On Wavelet Features for Texture Discrimination

Chaur-Chin Chen ( ) *

Department of Computer Science
National Tsing Hua University
Hsinchu 300, Taiwan
Fax: (03) 572-3694
e-mail: cchen@cs.nthu.edu.tw

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Abstract

Texture features derived from wavelet transforms have recently been exploited for texture discrimination, image retrieval from a database, region classification for satellite images. Most works demonstrate that the error rate for texture classification is reduced as the number of texture features increases but seldom mentioned how to select *good* features derived from a specified wavelet transform. This report provides experiments to show that a few wavelet features might perform well if Whitney's procedure is applied to select a *suboptimal* set of features. We test Daubechies four wavelet textures on three sets of database including (1) textures synthesized by Generalized Ising models (GIM), (2) textures synthesized by Gauss Markov random fields (GMRF), (3) natural textures scanned from Brodatz's Album. A comparison with the features derived from Fourier transform, another filtering method, shows that both approaches can achieve perfect results if an appropriate set of features are used.

1 Introduction

Texture analysis has been an active research area in Computer Vision and Pattern Recognition since three decade ago [12]. Among which, texture feature definition, selection, and extraction are the major researches with applications on recognition and discrimination. The commonly used texture features such as directionality, coarseness, regularity, and etc. [18] could be derived from Co-occurrence matrices [12], random field models [3] [4] [9] [14], fractal models [17], filtering methods [2] [5] [7] [13] [15] [16]. Many researchers reported a comparison for a variety of texture features [6] [8] [17] [19]. However, like the difficulty of precisely defining a texture, a best set of textures has never existed. People encounter the problem of selecting a small number of discriminant features from a large set of potential features. The recent reports tend to emphasize the importance of wavelet features but ignore the feature selection problem. This paper reminds that Whitney's method [20] can guide to select a small set of discriminant features among a large set of potential features.

The remaining of this paper is organized as follows. Section 2 reviews wavelet features from the Daubechies four transform [10]. Section 3 reviews Fourier features from the Fourier transform [19]. Section 4 shows the experimental results on three data sets Section 5 gives the conclusion.

2 Daubechies four Wavelet Transform

This paper investigates the features derived from the Daubechies four wavelet transform (Daub4) [10] which can be briefly described as follows. Let X be an image of size $N \times N$ and P and Q are row and column permutation matrices corresponding to downsampling processes as introduced in [10], respectively. Then, the output Y of the 3-scale Daub4 can be depicted as follows.

$$Y \;\leftarrow\; P \;*_4\; W \;*_3\; X \;*_1\; W^t \;*_2\; Q$$

where

$$c_0 = \tfrac{1+\sqrt{3}}{4\sqrt{2}},\;\; c_1 = \tfrac{3+\sqrt{3}}{4\sqrt{2}},\;\; c_2 = \tfrac{3-\sqrt{3}}{4\sqrt{2}},\;\; c_3 = \tfrac{1-\sqrt{3}}{4\sqrt{2}}$$

and ${c_0}^2 + {c_1}^2 + {c_2}^2 + {c_3}^2 = 1$ implies that the transform matrix $W = Daub4$ given below is orthogonal.

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$$\begin{bmatrix} c_0 & c_1 & c_2 & c_3 & & & & & & \\ c_3 & -c_2 & c_1 & -c_0 & & & & & & \\ & & c_0 & c_1 & c_2 & c_3 & & & & \\ & & c_3 & -c_2 & c_1 & -c_0 & & & & \\ & & & & & & \ddots & & & \\ c_2 & c_3 & & & & & & & c_0 & c_1 \\ c_1 & -c_0 & & & & & & & c_3 & -c_2 \end{bmatrix}$$

The 3-scale wavelet transform partitions an image into 10 blocks numbered from 1 to 10 with Block 1 containing the lowest-frequency coefficients and Block 10 containing the highest-frequency coefficients [6] [15]. The variance of wavelet coefficients located in each block is then computed as a feature, thus ten wavelet features are derived from 10 blocks. The features measure the coarseness and directionality of a texture [18] at a certain level [6].

3 Fourier Transform

The discrete Fourier transform of an image $\{f(x, y)\}$ of size $m \times n$ can be defined as

$$F(u, v) \;=\; \frac{1}{mn} \sum_{x=0}^{m-1} \sum_{y=0}^{n-1} f(x, y) exp\left[-2j\pi(\frac{ux}{m} + \frac{vy}{n})\right] \tag{1}$$

A wedge-shaped region is defined as

$$W_{s,t} = \{(u, v) \mid s \leq \arctan(v/u) < t\} \tag{2}$$

A ring-shaped region is defined as

$$R_{L,U} = \left\{(u, v) \mid L^2 \leq u^2 + v^2 < U^2\right\} \tag{3}$$

The first eight features based on wedge-shaped regions are defined as the variances of Fourier power spectrum with region sections separated by $[s,\ s + \pi/4)$, where $s \in \{0, \pi/4, \ldots, 7\pi/4\}$. Similarly, the other four features are defined as the variances of Fourier power spectrum of ring-shaped regions with [L,U) = [2,4), [4,8), [8,16), [16,32), respectively. The features respond the coarseness and directionality of a texture. The details are referred to [6] [19].

4 Experiments

Previous researchers [6] [15] [19]. naturally order the features from the subbands with the lowest frequency to the one with the highest frequency which usually leads to an unexpected poor performance even all features are used up. Instead, we evaluate texture features by means of Whitney's nonparametric procedure. The idea is tested on three data sets described below.

4.1 Experiments on Data Set 1

This data set consists of 100 128×128 texture images of four categories, each category contains 25 texture patterns generated from Generilized Ising models [4] [11] with four parameters. Four textures with one texture from each category are displayed in Figure 1.

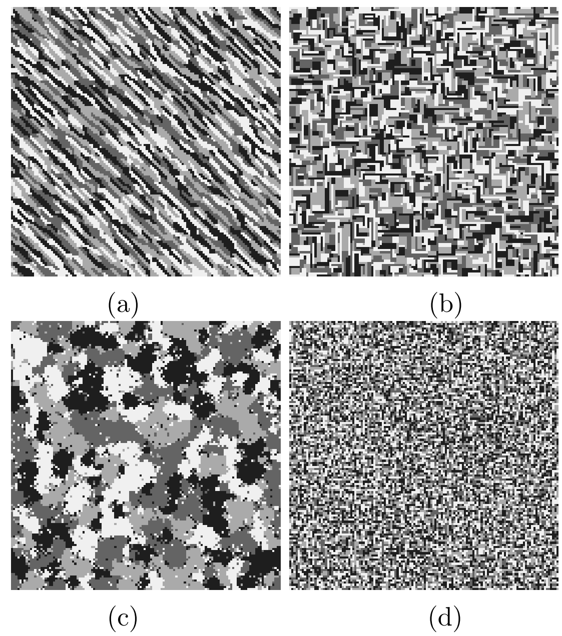

Figure 1: Textures Generated from GIM

4.2 Experiments on Data Set 2

This data set consists of 100 128×128 texture images of four categories, each category contains 25 texture patterns generated from Gauss Markov random field models (GMRF) [3][11] with six parameters. Four textures with one texture from each category are displayed in Figure 2.

4.3 Experiments on Data Set 3

This data set consists of 96 128×128 texture images of six categories, each category contains 16 nonoverlapped texture patterns D04, D06, D09, D16, D24, D77

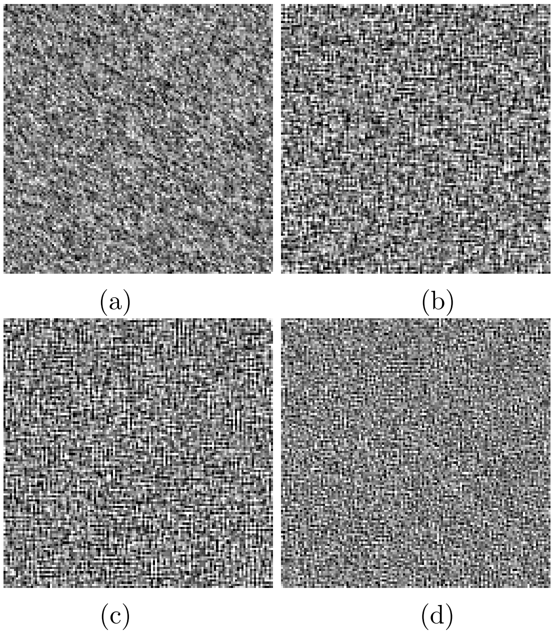

Figure 2: Textures Generated from GMRF

scanned from Brodatz's book [1]. Six textures with one texture from each category are displayed in Figure 3.

4.4 Performance

Our experiments show that for Data Set 1, wavelet features #7 and #2 can perfectly discriminate the textures and Fourier features #3 and #10 can completely discriminate the textures. For Data Set 2, wavelet features #6 and #2 can perfectly discriminate the textures and Fourier features #1 and #3 can completely discriminate the textures. For Date Set 3, the errors for the ordered features according to Whitney's procedure are listed in Table 1. We conclude that two or three features should be enough to discriminate both natural and artifical textures. Blindly using more wavelet or Fourier features does not necessarily improve the results.

5 Discussion and Conclusion

This paper shows that textures can be discriminated by computer if they are visually discriminated. Filtering methods for deriving texture features such as wavelet texture features are good approaches. A traditional pattern recognition strategy for finding an efficient set of texture features should be considered.

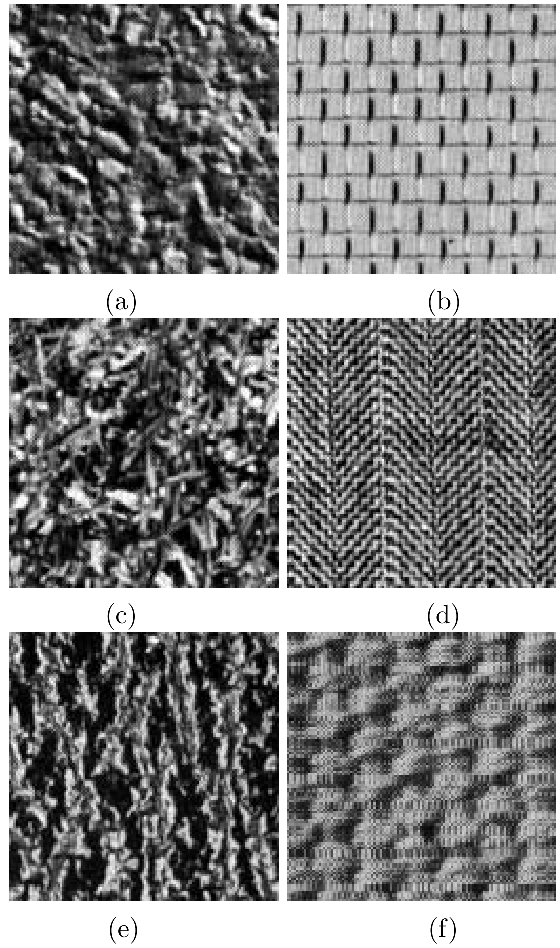

Figure 3: Textures Scanned from Brodatz's Album

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Wavelet		Fourier	
Feature #	Error	Feature #	Error
7	15/96	12	18/96
5	0/96	5	0/96
2	0/96	3	0/96
6	0/96	4	0/96
8	0/96	6	0/96
9	0/96	7	0/96
10	0/96	8	0/96
4	2/96	11	0/96
3	3/96	9	0/96
1	3/96	1	0/96
		10	5/96
		2	8/96

Table 1: Whitney's Errors on Data Set 3

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