Texture Recognition in Images using Wavelets

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Abstract- This paper outlines a scheme for image texture recognition using Wavelet transforms. The texture image is decomposed at 3 levels using a 2-D Haar Wavelet and a combined coefficient based on the decomposition matrices is used as a discrimination feature. The combined coefficient is obtained by using standard deviations of the approximation and detail Wavelet coefficients at each of the levels. The proposed scheme is tested on a dataset of 260 images divided into 4 categories, and demonstrates accuracies around 95% which is at par with those reported in extant literature.

Keywords – texture recognition; Wavelet decomposition; pattern recognition; computer vision;

I. INTRODUCTION

Over the last decade, a number of multimedia based applications like digital photo albums, computer based training packages, games and home entertainment, on-line galleries and information kiosks, have led to the growth of large repositories of digital media all over the world. In this scenario, a fast and effective mechanism for retrieval of digital media content from these repositories assumes fundamental importance. Texture is an importance visual property, which has been utilized by content based retrieval systems to recognize patterns within images to aid in their retrieval. Texture refers to visual patterns or spatial arrangement of pixels that regional intensity or color alone cannot sufficiently describe. It is difficult to obtain a general mathematical model for various textures because of the large variation in their properties.

A first example of the derivation of features using texture operators is the set of texture energy measures formulated by Laws in [1]. A set of simple masks in horizontal, vertical and diagonal directions have subsequently been used to isolate and identify textures [2]. Authors like Tamura [3] made an attempt at defining a set of visually relevant texture features like coarseness, contrast, directionality, line-likeness, regularity, roughness. Grey Level Co-occurrence Matrix (GLCM), proposed by Haralick [4] indicating the probability of grey level *i* occurring in the neighbourhood of grey level *j* at a distance *d* along direction q in an image, have proven to be popular and effective for texture recognition. Two state Markov models to detect texture edges characterized by changes in first order statistics have been proposed in [5]. Pentland reports a high degree of correlation between fractal dimensions and human estimates of roughness [6]. Gabor filters have been used in several image analysis applications including texture classification and segmentation [7, 8]. Each filter responds maximally to features from an image that has similar local frequency content and orientation. The main disadvantage of Gabor filters is that they are computationally expensive. Texture recognition has been investigated using affine regions, where emphasis is placed on locating perceptually salient primitives such as blobs [9]. Within a 3×3 pixels window moving across the texture image, the absolute value of first 5 coefficients of Discrete Fourier Transform (DFT) have been used for texture description [10]. In [11] the authors describe a parallel algorithm for segmentation using simultaneous auto-regressive (SAR) random field models and multidimensional cluster analysis. Bovik et al [12] suggest the restriction of the choice of Gabor filters to those with isometric gaussians (aspect ratio one). In [13] the authors have used the one sided linear prediction (OSP) model, popularly known as auto-regressive (AR) model, to derive texture descriptors in terms of the prediction coefficients. The present work investigates techniques for improving texture recognition accuracy by using a set of Wavelet Decomposition Matrices (WDM). The organization of the paper is as follows : Section 2 contains an overview of Wavelets, section 3 describes the proposed approach, section 4 provides details of experimentations and results, section 5 provides an overall conclusion and the scope for future research.

II. WAVELETS – AN OVERVIEW

A *Wavelet* is a mathematical function used to analyze a time dependent signal at different resolutions. The Discrete Wavelet Transform (DWT) analyses the signal at different resolutions by decomposing it into an *approximation* coefficient and a set of *detail* coefficients. The Haar Wavelet, proposed by Alfred Haar [14], transforms a 1-D signal into a set of averages and differences as depicted in (1).

$$\mathbf{x} = (x_1, x_2, \ldots, x_N) \rightarrow (s_1, \ldots, s_{N/2} \mid d_1, \ldots, d_{N/2})$$

$$= \frac{x_{2k-1} + x_{2k}}{2}, \quad d_k = \frac{x_{2k-1} - x_{2k}}{2}, \quad k = 1, \ldots, N/$$

where s_k

As an example the Haar Wavelet transform for a 4-element 1 D signal x1, x2, x3, x4 by (2).

$$W_4.X=\frac{1}{2}\begin{bmatrix}1&1&0&0\\0&0&1&1\\1&-1&0&0\\0&0&1&-1\end{bmatrix}.\begin{bmatrix}x_1\\x_2\\x_3\\x_4\end{bmatrix}=\frac{1}{2}\begin{bmatrix}x_1+x_2\\x_3+x_4\\x_1-x_2\\x_3-x_4\end{bmatrix} \qquad \textbf{(2)}$$

For a 2-D signal matrix *A* (N×N) the corresponding Haar Wavelet transform is defined in (3).

Here, b is the *blur* or approximation coefficient and h_n ,v_n ,d_n are the *horizontal*, *vertical* and *diagonal* detailed coefficients at level n . The b matrix of a specific level is used as the data matrix for the next level. The data matrix is partitioned into 2×2 cells $\begin{bmatrix}a_{11}&a_{12}\\a_{21}&a_{22}\end{bmatrix}$ and for each cell the approximation and detail coefficients are computed as shown in (4) below.

$$\begin{aligned}b(i,\ j)&=-\tfrac{1}{4}\ (a_{11}\ a_{12}\ a_{21}\ \ a_{22})\\h(i,\ j)&=-\tfrac{1}{4}\ \{(a_{11}a_{12})\ \ (a_{21}\ \ a_{22})\}\\v(i,\ j)&=-\tfrac{1}{4}\ \{(a_{11}a_{21})\ \ (a_{12}\ \ a_{22})\}\\d(i,\ j)&=-\tfrac{1}{4}\ \{(a_{11}a_{22})\ \ (a_{12}\ \ a_{21})\}\end{aligned} \qquad (4)$$

III. PROPOSED APPROACH

The texture image is decomposed using a Haar Wavelet with 3-level decomposition producing following coefficients, normalized to be within the range [0,1].

b, h1, d1, v1, h2, v2, d2, h3, v3, d3 **(5)**

Standard deviations (σ) of the matrices are computed and added to the original, where k=1,2,3

$$\begin{aligned}B&=b+\sigma b\\H_k&=h_k+\sigma\ h_k\\V_k&=v_k+\sigma v_k\\D&=d_k+\sigma d_k\end{aligned} \qquad \textbf{(6)}$$

For the horizontal and diagonal coefficients, the difference between adjacent elements along each row are computed and summed over the entire matrix. For the vertical coefficient the differences are computed along a column. A set of difference are computed along a column. matrices are generated as indicated in (7).

$$\begin{aligned}H_{d,k}&=\sum_{i=1}^{n_k}\sum_{j=1}^{n_k=1}H_k(j)-H_k(j+1)\\D_{d,k}&=\sum_{i=1}^{n_k}\sum_{j=1}^{n_k=1}D_k(j)-D_k(j+1)\\V_{d,k}&=\sum_{i=1}^{n_k}\sum_{j=1}^{n_k-1}V_k(i)-V_k(i+1)\\A_d&=\sum_{i=1}^{n_k}\sum_{j=1}^{n_k-1}A(j)-A(j+1)\end{aligned} \qquad \textbf{(7)}$$

Here k=1,2,3 and n_k is the number of elements along a row or column of a matrix at level k. All the difference matrices are averaged to generate a feature value for the media file, as shown in (8) and henceforth referred to as the *combined Wavelet coefficient*.

$$F = \frac{1}{10}(A_d + H_{d,1} + V_{d,1} + D_{d,1} + H_{d,2} + V_{d,2} + D_{d,2} + H_{d,3} + V_{d,3} + D_{d,3}) \quad (8)$$

A texture class consists of a set of member images $T_i = \{t_1, t_2, \ldots, t_n\}_i$ $\{t_1^w, t_2^w, \ldots, t_n^w\}$. The texture class is mapped to the boundary values of this feature for its member images as depicted in (9).

$$T_i = \{t_{max}^W, t_{min}^W\}_i \quad (9)$$

A test image s_j is assigned a weight of 1 for texture class T_i if its combined Wavelet coefficient s_i^w satisfies the following condition i.e.

$$t_{max,i}^W \geq s_j^W \geq t_{min,i}^W \quad (10)$$

IV. EXPERIMENT AND RESULT

The dataset consists of 260 texture images downloaded from various Web-sites [15, 16, 17, 18] and divided into 4 categories of 65 images each : bark, sky, leather and stone. The training set consists of 60 images : 15 samples from each category. Some representative samples are shown below in fig1.

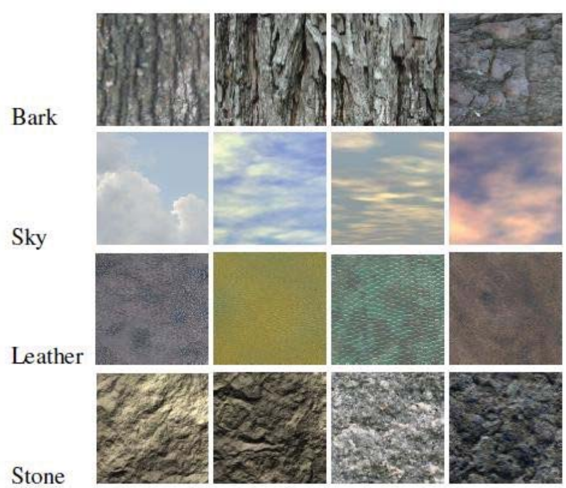


Figure 1. Training set texture samples

The combined Wavelet coefficient is computed for each image sample and is tabulated in Table 1 below.

TABLE I. TRAINING SET FEATURE VALUES

	Bark	Stone	Leather
2492.00	3228.48	5498.73	6475.58
1669.80	4079.58	5491.96	6745.76
1247.71	3772.03	6002.11	6116.17
1650.77	3800.62	5633.23	6627.81
1845.21	3403.57	5051.08	7686.35
1923.38	13741.57	5112.10	7374.31
2035.62	4138.19	5383.54	7441.61
1300.10	3619.91	5042.52	6999.46
2042.78	4353.42	5135.96	6710.66
1899.03	3828.27	5107.05	6594.94

2681.96	3967.69	5024.75	7172.14
2336.73	4463.85	5038.53	6496.38
2724.36	4136.47	5803.21	6376.15
2635.59	4159.09	5932.40	6692.31
2081.16	3978.59	5634.54	7165.45

Fig. 2 gives a visual perspective of the feature values for the training set files

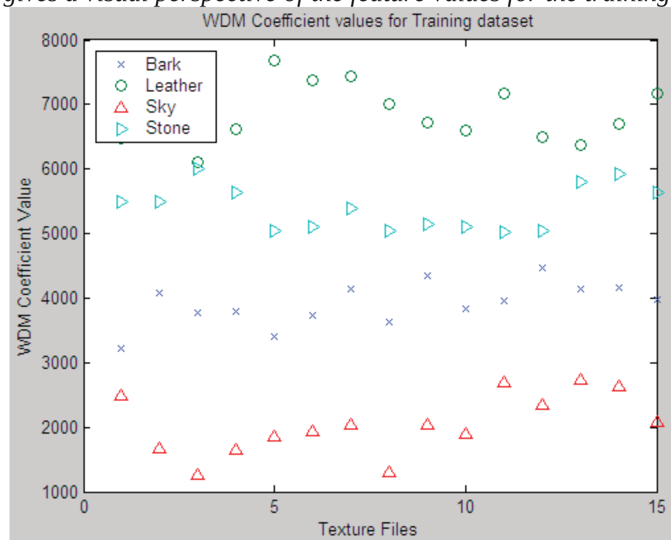


Figure 2. Training set discrimination plot

Table 2 shows the optimum boundary values for classifying each category. The optimum values are determined so that the training set images may be equally distributed over the classes as far as possible.

TABLE II. TRAINING SET BOUNDARY VALUES

	Minimum	**Maximum**
Sky	1000	3000
Bark	3000	4500
Stone	5000	6000
Leather	6000	8000

The testing set consists of 200 images : 50 samples from each category. Some representative samples are shown in Fig. 3.

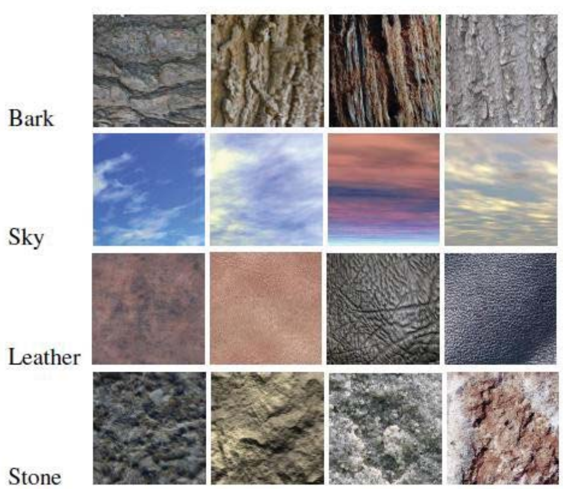


Figure 3. Testing set texture samples

The feature values are shown in Table 3 and the corresponding plots in Fig. 4.

TABLE III. TESTING SET FEATURE VALUES

Sky

2281.50	1143.17	1664.93	1845.21	2035.62	2111.56
2622.15	2248.99	2304.39	2650.81	3138.43	2290.28
1648.32	1602.57	1270.23	2042.78	2304.59	1880.37
1859.81	1990.01	1880.14	2158.84	2703.03	2166.23
2999.81	2696.68	2009.39	2306.29	2667.15	2302.92
2724.36	2185.78	2209.6	2082.75	1039.91	2116.97
1870.59	2575.33	1685.39	2509.65	2509.65	1595.28
2332.53	1976.93	2153.84	1679.13	1743.98	2725.91
1959.21	1478.67				

Bark

3732.20	4010.94	3668.62	3549.69	4051.87	4051.87
3440.99	4318.44	4433.48	4389.40	4398.07	3235.57
3933.90	3791.97	4241.42	4030.34	3740.86	3933.19
3713.94	5061.59	4964.58	3900.01	3519.41	4104.45
3955.73	3549.51	3370.26	3823.22	3944.27	4253.06
3675.66	4407.25	4348.30	4305.51	4139.83	4298.47
4332.16	3638.44	4446.33	4433.52	3824.01	4278.87
4251.26	4191.51	4322.61	4088.70	3733.78	3816.20
3498.88	3992.69				

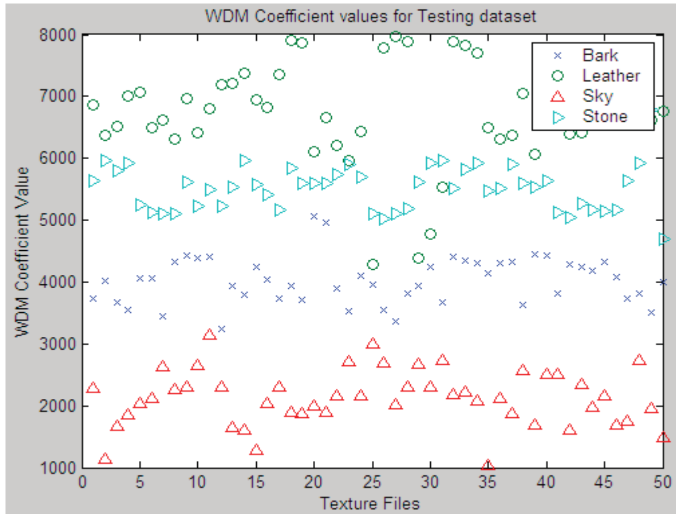
Stone

5644.37	5955.67	5806.69	5924.71	5247.77	5131.61
5099.30	5112.23	5609.70	5233.35	5486.38	5233.35
5527.15	5962.91	5568.52	5409.34	5160.60	5843.46
5593.56	5594.13	5598.16	5731.47	5898.41	5703.30
5112.61	5020.11	5094.64	5182.66	5616.54	5917.12
5971.04	5514.69	5814.79	5916.10	5462.36	5507.06
5897.34	5593.35	5541.33	5633.27	5124.30	5042.28
5271.54	5169.80	5150.01	5160.29	5634.54	5932.40
6784.23	4687.89				

Leather

6856.49	6367.94	6520.16	6997.85	7065.06	6492.83
6621.14	6314.67	6968.31	6409.12	6803.59	7181.82
7206.32	7381.50	6937.79	6828.04	7356.32	7917.85
7876.09	6108.93	6649.80	6213.80	5971.04	6431.53
4291.29	7792.09	7971.57	7892.34	4380.50	4766.10
5536.19	7892.34	7830.92	7694.35	6492.83	6305.08
6371.37	7038.98	6055.62	7004.67	6786.35	6390.99
6403.73	7088.33	6664.68	7054.45	6884.56	6868.12
6618.98	6760.97				

FIGURE 4. TESTING SET DISCRIMINATION PLOT



Based on the boundary values determined for each category, the accuracies for classification are depicted in Table 4.

TABLE IV. CLASSIFICATION ACCURACY

Texture Category	Number of samples taken	Samples correctly classified	Accuracy (%)
Sky	50	49	98
Bark	50	48	96
Stone	50	49	98
Leather	50	45	90

V. CONCLUSION AND FUTURE SCOP

This paper outlines a scheme for image texture recognition based on a three level decomposition using Haar Wavelets to other popular texture discrimination techniques found in extant literature, Wavelet based methods have been seen to provide better results and have lower computational complexities than Gabor filter based approaches. The proposed algorithm has demonstrated an overall recognition accuracy of 95.5% compared to 87% for Gabor Filters as reported in [7], and 87.4% for Discrete Fourier Transform (DFT) as reported in [10]. To improve on the results additional measures are required to address the problems related to variations in brightness, contrast and tonal range of the images. One way to tackle this problem is via histogram normalization; another methodology providing scope for further research is to combine color and texture, e.g. wood textures combined with its various hues.

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