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EFFECTIVE MULTI-RESOLUTION TRANSFORM IDENTIFICATION FOR CHARACTERIZATION AND CLASSIFICATION OF TEXTURE GROUPS

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Abstract
Texture classification is important in applications of computer image analysis for characterization or classification of images based on local spatial variations of intensity or color. Texture can be defined as consisting of mutually related elements. This paper proposes an experimental approach for identification of suitable multi-resolution transform for characterization and classification of different texture groups based on statistical and co-occurrence features derived from multi-resolution transformed sub bands. The statistical and co-occurrence feature sets are extracted for various multi-resolution transforms such as Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Double Density Wavelet Transform (DDWT) and Dual Tree Complex Wavelet Transform (DTCWT) and then, the transform that maximizes the texture classification performance for the particular texture group is identified.

Keywords:
Texture, Multi-Resolution Transforms, Statistical and Co-occurrence Features

1. INTRODUCTION

Texture-oriented research has aroused considerable interests in the past few decades. For years, researchers have attempted to duplicate the ability of the human brain, to understand the content of images by interpreting the features of the object in the scene, by developing image understanding algorithms for applications including robotic vision, industrial monitoring, remote sensing, assisted medical diagnosis and automated target recognition [1]. Among basic image primitives, texture is one important cue for image understanding. Although no formal definition of texture exists, intuitively this descriptor provides measure of properties such as smoothness, coarseness and regularity. Texture is the characteristic placement and arrangement of repetition of tone or color in an image. These repeating elements are referred to as “Texels”. A Texel contains several pixels, whose placement could be periodic, quasi-periodic or random. Natural textures are generally random, whereas artificial textures are often deterministic or periodic. Alternatively, texture may be defined as a visual pattern that has properties of homogeneity that do not result from the presence of only a single color or intensity. Texture can be grouped as follows: (1) Micro, (2) Macro, (3) Regular, (4) Random, (5) Coarse, (6) Fine, (7) Periodic, (8) Aperiodic, (9) Deterministic, (10) Nondeterministic (11) Stochastic, (12) Non-stochastic, (13) Weak and (14) Strong. Image segmentation, scene analysis, and object recognition are often based on texture identification. Analysis of images requires the identification of proper attributes or features that differentiate the images for classification, segmentation and recognition. The features are assumed to be uniform within the regions containing the same property of texture. The lack of a universal, formal definition of texture makes the construction of features for texture identification hard. Various feature extraction and classification techniques have been suggested in the past for the purpose of texture analysis. Initially texture analysis was based on the first order or second order statistics of textures [2], [3], [4], [5] and [6]. It is well known that the co-occurrence matrix features are first proposed by [5]. More recently methods based on multi-resolution such as wavelet transform have received a lot of attention [7] and [8].

In this paper, the multi-resolution transforms like DWT, SWT, DDWT and DTCWT are applied on the above texture groups and statistical features and co-occurrence features are extracted from the approximation and detail regions of wavelet transformed sub-bands, at different scales and used for classification. Then, the particular multi-resolution transform that maximizes the texture classification performance for a particular texture group is identified.

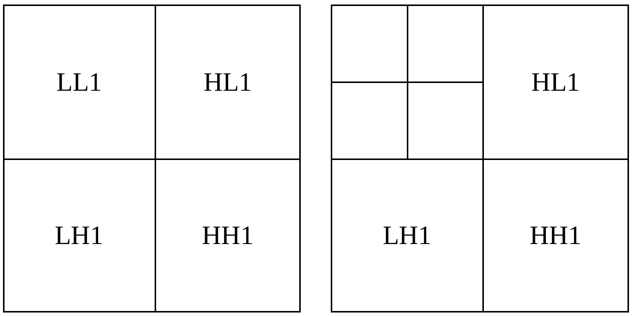
This paper is organized as follows: In section 2, the Multi-resolution transforms, which includes Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Double Density Wavelet Transform (DDWT) and Dual Tree Complex Wavelet Transform (DTCWT) are discussed. In section 3, the feature extraction and the texture classification system are explained. The experimental results and discussion are given in section 4. Finally, concluding remarks are given in section 5.

2. MULTI-RESOLUTION TRANSFORMATIONS

Multi-scale methods are based on image transformations that reduce image resolution, and they are able to segment objects of different sizes depending on the chosen resolution [9]. The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one image is broken down into many lower resolution components. This is called the wavelet decomposition.

2.1 DISCRETE WAVELET TRANSFORM

Wavelets are functions generated from one single function Ψ by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [10].



(a) One level (b) Two level

Fig.1. Image Decomposition

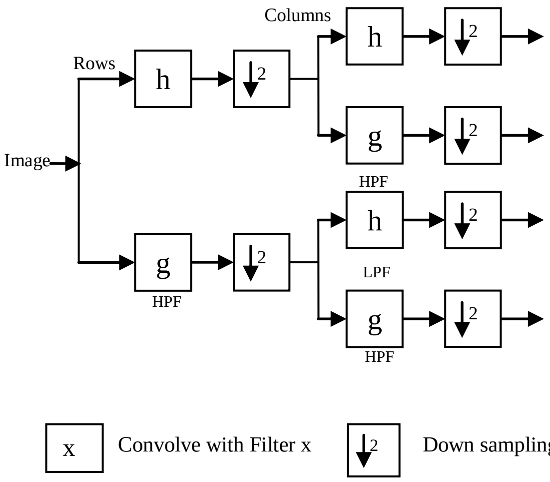


Fig.2. DWT Filter Bank for One-Level Image Decomposition

The Discrete Wavelet Transform (DWT) is identical to a hierarchical sub band system where the sub bands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided i.e., decomposed into four sub bands and critically sub sampled as shown in Fig.1(a). The sub bands labeled LH1, HL1 and HH1 represent the finest scale wavelet coefficients, i.e., detail images while the sub band LL1corresponds to coarse level coefficients, i.e., approximation image. These four sub bands arise from separate applications of vertical and horizontal filters, as shown in Fig.2. To obtain the next coarse level of wavelet coefficients, the sub band LL1 alone is further decomposed and critically sampled. This results in two-level wavelet decomposition as shown in Fig.1(b) [11] and [12].

2.2 STATIONARY WAVELET TRANSFORM

The standard DWT is a non-redundant and compact representation of signal in transform domain. The decimation step after filtering makes the standard DWT time shift-variant. The stationary wavelet transform (SWT) has a similar tree structured implementation without any decimation (sub-sampling) step. The main strength of SWT is its time-invariance property [13] which is useful in many applications. The SWT algorithm is slightly different from that of DWT. In literature, the SWT is interpreted in various ways, such as, redundant, non-decimated, over complete or shift-invariant wavelet transform. Fig.3 shows the SWT filter bank for one-level image decomposition. The four sub-bands obtained after the decomposition are approximation (LL) and detail, namely, horizontal (LH), vertical (HL) and diagonal (HH) sub-bands. LL band can be fed into a similar filter bank for next level of decomposition. Since, SWT does not include down sampling operations, it is a redundant transform. The size of the sub-bands remains the same for the decomposed image for any levels of decomposition in Stationary Wavelet transform.

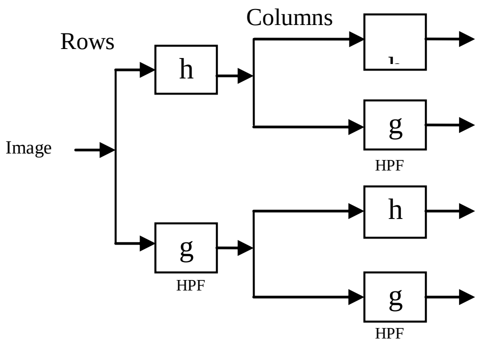
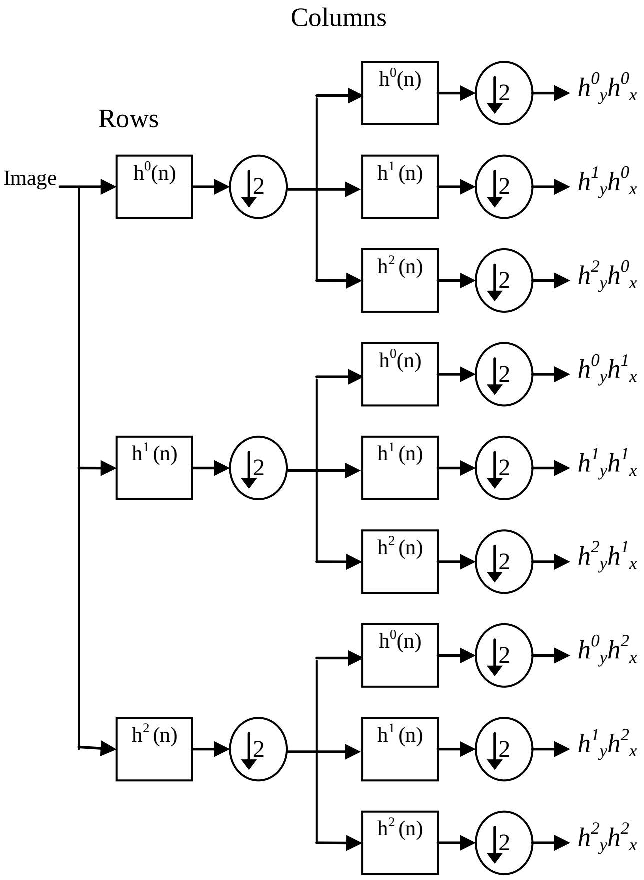


Fig.3. SWTFilter Bank for One-Level Image Decomposition

2.3 DOUBLE DENSITY WAVELET TRANSFORM

Recently a new transform called Double Density Wavelet Transform (DDWT) is developed. The double density wavelet provides higher directional selectivity, better peak signal to noise ratio and visual perception than the spatial domain methods and other frequency domain methods. DDWT is a shift insensitive, directional, complex wavelet transform with a very low redundancy factor of two regardless of the number of scales. Double density wavelets have a single scaling function (φ) and two wavelet functions (ψ_1, ψ_2). Therefore, it has a single low pass filter and two high pass filters. The two wavelets are shifted by half the time period, i.e., $\psi_1(t) = \psi_2\left(t - \frac{1}{2}\right)$. The analysis filter bank of DDWT for one level of image decomposition, shown in Fig.4 (a) produces nine sub bands as shown in Fig. 4(b) [14], namely, $h_y^0 h_x^0, h_y^1 h_x^0, h_y^2 h_x^0, h_y^0 h_x^1, h_y^1 h_x^1, h_y^2 h_x^1, h_y^0 h_x^2, h_y^1 h_x^2, h_y^2 h_x^2$. At a given level in the iterated filter bank, this separable extension produces nine 2-D sub-bands, which are labeled as $h_y^i h_x^j$, $i,j \in \{0,1,2\}$ The subscript *x* indicates filtering along the row dimension, while subscript *y* denotes filtering along the column dimension. The superscripts 0, 1, 2 indicate the particular filter h^0, h^1, h^2 used to filter along a specified dimension to create the sub-band.



(a)

h^0h^0	h^0h^1	h^0h^2
h^1h^0	h^1h^1	h^1h^2
h^2h^0	h^2h^1	h^2h^2

(b)

Fig.4. DDWT Decomposition: (a) Analysis Filter Bank; (b) DDWT Sub-bands

2.4 DUAL TREE COMPLEX WAVELET TRANSFORM

Discrete wavelet decompositions suffer from two main problems (i) Lack of shift invariance (ii) Poor directional selectivity for diagonal features, because the wavelet filters are separable and real. Complex wavelets overcome these two key problems by introducing limited redundancy into the transform [15]. However, a further problem arises here because perfect reconstruction becomes difficult to achieve for complex wavelet decompositions beyond level 1, when the input to each level becomes complex. To overcome this, dual-tree complex wavelet transform [15] (DTCWT) was introduced, which allows perfect reconstruction while still providing the other advantages of complex wavelets. Complex Wavelets Transforms (CWT) use complex-valued filtering (analytic filter) that decomposes the real/complex signals into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute amplitude and phase information, just the type of information needed to accurately describe the energy localizations of oscillating functions (wavelet basis). The dual-tree complex wavelet transform gives rise to wavelets in six distinct directions. In each direction, one of the two wavelets can be interpreted as the real part of a complex-valued wavelet, while the other wavelet can be interpreted as the imaginary part of a complex-valued wavelet. Because the complex version has twice as many wavelets as the real version of the transform, the complex version is four times expansive.

3. FEATURE EXTRACTION

Feature extraction is concerned with the detection and localization of particular image patterns, which represent significant features of the image. The intensity mean and variance (or standard deviation) is two such features frequently used because of their relevance to the appearance of an image. Mean is a measure of average brightness and variance is a measure of dispersion within a set of sample data.

$$\text{Mean (M)} = \frac{1}{N^2}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j) \tag{1}$$

$$\text{Standard Deviation (SD)} = \frac{1}{N^2}\sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left[p(i,j)-M\right]^2} \tag{2}$$

where $p(i,j)$ is the transformed value in (i,j) for any sub-band of size NxN.

The co-occurrence matrix is a common method for feature extraction. It consists of co-occurring probabilities of all pair-wise combinations of gray levels (i, j) in the fixed-size spatial window, provided the two parameters: inter-pixel distance and orientation are given. These two terms together with gray level quantization and window size determines the co- occurrence probabilities, which are stored in the co-occurrence matrix [16]. The gray-level co-occurrence matrix $C\ (i, j)$ is defined by first specifying a displacement vector $d = (dx, dy)$ and counting all i and j. In this work the position operator used is $(1,1)$ which has the interpretation: one pixel to the right and one pixel below.

In the texture image, if the black pixels are randomly distributed throughout the image with no field structure, the gray-level co-occurrence matrix will not have any preferred set of gray level pairs. In such case, the matrix is expected to be uniformly populated. Then the feature, which measures the randomness of gray-level distribution, is the entropy. The entropy is highest when all entries in $C(i, j)$ are equal; such a matrix correspond to an image in which there are no preferred gray level pairs for the specified distance vector d. Similarly, energy or second angular moment is an image homogeneity measure, the more homogeneous the image, the larger the value. Contrast is the measure of local image variations, i.e., the measure of image linearity, linear directional structures in direction φ result in large correlation values in this direction. The features contrast, total energy, local homogeneity, cluster shade, cluster prominence and information measure of correlation, defined using the gray level co-occurrence matrix, are computed [11].

3.1 TEXTURE CLASSIFICATION SYSTEM

The texture classification system is shown in Fig.5. It consists of two sections, namely (i) texture training phase and (ii) texture classification phase.

3.1.1 Texture Training Phase:

In the texture training phase, the known textures are decomposed using wavelet transforms. Then, mean and standard deviation of approximation and detail sub-bands of three level decomposed images (i.e., LL_k, LH_k, HL_k, HH_k; for $k=1,2,3$) are calculated as features and stored in features library, using the Eq.(1) and Eq.(2).

In addition, various conventional co-occurrence features such as contrast, energy, entropy, local homogeneity, cluster shade, cluster prominence, and information measure of correlation are calculated from co-occurrence matrix $C(i,j)$, derived for wavelet transformed sub-bands using the formula[2] and stored in the features library.

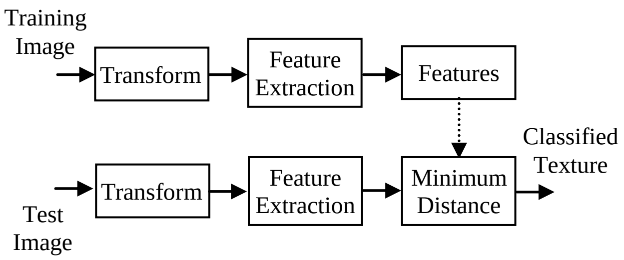


Fig.5. Texture Classification System

3.1.2 Texture Classification Phase:

Here, the test texture image is decomposed into sixteen equal sized sub images of size *128x128*, and four equal sized sub images of size *256x256*, which sums to a total of 20 sub images. Then, these 20 sub images are decomposed using DWT, SWT, DDWT and DTCWT and a similar set of statistical and co-occurrence features are extracted and compared with corresponding feature values stored in the feature library. The classification is done using the Minimum Distance Criterion which is given as,

$$\text{Distance}\ (i) = \sum_{j=1}^{n} abs\ [f_j(x) - f_j(i)] \qquad (3)$$

where, $f_j(x)$ - Feature of unknown Texture image

$f_j(i)$ - Feature of known i^{th} Texture image

n - Number of Features

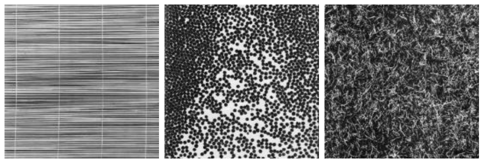
The texture image which has the minimum distance when compared with the test image is classified as the resultant image. The success of classification is measured using the classification gain (G) and is calculated using "Eq. (4)".

$$G\ (\%) = \frac{Ccorr}{M} x100 \qquad (4)$$

where, *Ccorr* is the number of such images correctly classified and *M* is the total number of such images belonging to the particular texture group.

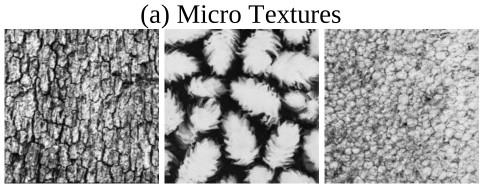
4. EXPERIMENTAL RESULTS AND DISCUSSION

Experiments are conducted with (i) 112 monochrome texture images, each of size *512x512*, obtained from Brodatz Image Database [17] and (ii) 122 monochrome texture images, each of size *512x512*, obtained from Vistex Image Database [18]. These 112 and 122 texture images are categorized into different texture groups such as Micro, Macro, Periodic, Aperiodic, Fine, Coarse, Regular, Random, Deterministic, Non-deterministic, Non-Stochastic, Stochastic, Strong and Weak. The texture groups contain overlapping texture images. The sample texture images of Brodatz Image Database for various texture groups are shown in Fig.6.



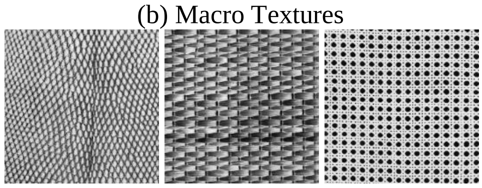
D49_512 D67_512 D110_512

(a) Micro Textures



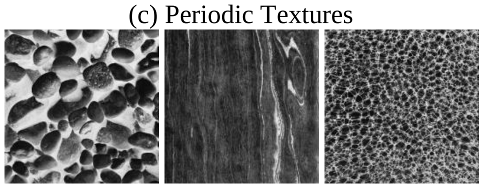
D73_512 D88_512 D112_512

(b) Macro Textures



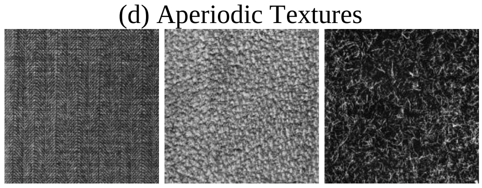
D35_512 D56_512 D101_512

(c) Periodic Textures



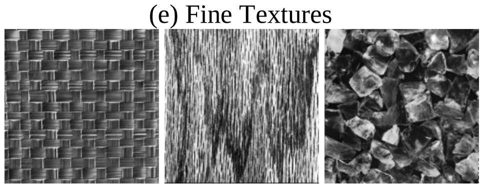
D31_512 D70_512 D111_512

(d) Aperiodic Textures



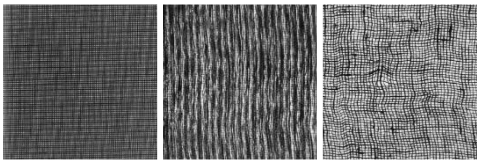
D17_512 D92_512 D109_512

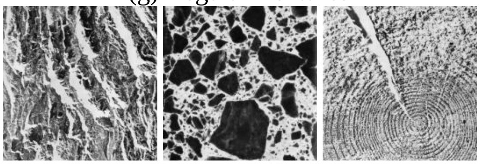
(e) Fine Textures

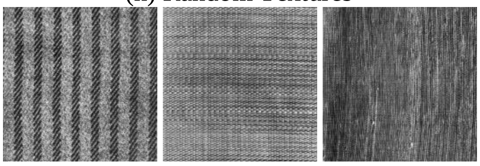


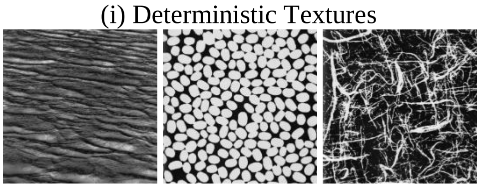
D64_512 D59_512 D99_512

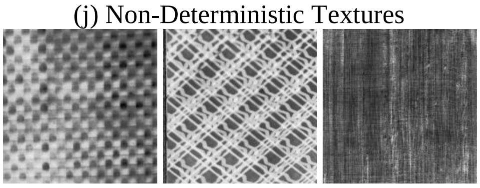
(f) Coarse Textures

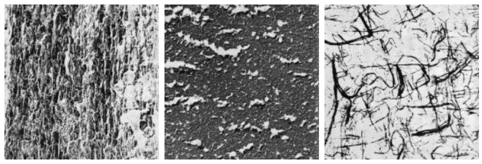

D21_512 D76_512 D104_512
(g) Regular Textures


D13_512 D62_512 D97_512
(h) Random Textures


D11_512 D55_512 D79_512
(i) Deterministic Textures


D37_512 D75_512 D107_512
(j) Non-Deterministic Textures


D08_512 D46_512 D78_512
(k) Non-Stochastic Textures


D12_512 D86_512 D108_512
(l) Stochastic Textures

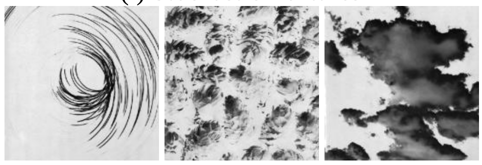

D43_512 D89_512 D91_512
(m) Weak Textures

Fig.6. Sample Texture Images for Texture Groups

Each texture image in a particular group is subdivided into sixteen *128 x 128* and four *256 x 256* non-overlapping image regions summing to a total of 20 texture sub images, which were used for classification. A separate database is maintained for each texture group. The number of texture images in each group that were used for training and classification is shown in Table.1.

Table.2 shows the results of texture classification using Multi-Resolution Transforms for Brodatz Texture Image Database. In the Table.2, the maximum classification gain obtained for each texture group is shaded, i.e., highlighted. From the Table.2, it can be observed that DDWT results in higher classification gain for 5 texture groups, such as, aperiodic, coarse, random, non-deterministic and stochastic texture groups whereas, DTCWT results in higher classification gain for 8 texture groups, such as, micro, macro, periodic, fine, regular, deterministic, non-stochastic and weak texture groups.

Table.1. Number of Texture Images used for Training and Classification

Texture Group	**Brodatz Texture Image Database**		**Vistex Texture Image Database**	
	Images used for Training	**Image Regions used for Classification**	**Images used for Training**	**Image Regions used for Classification**
Micro	35	700	44	880
Macro	77	1540	78	1560
Periodic	48	960	29	580
Aperiodic	57	1140	93	1860
Fine	37	740	43	860
Coarse	68	1360	79	1580
Regular	51	1020	30	600
Random	54	1080	93	1860
Deterministic	49	980	30	600
Non-Deterministic	56	1120	91	1820
Non-Stochastic	51	1020	30	600
Stochastic	54	1080	91	1820
Weak	11	220	20	400

Graphical Analysis of Texture Classification Results using Multi-Resolution Transforms for different texture groups for Brodatz Texture Image Database is shown in Fig.7.

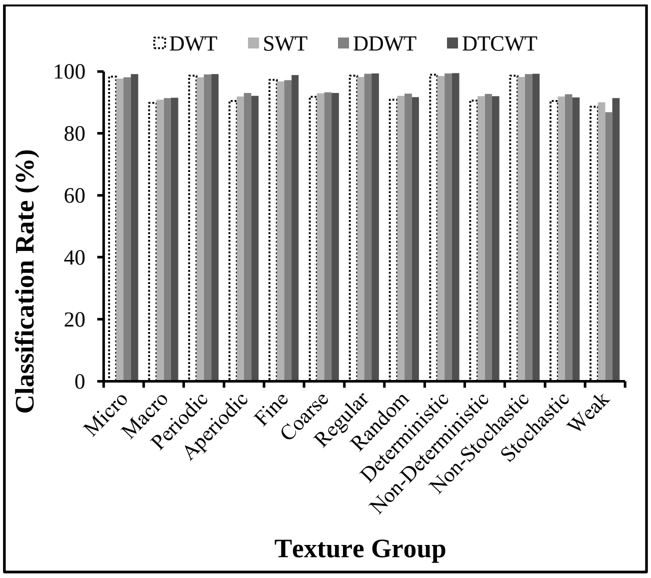


Fig.7. Graphical Analysis of Texture Classification Results using Multi-Resolution Transforms for different Texture Groups of BrodatzTexture Image Database

The results of texture classification using Multi-Resolution Transforms for Vistex Texture Image Database is shown in Table.3. In the Table.3, the maximum classification gain obtained for each texture group is shaded, i.e., highlighted. From the Table 3, it can be observed that DTCWT results in highest classification gain for all texture groups in Vistex database.

The graphical analysis of texture classification results using multi-resolution transforms for different texture groups for Vistex Texture Image Database is shown in Fig.8. Further, from both the tables it is observed that for macro, aperiodic, coarse, random, non-deterministic and stochastic texture groups, the classification rate is lower by 5.77% to 9.99%, compared with micro, periodic, fine, regular, deterministic and non-stochastic texture groups respectively.

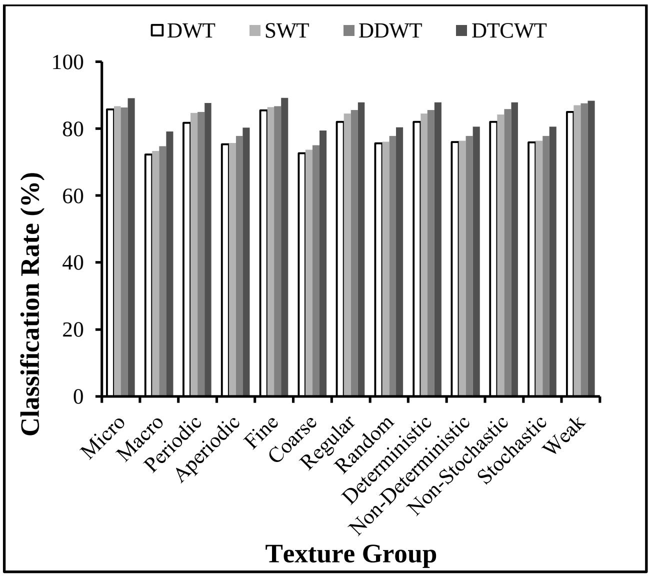


Fig.8. Graphical Analysis of Texture Classification Results using Multi-Resolution Transforms for Different Texture Groups of Vistex Texture Image Database

Table.2. Results of Texture Classification for Multi-Resolution Transforms for Brodatz Texture Image Database

Texture Group	Discrete Wavelet Transform		Stationary Wavelet Transform		Double Density Wavelet Transform		Dual Tree Complex Wavelet Transform	
	No. of Matches	Classification Rate	No. of Matches	Classification Rate	No. of Matches	Classification Rate	No. of Matches	Classification Rate
Micro	688	98.29	684	97.71	687	98.14	694	99.14
Macro	1383	89.81	1399	90.84	1407	91.36	1409	91.49
Periodic	947	98.65	942	98.13	951	99.06	952	99.17
Aperiodic	1031	90.44	1048	91.93	1061	93.07	1050	92.11
Fine	720	97.30	716	96.76	719	97.16	731	98.78
Coarse	1249	91.84	1264	92.94	1268	93.24	1265	93.01
Regular	1006	98.63	1002	98.24	1012	99.22	1013	99.31
Random	981	90.83	995	92.13	1003	92.87	990	91.67
Deterministic	969	98.88	965	98.47	973	99.29	974	99.39
Non-Deterministic	1014	90.54	1031	92.05	1038	92.68	1031	92.05
Non-Stochastic	1006	98.63	1002	98.24	1011	99.12	1012	99.22
Stochastic	977	90.46	992	91.85	1000	92.59	989	91.57
Weak	195	88.64	198	90.00	191	86.82	201	91.36

Table.3. Results of Texture Classification for Multi-Resolution Transforms for Vistex Texture Image Database

Texture Group	Discrete Wavelet Transform		Stationary Wavelet Transform		Double Density Wavelet Transform		Dual Tree Complex Wavelet Transform	
	No. of Matches	Classification Rate	No. of Matches	Classification Rate	No. of Matches	Classification Rate	No. of Matches	Classification Rate
Micro	754	85.68	763	86.70	759	86.25	784	89.09
Macro	1127	72.24	1144	73.33	1166	74.74	1234	79.10
Periodic	474	81.72	491	84.66	493	85.00	508	87.59
Aperiodic	1400	75.27	1407	75.65	1446	77.74	1493	80.27
Fine	735	85.47	743	86.40	745	86.63	767	89.19
Coarse	1147	72.59	1164	73.67	1185	75.00	1254	79.37
Regular	492	82.00	507	84.50	513	85.50	527	87.83
Random	1406	75.59	1414	76.02	1447	77.80	1494	80.32
Deterministic	492	82.00	507	84.50	513	85.50	527	87.83
Non-Deterministic	1381	76.00	1389	76.32	1415	77.75	1467	80.60
Non-Stochastic	492	82.00	505	84.17	515	85.83	527	87.83
Stochastic	1381	75.88	1389	76.32	1415	77.75	1467	80.60
Weak	340	85.00	348	87.00	350	87.50	353	88.25

5. CONCLUSION

From the analysis of texture classification results obtained with Brodatz Texture Image Database using Multi-Resolution transforms, it is inferred that the Dual Tree Complex wavelet transform improves the percentage of correct classification for micro, macro, periodic, fine, regular, deterministic, non-stochastic and weak texture groups while the Double Density wavelet transform gives better results for aperiodic, coarse, random, non-deterministic and stochastic texture groups.The similar work, carried out with Vistex Texture Image using Multi-Resolution transforms leads to the conclusion that the Dual Tree Complex Wavelet Transform gives better classification results for all texture groups.

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