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Image Classification Schemes Based on Sliced Radial Energy Distribution of DFT and the Statistical Moments of Haar Wavelet

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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 Haar transform (DHT) and discrete Fourier transform DFT. Two sets of features are proposed; the first set was extracted using the traditional DFT, while the second used DHT. The features from the Fourier domain are calculated using the radial distribution of spectra, while for those extracted from Haar Wavelet the statistical distribution of various relative moments was adopted. 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 seven bands of color component (i.e., red, green, blue, and gray….). 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 DHT was 99.98 for the testing sets and 99.71 for the training sets, while the final result of DFT was 98.63 for the testing sets and 93.74 for the training sets.

Keywords: Texture Pattern recognition; Haar transforms; energy feature; Statistical moment; Euclidean measure.

مخططات تصنيف الصور القائمة على توزيع شرائح الطاقة الشعاعية من *DFT* والعزوم الإحصائية للمويجات من *Haar*

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الخلاصه

يستخدم التعرف على الانماط المختلفة للنسيج في تطبيقات كثيرة لتصنيف النسيج له مظهر مميز. تهدف ورقة البحث هذه إلى توفير مخطط محسّن لتوفير قرارات تصنيف محسّنة مع الحاجة إلى تقليل وقت المعالجة بشكل ملحوظ.

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في هذا البحث تم دراسة الخصائص المميزة للقوام عن طريق استخراجها من صور نسيج مختلفة باستخدام تحويل هار المنفصل (DHT) وتحويل فورير المنفصل. تم اقتراح مجموعتين من الميزات: المجموعة الأولى تم استخراج الصفات باستخدام DFT التقليدي؛ المجموعة الثانية استخدم DHT. يتم احتساب الميزات من مجال فورير باستخدام التوزيع الشعاعي للأطياف، بينما تم اعتماد توزيع العزوم الإحصائية النسبية لتلك المستخرجة من Haar Wavelet. تم استخدام أربعة أنواع من مقاييس المسافة التقليدية لأغراض قرار التصنيف. تم تطبيق الطريقة المدروسة على 475 صنفًا من المجموعات التي تنتمي إلى 32 مجموعة من قاعدة بيانات صور سالزبورج، تحتوي كل مجموعة على 16 صورة لكل صنف، لذا تم اختبار إجمالي 7600 صورة. تم فصل كل صورة إلى سبعة نطاقات من مكون اللون (مثل الأحمر والأخضر والأزرق والرمادي ...). تم حساب مقاييس/معاملات المتوسط والانحراف المعياري لتحديد تحليل الانتشار inter/ entra لكل ميزة لاكتشاف أفضل الميزات التمييزية التي يمكن استخدامها. النتيجة النهائية لتحويل هار كانت 99.98 للمجموعات الاختبارية و 99.71 للمجموعات التدريبية, بينما النتيجة النهائية لتحوير فورير كانت 98.63 للمجموعات الاختبارية و 93.74 للمجموعات التدريبية.

1. Introduction

Texture is the expression used to describe the surface of a given object or region, and it is one of the main features used in image processing and pattern recognition; it refers to the shape, structure and arrangement of the parts of things within the image. One can intuitively associate several image characteristics such as smoothness, coarseness, depth, regularity etc. with texture [1]. Image textures may be synthesized by visual patterns composed of entities or regions with sub-patterns with the properties of brightness, colour, structure, size, etc. Texture can be regarded as a uniformity grouping in an image [2]. There are many definitions to the texture, some of which are perceptually stimulated, while the others are driven completely by the experience in which the definition will be used [3].

In recent years, researchers studied variant types of features for texture classification and pattern recognition. Many of these features represent the local behaviour of the texture. Vandana *et al*. [4] applied different transforms such as DCT (Discrete Cosine Transform), Haar, Hartley, Walsh and Kekre in combination for creating 20 different hybrid wavelets. These hybrid wavelets are used on the database images to create feature vector coefficients, they are then put through to Intra Class testing and Inter Class testing, and their performance is evaluated and matched. Yu *et al*. [5] suggested a novel ear recognition approach by applying wavelet transforms and ULBPs. At the same time, they used the block division and multiresolution ideas in this approach. Their results suggested that the wavelet transform and uniform local binary patterns (ULBPs) were valuable methods to reveal the texture features of ear images. Panchal *et al*. [6] improved a low cost and fast computing system for the identification and verification of the fingerprint by utilizing a wavelet-based approach and compared the results with the traditional discrete Fourier transform (DFT), FFT, and FRIRV techniques which made the system simple and less space and time-consuming. Singha *et at*. [7] Proposed a system and demonstrated a promising and faster retrieval method to extract the texture and colour features by applying wavelet transformation and colour histogram. The combination of these features is robust to the scaling and translation of objects in an image. As a result, there is a substantial boosting in the retrieval speed. The whole indexing time for the 1000 image database is 5-6 minutes. Also, Busch *et at*. [8] Developed and improved classification rates by analysing the image with more than one wavelet which provided additional information about the texture. Experimental evidence provided support to this theory, showing that, for simple energy features, error rates are halved when multiple wavelets are employed. The next sections are organized as follows; in the next section, an overview of the texture analysis methods used in this research is presented by clarifying some of the concepts related to the used methods and the attributes that can be derived from them. Section 3 explains the adopted methodology in this study. In the fourth section the attained results are presented. Finally, in the last section, the main conclusions are presented.

In this stage, two separate sets of features were used to generate the feature vectors and tested for the verification purpose; they are the energy-based features using DFT and the statistical moments using DHT.

2.1 Haar Wavelet Transform

Haar wavelets are being exceedingly used since their origination by Haar [9][10][11]. 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 Discreet Haar wavelets (DHW) to compute the feature vector, which produces a good result and have been found to perform well in classification. DHW allows to speed up the wavelet calculation phase for thousands of sliding windows of various sizes in an image. The DHW transform 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 [12]:

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 [13] [14] [15]. Thus, this paper selects DHT 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 DHT based on the pyramid decomposition [1].

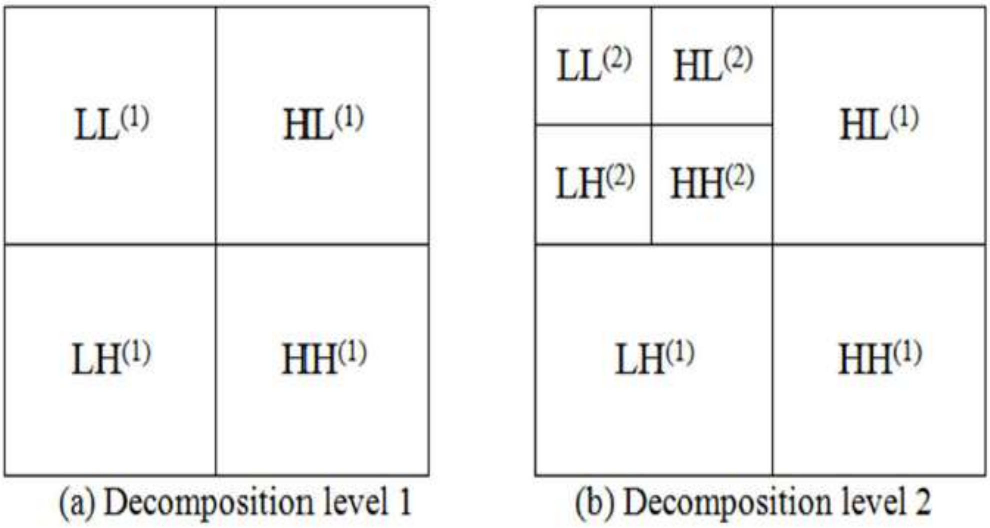

Figure 1- Pyramid decomposition using Haar wavelet filter.

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:

$$Mom(n) = \frac{1}{k}\sum_{i=0}^{p-1}[S(i) - \bar{S}]^n \quad (1)$$

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

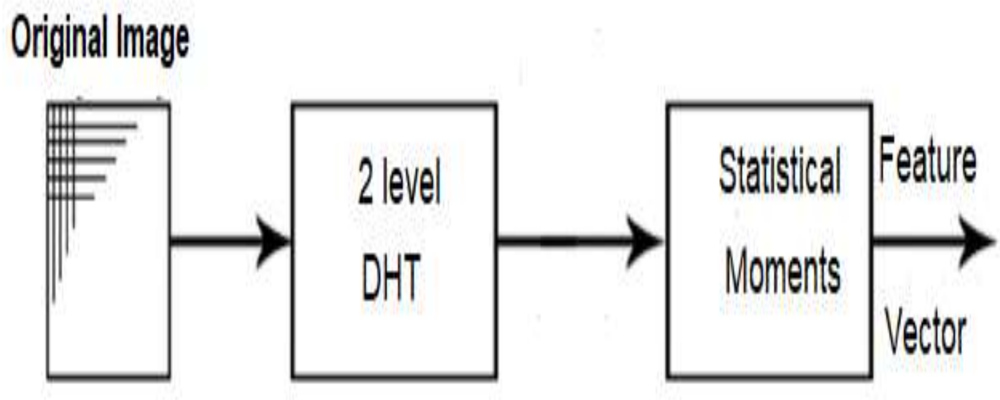

Figure 2- DWT technique.

$$\bar{S} = \frac{1}{k}\sum_{i=0}^{k-1}(s(i) - \bar{s})^n \quad (2)$$

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 DFT

The discrete Fourier transform (DFT) is one of the most important tools which has been extensively used not only for understanding the nature of an image and its formation but also for processing the image [16][17]. Power spectra consist of the sine and cosine components and different frequencies. High frequencies are concentrated at the end of the transformed components, while the low frequencies at the beginning of the signal. Hence, in this paper DFT algorithm has been used to the task to transform from spatial to the frequency domain (i.e., DFT). The transform using DFT to an image f(x, y) of a size of M xN was applied using the following general equation (3) [1].

$$F(u,v) = \frac{1}{N}\frac{1}{M}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1} f(x,y)e^{-j2\pi(\frac{ux}{N}+\frac{vy}{M})} \quad (3)$$

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

$$F(u,v) = \sqrt{R^2(u,v) + I^2(u,v)} \quad (4)$$

Where, R(u,v) represents the real part and I(u,v) the imaginary part of DFT. After calculating the power spectra, the result are shown in Figure- 3. Next, the central slice theorem was used to obtain the feature by different angle, repeating this process for all values of θ between 0 and π, and using five angles to get as much powerful features as possible to use them to generate the feature vector.

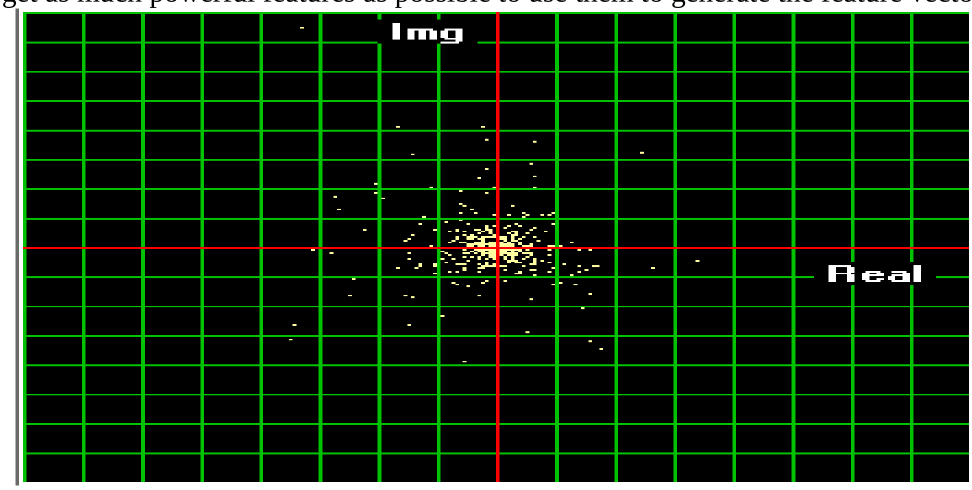

Figure 3- DFT for image

3. MATERIALS AND METHODS

3.1 Data Description

The applied examination methods for DHW and DFT features have been tested on various color images in 32 data sets. Seven 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 deferent 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. Some of these samples are presented (see Figure-1).

Table 1- The Tested Salzburg Texture Image Database (STex).

Class	Sub Class	Total image	Class	Sub Class	Total image
Porcelain	2	32	Floor	11	176
Track	2	32	Rubber	11	176
Straw	3	48	Bark	13	208
Tire	3	48	Flower	13	208
Tree	3	48	Marble	13	208
Grass	4	64	Technic	14	224
Rattan	4	64	Hair	15	240
Sponge	4	64	Paint	15	240
Tiles	4	64	Bush	18	288
Building	5	80	Gravel	20	320
Leaf	5	80	Stone	29	464
Styrofoam	6	96	Wall	30	480
Leather	7	112	Metal	31	496
Plastic	8	128	Wood	41	656
Food	10	160	Misc	44	704
Paper	10	160	Fabric	77	1232

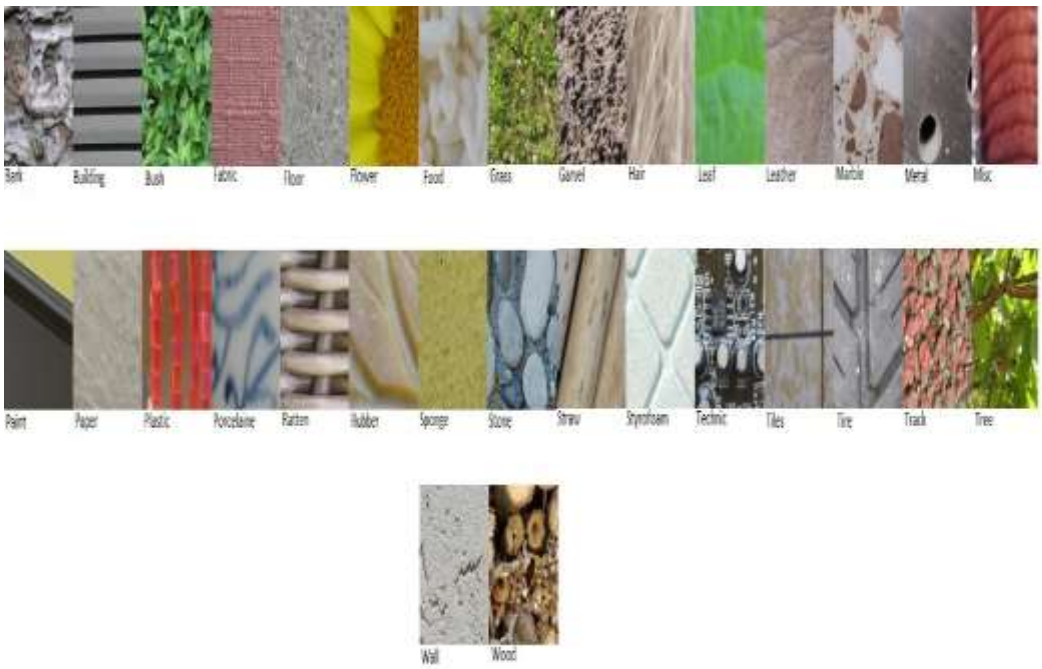

Figure 4- Samples of the classes of data sets used in this research.

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 seven color bands (or channels). The basic color components are Red, Green, Blue, (Gray1, Gray2, PU and Pv) and these gray color values were evaluated by the equations 5-8. The second step divides the images into four sub-images, each sub-image has a size 64×64 pixels.

$$pGry1(Xx,Yy) = Red(X,Y) + Grn(X,Y) + Blu(X,Y) \quad (5)$$

$$pGry2(Xx,Yy) = 0.299*Red(X,Y)+0.587*Grn(X,Y)+0.11*Blu(X,Y) \quad (6)$$

$$pU(Xx,Yy) = -0.147*Red(X, Y)-0.289*Grn(X,Y)+0.436* Blu(X,Y) \quad (7)$$

$$pV(Xx,Yy) = 0.615*Red(X, Y)-0.515*Grn(X,Y)-0.1*Blu(X,Y) \quad (8)$$

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 DHT and DFT. From each sub-image, 420 features for DHT and 840 features for DFT 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 [18].

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 ($\overline{F}$) 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 [19]:

$$F(c,f) = \frac{1}{s}\sum_{i=1}^{s} F(c,fi)\ , \quad (9)$$

$$\sigma(c,f) = \sqrt{\frac{1}{s}\sum_{i=1}^{s} F(c,fi) - F(c,fi)^2}\ , \quad (10)$$

Where c, f, s are the classes number, feature number and sample number, respectively.

While, in the matching stage, their similarity degrees were computed with the feature vector extracted from the samples. The similarity distance measure for feature (f) was computed using the feature value determined from the sample and the corresponding feature template mean value as well as the standard deviation (determined for each class). The most commonly used similarity measure is the Euclidean distance measure (D_1), but, the main weakness of the basic Euclidean distance function is that if one of input features has a relatively large range, then it can overpower the effectiveness of other features. The considered matching problem here is dynamic; that is every feature may not have similar behaviors like the others. Hence, another type of similarity distance measures (such as D_2, D_3 and D_4) were computed. The results of using these four distance measures were compared and revealed that the results of measure D_4 are always better than those of the others; thus, the normalized Euclidean distance (D_4) was used to evaluate the similarity degree between the extracted feature vectors of the samples (f_j) and the templates representing the classes [19]:

$$D_1(\overline{T_\iota},\overline{F_J}) = \sum_{k=1}^{m}\left|T_i(k) - f_j(k)\right| \quad (11)$$

$$D_2(\overline{T_\iota},\overline{F_J}) = \sum_{k=1}^{m}\left(T_i(k) - f_j(k)\right)^2 \quad (12)$$

$$D_3(\overline{T_\iota},\overline{F_J}) = \sum_{k=1}^{m}\left|\frac{T_i(k) - f_j(k)}{\sigma_i(k)}\right| \quad (13)$$

$$D_4(\overline{T_\iota},\overline{F_J}) = \sum_{k=1}^{m}\left(\frac{T_i(k) - f_j(k}{\sigma_i(k)}\right)^2 \quad (14)$$

Where $\overline{T_\iota}$ is the template (mean) of class i, and σ_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 was calculated for each distance using the following equation [20]:

$$\eta(\%) = \frac{Total\ no.of\ samples - No.of\ misclassified\ samples}{Total\ no.of\ samples} \times 100\% \quad (15)$$

4. EXPERIMENT RESULTS

Salzburg Texture Image Database (STex) was used for the classification of about 6700 images. Each image was divided into four sub-images, and each image vector had 420 features in DHW and 840 features in DFT. The tables below (2-9) show DFT results, with each table representing the results of how many features were used to perform the classification; for example, Table-1 represents the D1, D2, D3 and D4 of one feature. Some classes had 100% classification efficiency and the others improved by adding features until the feature seven. Table- 9 represents the final result of DFT while Tables- 10-16 represent the results of DHW. When we compared between two results, as in Figure-5, it is clear that the Haar transform has batter results. It is fast and computationally inexpensive to perform the robust method of feature classification and pattern recognition. Our results show that 23 classes had 100 scores, 7 classes had above 99 scores, and the rest had above 98.87 scores. Furthermore, Tables-(18 and 19) show the combination of seven unique features that led to this result. Each class has different combination features, so that the first feature in Table-18 is related to the result of Table- 2, the combination of the first and second features led to Table-3, and so on until all the seven features led to the final result in Table-9 for DFT, while Table- 19 is related to DHW. We can say that the DHW could extract better features than DFT. These seven features represent the discriminated features that led to the result of each class. In other words, they are the identification of each class.

Table 2- The results of DFT using single feature.

Feature No.	Type	Sub Class	D1	D2	D3	D4
1	Porcelain	2	99.21	99.21	98.43	98.43
1	Track	2	100	100	100	100
1	Straw	3	96.87	96.87	96.87	96.87
1	Tire	3	81.77	81.77	82.29	82.29
1	Tree	3	83.85	83.85	82.81	82.81
1	Grass	4	78.9	78.9	80.07	80.07
1	Rattan	4	91.01	91.01	89.06	89.06
1	Sponge	4	84.76	84.76	86.71	86.71
1	Tiles	4	92.96	92.96	93.35	93.35
1	Building	5	65.93	65.93	66.25	66.25
1	Leaf	5	74.37	74.37	75.62	75.62
1	Styrofoam	6	84.63	84.63	85.15	85.15
1	Leather	7	66.21	66.21	59.37	59.37
1	Plastic	8	62.5	62.5	57.03	57.03
1	Food	10	50.31	47.81	47.81	47.81
1	Paper	10	64.84	64.84	63.12	63.12
1	Floor	11	52.65	52.65	51.87	51.87
1	Rubber	11	52.03	52.03	43.43	43.43
1	Bark	13	45.46	45.46	45.46	45.46
1	Flower	13	41.71	41.71	40.31	40.31
1	Marble	13	52.96	52.96	47.81	47.81
1	Technic	14	48.59	48.59	46.25	46.25
1	Hair	15	36.71	36.71	36.09	36.09
1	Paint	15	54.84	54.84	49.84	49.84
1	Bush	18	53.59	53.59	52.18	52.18
1	Gravel	20	53.75	53.75	52.96	52.96
1	Stone	29	44.21	44.21	43.59	43.59
1	Wall	30	59.06	59.06	56.87	56.87
1	Metal	31	51.71	51.71	46.4	46.4
1	Wood	41	69.21	69.21	67.96	67.96
1	Misc	44	66.4	66.4	63.43	63.4
1	Fabric	77	55.15	55.15	51.25	51.25

Table 3- The results of DFT using two features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
2	Porcelain	2	100	100	100	100
2	Track	2	100	100	100	100
2	Straw	3	98.95	98.95	98.95	98.95
2	Tire	3	92.7	92.18	93.22	92.7
2	Tree	3	96.35	96.87	95.31	96.35
2	Grass	4	89.84	92.57	91.79	91.79
2	Rattan	4	96.09	96.48	96.48	96.48
2	Sponge	4	95.31	94.92	96.87	97.65
2	Tiles	4	100	99.21	100	100
2	Building	5	79.06	80	83.43	84.06
2	Leaf	5	90.31	90.62	88.75	89.68
2	Styrofoam	6	98.95	98.95	99.73	100
2	Leather	7	84.37	80.85	80.85	81.64
2	Plastic	8	84.57	85.15	85.15	85.93
2	Food	10	70	71.71	70.31	72.03
2	Paper	10	92.03	91.87	94.84	94.37
2	Floor	11	80.62	80.15	82.03	82.96
2	Rubber	11	77.5	78.12	70	70.6
2	Bark	13	78.28	79.68	79.53	79.68
2	Flower	13	60	58.9	59.06	57.5
2	Marble	13	77.34	77.18	77.5	79.37
2	Technic	14	74.53	73.59	72.96	72.65
2	Hair	15	56.25	56.09	56.4	57.65
2	Paint	15	79.37	79.37	80.31	82.34
2	Bush	18	80.46	81.71	81.25	82.81
2	Gravel	20	84.37	84.37	86.4	86.25
2	Stone	29	67.81	68.43	65.78	67.65
2	Wall	30	85.93	86.4	85.31	86.87
2	Metal	31	74.21	73.43	68.43	70.4
2	Wood	41	91.25	91.71	92.34	93.28
2	Misc	44	92.81	91.4	91.09	91.71
2	Fabric	77	84.06	84.37	84.53	85.46

Table 4- The results of DFT for three features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
3	Porcelain	2	100	100	100	100
3	Track	2	100	100	100	100
3	Straw	3	100	99.47	100	100
3	Tire	3	95.31	96.35	95.83	95.83
3	Tree	3	98.43	98.43	99.47	97.91
3	Grass	4	92.96	95.31	94.14	95.31
3	Rattan	4	97.26	98.04	98.82	98.82
3	Sponge	4	96.48	96.48	97.65	98.43
3	Tiles	4	100	100	100	100
3	Building	5	85.31	86.25	90.31	90.62
3	Leaf	5	91.25	92.5	89.68	90.31
3	Styrofoam	6	99.47	100	100	100
3	Leather	7	88.28	88.86	87.5	89.06
3	Plastic	8	88.08	88.67	91.21	93.16
3	Food	10	76.25	78.12	74.53	76.25
3	Paper	10	96.71	97.18	98.43	98.9
3	Floor	11	83.75	85.15	85.93	87.03
3	Rubber	11	83.12	84.21	79.84	83.28
3	Bark	13	87.34	89.06	87.96	90.93
3	Flower	13	64.53	65.31	62.65	62.96
3	Marble	13	82.65	84.68	82.96	85.65
3	Technic	14	79.21	78.75	79.37	81.56
3	Hair	15	67.5	67.18	67.65	69.53
3	Paint	15	86.09	86.09	88.59	91.4
3	Bush	18	89.21	90.46	89.06	91.56
3	Gravel	20	93.12	92.34	95	95.15
3	Stone	29	75.46	76.25	79.06	80.93
3	Wall	30	89.68	90	88.28	91.25
3	Metal	31	78.59	78.12	73.43	75.31
3	Wood	41	96.71	97.03	96.56	97.34
3	Misc	44	95.93	95.62	94.37	93.9
3	Fabric	77	93.9	95	95.46	97.03

Table 5- The results of DFT for four features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
4	Porcelain	2	100	100	100	100
4	Track	2	100	100	100	100
4	Straw	3	100	99.4	100	100
4	Tire	3	95.83	97.39	97.39	97.39
4	Tree	3	98.43	98.43	98.43	97.91
4	Grass	4	96.48	97.26	95.7	96.09
4	Rattan	4	98.43	98.82	98.82	99.21
4	Sponge	4	96.48	96.48	98.04	98.43
4	Tiles	4	100	100	100	100
4	Building	5	87.81	89.06	91.25	93.12
4	Leaf	5	91.25	92.81	89.37	89.68
4	Styrofoam	6	99.47	100	100	100
4	Leather	7	88.86	90.23	88.08	90.23
4	Plastic	8	89.64	91.4	93.16	96.28
4	Food	10	76.25	78.12	74.53	76.25
4	Paper	10	98.12	98.9	99.68	100
4	Floor	11	87.81	89.21	87.5	89.06
4	Rubber	11	84.84	85.93	85.46	89.53
4	Bark	13	90.62	91.56	91.25	94.06
4	Flower	13	67.34	69.21	65.64	67.65
4	Marble	13	86.09	86.25	84.84	87.18
4	Technic	14	80.78	80.78	82.65	83.59
4	Hair	15	71.4	72.96	74.84	76.56
4	Paint	15	87.65	90.93	90.93	93.28
4	Bush	18	90.15	91.25	91.09	92.65
4	Gravel	20	95	94.68	95.62	96.09
4	Stone	29	84.21	84.53	83.43	86.4
4	Wall	30	91.71	91.71	89.68	92.18
4	Metal	31	80.62	80.93	76.87	78.12
4	Wood	41	96.87	97.18	97.5	98.12
4	Misc	44	96.25	95.93	95.78	95.46
4	Fabric	77	95.46	95.93	98..12	98.9

Table 6- The results of DFT for five features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
5	Porcelain	2	100	100	100	100
5	Track	2	100	100	100	100
5	Straw	3	100	99.47	100	100
5	Tire	3	96.35	98.43	97.91	98.43
5	Tree	3	98.43	98.43	98.95	98.43
5	Grass	4	97.26	97.65	96.09	96.48
5	Rattan	4	99.21	98.82	99.6	99.21
5	Sponge	4	96.48	96.48	98.04	98.43
5	Tiles	4	100	100	100	100
5	Building	5	89.68	90	92.18	93.43
5	Leaf	5	91.25	92.81	88.75	90
5	Styrofoam	6	100	100	100	100
5	Leather	7	89.25	91.01	87.69	91.21
5	Plastic	8	90.62	91.79	94.72	97.26
5	Food	10	80.4	82.34	77.96	80.31
5	Paper	10	98.21	99.06	99.84	100
5	Floor	11	88.59	90	89.06	90.4
5	Rubber	11	85.93	86.71	89.06	90.93
5	Bark	13	92.18	92.65	92.34	95.62
5	Flower	13	68.5	69.68	66.25	69.21
5	Marble	13	87.03	87.65	86.09	87.65
5	Technic	14	82.03	81.87	83.28	85.46
5	Hair	15	74.37	75.93	76.09	78.9
5	Paint	15	88.28	89.21	92.65	94.53
5	Bush	18	90.31	91.87	92.03	94.06
5	Gravel	20	95.62	96.25	95.46	96.4
5	Stone	29	86.71	87.18	85.62	87.81
5	Wall	30	92.34	92.34	90.15	92.81
5	Metal	31	82.34	81.87	79.68	82.34
5	Wood	41	97.03	97.5	97.96	98.43
5	Misc	44	96.4	95.93	95.93	96.25
5	Fabric	77	96.25	96.4	99.06	99.37

Table 7- The results of DFT for six feature.

Feature No.	Type	Sub Class	D1	D2	D3	D4
6	Porcelain	2	100	100	100	100
6	Track	2	100	100	100	100
6	Straw	3	100	99.47	100	100
6	Tire	3	97.39	98.43	98.43	98.34
6	Tree	3	98.43	98.43	99.47	98.43
6	Grass	4	97.65	98.43	96.09	96.48
6	Rattan	4	99.6	98.82	99.21	99.21
6	Sponge	4	96.48	96.48	98.04	98.43
6	Tiles	4	100	100	100	100
6	Building	5	90	90.31	93.12	94.37
6	Leaf	5	91.25	92.81	89.06	90.31
6	Styrofoam	6	100	100	100	100
6	Leather	7	90.03	91.4	88.86	91.01
6	Plastic	8	91.01	91.99	95.5	97.65
6	Food	10	80.78	83.12	79.37	81.25
6	Paper	10	98.59	99.06	100	100
6	Floor	11	89.37	90.31	90	90.93
6	Rubber	11	86.56	87.03	90	92.65
6	Bark	13	92.5	92.96	93.28	96.09
6	Flower	13	69.37	70.15	70	72.03
6	Marble	13	87.5	87.96	85.65	88.28
6	Technic	14	83.28	82.34	83.59	85.78
6	Hair	15	75.93	77.18	77.81	80.15
6	Paint	15	88.75	89.53	92.03	95.46
6	Bush	18	90.78	92.18	93.43	94.68
6	Gravel	20	96.25	97.03	96.25	96.56
6	Stone	29	87.81	88.9	88.9	89.68
6	Wall	30	92.65	92.5	90.15	93.12
6	Metal	31	82.96	82.96	81.4	83.9
6	Wood	41	97.03	97.65	98.28	98.9
6	Misc	44	96.4	96.25	97.03	96.71
6	Fabric	77	97.03	97.81	99.84	100

Table 8- The results of DFT for seven features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
7	Porcelain	2	100	100	100	100
7	Track	2	100	100	100	100
7	Straw	3	100	99.47	100	100
7	Tire	3	97.39	98.43	98.43	98.95
7	Tree	3	98.43	98.43	99.49	98.95
7	Grass	4	98.04	98.82	96.09	96.48
7	Rattan	4	99.6	98.82	99.6	99.21
7	Sponge	4	96.48	96.48	98.04	98.43
7	Tiles	4	100	100	100	100
7	Building	5	90.31	90.31	93.43	94.37
7	Leaf	5	91.25	92.81	90	90.31
7	Styrofoam	6	100	100	100	100
7	Leather	7	90.03	91.6	89.45	91.21
7	Plastic	8	91.21	91.99	95.5	98.04
7	Food	10	80.93	84.21	80.15	82.18
7	Paper	10	98.59	99.06	100	100
7	Floor	11	70.31	70.62	71.4	72.96
7	Rubber	11	86.71	87.81	91.09	92.34
7	Bark	13	92.5	93.43	94.06	96.4
7	Flower	13	80.93	84.21	80.15	82.18
7	Marble	13	87.65	88.43	86.71	88.43
7	Technic	14	83.43	82.96	84.37	86.09
7	Hair	15	76.4	77.34	78.75	81.4
7	Paint	15	88.9	90	92.65	95.93
7	Bush	18	90.93	92.34	94.06	94.84
7	Gravel	20	96.56	97.65	96.25	97.03
7	Stone	29	88.43	89.53	90	90
7	Wall	30	92.65	92.5	91.25	93.12
7	Metal	31	83.12	83.75	82.81	85.31
7	Wood	41	97.03	97.81	98.9	98.9
7	Misc	44	96.4	96.25	96.56	96.71
7	Fabric	77	97.34	98.59	99.84	100

Table 9- The finals result of DFT for seven features.

Feature No.	Type	Sub Class	Training Data	Testing data	Total Data
7	Porcelain	2	100	100	100
7	Track	2	100	100	100
7	Straw	3	100	100	100
7	Tire	3	98.95	100	99.475
7	Tree	3	98.95	100	99.475
7	Grass	4	96.48	100	98.24
7	Rattan	4	99.21	100	99.605
7	Sponge	4	98.43	100	99.215
7	Tiles	4	100	100	100
7	Building	5	94.37	99.8	97.085
7	Leaf	5	90.31	94.3	92.305
7	Styrofoam	6	100	100	100
7	Leather	7	91.21	97.99	94.6
7	Plastic	8	98.04	100	99.02
7	Food	10	82.18	97.35	89.765
7	Paper	10	100	100	100
7	Floor	11	72.96	92.91	82.935
7	Rubber	11	92.34	97.71	95.025
7	Bark	13	96.4	99.37	97.885
7	Flower	13	82.18	98.5	90.34
7	Marble	13	88.43	95.14	91.785
7	Technic	14	86.09	97.32	91.705
7	Hair	15	81.4	96.79	89.095
7	Paint	15	95.93	99.98	97.955
7	Bush	18	94.84	98.87	96.855
7	Gravel	20	97.03	100	98.515
7	Stone	29	90	96.54	93.27
7	Wall	30	93.12	98.36	95.74
7	Metal	31	85.31	96.45	90.88
7	Wood	41	98.9	100	99.45
7	Misc	44	96.71	99.06	97.885

7	Fabric	77	100	100	100

Table 10- The results of DHT for single features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
1	Porcelain	2	99.21	99.21	99.21	99.21
1	Track	2	99.21	99.21	99.21	99.21
1	Straw	3	98.95	98.95	98.95	98.95
1	Tire	3	86.97	86.97	87.5	87.5
1	Tree	3	94.79	94.79	97.91	97.91
1	Grass	4	93.75	93.75	95.31	95.31
1	Rattan	4	99.6	99.6	99.6	99.6
1	Sponge	4	91.01	91.01	90.62	90.62
1	Tiles	4	90.23	90.23	95.7	95.7
1	Building	5	71.25	71.25	68.43	68.43
1	Leaf	5	81.56	81.56	80	80
1	Styrofoam	6	95.31	95.31	97.65	97.65
1	Leather	7	80.07	80.07	77.92	77.92
1	Plastic	8	90.62	90.62	88.67	88.67
1	Food	10	58.43	58.43	53.59	53.59
1	Paper	10	78.12	78.12	75.93	75.93
1	Floor	11	59.21	59.21	59.37	59.37
1	Rubber	11	62.96	62.96	62.34	62.34
1	Bark	13	60	60	57.18	57.18
1	Flower	13	60.62	60.62	53.43	53.43
1	Marble	13	61.4	61.4	56.25	56.25
1	Technic	14	70.46	70.46	72.81	72.81
1	Hair	15	50.62	50.62	45.78	45.78
1	Paint	15	82.5	82.5	79.06	79.06
1	Bush	18	64.84	64.84	63.43	63.43
1	Gravel	20	73.75	73.75	72.34	73.34
1	Stone	29	54.84	54.84	53.43	53.43
1	Wall	30	72.65	72.65	70.31	70.31
1	Metal	31	61.87	61.87	59.37	59.37
1	Wood	41	78.12	78.12	71.4	71.4
1	Misc	44	82.18	82.18	77.5	77.5

1	Fabric	77	74.84	74.84	70.31	70.31

Table 11- The results of DWH for two features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
2	Porcelain	2	99.25	99.25	99.25	99.25
2	Track	2	99.6	99.6	99.6	99.6
2	Straw	3	98.5	98.5	98.5	98.5
2	Tire	3	93.22	93.75	93.22	93.75
2	Tree	3	99.47	99.47	99.47	99.47
2	Grass	4	99.6	99.6	99.6	99.6
2	Rattan	4	99.5	99.5	99.5	99.5
2	Sponge	4	99.6	99.6	99.6	99.6
2	Tiles	4	99.6	99.6	99.6	99.6
2	Building	5	90.31	90.62	94.68	95
2	Leaf	5	95.62	95.62	96.87	97.5
2	Styrofoam	6	99.3	99.3	99.3	99.3
2	Leather	7	94.14	94.14	93.75	94.33
2	Plastic	8	99.6	99.8	99.8	99.8
2	Food	10	87.18	86.09	88.28	88.43
2	Paper	10	96.4	95.62	99.37	99.37
2	Floor	11	81.71	80	86.25	87.5
2	Rubber	11	95.31	95.15	96.25	96.4
2	Bark	13	91.4	91.4	94.84	96.56
2	Flower	13	83.59	82.96	80.46	81.09
2	Marble	13	89.37	87.03	91.87	92.81
2	Technic	14	87.65	88.12	91.87	93.28
2	Hair	15	75.78	75	74.37	74.21
2	Paint	15	93.75	93.28	94.84	95.78
2	Bush	18	89.06	89.53	91.4	91.09
2	Gravel	20	96.4	95.46	97.81	97.5
2	Stone	29	86.71	86.4	84.21	86.09
2	Wall	30	90.46	90	93.75	93.59
2	Metal	31	87.34	87.96	89.06	90.31
2	Wood	41	96.71	96.4	97.65	99.21
2	Misc	44	96.71	97.03	98.75	99.21

2	Fabric	77	95.62	95.78	99.21	99.68

Table 12- The results of DWH for three features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
3	Porcelain	2	100	100	100	100
3	Track	2	100	100	100	100
3	Straw	3	100	100	100	100
3	Tire	3	94.79	97.39	96.35	96.87
3	Tree	3	100	100	100	100
3	Grass	4	100	100	100	100
3	Rattan	4	100	100	100	100
3	Sponge	4	100	100	100	100
3	Tiles	4	100	100	100	100
3	Building	5	98.43	98.12	99.68	99.68
3	Leaf	5	96.87	95.93	99.37	99.06
3	Styrofoam	6	100	100	100	100
3	Leather	7	96.28	95.7	95.7	96.48
3	Plastic	8	99.8	99.8	99.8	99.8
3	Food	10	91.25	91.4	95.15	95.62
3	Paper	10	99.84	99.84	99.84	99.84
3	Floor	11	93.28	92.18	93.9	94.68
3	Rubber	11	99.37	99.37	99.06	99.21
3	Bark	13	97.03	97.65	98.28	99.21
3	Flower	13	92.65	92.34	89.68	92.5
3	Marble	13	92.96	91.71	96.56	97.34
3	Technic	14	95.46	96.4	98.28	98.75
3	Hair	15	82.96	83.12	86.25	87.5
3	Paint	15	98.59	98.59	99.06	98.9
3	Bush	18	93.9	93.43	96.56	97.5
3	Gravel	20	98.12	98.12	99.53	99.68
3	Stone	29	92.03	92.81	93.59	96.4
3	Wall	30	94.53	94.21	95.78	96.71
3	Metal	31	94.68	93.59	95.62	95.93
3	Wood	41	99.37	99.68	99.84	99.84
3	Misc	44	98.43	99.21	99.84	99.84

3	Fabric	77	99.68	99.53	99.53	99.53

Table 13- The results of DWH for four features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
4	Porcelain	2	100	100	100	100
4	Track	2	100	100	100	100
4	Straw	3	100	100	100	100
4	Tire	3	96.35	97.91	97.39	98.95
4	Tree	3	100	100	100	100
4	Grass	4	100	100	100	100
4	Rattan	4	100	100	100	100
4	Sponge	4	100	100	100	100
4	Tiles	4	100	100	100	100
4	Building	5	99.68	99.68	99.68	99.68
4	Leaf	5	98.43	96.25	99.68	99.68
4	Styrofoam	6	100	100	100	100
4	Leather	7	97.26	96.48	97.65	97.85
4	Plastic	8	100	100	100	100
4	Food	10	93.28	92.81	97.03	98.43
4	Paper	10	100	100	100	100
4	Floor	11	95.62	95.93	97.81	97.34
4	Rubber	11	99.53	99.84	99.53	99.68
4	Bark	13	98.59	99.37	99.84	99.84
4	Flower	13	94.84	95.46	93.59	94.06
4	Marble	13	95.15	93.9	97.81	99.06
4	Technic	14	96.87	97.96	99.84	99.84
4	Hair	15	85.46	85.15	92.34	93.28
4	Paint	15	99.37	99.37	99.84	99.84
4	Bush	18	96.25	95.46	97.81	99.21
4	Gravel	20	99.37	99.68	99.84	99.84
4	Stone	29	96.25	96.09	97.65	98.9
4	Wall	30	95	95.31	97.65	97.65
4	Metal	31	95.93	95.78	97.18	98.12
4	Wood	41	99.84	99.84	99.84	99.84
4	Misc	44	100	100	100	100

4	Fabric	77	100	100	100	100

Table 14- The results of DWH for five features.

Feature No.	Type	Sub Class	D1	D2	D3	D4
5	Porcelain	2	100	100	100	100
5	Track	2	100	100	100	100
5	Straw	3	100	100	100	100
5	Tire	3	96.87	97.91	97.39	99.47
5	Tree	3	100	100	100	100
5	Grass	4	100	100	100	100
5	Rattan	4	100	100	100	100
5	Sponge	4	100	100	100	100
5	Tiles	4	100	100	100	100
5	Building	5	100	100	100	100
5	Leaf	5	98.75	96.25	99.68	99.68
5	Styrofoam	6	100	100	100	100
5	Leather	7	97.65	96.87	99.02	99.02
5	Plastic	8	100	100	100	100
5	Food	10	94.21	93.75	98.12	98.75
5	Paper	10	100	100	100	100
5	Floor	11	97.34	97.34	98.28	98.75
5	Rubber	11	100	100	100	100
5	Bark	13	99.84	100	100	100
5	Flower	13	95.15	96.56	95.93	96.09
5	Marble	13	97.03	95.46	98.75	99.68
5	Technic	14	98.12	98.43	100	100
5	Hair	15	87.81	87.03	94.68	95.46
5	Paint	15	99.5	99.68	100	100
5	Bush	18	97.5	96.87	98.59	99.84
5	Gravel	20	100	100	100	100
5	Stone	29	96.87	97.18	99.06	99.68
5	Wall	30	95.31	96.25	97.81	98.12
5	Metal	31	98.12	97.03	98.59	99.21
5	Wood	41	99.6	99.6	99.6	99.6
5	Misc	44	100	100	100	100

5	Fabric	77	100	100	100	100

Table 15- The results of DWH for six features.

No. Feature	Type	Sub Class	D1	D2	D3	D4
6	Porcelain	2	100	100	100	100
6	Track	2	100	100	100	100
6	Straw	3	100	100	100	100
6	Tire	3	97.39	97.91	97.91	100
6	Tree	3	100	100	100	100
6	Grass	4	100	100	100	100
6	Rattan	4	100	100	100	100
6	Sponge	4	100	100	100	100
6	Tiles	4	100	100	100	100
6	Building	5	100	100	100	100
6	Leaf	5	98.75	96.25	99.68	100
6	Styrofoam	6	100	100	100	100
6	Leather	7	97.56	96.87	99.21	99.41
6	Plastic	8	100	100	100	100
6	Food	10	94.68	95.31	98.21	99.37
6	Paper	10	100	100	100	100
6	Floor	11	97.96	97.5	99.06	99.21
6	Rubber	11	100	100	100	100
6	Bark	13	100	100	100	100
6	Flower	13	95.15	96.56	95.93	96.09
6	Marble	13	98.12	96.4	98.9	99.84
6	Technic	14	99.37	99.06	100	100
6	Hair	15	88.75	88.28	96.25	97.5
6	Paint	15	100	100	100	100
6	Bush	18	97.96	97.18	99.06	100
6	Gravel	20	100	100	100	100
6	Stone	29	97.96	98.12	99.84	99.84
6	Wall	30	95.93	96.87	97.96	98.12
6	Metal	31	98.12	97.81	98.9	99.37
6	Wood	41	100	100	100	100
6	Misc	44	100	100	100	100

6	Fabric	77	100	100	100	100

Table 16- The results of DWH for seven features.

No. Feature	Type	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	98.12	98.12	99.37	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 17- The finals result of DWH for seven features.

No. Feature	Class	No. of Sub Class	Training Data	Testing data	Total Data
7	Porcelain	2	100	100	100
7	Track	2	100	100	100
7	Straw	3	100	100	100
7	Tire	3	100	100	100
7	Tree	3	100	100	100
7	Grass	4	100	100	100
7	Rattan	4	100	100	100
7	Sponge	4	100	100	100
7	Tiles	4	100	100	100
7	Building	5	100	100	100
7	Leaf	5	100	100	100
7	Styrofoam	6	100	100	100
7	Leather	7	99.8	100	99.9
7	Plastic	8	100	100	100
7	Food	10	99.37	100	99.685
7	Paper	10	100	100	100
7	Floor	11	99.21	100	99.605
7	Rubber	11	100	100	100
7	Bark	13	100	100	100
7	Flower	13	96.87	99.42	98.145
7	Marble	13	99.84	100	99.92
7	Technic	14	100	100	100
7	Hair	15	97.96	100	98.98
7	Paint	15	100	100	100
7	Bush	18	99.84	100	99.92
7	Gravel	20	100	100	100
7	Stone	29	100	100	100
7	Wall	30	98.28	100	99.14
7	Metal	31	99.68	100	99.84
7	Wood	41	100	100	100

7	Misc	44	100	100	100
7	Fabric	77	100	100	100

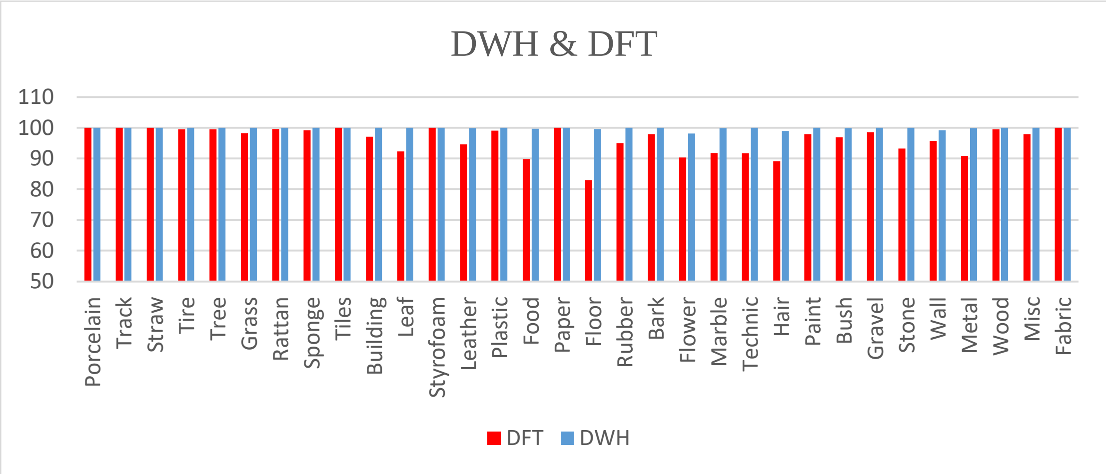

Figure 5- Compaction between the result of DFT and DHW.

Table 18- The combination of features of DHW.

Class	No. of Sub Class	No of image	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
Porcelain	2	32	0	50	3	4	5	5	3
Track	2	32	0	1	0	0	0	0	87
Straw	3	48	0	373	0	0	0	0	0
Tire	3	48	307	405	136	404	362	132	2
Tree	3	48	0	365	0	7	22	27	27
Grass	4	64	13	120	0	0	3	5	5
Rattan	4	64	0	148	0	0	5	0	5
Sponge	4	64	7	300	0	0	300	0	0
Tiles	4	64	5	408	0	5	0	5	3
Building	5	80	4	415	10	5	300	0	2
Leaf	5	80	76	322	403	305	362	308	308
Styrofoam	6	96	1	78	2	0	2	1	5
Leather	7	112	345	361	78	316	187	110	120
Plastic	8	128	303	365	0	0	0	0	0
Food	10	160	315	369	124	53	361	74	47
Paper	10	160	150	328	315	0	0	0	0
Floor	11	176	146	374	50	324	7	366	166
Rubber	11	176	58	404	313	32	9	10	26
Bark	13	208	134	378	410	3	70	53	75
Flower	13	208	164	363	253	157	378	334	367
Marble	13	208	49	384	335	139	379	309	369
Technic	14	224	39	402	151	333	46	3	10
Hair	15	240	58	318	400	353	340	111	375
Paint	15	240	126	380	316	51	5	0	17
Bush	18	288	85	375	122	351	382	349	139
Gravel	20	320	303	370	93	0	45	0	1
Stone	29	464	14	319	349	173	344	227	413
Wall	30	480	5	373	171	259	364	229	132
Metal	31	496	9	214	333	404	314	45	369
Wood	41	656	251	384	303	5	10	9	15

Misc	44	704	28	318	365	17	58	14	303
Fabric	77	1232	361	379	12	17	25	30	15

Table 19- The combination of feature of the DFT.

Class	No. of Sub Class	No of image	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7
Porcelain	2	32	2	192	0	0	0	0	0
Track	2	32	0	1	0	1	0	0	0
Straw	3	48	17	676	600	1	16	9	152
Tire	3	48	728	771	90	280	10	67	601
Tree	3	48	603	795	81	0	746	28	58
Grass	4	64	136	675	728	194	737	1	10
Rattan	4	64	269	794	617	320	656	76	640
Sponge	4	64	668	810	9	600	256	600	632
Tiles	4	64	258	651	0	3	98	0	120
Building	5	80	637	763	72	368	651	755	40
Leaf	5	80	596	796	188	235	789	189	475
Styrofoam	6	96	33	745	33	41	41	24	27
Leather	7	112	10	723	616	744	618	1	32
Plastic	8	128	96	787	736	743	650	755	828
Food	10	160	676	758	632	32	776	65	651
Paper	10	160	416	746	625	18	144	289	688
Floor	11	176	9	783	623	60	328	59	769
Rubber	11	176	60	673	824	32	288	632	636
Bark	13	208	316	798	373	752	137	480	792
Flower	13	208	284	646	76	800	448	330	733
Marble	13	208	17	797	668	608	697	276	675
Technic	14	224	39	784	272	284	721	314	269
Hair	15	240	376	676	115	737	716	757	696
Paint	15	240	253	677	787	58	249	635	747
Bush	18	288	74	636	834	130	672	240	121
Gravel	20	320	744	797	36	636	168	632	136
Stone	29	464	624	795	557	264	752	2	280
Wall	30	480	29	798	288	656	48	554	17
Metal	31	496	724	761	404	676	244	196	721
Wood	41	656	26	316	756	775	252	608	665
Misc	44	704	76	755	678	752	56	795	16
Fabric	77	1232	17	678	356	737	648	376	456

5. CONCLUSIONS

Within this paper, two methods are introduced; DHW and DFT. The introduced methods were applied to texture image such that each belongs to a certain class, with a need to handle the problems that occurred due to overlapping and shadowing. The gray, red, blue. and green bands have the major attained recognition rate and they are very important bands since they they participate to over 90% of the results, while the other three bands present in the preprocessing stage participate to the rest. Also, the distance four shown in the Tables-(2-15) represents the best recognition rate result. The best recognition rates of the proposed method were %100 for the classification accuracy rate. The DHW is better than DFT because smooth edges and image boundary effects can prevent accurate texture analysis. DHW was found to be suitable for high periodic textures.

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