

MULTISCALE ASYMMETRY SIGNATURES FOR TEXTURE ANALYSIS

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ABSTRACT

This paper investigates model-based texture feature extraction from image multiscale representations. This approach offers a better texture characterization compared to using the classical energy output of a multiscale filterbank. The existing models assume symmetric density functions and we observe that this assumption is violated for some texture classes. This property is exploited to obtain improved texture characterization which can be used for texture classification, segmentation and retrieval.

1. INTRODUCTION

Texture analysis is a classical image processing topic that has received a lot of attention in the past decades. It still does because the correct characterization of texture in an image is of fundamental importance in many applications: medical, computer vision, remote sensing,

This paper deals with feature extraction from multiscale image representation. This representation, which is inspired on the fundamental mammalian visual system, has proved to be very well suited for image analysis in general [1]. The intense study of the wavelet transformation in the past decade has provided a thorough mathematical framework for multiscale image analysis and has been used extensively [2].

The classical scheme for wavelet texture analysis is identical to that of other filter based schemes: apply a filterbank to the original image, measure the energies from the resulting subband images, and use these features as a 'fingerprint' for a specific texture class (e.g. [3]). In recent work, we have extended this idea by modelling the wavelet detail coefficients on each scale by a generalized gaussian density function which improved characterization [4]. This was later confirmed in [5] and in related work Bessel K forms were used as model [6].

However, all these schemes rely on symmetric models for the detail coefficients histogram - an assumption which is does not hold true for all textures. We investigate in this paper the nature of these asymmetry and try to exploit it to improve texture characterization by introducing the *multiscale asymmetry signatures*. Experiments are conducted on

an illumination invariant classification problem on a database of 68 textures.

2. WAVELET TEXTURE SIGNATURES

2.1. Energy signatures

The (fast) wavelet transform [7] has been described (and used) extensively in many other papers. Briefly, the computation of the wavelet detail images D_{ji} for scale j is performed using:

$$L_j(b_i, b_j) = [H_x * [H_y * L_{j-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (1)$$

$$D_{j1}(b_i, b_j) = [H_x * [G_y * L_{j-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (2)$$

$$D_{j2}(b_i, b_j) = [G_x * [H_y * L_{j-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (3)$$

$$D_{j3}(b_i, b_j) = [G_x * [G_y * L_{j-1}]_{\downarrow 2,1}]_{\downarrow 1,2}(b_i, b_j) \quad (4)$$

* denotes the convolution operator, $\downarrow_{2,1}$ ($\downarrow_{1,2}$) subsampling along the rows (columns) and $L_0 = I(\vec{x})$ is the original image.

The histogram of the wavelet detail coefficients will be noted as $h_{ji}(u)$; $h_{ji}(u) du$ thus is the probability that a wavelet coefficient $D_{ji}(\vec{b})$ has a value between u and $u+du$. We shall refer to $h_{ji}(u)$ as the *wavelet detail histogram*.

The (normalized) energy of a detail image D_{ni} is defined as

$$E_{ni} = \frac{1}{N} \sum_{j,k} (D_{ni}(b_j, b_k))^2 \quad (5)$$

where N is the total number of wavelet coefficients in D_{ji} . The *wavelet energy signatures* $\{E_{ji}\}_{j=1..d, i=1,2,3}$ reflect the distribution of energy along the frequency axis over scale and orientation and have proven to be very powerful for texture characterization.

Since G in (2)-(4) is a pure highpass filter, the mean of the wavelet detail coefficients equals zero. Consequently, the energy is exactly their variance. Employing energy as a texture feature is thus equivalent to characterizing the detail histogram by a gaussian. In [4], the model

$$h(u) = K e^{-(|u|/\alpha)^\beta} \quad (6)$$

proved to be more adequate.

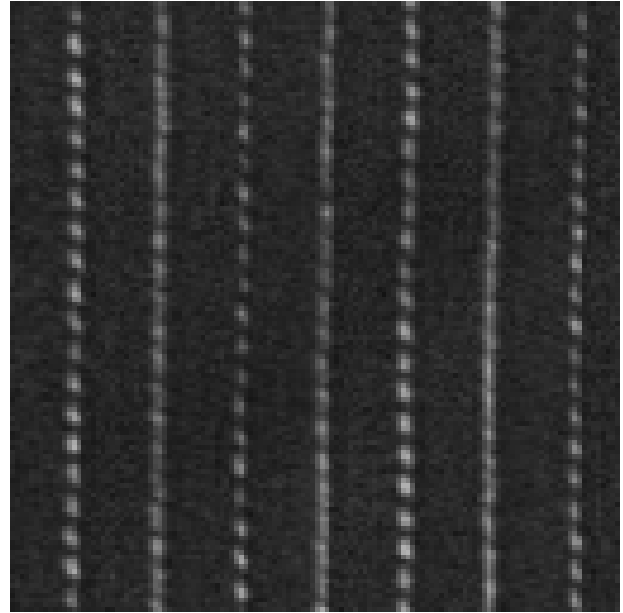
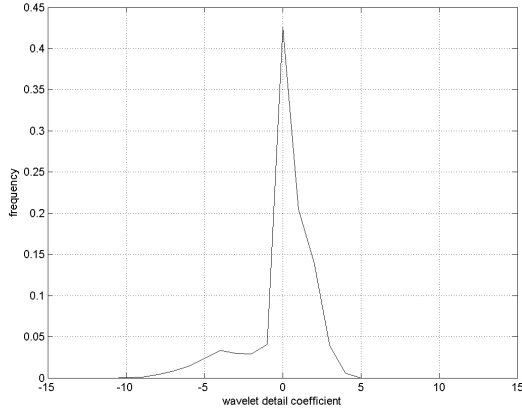


Fig. 1. Example of a texture with a high Asymmetry ($A_{22} = 0.66$) and wavelet detail histogram D_{22} .

2.2. Asymmetry signatures

However, all feature extraction schemes proposed so far rely on symmetric models for the detail coefficients. To get more insight on the implications of this assumption consider a texture consisting of bright vertical lines on a dark background. The positive (negative) detail coefficients of the vertical detail images D_{j2} , which correspond to bright-dark (dark-bright) transitions, represent the ending edge (beginning edge) of the line. The symmetry assumption thus implies that ending and beginning edge of the lines 'look the same'. This is not necessarily true in general. A texture might for example consist of lines with one sharp and smooth edge. Furthermore, this asymmetry is often not directly noticeable by directly inspecting the texture image, but may be very pronounced at one of the scales in its multiscale representation. Some examples of this are given below.

To our knowledge, no schemes explicitly incorporate possible texture asymmetry. Therefore, let us define the *multiscale asymmetry signatures*:

$$A_{ni} = \int_0^{\infty} |h_{ni}(u) - h_{ni}(-u)| u du \quad (7)$$

In the experimental section we will investigate the value of this quantity as an extra texture descriptor.

3. EXPERIMENTS

For our experiments, we have used the Outex 13 dataset [8], which contains 68 (color) texture classes. A separate test

and training set is provided each containing 10 independent samples per class. The images were transformed to gray levels and then normalized as follows:

$$I'(\vec{x}) = \frac{I(\vec{x}) - \mu}{s} \quad (8)$$

where μ and s are the gray level mean and standard deviation. This makes the scheme invariant to changes in illumination intensity.

3.1. What are asymmetric textures?

An example of a texture with a high A is shown in figure 1. The detail histogram shows that, for this scale and direction, the energy of the positive detail coefficients is concentrated in the low values (indicating more 'small' bright-dark transitions) while for the negative ones more energy is in high values (thus more 'big' dark-bright transitions). This feature is clearly not captured when using energy signatures.

Another illustrative example is shown in figure 2. The detail histogram (bottom right) shows a striking dissimilarity between negative and positive coefficients. The histogram is even clearly bi-modal - a feature which also is not captured in the existing models, but is revealed by the asymmetry signature. We have investigated the spatial position of the coefficients > 9 and < -9 in the original image. Figure 2(bottom left) shows the location of these coefficients and demonstrates that these indeed correspond to the beginning and ending of a woodnerve-edge. The asymmetry signature reveals that there is more energy in the end of the edge

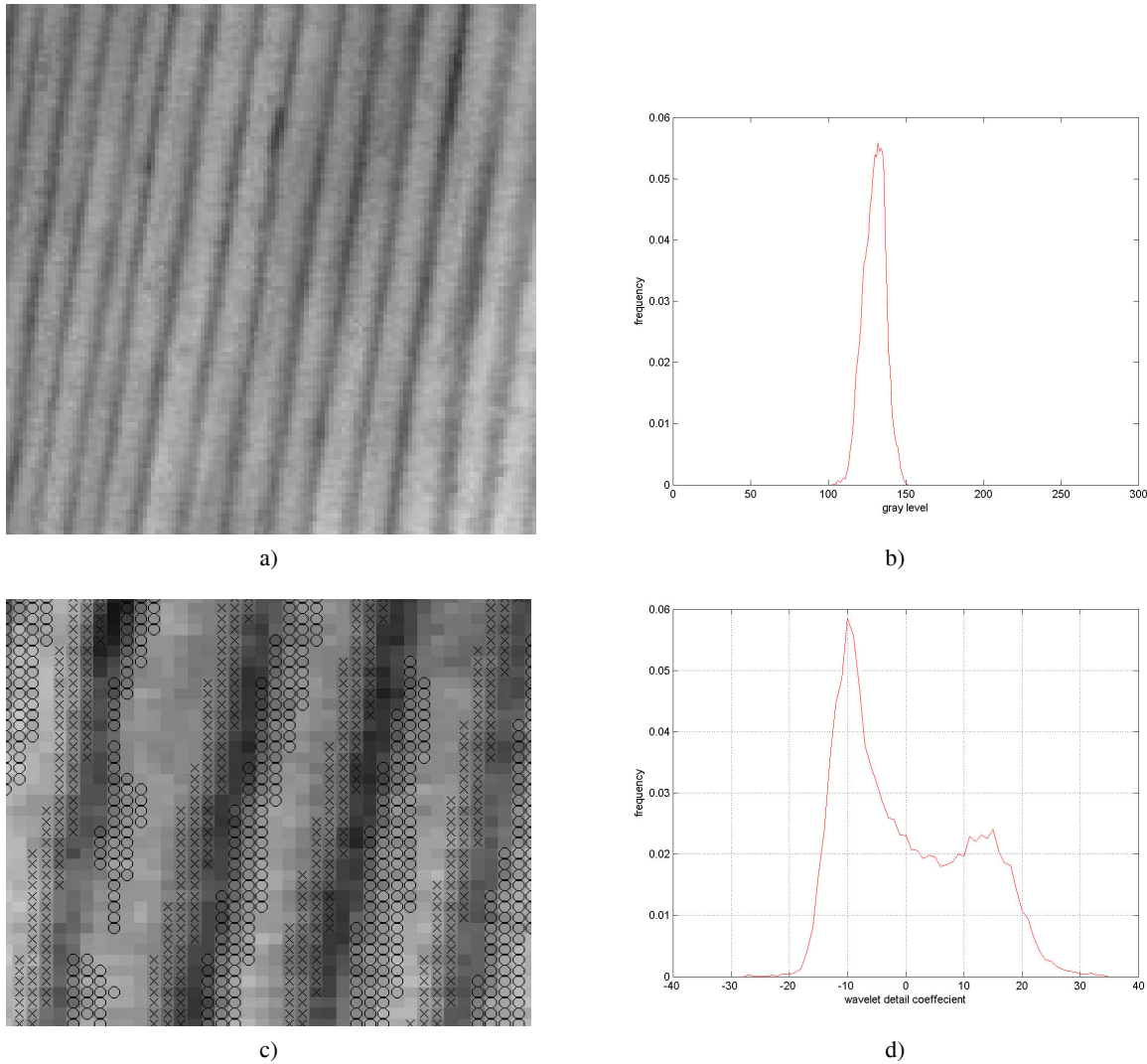


Fig. 2. Example of a texture with a $A_{22} = 0.43$. Top : original image and detail histogram D_{22} . Bottom: detail of original image with detail coefficients < -9 marked by o and detail coefficients > 9 marked by x.

then in the beginning. Interestingly, this asymmetry is not detectable in the (original) image histogram (top right).

3.2. Texture recognition

In this section we aim on evaluating the usefulness of the described features in a supervised classification problem. The energy and asymmetry signatures were computed using a wavelet decomposition of depth 4 resulting in 13 energy signatures and 12 asymmetry signatures. Thus two features sets are compared consisting of 1. only energy signatures (E feature set), and 2. energy + asymmetry signatures (E+A feature set).

To estimate the recognition performance of a feature set, a knn-classifier with a leave-one-out method was used.

Since it is known that the best performance is not achieved by using a large number of features [9], feature selection was applied to determine the optimal feature set. The Floating Forward Feature Selection scheme (FFFS) has been used [10]. The outcome of this algorithm is that for each dimensionality d , a combination of the best performing d features is found. The results can then be analyzed in a (feature subset dimensionality, classification error) graph. The minimum in this curve corresponds to the combination of parameters which overall performed best.

Figure 3 shows the results of applying this scheme to the the training sets based on Energy and Energy + Asymmetry signatures. An improved error rate for the E+A features is seen. The minimum error rate was obtained with 9 features for the Energy signatures. Next, the best 9 features for both

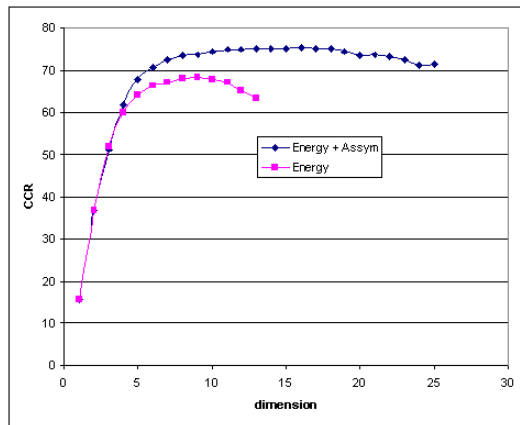


Fig. 3. Classification error rate (in function of number of selected features) for 1. The energy signatures, and 2. energy + asymmetry features.

the E and E+A feature set were selected and the test samples were classified by knn classification using the training set as a reference. This gave following results: results:

feature set	error rate on test-set
energy	30.74%
energy + asymmetry	22.94%

And this confirms that adding the asymmetry signatures resulted in an improved texture characterization.

We must note that this dataset was not selected in any way to contain textures that showed specific asymmetry. It is expected that the usefulness of the asymmetry signatures is data-dependent; i.e. they are only of value for textures that exhibit asymmetry on a particular decomposition scale. Statistical analysis of all computed asymmetry signatures showed that the 90th percentile is equal to 0.19.

4. CONCLUSION

We have investigated texture feature extraction from multi-scale image representations. It was noted that the histogram of the wavelet detail coefficients was not always symmetric and unimodal as most models assume. This fact was exploited for an improved texture characterization.

5. REFERENCES

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