Image Classification Schemes Based on Statistical Moments of Wavelet and Sliced Radial Energy Distribution of DCT

Hashim Abbas1* & Loay E. George2
1, Department of Optics Techniques, College of Health and Medical Technology, Al Ayen University, Iraq
2Assistant of the University president for Scientific Affair, University of Information Technology & communication, , Iraq
abbashashim88@gmail.com

Abstract
Texture recognition is used in various pattern recognition applications and texture classification that possess a characteristic appearance. This research paper aims to provide an improved scheme to provide enhanced classification decisions and to decrease processing time significantly. This research studied the discriminating characteristics of textures by extracting them from various texture images using discrete Wavelet transform (DWT) and discrete Cosine transform DCT. Two sets of features are proposed; the first set was extracted using the traditional DCT, while the second used DWT. The features from the Cosine domain are calculated using the radial distribution of spectra, while for those extracted from Wavelet was statistical distribution of various relative moments. Four types of Euclidean distance metrics were used for classification decision purposes. The considered method was applied on 475 classes of textures belonged to 32 sets from Salzburg Texture Image Database, each set holding 16 images per class, so the a total of 7600 images were tested. Each image was separated into three bands of color component (i.e., red, green, blue). Concepts of average and standard deviation were calculated to determine the inter/intra scatter analysis for each feature to find out the best discriminating features that can be used. The final result of DWT was 99.98 for the testing sets and 99.71 for the training sets, while the final result of DCT was 99.06 for the testing sets and 96.77 for the training sets.

1. Introduction
Texture plays an important role in image analysis and analyzing. Essentially, there is no unique definition of texture and there are many ways to describe it. Some definitions are perceptually motivated, and others are came completely by the application in which the definition will be used [1]. That makes texture analysis a difficult and challenging problem; it is a very large and spectacular field of research. Texture analysis is a basic matter in image processing and computer vision. Some of the applications that demonstrate the importance of texture analysis are found in industrial inspection, document segmentation, remote sensing of earth resources, rock classification, fabric classification, and medical imaging. There are two main texture analysis problems, texture classification, and texture segmentation. In texture classification, textures image are arranged into different classes and each observed image will be analyzed determine to which one of the given set of texture classes [2].

Texture analysis techniques are grouped into five main groups, in general, namely: (1) structural, (2) statistical,(3) signal processing, (4) model-based stochastic and (5) morphology based methods [3]. Most of which consist of two successive stages: feature extraction and feature based classification [2].Clearly, due to the repetition in the texture analysis, this paper will focus on to extract the feature vectors. Over the years, researchers have studied variant types of features for texture classification. Many of these features represent the local behavior of the texture. A review of the recent trends in texture classification was given by YuMing [2]. Al-Kadi [4] used five different texture methods to classify the patterns using a naïve Bayesian classifier. Three of them were statistical Kim, Chang Kim, and Kang [5] used the fractal incorporating with fractal dimension and the gray level co they showed that the GLCM shows relatively low accuracy and a lack of speed performance, and to improve the accuracy, there is a need to combining the GLCM with other methods. Ling, Ming, and YuMing [2] pointed out that an important texture characteristic is directionality, and without directional information, it may be impossible to distinguish textures that have no difference otherwise. He proposed five feature vectors in order to discriminate these aspects. Since the images of woven fabric can be
considered as having a directional texture due to the periodical nature. [6] Used a statistical approach based on the anal images in horizontal and vertical directions.

2.1 Discrete Wavelet Transform

Wavelets are being exceedingly used since their origination by Haar [7][8][9]. Haar used these functions to provide an example of a countable orthonormal system for the space of square-integrable functions on the real line. In this paper, we have used Discrete Wavelets Transform (DWT) to compute the feature vector, which produces a good result and have been found to perform well in classification. DWT allows to speed up the wavelet calculation phase for thousands of sliding windows of various sizes in an image. The DWT computation of a two-dimensional image is decomposed into four frequency sub-bands, namely LL, LH, HL, and HH, where L denotes low frequency and H denotes high frequency [10]:

**Top left:** 2-D lowpass filter (L-L), approximation subband.

**Top right:** horizontal highpass and vertical lowpass filter (H-L).

**Lower left:** horizontal lowpass and vertical highpass filter (L-H).

**Lower right:** 2-D highpass filter (H-H).

The wavelet decomposition could be repeated on all sub-bands (approximation and detail subbands) or on the approximation subband; these two schemes are called packet & dyadic schemes, respectively. There are lots of popular wavelets to be selected, such as Daubuchies, Mexican Hat and Morlet, etc. These wavelets possess a good resolution and smooth traits, but they are not useful because of the common disadvantage of being considerably time-consuming. Compared with these wavelets, Haar wavelet is easy to perform, fast, has a shorter filter, and easily describe small texture structure [11] [12] [13]. Thus, this paper selects DWT to make wavelet decomposition. After applying this transform on the complete image, the LL-subband output from any stage can be decomposed further. Figure -1 shows the result of one and two levels DWT based on the pyramid decomposition [13].

![Wavelet Decomposition](image)

**Figure-1 show two levels DWT based on the pyramid decomposition**

After transforming the input image into a two-level wavelet transform, the following statistical moment is proposed to extract main features from the output of wavelet transforms, as shown in Figure-2. They are described by the following equation:

\[
Mom(n) = \frac{1}{k} \sum_{i=0}^{k-1} \left[ s(i) - \bar{s} \right]^n
\]

Where: \( s(i) \) is the \( i^{th} \) sample, \( k \) is the image length, and \( \bar{s} \) is the mean which is determined as:

\[
\bar{s} = \frac{1}{k} \sum_{i=0}^{k-1} \left[ s(i) - \bar{s} \right]^n
\]

The power \( n \) is taken as 0.25, 1.5 and 3, and the extracted feature vector goes to the next step which is matching stage.

2.2 Discrete Cosine Transform (DCT)

One of the priorities of the DCT is its energy compaction property, the signal energy is concentrated on a few components while most other components are negligibly small or zero. This assist to separate an image into parts (or spectral subbands) of hierarchical importance (with respect to the image’s visual quality). As known JPEG compression technology uses the DCT to compress an image. The Fourier transform kernel is complex valued. The DCT is produced by using only the real part of Fourier complex kernel, Let \( f(x,y) \) indicate an image in spatial domain,
and let $F(u,v)$ indicate an image in frequency domain. The general equation for a 2D DCT is defined as

$$F(u,v) = C(u)C(v) \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} f(x,y) \cos \left( \frac{(2x+1)u\pi}{2N} \right) \cos \left( \frac{(2y+1)v\pi}{2N} \right)$$  \hspace{1cm} (3)$$

Where $F(u,v)$ is the coefficient of the DCT. Then, the power spectra can be obtained using the following equation:

$$P(x,y) = \sqrt{R^2(x,y) + I^2(x,y)}$$  \hspace{1cm} (4)$$

After calculating the power spectra, the result are shown in figure 3. Next, extract 420 features for each sub-image, and determined Sliced Radial Energy Distribution (4), by using the central slice theorem to obtained feature by different angle repeating this process for all values of $0$ between $0$ and $\pi$, using three angles to get as much as possible powerful features.

3. MATERIALS AND METHODS

3.1 Data Description

The applied examination methods for DWT and DCT features have been tested on various color images in 32 data sets. Three combinations of color images were used, each is a BMP with 256 gray levels, while the size of each image is 128x128 pixels. The sets are shown in Table-1 below, with each set consisting of the different number of classes and 16 samples into each class. The used sets are loaded from Salzburg Texture Image Database (STex); it is a large collection of color texture images that have been captured around Salzburg, Austria. The images have been selected to be used in texture analysis experiments.

| Class  | Sub Class | Total image |
|--------|-----------|-------------|
| Porcelain | 2         | 32          |
| Track   | 2         | 32          |
| Straw   | 3         | 48          |
| Tire    | 3         | 48          |
| Tree    | 3         | 48          |
| Grass   | 4         | 64          |
| Rattan  | 4         | 64          |
| Sponge  | 4         | 64          |
| Tiles   | 4         | 64          |
| Building | 5         | 80          |
| Leaf    | 5         | 80          |
| Styrofoam | 6        | 96          |
| Leather | 7         | 112         |
| Plastic | 8         | 128         |
| Food    | 10        | 160         |
| Paper   | 10        | 160         |

| Class  | Sub Class | Total image |
|--------|-----------|-------------|
| Floor  | 11        | 176         |
| Rubber | 11        | 176         |
| Bark   | 13        | 208         |
| Flower | 13        | 208         |
| Marble | 13        | 208         |
| Technic | 14       | 224         |
| Hair   | 15        | 240         |
| Paint  | 15        | 240         |
| Bush   | 18        | 288         |
| Gravel | 20        | 320         |
| Stone  | 29        | 464         |
| Wall   | 30        | 480         |
| Metal  | 31        | 496         |
| Wood   | 41        | 656         |
| Misc   | 44        | 704         |
| Fabric | 77        | 1232        |

3.2 Methodology

- This section presents the performed steps and consists of the following stages:
- Prep-processing stage.
- Features vector extraction stage.
- Classification stage.

3.2.1 Prep-processing stage

The first stage in any recognition system is preprocessing. In this stage, a sequence of image processing operations is utilized to make the image (that is loaded to the system as an input) appropriate for extracting the related information to obtain the best recognition results. In this research, the following pre-processing steps were applied; to read images and color decomposition as a first step, the loaded images were decomposed into three color bands (or channels). The basic color components are Red, Green, Blue, and these gray color values were evaluated. The second step divides the images into four sub-images, each sub-image has a size 64x64 pixels.

3.2.2 Features Extraction Stage

After performing the previous steps (reading the image, color decomposition, splitting), the
feature extraction stage was applied to extract some of the textural attributes. The aim of the feature extraction is to obtain a set of texture measures that can be used to distinguish among different texture pattern classes. In this paper, one of the most important texture analysis methods was used to extract a certain kind of feature vector by utilizing the DWT and DCT. From each sub-image, 420 features for each DHT and DCT were extracted. Also, some variants for this method are introduced to develop more efficient sets of discriminating features.

3.2.3 Features Analysis and Selection Stage

A training set of samples was applied to train the classifier and to address the feature list. While, the test set was applied to assess the recognition accuracy of the system (after the training phase). To obtain a robust recognition performance, this step is claimed to reduce the feature size and to choose the most related and discriminative features companion with the lowest intra-distance and highest inter-distance among the discriminations, then combining the best set of features that led to the best verification result [14].

3.2.4 Classification Stage

In this research, the classification of those attributes was complete due to their inter-class stability. Through the practicing phase, certain features were selected from the overall set of features; the selection was due to the comprehensive tests which were proceeded on the set of samples to find out the best features that can be utilized to yield highest matching results.

3.2.4.1 Matching

The matching steps determine the match outcome (or in other words, the similarity measure) between the feature vectors extracted from the input samples and the stored templates. The similarity result should be high for samples categorized to the same class and least for those categorized to different classes. Sample matching is usually a difficult pattern recognition task due to large intra-class variations (i.e., variations in sample images for the equivalent class) and large inter-class similarity (i.e., the similarity between sample images from the altered class). In this paper, the features extracted in the preceding stage have been used to match either the tested samples data previously stored in the database (i.e., belong to training set) or other samples (i.e., testing set). To accomplish matching, the features of the samples that belong to the training set were used to yield the template mean feature vector for each class. The mean feature vector (F) of each class and the corresponding standard deviation vector (σ) were determined and saved in a dedicated database during the training phase. These parameters were used as template vectors. They were determined using the following equations [15]:

\[ F(c, f) = \frac{1}{S} \sum_{i=1}^{S} F(c, f_i) \]  \hspace{1cm} (5)

\[ D_2(T_i, F_j) = \sum_{k=1}^{m} (T_i(k) - f_j(k))^2 \] \hspace{1cm} (6)

\[ D_3(T_i, F_j) = \sum_{k=1}^{m} \frac{|T_i(k) - f_j(k)|}{\sigma_i(k)} \] \hspace{1cm} (7)

\[ D_4(T_i, F_j) = \sum_{k=1}^{m} \left( \frac{T_i(k) - f_j(k)}{\sigma_i(k)} \right)^2 \] \hspace{1cm} (8)

Where \( T_i \) is the template (mean) of class i, and \( \sigma_i \) is the standard deviation of class i. In order to maximize the probability of the match classification and minimize misclassification rate. The efficiency of classification is calculated for each distance using the following equation [11]:

\[ \eta(\%) = \frac{Total\ no.\ of\ samples - No.\ of\ misclassified\ samples}{Total\ no.\ of\ samples} \times 100\% \] \hspace{1cm} (9)

4. EXPERIMENT RESULTS

Salzburg Texture Image Database (STex) was used for the classification, about 6700 images, each image was divided into four sub-image, each image vector has 420 feature in DWT and DCT, the tables below (2, 3) show DWT result, represent the result of seven features that used to perform the classification, which represent the D1, D2, D3 and D4 of one feature some classes had 100%. Table (3) represents the testing and training result of DWT. However, the tables from (4-5) represent the result of DCT, when we compared between two results as in figure (3) that clear DWT has better results, it is fast and computationally unexpansive to perform the robust method of feature classification and pattern recognition. Our results in DWT show that: 23 classes have 100 scores, 7 classes have above 99 scores, and the rest above 98.87, While DCT showed result less than DWT.

Table-2: The result of DWT applying seven features
| No. Feature | Class          | No. of Sub Class | D1   | D2   | D3   | D4   |
|-------------|----------------|-----------------|------|------|------|------|
| 7           | Porcelain      | 2               | 100  | 100  | 100  | 100  |
| 7           | Track          | 2               | 100  | 100  | 100  | 100  |
| 7           | Straw          | 3               | 100  | 100  | 100  | 100  |
| 7           | Tire           | 3               | 97.39| 97.91| 97.91| 100  |
| 7           | Tree           | 3               | 100  | 100  | 100  | 100  |
| 7           | Grass          | 4               | 100  | 100  | 100  | 100  |
| 7           | Rattan         | 4               | 100  | 100  | 100  | 100  |
| 7           | Sponge         | 4               | 100  | 100  | 100  | 100  |
| 7           | Tiles          | 4               | 100  | 100  | 100  | 100  |
| 7           | Building       | 5               | 100  | 100  | 100  | 100  |
| 7           | Leaf           | 5               | 98.75| 96.25| 100  | 100  |
| 7           | Styrofoam      | 6               | 100  | 100  | 100  | 100  |
| 7           | Leather        | 7               | 97.65| 96.87| 99.6 | 99.8 |
| 7           | Plastic        | 8               | 100  | 100  | 100  | 100  |
| 7           | Food           | 10              | 94.84| 95.93| 98.75| 99.37|
| 7           | Paper          | 10              | 100  | 100  | 100  | 100  |
| 7           | Floor          | 11              | 98.43| 97.96| 99.21| 99.21|
| 7           | Rubber         | 11              | 100  | 100  | 100  | 100  |
| 7           | Bark           | 13              | 100  | 100  | 100  | 100  |
| 7           | Flower         | 13              | 96.25| 97.65| 96.56| 96.87|
| 7           | Marble         | 13              | 98.21| 96.87| 98.9 | 99.84|
| 7           | Technic        | 14              | 99.53| 99.37| 100  | 100  |
| 7           | Hair           | 15              | 89.68| 89.21| 96.87| 97.96|
| 7           | Paint          | 15              | 100  | 100  | 100  | 100  |
| 7           | Bush           | 18              | 98.75| 98.12| 99.17| 99.84|
| 7           | Gravel         | 20              | 100  | 100  | 100  | 100  |
| 7           | Stone          | 29              | 97.96| 98.75| 100  | 100  |
| 7           | Wall           | 30              | 95.93| 97.03| 97.96| 98.28|
| 7           | Metal          | 31              | 98.12| 98.43| 99.06| 99.68|
| 7           | Wood           | 41              | 100  | 100  | 100  | 100  |
| 7           | Misc           | 44              | 100  | 100  | 100  | 100  |
| 7           | Fabric         | 77              | 100  | 100  | 100  | 100  |

Table-3: The final result of DWT
| No. Feature | Class  | No. of Sub Class | D1   | D2   | D3   | D4   |
|-------------|--------|------------------|------|------|------|------|
| 1 | Porcelain | 2 | 100 | 100 | 100 | 100 |
| 2 | Track | 2 | 100 | 100 | 100 | 100 |
| 3 | Straw | 3 | 98.95 | 97.91 | 100 | 100 |
| 4 | Tire | 3 | 92.7 | 92.18 | 98.95 | 100 |
| 5 | Tree | 3 | 96.35 | 96.35 | 100 | 100 |
| 6 | Grass | 4 | 98.82 | 99.21 | 100 | 100 |
| 7 | Rattan | 4 | 96.82 | 95.7 | 99.21 | 98.82 |
| 8 | Sponge | 4 | 96.09 | 95.7 | 99.21 | 98.82 |
| 9 | Tiles | 4 | 92.7 | 92.18 | 98.95 | 100 |
| 10 | Building | 5 | 92.5 | 93.43 | 99.06 | 99.06 |
| 11 | Leaf | 5 | 91.25 | 91.56 | 95.62 | 96.25 |
| 12 | Styrofoam | 6 | 99.21 | 98.95 | 100 | 100 |
| 13 | Leather | 7 | 82.81 | 80.85 | 95.5 | 95.31 |
| 14 | Plastic | 8 | 76.17 | 77.35 | 94.53 | 95.31 |
| 15 | Food | 10 | 77.5 | 75.15 | 97.98 | 98.68 |
| 16 | Paper | 10 | 87.5 | 86.87 | 99.53 | 99.21 |
| 17 | Floor | 11 | 71.71 | 71.25 | 91.25 | 92.03 |
| 18 | Rubber | 11 | 84.53 | 83.43 | 94.84 | 93.9 |
| 19 | Bark | 13 | 86.25 | 86.25 | 99.06 | 99.06 |
| 20 | Flower | 13 | 65.62 | 65 | 79.53 | 81.56 |
| 21 | Granite | 13 | 79.06 | 78.28 | 93.12 | 94.68 |
| 22 | Technic | 14 | 71.28 | 71.87 | 92.5 | 92.34 |
| 23 | Hair | 15 | 68.43 | 69.06 | 89.84 | 91.09 |
| 24 | Paint | 15 | 88.75 | 88.43 | 98.28 | 97.81 |
| 25 | Bush | 18 | 86.71 | 86.09 | 96.09 | 96.56 |
| 26 | Gravel | 20 | 86.56 | 85.46 | 98.59 | 98.9 |
| 27 | Stone | 29 | 75.9 | 74.21 | 94.06 | 94.68 |
| 28 | Wall | 30 | 84.84 | 86.25 | 95.31 | 95.62 |
| 29 | Metal | 31 | 80 | 75.93 | 97.5 | 97.5 |
| 30 | Wood | 41 | 91.4 | 90.78 | 99.37 | 98.9 |
| 31 | Misc | 44 | 87.81 | 85.15 | 99.06 | 98.59 |
| 32 | Fabric | 77 | 91.4 | 90 | 100 | 100 |

Table 4: The Result of DFT (with Seven Features)

| No. Feature | Class  | No. of Sub Class | Training Data | Testing Data | Total Data |
|-------------|--------|------------------|---------------|--------------|------------|
| 1 | Porcelain | 2 | 100 | 100 | 100 |
| 2 | Track | 2 | 100 | 100 | 100 |
| 3 | Straw | 3 | 100 | 100 | 100 |
| 4 | Tire | 3 | 100 | 100 | 100 |
| 5 | Tree | 3 | 100 | 100 | 100 |
| 6 | Grass | 4 | 100 | 100 | 100 |
| 7 | Rattan | 4 | 100 | 100 | 100 |
| 8 | Sponge | 4 | 98.82 | 99.9 | 99.36 |
| 9 | Tiles | 4 | 100 | 100 | 100 |
| 10 | Building | 5 | 99.06 | 100 | 99.53 |
| 11 | Leaf | 5 | 96.25 | 99.93 | 98.09 |
| 12 | Styrofoam | 6 | 100 | 100 | 100 |

Table 5: The Final Results of DFT
5. CONCLUSIONS

Within this paper, two methods are introduced; DWT and DCT. The introduced methods were applied to texture image such that each belongs to a certain class, with a need to handily the problems that occurred due to overlapping and shadowing. The, red blue green bands have major attained recognition rate they are very important bands, also the distance four shows in the tables (2,4) represent the best recognition rate result. The best recognition rates of the proposed method were (%100) for the classification accuracy rate. The DWT is better than GM as shown in figure (2), because smooth edges and image boundary effects can prevent accurate texture analysis, while DCT is suitable for high periodic textures.

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|    | Leather | 7 | 95.31 | 98.39 | 96.85 |
|----|--------|---|-------|-------|-------|
|    | Plastic | 8 | 88.67 | 95.69 | 92.65 |
|    | Food   | 10| 95.12 | 100   | 99.65 |
|    | Paper  | 10| 100   |       |       |
|    | Floor  | 11| 92.03 | 95.56 | 94.795|
|    | Rubber | 11| 93.3  | 99.06 | 96.48 |
|    | Bark   | 13| 99.86 | 100   | 99.53 |
|    | Flower | 13| 84.56 | 93.32 | 88.44 |
|    | Marble | 13| 96.68 | 88.22 | 96.45 |
|    | Technic| 14| 96.24 | 97.41 | 94.875|
|    | Hair   | 15| 91.09 | 95.04 | 93.065|
|    | Paint  | 15| 97.81 | 100   | 98.905|
|    | Bush   | 18| 96.56 | 99.65 | 98.103|
|    | Gravel | 20| 98.9  | 100   | 99.45 |
|    | Stone  | 29| 94.68 | 98.33 | 96.455|
|    | Wall   | 30| 95.02 | 97.99 | 96.805|
|    | Metal  | 31| 97.5  | 99.87 | 98.083|
|    | Wood   | 41| 98.9  | 100   | 99.45 |
|    | Misc   | 44| 98.59 | 100   | 99.295|
|    | Fabric | 77| 100   | 100   | 100   |

Figure-2: Comparability between DWT, DCT
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