done in the first process.
c) All the images conversion have the extension of (256325633 uint8), and the algorithm of (2-D DMWT) and (RT) can't work under these extension (unsigned integer). So must convert (uint8) object into numeric object such as a (double) to work these algorithm properly.

After complete these process, then applied 2-D discrete multiwavelet transform(2-D DMWT) upon the image have the dimension (2563256 pixels (double)). The result is matrix of (2563256) divided into four sub band and each sub band also divided into four sub band.

For practical example, applying 2-D discrete multiwavelet transform on **Horse** image that showed in figure(10), and the result is shown in figure(7) below:

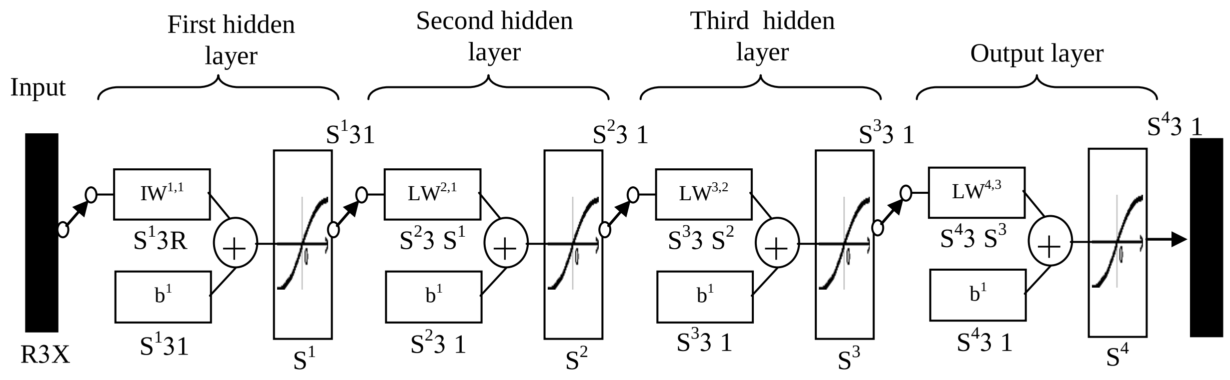
Figure(7): The Application of 2-D DMWT on Horse Image

This lead to the 2-D DMWT used to extract useful information from the signal. This useful information found in the first sub band which is contain most of the original signal energy. After extraction information from 2-D DMWT, the radon transform (RT) applied to each sub band in the final matrix, and it rearrange the data with respect to the angle and centre the signal around the origin. Figure(8) below shows the application of radon transform into each sub band of the 2-D multiwavelet coefficient matrix.

Figure(8): The Application of Radon Transform on 2-D DMWT Coefficient Matrix of Horse Image

In this work, recognition being when the coefficients from feature extraction step were obtained. The method that used here is neural network. Various architecture of neural network (NN), with four layers were tested. The differences in creating variable number of neurons in the intermediary hidden layers, lead to equilibrium between estimate accuracy and computational cost. The net configurations that was used with up to 150 neurons in the first intermediary layer, 50 neurons in the second intermediary layer, 25 neurons in the third intermediary layer and 15 neurons in the output layer. The computational experiments were carried out using the Neural Network Toolbox of the MATLAB (7.6.0 (R2008a)) software. The algorithm that the NNs used in this system was back propagation training algorithm, which tries to minimize the mean square error between the network output and the corresponding target value.

Each training iteration is normally called an epoch. After each iteration the weight and bias are then adjusted to decrease the error. In this algorithm, there are five training parameters epoch, goal, time, min-grad, and learning rate (lr). If the learning rate (lr) is made too large, the algorithm become unstable, and if (lr) is set too small, the algorithm taken long time to convergence. The network that used in this work contain four layer and the feed forward is illustrated in figure(9):



Where:

R: represent the dimension of input image, R=256.

X: represent the number of input image must be training, X=600.

$IW^{1,1}$:represent the weight matrix in the first hidden layer.

S^1:represent the number of neurons in the first hidden layer, S^1=150 neurons.

b^1:the bias vector in the first hidden layer.

$LW^{2,1}$: represent the weight matrix in the second hidden layer.

S^2:represent the number of neurons in the second hidden layer, S^2=50 neurons.

b^2:the bias vector in the second hidden layer.

$LW^{3,2}$: represent the weight matrix in the third hidden layer.

S^3:represent the number of neurons in the third hidden layer, S^2=25 neurons.

b^3:the bias vector in the third hidden layer.

$LW^{4,3}$: represent the weight matrix in the output layer.

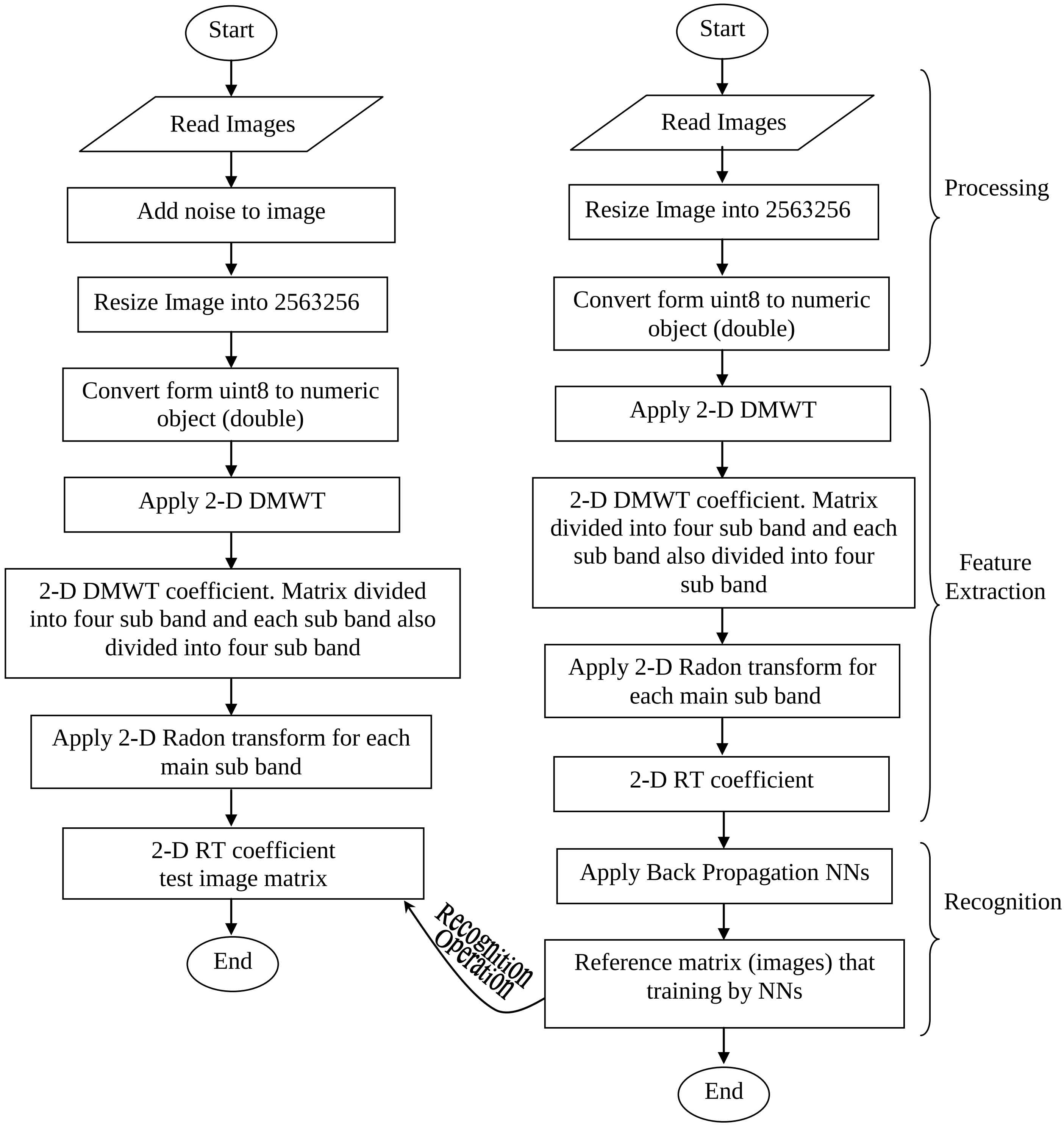
S^4:represent the number of neurons in the output layer, S^2=15 neurons.

b^4:the bias vector in the output layer.

Figure(9): The network architecture of NNs that used in the system

Each column represent the one image, and every 40 columns represent the same image, these columns have the same desired and output and differs from the other image.

The following two flowchart show the procedure that used. In the first flowchart show the procedure that used in the proposed system in case of training set. The second flowchart show the procedure that used in testing set.



Flowchart (2), Testing Processing

Flowchart (1), Training Processing

9. Date Sets

In order to prove the efficiency of the proposed method, a series of images are taken. There are fifteen categories of original images, namely, cat, natural, sunset, car, water full, tree, flowers, buildings, lion, training, toucan, baby, horse, motor, and warship, used in the experiments. In each category of images, there are 60 dependent images and there 15 category are shown in figure(10):

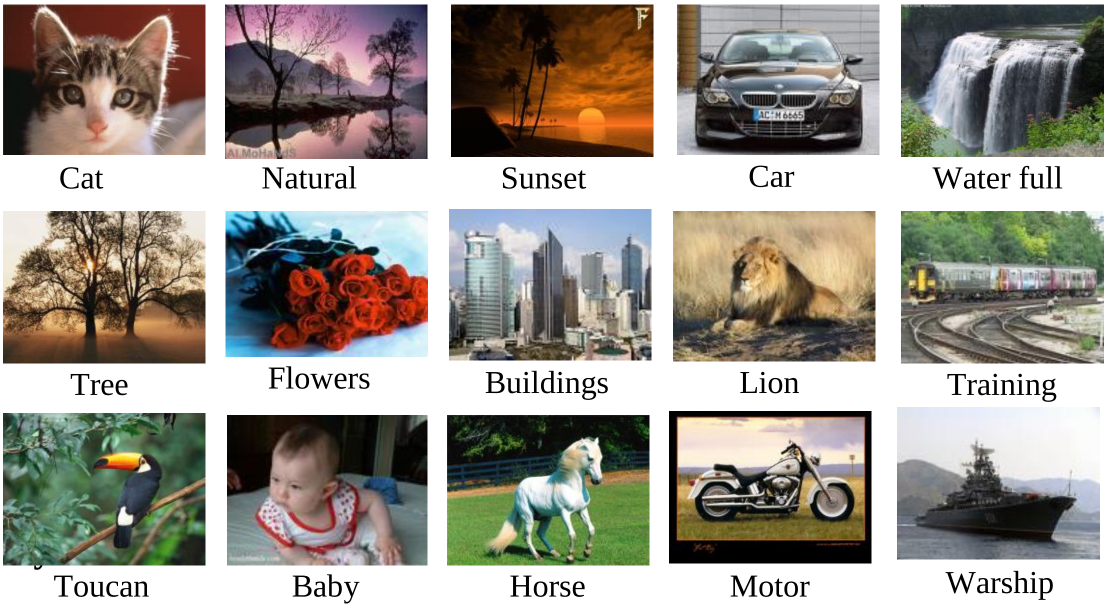


Figure (10): Images Used in Experiences

There are two parts in performing image classification. One is for training the neural network, and the other is for testing. In order to make findings more reliable, many more images are obtained by internet and the others by translating the original images. Example for the translating the original images, a window is set up for an original image, and it shifts from left to right, then top to bottom. Of course, the object must be contained in the window. But, the background is changing with the shifting window. Corresponding to each window, a new copy of image is generated. Therefore, from each image, 45 new images are generated from this translation operation, and by using internet getting on 15 copy of images. So the total number of copies for each image is 60. The number of copies of each image that used in training set is 40, and for all images are 600 that used in training sets. The remaining is 20 copies for each image used in testing sets, so the number of overall images that used in testing set are 300.

10. Result of the proposed method:

The result of the classification are reported in this section. In this work, 150-50-25-15 neurons in the network structure was used. Using large number of hidden nodes can potentially improve the accuracy and convergence of the back propagation algorithm but at the cost of increasing the computational processing time. Table(1), shows the result of applying the combination of 2-D DMWT, RT, and NNs into different images. For each images there are two part, the first one number of images used in the training set, and the second part number of images used in testing set. These two part applied for each image in category. Therefor, for each image there are 40 images used for training set and 20 images used for testing set. The over all image that used in the training set are 600 images, and 300 images are used for testing set. The best efficiency of 100% was obtained for all images in the training set, and 99.3%

for the testing set. The recognition rate for all images in the testing set after applying multi-noise was 98.6%. From the table below can conclude that the recognition rate that obtained from two transform combine together are better that applied one transform alone.

Tables (1), The Results of applying 2-D DMWT and RT

Name of Image	Number of Images Used in Training Set	Number of Images Used in Testing Set	Recognition Rrate For Training Set (Reference Images)	Recognition Rate For Addition One Noise and Applying 2-D DMWT and RT (Testing Images)	Recognition rate for applying 2-D DMWT (testing images)	Recognition Rate For Addition Multi-Noise and Apply 2-D DMWT and RT (Testing Images)
Cat	**40**	**20**	**100%**	**100%**	**90%**	**100%**
Natural	**40**	**20**	**100%**	**100%**	**80%**	**95%**
Sunset	**40**	**20**	**100%**	**100%**	**85%**	**100%**
Car	**40**	**20**	**100%**	**100%**	**100%**	**100%**
Water full	**40**	**20**	**100%**	**100%**	**80%**	**100%**
Tree	**40**	**20**	**100%**	**100%**	**90%**	**100%**
Flowers	**40**	**20**	**100%**	**100%**	**95%**	**100%**
Building	**40**	**20**	**100%**	**95%**	**75%**	**95%**
Lion	**40**	**20**	**100%**	**100%**	**75%**	**100%**
Training	**40**	**20**	**100%**	**100%**	**80%**	**100%**
Toucan	**40**	**20**	**100%**	**95%**	**70%**	**90%**
Baby	**40**	**20**	**100%**	**100%**	**90%**	**100%**
Horse	**40**	**20**	**100%**	**100%**	**85%**	**100%**
Motor	**40**	**20**	**100%**	**100%**	**100%**	**100%**
Warship	**40**	**20**	**100%**	**100%**	**85%**	**100%**
			Average=100%	Average=99.3%	Average=85.3%	Average=98.6%

11. Conclusion

The aim of this work is to classification the noisy images. also, a combination of 2-D discrete multiwavelet transform (2-D DMWT), radon transform (RT), and neural network (NNs) were proposed to recognition a noisy image. The proposed multiwavelet and radon transform that used in feature extraction part gives some benefit in the system like low computational complexity and low memory requirement.

The multiwavelet transform better than scalar wavelet via the filter that used in multiwavelet that have the property of orthogonally, symmetry, and high order of approximation combined together while scalar wavelet can't combined. The source images decomposing by multiwavelet to get low-frequency approximation sub-image and high-frequency detail sub-images of source image.

One important advantage of neural networks is their ability to learn internal information in the data and recall the knowledge acquired at the learning stage to conduct the classification. The back propagation neural network has the simplest architecture of the various artificial neural networks that have been developed for image classification. As the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase.

The recognition rate that obtained form this combine transform was 100% for the training set and 99.3% for testing set, and from this rate conclude that the combine transforms give result better than the one transform applied alone.

12. References:

Anjum M. and Javed M., 2006, "Face Image Dimension Reduction Using Wavelets and Decimation Alghorithm", National University of Sciences and Technology Peshawar Road, Rawalpindi 46000, Pakistan, 2006.

Bracewell N., 1995 “Two-Dimensional Imaging”, Englewood Cliffs, Prentice Hall, pp. 505-537, 1995.

Diaz M., 2000, " Wavelet Features for Color Image Classification", Electrical and Computer Engineering Department University of Puerto Rico, 2000.

Dougherty G., 2009, *Digital Image Processing for Medical Applications* , ISBN-13 , First published, 2009.

Durai S. and Saro E., 2007 " Image Compression with Back-Propagation Neural Network using Cumulative Distribution Function", *International Journal of Applied Science, Engineering and Technology* 3,4 Fall 2007.

Fu Y., Huang T. and Fellow L., 2008," Image Classification Using Correlation Tensor Analysis", *IEEE Transactions On Image Processing*, VOL. 17, NO. 2, February 2008.

Gavlasov´a A., Proch´azka A. and Mudrov´ M., 2005, " Wavelet Use For Image Classification", Prague Institute of Chemical Technology Department of Computing and Control Engineering, 2005.

Gonzalez C., Sossa H., Felipe M. and Pogrebnyak O., "Wavelet transforms and neural networks applied to image retrieval", *Proceedings of International Conference on Pattern Recognition, Hong Kong*, pp. 909-912, 2006.

Jin R., Hauptmann A. and Yan R., 2003, " Image Classification Using a Bigram Model", School of Computer Science Carnegie Mellon University Pittsburgh, AAAI Technical Report SS-03-08, 2003.

Kupce E. and Freeman R., 2004 “The Radon Transform: A New Scheme for Fast Multidimensional NMR”, Concepts in Magnetic Resonance, Wiley Periodicals, Vol. 22, pp. 4-11, 2004.

Lee L., Tsai and Shieh J., 2006 "Applied the Back Propagation Neural Network to Predict Long-Term Tidal Level", *Asian Journal of Information Technology* 5(4):396-401, 2006.

Lorenzi A., Silva Filho P. and Campagnolo L., 2003 " Using a Back Propagation Algorithm to Create a Neural Network for Interpreting Ultrasonic Readings of Concrete", Universidade Federal do Rio Grande do Sul, Porto Alegre, 2003.

Lotfi M., Solimani A., Dargazany A., Afzal H. and Bandarabadi M., 2009," Combining Wavelet Transforms and Neural Networks for Image Classification", *IEEE 41st Southeastern Symposium on System Theory, University of Tennessee Space, Institute Tullahoma*, March 15-17, 2009.

Moghadas K. and Gholizadeh S., 2008 " A New Wavelet Back Propagation Neural Networks for Structural Dynamic Analysis", Engineering Letters, 16:1, EL_16_1_03 , 19 February 2008.

Park B., Lee W. and Kim K., “Content based image classification using a neural network”, Pattern Recognition Letters, Vol. 25, No. 3, pp. 287-300, 2004.

Ramos O. and Valveny E., 2003 "Radon Transform for Lineal Symbol Representation", *The Seventh International Conference on Document Analysis and Recognition*, 2003.

Sapkal T., Bokhare C. and Tarapore Z., 2006" Satellite Image Classification using the Back Propagation Algorithm of Artificial Neural Network", 2006.

Tayel B. and El-Bouridy E.,2006," ECG Images Classification Using Feature Extraction Based On Wavelet Transformation And Neural Network", *International Conference, Sharm El Sheikh, Egypt*, 13 - 15 June 2006.

Tekalp M. and Pavlovic G., 1998, "Digital image restoration", Springer-verlang, A. K., Katsagglos ed., 1998.

Umbangh E., 1998 "Computer vision and image processing", A practical approach using CVIP tools, Upper Saddle River, 1998.

Vaseghi V., 2008, *Advanced Digital Signal Processing and Noise Reduction*, Fourth Edition, ISBN 978 , first published, 2008.

Zhang S., Xue X. and Zhang X., 2005 " Feature Extraction and Classification with Wavelet Transform and Support Vector Machines", *IEEE*, 2005.

Zou W. and Li Y., 2007," Image Classification Using Wavelet Coefficients in Low-pass Bands", *Proceedings of International Joint Conference on Neural Networks*, August 12-17, 2007.