DICTA2002: Digital Image Computing Techniques and Applications, 21--22 January 2002, Melbourne, Australia.

Texture Classification Using Multiple Wavelet Analysis

Andrew Busch, Wageeh W. Boles
Research Concentration in Speech, Audio and Video Technology,
Queensland University of Technology
a.busch@qut.edu.au, w.boles@qut.edu.au

Abstract

The successful use of the wavelet transform in the field of texture analysis has been well documented in literature. Simple energy features, as well as first and second-order statistics of the wavelet coefficients, have both been used successfully for this purpose. It is our conjecture that analysing the image with more than one wavelet will provide additional information about the texture, thus improving classification rates. Experimental evidence supports this theory, showing that for simple energy features error rates are halved when multiple wavelets are employed.

1. Introduction

Texture analysis is an important field of image analysis, and plays a role in many tasks, such as medical imaging, machine vision, and content indexing of large image databases. Whilst numerous methods have been proposed through the last few decades, the problem of texture analysis remains a challenging area of research. No single method has yet been shown to perform to a high level in all situations, over a wide variety of both natural and artificial textures. Figure 1 shows an example of some of these textured images from the widely used Brodatz album [1].

Much initial focus on texture analysis relied on the assumption that texture could be characterised by the local statistical properties of pixels' grey level values. First order statistics, such as mean, variance and histograms, as well as second level statistics such as co-occurrence matrices have been used with varying levels of success. The conjecture that such statistics sufficed for texture classification was soon rejected, and a variety of new techniques emerged, such as Markov field models, fractals, and connected component analysis [2].

A common weakness of all of these methods is that the texture is analysed on only a single scale, a limitation that has been quickly overcome by the use of multi-resolution analysis methods. This approach is further justified by studies of the human visual system, which have shown that certain cells in the visual cortex respond only to particular spatial frequencies and/or orientations [3-5]. More recently, Gabor filters have been utilised in a variety of ways to solve the problems of texture segmentation and classification [6, 7]. Typically, a bank of such filters are constructed, with each tuned to a specific spatial frequency and orientation. The energy of each filter output is then used to either segment or classify the image.

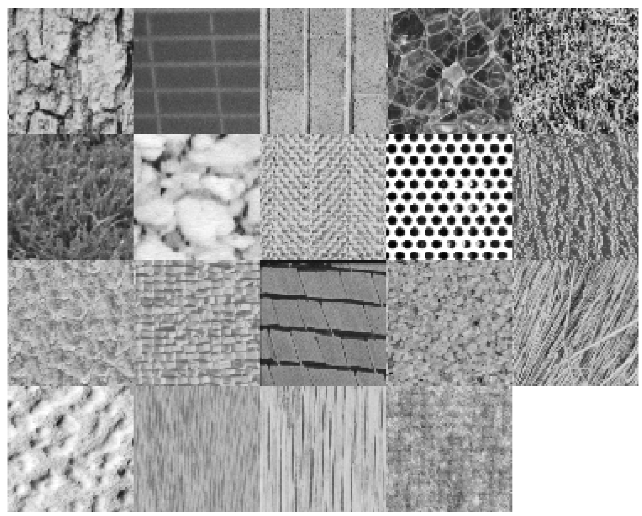


Figure 1. Example of textured images from Brodatz album. Top to bottom, left to right: bark, brick, bubbles, grass, gravel, herringbone, hexagon, leather, pigskin, raffia, sand, straw, wall, water, wood, wool

Over the last ten years, the wavelet representation has emerged as a more solid, formal mathematical framework for multi-scale image analysis [8, 9]. One variation of this transform decomposes an image into detail images in three directions, and a low frequency approximation image. By applying the transformation recursively to the low frequency approximation, a series of detail coefficients are obtained. Features extracted from these coefficients are numerous, including the total energy, statistical representations such as mean and standard deviation, histogram properties, and co-occurrence matrix features [10].

In this paper, we will expand upon this work, and take advantage of the extensive work that has been done in the development of the wavelet transform. Over the last ten years, numerous wavelet have been proposed which possess different properties, and are optimal or near-optimal in a particular sense. By combining features obtained from numerous such wavelets, it is our conjecture that a more powerful set of classifying features will be obtained. To compare our method to single wavelet methods, wavelet energy features are extracted from a variety of textured images from the Brodatz album using both approaches. Classification results both are compared, and conclusions drawn. These results are also compared with more complicated algorithms, which utilise first and second order statistical features of wavelet coefficients.

2. Wavelet Texture Features

When used for the purpose of image analysis, the wavelet transform is typically computed by applying a separable filterbank to the image, given by

$$
\begin{aligned}
A_n &= \left(H_x * \left(H_y * A_{n-1}\right)_{\downarrow 2,1}\right)_{\downarrow 1,2}\\
H_n &= \left(G_x * \left(H_y * A_{n-1}\right)_{\downarrow 2,1}\right)_{\downarrow 1,2}\\
V_n &= \left(G_x * \left(H_y * A_{n-1}\right)_{\downarrow 2,1}\right)_{\downarrow 1,2}\\
D_n &= \left(G_x * \left(G_y * A_{n-1}\right)_{\downarrow 2,1}\right)_{\downarrow 1,2}
\end{aligned}
$$

where * represents two-dimensional convolution, $\downarrow$ represents down-sampling by the given factor in each dimension, and H and G are the low and highpass filters, respectively. The approximation image A is obtained by lowpass filtering in both directions, while the detail coefficients H_n, V_n, and D_n are obtained via highpass filtering in one or more directions, thus providing information about a particular scale in either the horizontal, vertical or diagonal direction. Due to the subsampling involved in this computation, the total number of coefficients is equal to the number of pixels in the original image, and images at each subsequent lower resolution level are half the size of the previous level.

A simple and powerful feature extracted from the wavelet coefficients is the average energy of each detail image. This is defined as the sum of the squares of each detail image, normalised for the total number of coefficients in the image. Such energy signatures provide a good indication of the total energy contained at specific spatial frequency levels and orientations. In addition to energy signatures, more complex features have also been extracted from the wavelet detail coefficients. Such features include histogram parameters of the individual coefficients, as well as second order statistics such as co-occurrence matrix features. These methods have shown to provide further classification accuracy, with error rates as low as 5% reported [10].

3. Multi-Wavelet Algorithm

Typical wavelet texture classification algorithms [10, 11] use a wavelet that is optimal in some sense, such as the family of bi-orthogonal spline wavelets, which provide excellent scale separation [12]. Such wavelets also provide excellent image reconstruction, a property much valued by researchers in the field as a measure of the wavelet's suitability. However, studies have shown that for some texture databases, better classification results are obtained when using the simple Haar wavelet, which is not optimal in any sense, and provides relatively poor image reconstruction [2]. One of the reasons suggested for this is that textured images respond more strongly to the discontinuous nature of the Haar wavelet, as many classes of textures contain such structures themselves. The Haar wavelet is also shift-invariant, and this is also thought to contribute to its surprisingly good performance [13]. Our experiments have shown that for many textures, the Haar wavelet provides almost perfect reconstruction, a phenomenon that is not evident for images in general.

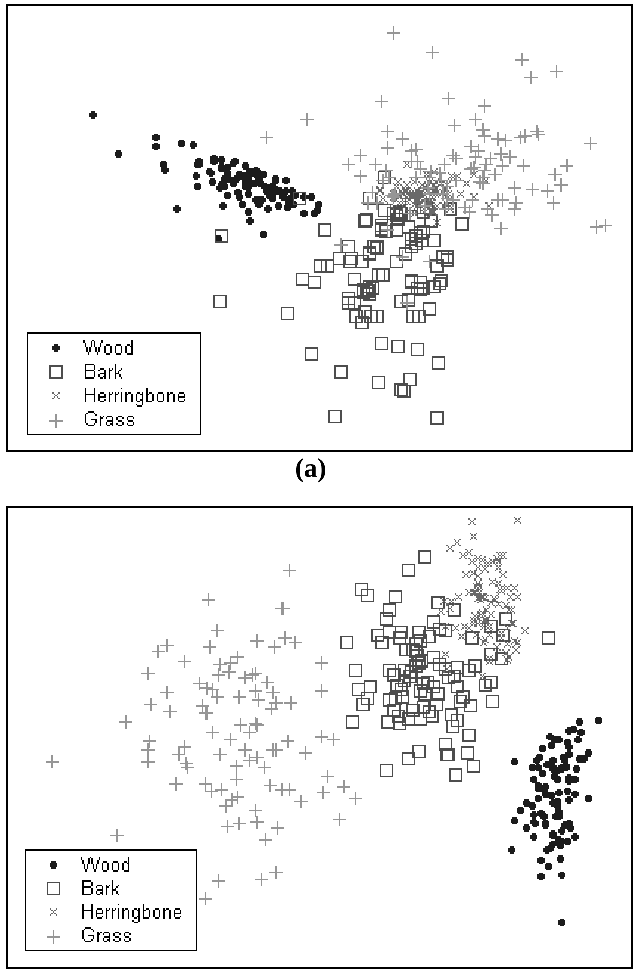
Many textured images contain unique regions with distinct shapes. Such regions will naturally respond more strongly to some wavelets than others. By decomposing such an image with two or more wavelets, particularly wavelets that differ significantly in waveform shape, vanishing moments, and regularity, a markedly different response is obtained at each resolution. Table 1 clearly shows this, by comparing the response of 19 different textures to both the Haar and Biorthogonal wavelets. As can been seen from this data, both wavelets produce a similar response in most cases at the first level of detail, however, are generally different at the second level. Furthermore, this difference does not appear to follow a pattern, with some textures (brick, roof, wool) exhibiting a significantly higher response for the biorthogonal spline wavelet, while others (grass, raffia, wood, hexagon) showing a greatly reduced response. It can also been seen that many texture pairs are quite closely clustered when only

Table 1. Average wavelet coefficient energies for Haar and Biorthogonal wavelets at 2 levels

Texture	Haar 1	Bior 1	Haar 2	Bior 2
Bark	9.68	9.88	11.88	8.11
Brick	12.30	12.30	13.53	20.25
Brick-2	10.45	10.54	11.08	13.18
Bubbles	5.55	5.68	9.99	8.13
Grass	7.57	8.00	27.21	16.03
Grass-2	3.77	3.87	10.56	11.33
Gravel	16.49	16.55	3.71	3.77
H-bone	12.44	12.63	14.58	11.87
Hexagon	14.20	15.26	46.07	33.14
Leather	7.15	7.41	29.57	27.35
Pigskin	10.62	10.71	6.38	5.85
Raffia	10.38	10.49	4.45	2.28
Roof	25.36	25.54	24.00	31.79
Sand	10.03	10.15	10.26	8.59
Straw	10.39	10.64	21.01	18.09
Wall	14.14	14.23	7.53	8.02
Water	10.60	10.62	1.28	1.48
Wood	13.11	13.19	2.07	1.42
Wool	8.79	8.86	15.74	19.26

one wavelet type is used (sand and brick-2 when using Haar wavelet only), but the interclass separation increases by over 50% when data from the second wavelet is added. Figure 2 shows an example of the increased separation provided by using both the Haar and biorthogonal spline wavelets, as compared to using only one or the other. Using linear discriminate analysis (LDA) [14], the two most discriminate features are plotted. As can be seen, when using two wavelets the separation between the feature clusters is greatly increased, without significantly affecting the compactness of the class. When using the Haar wavelet only, there is significant overlap between the bark, herringbone and grass clusters. When adding the biorthogonal wavelet analysis features, this overlap is virtually eliminated.

Using our algorithm, a total of 12 features are extracted from each texture sample from each analysing wavelet. These features consist of energy signatures from the three wavelet detail coefficient matrices for each level of wavelet decomposition, to a total of 4 levels. This extraction process is repeated for each wavelet, such that for two wavelets a total of 24 features are obtained. Experimental evidence has shown that after the fourth level of decomposition, very little texture information is found, and classification rates are actually



(b)

Figure 2. LDA cluster representation of (a) Haar only, and (b) Haar and Biorthogonal feature sets for four texture samples

decreased due to the unwanted influence of image intensity which is strongly present in such low-frequency features. Additionally, the energy signature from the first decomposition, that is, the highest frequency components, was also found to contain little information of value. However, removing these features did lead to a slight reduction in classification performance, and thus they were included.

No feature selection algorithm was applied to this set of features, in order to provide a valid comparison with energy signature features obtained from a single wavelet. Examination of experimental results suggests that proper feature selection could result in a greatly reduced feature-set dimensionality, which would likely further improve classification performance. It can be seen from Table 1 that the energy signatures at the first level of decomposition are extremely similar for both the Haar and biorthogonal wavelets. This would indicate that one of these features could be removed with no adverse effect on performance.

4. Experimental Results

Texture classification experiments were conducted using our multiple wavelet algorithm, and compared to single wavelet methods for comparison. 19 textured images from the Brodatz album were used for the experiments, with each image divided into two regions. The first of these regions was used for training the classifier, while the second was used for testing. A Gaussian Mixture Model classifier (GMM) [15] was used in these experiments, with 5 Gaussian mixtures used for each texture model.

Results of these experiments are encouraging, with classification accuracy significantly improved when utilising the second wavelet. Individual classification rates for each texture and overall performance are shown in Table 2, compared to those obtained using only a single wavelet. It must be noted that no feature selection algorithm has been employed for these experiments, and this may improve accuracy further as redundant and spurious features are removed. Plotting these classification scores as a graph as in Figure 3 shows more clearly the improved performance offered by utilising two wavelets. While in some cases the biorthogonal wavelet significantly outperforms the Haar, and vice versa, in all cases the combined feature set performs as well or better than either wavelet alone.

The computational speed of the algorithm is quite acceptable, with training times of only a few minutes for 2000 training samples. Classification of a single image is carried out in less than a second, slightly less than twice the time of single wavelet energy signature classification. Our method is significantly faster to compute than using the co-occurrence features presented in [10], and shows similar overall classification accuracy of ~95%. Additional experiments were conducted after adding small amounts of white noise to the input images with no perceptible effect on the classification accuracy of all texture classes.

5. Conclusions and Future Research

We have presented a new method for classifying textured images based on the use of multiple analysing wavelets. Experimental evidence has shown this method to provide substantial improvement over single wavelet methods, with classification error rates halved for energy signature features. Additionally, the method described provides greater class separation in feature space, and good robustness against noise. The algorithm is computationally efficient, taking approximately one-fifth the time of a method employing wavelet coefficient histogram and co-occurrence features which obtains similar classification accuracy.

Future research in this area will concentrate on finding an optimal wavelet pair for texture classification using this algorithm. The technique will also be

Table 2. Texture classification results using (a) Haar wavelet only, (b) Biorthogonal wavelet only, and (c) both wavelets

Texture	Accuracy (Haar)	Accuracy (Biorth.)	Accuracy (both)
Bark	85%	79%	85%
Brick	100%	98%	100%
Brick-2	88%	75%	87%
Bubbles	79%	83%	83%
Grass	63%	83%	88%
Grass-2	96%	94%	98%
Gravel	96%	89%	97%
Herringbone	97%	97%	97%
Hexagon	100%	100%	100%
Leather	91%	93%	98%
Pigskin	86%	71%	94%
Raffia	83%	92%	98%
Roof	88%	92%	95%
Sand	63%	60%	81%
Straw	95%	87%	96%
Wall	84%	82%	96%
Water	97%	94%	96%
Wood	94%	95%	100%
Wool	81%	89%	94%
Total	**88%**	**87%**	**95%**

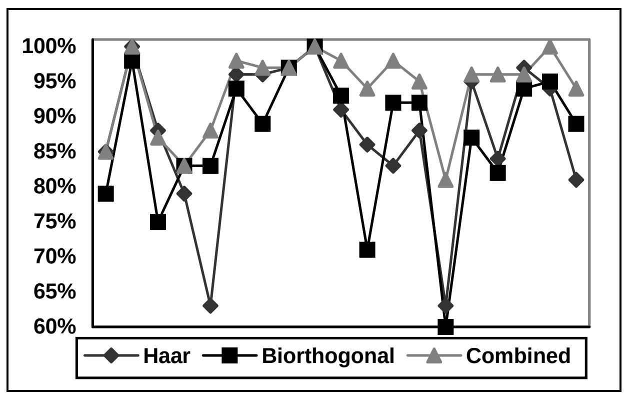


Figure 3. Classification accuracy plots for Haar wavelet, Biorthogonal wavelet, and combined for each texture class

expanded to use a more powerful set of features derived from wavelet coefficients, such as first and second order statistics. Feature selection will also be investigated, with the aim of reducing the dimensionality of the feature vector used for classification and improving both computational efficiency and overall accuracy.

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