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Optimal Approach for Texture Analysis and Classification Based on Wavelet Transform and Neural Network

Hassana Grema Kaganami, Shaker K. Ali and Zou Beiji

School of Information Science and Engineering
Central South University
Changsha, 410083, China
hgkaganami@gmail.com
shalynar@hotmail.com
bjzou@vip.163.com

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Abstract. *our aim in this work is to achieve an optimal approach of textures analysis and classification by combining Wavelet Transform and Neural Network. To reach a suitable way for textures recognition we first use Wavelet Transform to decompose texture into sub-images which are in turn analysed and finally features are extracted. The Neural Network uses the extracted features to classify the different types of textures.*

In this paper, we have analysed five types of textures and for each five different pictures have been used. We have obtained more accurate results.
Keywords: texture analysis; Wavelet Transforms; neural network.

1. **Introduction.** Wavelet Transform is used to analyse textures in order to sort out their different types. The goal of such analysis is to get the features that will allow us to distinguish the types of textures. In general the transformation process performed by convoluting of the given signal with their basis function which are usually orthogonal, which make the transformation revertible, this means that the original function in the original domain can be extracted without losing information [1].

The Fourier transform is a convolution transformation which transforms the signal from its time domain to the frequency domain. A wide area of application is found with the use of the Fast Fourier transformation algorithm (FFT) which extends two-dimension field [2].

The lack of localization (i.e., not knowing when in times the frequencies occur) with Fourier and other related transforms is a major drawback, and is partly what led the mathematician to explore Wavelet Theory. The Wavelet Transform (WT) is found to be more efficient than Fourier transform (WT) [3].

The Discrete Wavelet Transform (DWT) is as fast as the Fast Fourier Transform (FFT) in which the linear operation that operates on data vector whose length is an integer power of two, transforming it into numerically different vectors of the same length [4]. The Wavelet Transform plays substantial role in multi-resolution technique [5 and6], particularly in image processing [7]. Wavelet Transform is very powerful model for texture discrimination [8].

We use Wavelet Transform (WT) to get features which are analysed through Artificial Neural Network (ANN). Artificial Neural Network are statistical simplified method of the real work system, is an information-processing paradigms that is inspired by human nervous systems, such as the brain, process information. The main purpose of ANN is to simulate human brain artificially [9]. ANN are a highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to environment.

In our work we used the Levenberg Marquardt algorithm (LMA), we obtain more accurate results.

Our paper is articulated as follows: In Section 2 we define wavelet transform whereas Section 3, discusses in detail the features extraction technique. In section 4, we introduce the Levenberg Marquardt algorithm while Section 5 gives the explanation of the experiments and finally a conclusion is drawn in section 6.

2. **Wavelet Transforms (WT).** In order to extract the most important features of textures, we use the DWT and this gives us more accurate results.

Wavelet transforms are widely applied in many fields for solving various problems. The continuous wavelet transform (CWT) of a signal, x(t), is the integral of the signal multiplied by scaled and shifted versions of a wavelet function and is defined by [10].

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{|a|}}\psi(\frac{t-b}{a})dt \tag{1}$$

Where, a and b are so called the scaling (reciprocal of frequency) and time localization or shifting parameters, respectively. Calculating wavelet coefficients at every possible scale is computationally a very expensive task. Instead, if the scales and shifts are selected based on powers of two, so-called dyadic scales and positions, then the wavelet analysis will be much more efficient. Such analysis is obtained from the DWT which is defined as,

$$DWT(j,k) = \frac{1}{\sqrt{|2^j|}}\int_{-\infty}^{\infty} x(t)\psi(\frac{t-2^jk}{2^j})dt \tag{2}$$

Where, a and b are replaced by 2^j and $k2^j$, respectively.

Mallat developed an efficient way for implementing this scheme by passing the signal through a series of low-pass (LP) and high-pass (HP) filter pairs named as quadrature mirror filters [11].

In the first step of the DWT, the signal is simultaneously passed through a LP and HP filters with the cut-off frequency being one fourth of the sampling frequency. The outputs from the low and high pass filters are referred to as approximation (A1) and detail (D1) coefficients of the first level, respectively. The output signals having half the frequency bandwidth of the original signal can be down sampled by two according to Nyquist rule. The same procedure can be repeated for the first level approximation and the detail coefficients to get the second level coefficients. At each step of this decomposition process, the frequency resolution is doubled through filtering and the time resolution is halved through down sampling. "Fig. 1" illustrates the third level wavelet decomposition of a signal [9]. These convolution functions are filters; one half of the output is produced by the "low-pass"

$$L_i = \frac{1}{2}\sum_{j=1}^{N} c_{j+1-2i} \times f_i \tag{3}$$

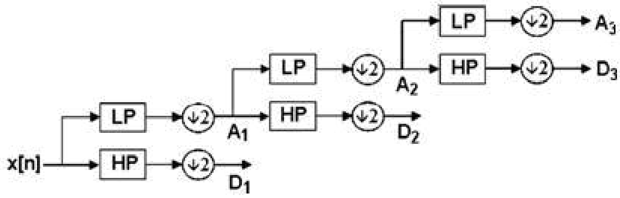

FIGURE 1. Third level wavelet decomposition of a signal.

while the other half is produced by high-pass filter function:

$$H_i = \frac{1}{2}\sum^{N} +j = 1(-1)c_{2i-j} \times f_i \tag{4}$$

where $i = 1, 2, ...N/2$, N is the input of row size, C's: are the coefficients and L and H are the output functions.

In many situations, the Low-pass output contains most of the "information content" of the input row. The High-pass output contains the differences between the true input and the value of the reconstructed input, if it is to be reconstructed from only the information given in the Low- pass (detailed) output.

The output of the Low- pass filter consists of the average of every two sample, and the output of the High-pass filter consists of the difference of two samples [11].

3. **Feature Extraction (FE).** The purpose of feature extraction is to collect new variables from the matrix of the image that concentrates information to separate classes. Most systems perform feature extraction as a pre-processing step, in obtaining global image features like color histogram or descriptors, shape and texture. Texture features have been modeled on the marginal distribution of wavelet coefficients using generalized Gaussian distributions [11].

After decomposing the images using Wavelet Transform, we can extract some important features using Mean, Standard Deviation and Variance.

The mean is implemented as follows [12].

$$mean = \frac{1}{RS}\sum_{r=0}^{R-1}\sum_{s=0}^{S-1} f(r,s) \tag{5}$$

The Standard Deviation (STD) is implemented as:

$$STD = \sqrt{\frac{\sum_{r=0}^{R-1}\sum_{s=0}^{S-1}(f(r,s) - mean)^2}{R \times S}} \tag{6}$$

The Variance is implemented as:

$$\varepsilon = \frac{1}{RS}\sum_{r=0}^{R-1}\sum_{s=0}^{S-1}(f(r,s) - mean)^2 \tag{7}$$

Where, $f(r,s)$ is the value of the pixel in this position.

More details will be given in the experiment section 5.

4. **Levenberg Marquardt Algorithm.** Levenberg Marquardt algorithm (LMA) is training algorithm used to train Multi layer Feed Forward networks (MLFF), based on non-linear optimization technique by minimizing the Sum of Squares of Error (SSE). LM algorithm is an implementation of Levenberg (1994) "A method for the solution of certain problem in least square method", and Marquardt (1963) "least square estimation of

nonlinear parameters". LM algorithm is regarded as an intermediate method between the Steepest Descent (SD) and the Gauss Newton (GN) methods.

It has better convergence properties than the other two methods, and it is well known that, it is the best choice in many off lines training of neural nets [13].

The reason is that, the neural nets minimization problem are often ill conditioned and LM algorithm disregards nuisance directions in the parameter space which influence the criterion marginally [14]. The search direction for the LM algorithm is defined by:

$$\triangle w = (JT \times J + \eta \times I) - 1 \times (-J \times \varsigma) \tag{8}$$

Where:

JT: Jacobean matrix of proper dimension.

$JT \times J$: Covariance matrix of proper dimension.

$\triangle w$: correction matrix of proper dimension.

η: learning parameter $1 >= \eta > 0$.

I: identity matrix.

ς: Difference between network output and desired output.

When η= size. The method represents Gauss-Newton method which is the largest possible update with the algorithm, while $\eta \to \infty$ will lead to the Steep Descent direction [14].

The learning rat η is varying according to the value of error before and after updating the parameters in each iteration. One of the advantages of LM is that; not all the iteration, which decreases the error, is used in updating the network parameters. Therefore, the error will never increase through the learning process, and hence it will have a stair-like performance surface.

Simulation results showed that, LM algorithm could reach any degree of accuracy with more epochs and degree of freedom in the hidden layers [14]. However, the Levenberg Marquardt method is just heuristic method and cannot be optimal but it works extremely well in practice therefore we cannot guarantee or ensure 100% that it will not fall into local minima because it is a heuristic method but there are some modifications [15, 16] to improve its accuracy and tries to avoid the local minimal. The algorithm of LM is as following:

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.

$$h_{0j} = \sum_{j=1} w_{ij} x_i + b_i \Rightarrow h_j = f(h_{0j}) \tag{9}$$

4-Compute output of the network.

$$yy = b_p + \sum w_{pi} hii \Rightarrow y = f(yy) \tag{10}$$

5-Calculate error term

ς=y-yd

6- Calculate correction term.

wb= [w1b1+ w2b2 + KKwpbp]

$$\triangle wb = (JT \times J + \eta \times I) \times (-JT \times \varsigma) \tag{11}$$

7- Update weights and biases.

Wij(new)=wij(old) + $\triangle$wb.

5. **Experiments.** Five sets of textures have been used each set have five images texture with size 128 × 128 gray level as a desired textures (source), the first group is for soil texture called ((bk1, bk2, bk3, bk4, bk5)), the second group is for wood texture called ((tree1 ,tree2 , tree3,tree4, tree5)), the third group is for grass called ((frm1, frm2, frm3, frm4, frm5)), the fourth group is for cotton tissue called ((ctn1, ctn2 ,ctn3 ,ctn4 ,ctn5)), and the fifth one is for woolly tissue called ((nsj1,nsj2,nsj3, nsj4 , nsj5)), as shown in "Fig.2." And 20 random textures have been used as a test textures, as shown in "Fig.3."

These textures will decompose into sub-bands which are analyzed by using DWT to third level, many waveletmother functions such as (coif1, coif2, Haar, db1, sym2,Ketc) have been used. After applying them we realize that the wavelet mother function (coif1) and (sym5) are better from the others, in the same time we observe that not all sub-bands of the texture are useful, so only the useful sub-bands are kept, using the features which collected as three values for each group: the first one from Mean, second one from STD and the last one Variance. These values collected as a range for each feature mean, STD and variance are not unique value, as shown in "table.1 and 2." The ranges will be three values that will be inputs for the Neural Network, which will decided the type of texture.

In training stage the ANN has been train to recognize the type of five textures depend on the input ranges in "table.1 and 2," the inputs of Neural Network are (3*5 =15) because we have five groups and each group has three ranges of values. The outputs must be one of the five, but when we find that some mixed types appeared, for example (the output is 45% cotton tissue and 55% from woolly tissue) so in this stage we have to handle this mistake by increasing the outputs of the ANN to 16 outputs (3*5+1=16). We solved this problem by adding percentage for each output. For example the output may be 3/3 (100%) or 2/3 (70%) or 1/3 (35%)) from any of five types. Only one mixed output that may contain mixed value or have not any similar from any one of the five types. The output must be delimiting the type of the texture and similarity percentage from the five types of texture. For example if the input vector is = [1 1 1] , the output must be 3/3(100%) from wood texture, if the input vector is= [1 1 2], the output must be 2/3(70%) from the wood texture, if the input vector is= [1 2 3] the output must be mixed texture , we have Another way for training the NN is by using combination the inputs from the feature extraction that have (125) probability and the output also became (125), because we have five types and every type has (25) Probability.

The training process finished with 69/250 epochs, Sum-Squared Error (SSE) = 2.60265×10^{-12} as illustrated in the "Fig.4." 20 images have been used, the result from the NN was great and the classification result of the testing image was near from 95

6. **Conclusion.** In this paper the features extraction from Mean, STD and Variance are used as keys for classification better than the researches which used; Max, Min and Median. We also tried to use; Max, Min and Median but the features extracted are not useful for classification, because a lot of features are similar. For example the Max values from cotton texture are 170 to 350, in same case Max value for the earth texture from 160 to 360; and Min and median have the same as Max. Mother Wavelet (Haar, Symmelet2, Symmelet5, Coiflet1, Coiflet2 and Daubechies) have been used, the result from Daubechies1 and Haar have the same, because they have the same coefficients. Also that Sym5 is a better than other, when we used the picture taken from normal camera not from satellite (remote sensing pictures) in this case the coif1 is the best as in [11].

Third levels of the WT decompose each picture into 12 sub-images; the experiments observed that some of sub-bands are not useful mean the features that extracted are not suitable in classification that depend on the feature extraction, as following:

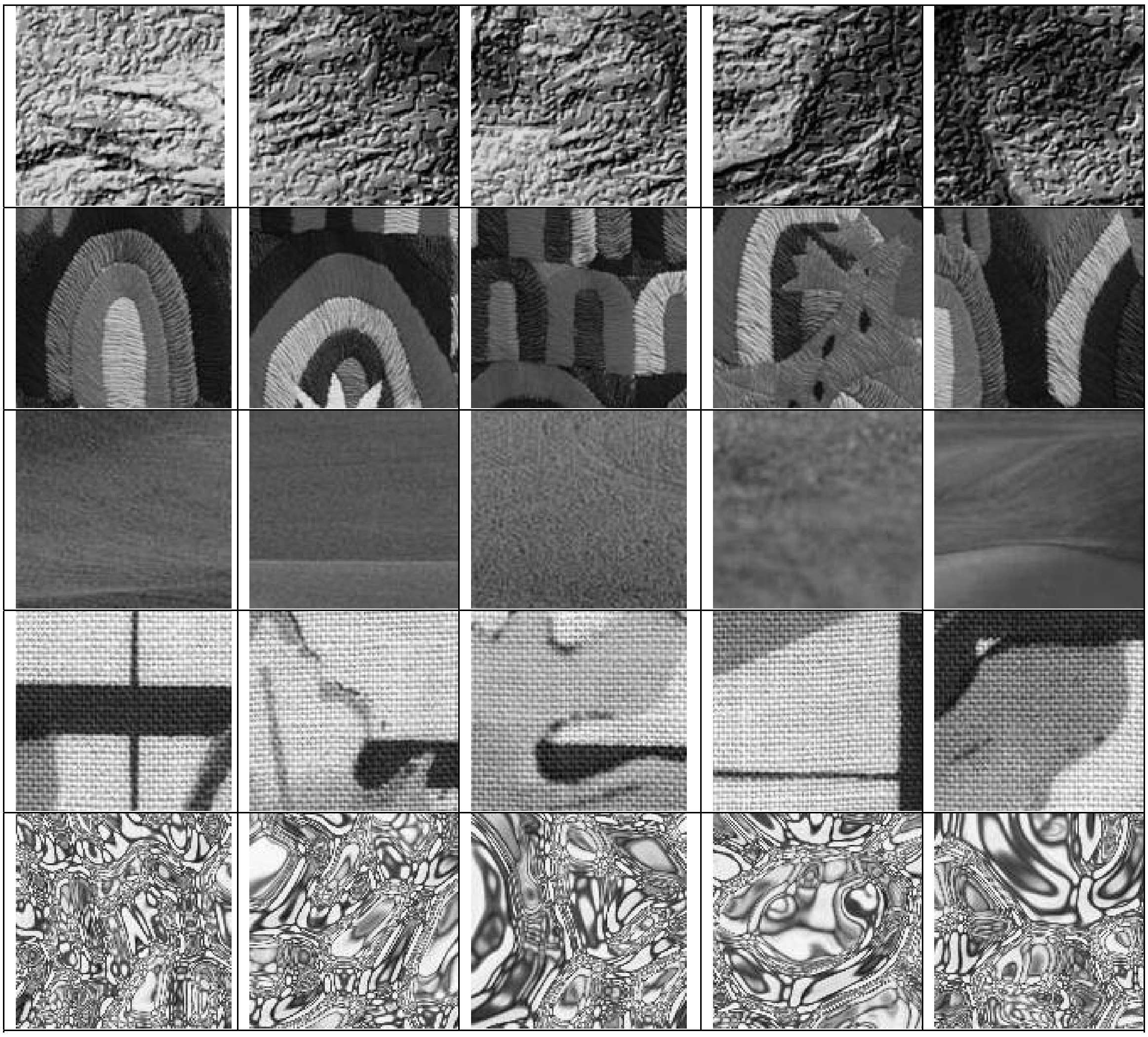

Figure 2. Illustrated five groups of textures.

Table 1. The Result from SYM5.

Group name	Range of STD	Range of Variance	Range of Mean
Wood	75-77	2226-2471	126-134
Grass	17-24	22-89	74-87
Soil	52-66	1219-1665	58-130
Cotton tissue	25-35	157-357	60-81
woolly tissue	42-51	339-446	107-150

- In the Mean all sub-bands (from LL1 to HH3) are useful and used in our classification process.
- In STD LL1, LL2, and LL3 are not useful and may be cause problems in the classification process; others are useful.
- In Variance the HH1, HH2, HH3, HL1, and LH1 only that are useful in the classification process.

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TABLE 2. This Result from COIF1.

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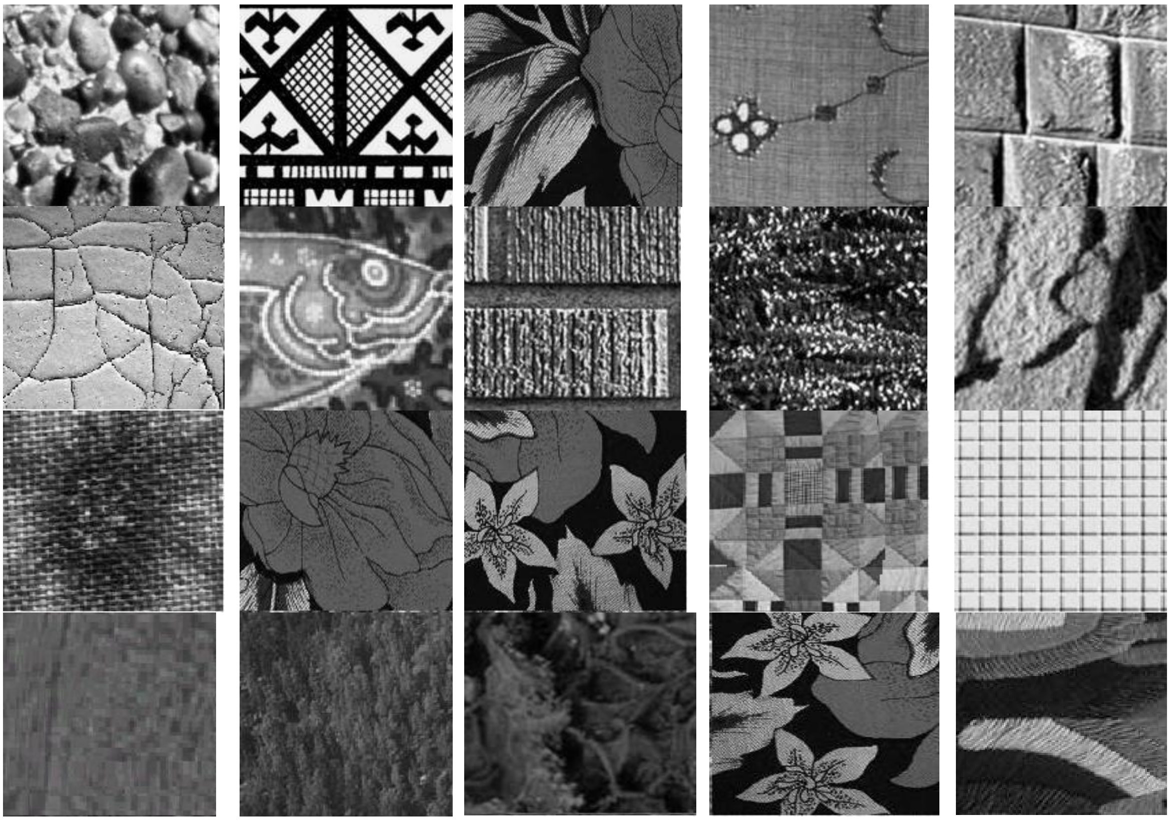

FIGURE 3. Illustrated the testing textures.

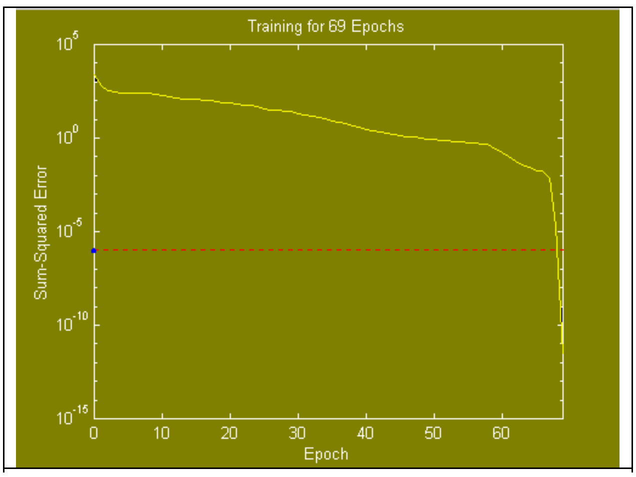

FIGURE 4. Illustrated the N.N trainign.

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