Wavelets for texture analysis, an overview

Conference Paper · August 1997

DOI: 10.1049/cp:19970958 · Source: IEEE Xplore

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Wavelets for Texture Analysis

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Abstract— This report gives an introduction to the application of wavelet based multiscale image analysis methods to texture analysis. It outlines the basic methods and comments on design issues. It also points to the literature and connections with related methods. The unfinishedness of the research in this area becomes clear from the discussion of some extra issues and from a short list of practical applications. *(latest revision 30/06/97)*

I. Introduction

Texture is an important cue for the analysis of many types of images. The term is used to point to intrinsic properties of surfaces, especially those that don't have a smoothly varying intensity. It includes intuitive properties like roughness, granulation and regularity. Some example textures from the Brodatz album [3] are shown in Fig. 1.

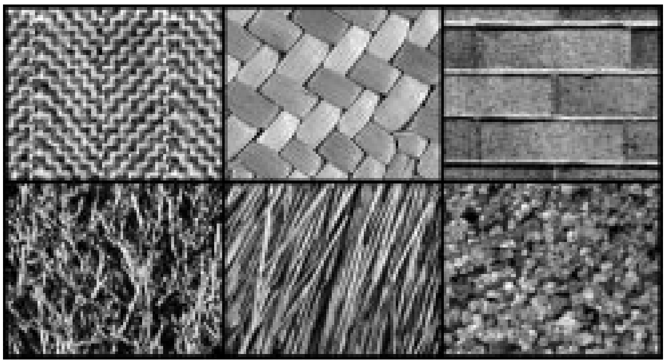

Fig. 1. Some examples of Brodatz textures: regular ones on top row, irregular ones on bottom row.

Texture can be defined as *the set of local neighbourhood properties of the gray levels of an image region.* Texture analysis is considered a challenging task. The ability to effectively classify and segment images based on textural features is of key importance in scene analysis, medical image analysis, remote sensing and many other application areas.

A wide variety of texture analysis methods has been proposed in the past. For reviews, see e.g. [28] and [32]. Statistical ones (e.g. the coocurrence matrix method) exploit the local correlations of image pixels on a fixed scale. Structural methods make a description using texture primitives and syntactic rules. Recently, there is an increased interest in model based approaches where several studies report highly succesful experiments using Markov random fields. Spectral methods look at the properties of Fourier spectra, hereby capturing global information about the energy distibution across scales. All these methods have in common that they extract the characteristics that are believed to be most important in particular texture characterisation problems. They highlight different aspects of texture, which is a too general and vague concept to encompass in a single description.

One of the most important aspects is of texture is scale. Psychovisual studies indicate that the human visual system processes images in a multiscale way [9]. The "early processing" in the brain performs a kind of spatial frequency analysis, and consequently, the visual cortex has separate cells that respond to different frequencies and orientations. It has even been observed that the responses correspond to Gabor-like functions. This multiscale processing, which humans obviously apply successfully to texture perception, is a strong motivation for texture analysis methods to start from the same ideas [2] [16].

II. Wavelet Multiresolution Analysis

A. Multiresolution and Wavelets

Multiresolution techniques intend to transform images into a representation in which both spatial and frequency information is present. To accomplish this, a lot of related techniques were developed, including Gabor, Haar, Walsh-Hadamard expansions, Gaussian and Laplacian pyramids, subband filtering, scale space, ...

In the last decade, a mathematical framework emerged which provides a more formal, solid and unified approach to multiresolution representations [25]. This wavelet paradigm is now well established and has found many applications in signal and image processing. Since at the same time some of its precursors can be reformulated into wavelet terminology, it has become a preferred tool for multiresolution analysis.

B. Wavelet Image Analysis

A wavelet transform decomposes a 1-D signal $f(x)$ onto a basis of wavelet functions:

$$(W_a f)(b) = \int f(x)\psi^{\star}_{a,b}(x)dx \tag{1}$$

Such a basis, which is usually taken complete and orthogonal, is obtained translating and dilating a single mother wavelet ψ:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a}) \tag{2}$$

The mother wavelet ψ is localized in both spatial and frequency domain and it has to satisfy the constraint of having zero mean.

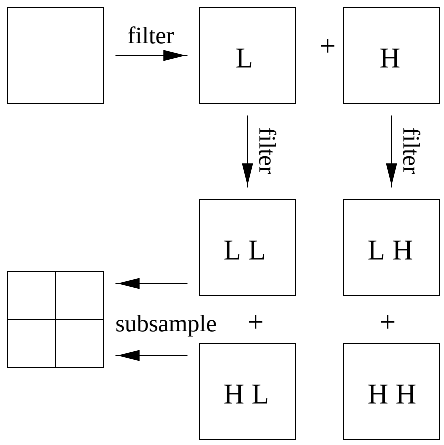

Fig. 2. 1 level of a wavelet decomposition in 3 steps: 1. Low and High pass filtering in horizontal direction, 2. the same in vertical direction, 3. subsampling.

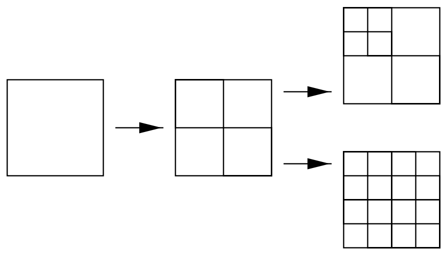

Fig. 3. first two levels of a pyramidal (top) and tree structured (bottom) wavelet decomposition.

When a and b are restrained to a discrete lattice ($a = 2^n$, $b \in \mathcal{Z}$), the discrete wavelet transform (DWT) is obtained. The DWT has an efficient implementation in the real space which uses quadrature mirror filters. In this every wavelet corresponds with a high and low pass filter. For the most common case with dilations by a factor of two, the scheme is called "dyadic" wavelet transform.

The wavelet decomposition of an 2-D image can be obtained by performing the filtering consecutively along horizontal and vertical directions (separable filter bank). This is depicted schematically in Fig. 2. It yields 4 subimages for 1 level of decomposition. Every subimage can be subsampled by a factor of 2, hereby retaining the possibility of a complete reconstruction. This leads to a representation with an equal amount of pixels as the original image. To construct a multilevel decomposition, this is repeated iteratively for the low pass subimages. The result is the standard pyramidal wavelet decomposition. When the detail images are also decomposed further, we obtain the tree-structured or wavelet packet decomposition (Fig 3.).

The wavelet image decomposition provides a representation that is easy to interpret. Every subimage contains information of a specific scale and orientation, which is conveniently separated. Spatial information is retained within the subimages.

C. Texture Features

To obtain features which reflect scale-dependent properties, one can extract a feature from each subimage separately. Since the coefficients of a subimage sum to zero, it is necessary to compute a nonlinear function of the coefficients. Widely used is the square, which leads to the energy when summed over a subimage. The use of energy is sound and has an obvious physical interpretation. Moreover, it is additive and its total is conserved by the transformations. The feature set now consists of energies of different scales, which is an important characteristic for texture analysis [4].

Several studies investigate alternative measures, but no general conclusion in favor of a particular measure can be drawn from them. Laine and Fan [19] compared energy and entropy features and found the latter to be less suitable. Manjunath and Ma [24] used absolute values and found that adding a second variance measure improved performance. The concept of using more than one feature from each subimage is gaining interest. For example, Zarita and Lelandais [39] use 5 features derived from a coocurrence matrix, which improves performance compared to the single feature case.

D. Feature reduction

An important problem in wavelet texture analysis is that the number of features tends to become large, especially for wavelet packet decompositions. A large number of features, although they may carry more information, make classification (and segmentation) much more difficult. This phenomenon is well known in pattern recognition as the curse of dimensionality.

There exist general feature reduction methods for dealing with this. A fundamental problem is that the predominant scales that carry the most useful information, can differ from one texture to another. It is advantageous to limit the number of features at the level of their generation, where the nature of the features can be taken into account. For segmentation, it is good practice to extract dominant features with a Karhunen- Loëve transform [35].

Another strategy is to use an extra criterion that evaluates features. For a tree-structured transform, a criterion can be used to decide if a subimage needs to be decomposed further. This is known as adaptive wavelet transform and was proposed in general by Coifman and Wickerhauser [7], who used an entropy criterion. An adaptive wavelet transform with a simple energy criterion is applied in [4], which showed to be an essential step in the methodology. Pichler et al [26] investigated a variance criterion and conclude that it performs poorly.

More advanced criteria can be based on class separability. This has been investigated by Etemad and Chellappa [10] and by Fatemi-Ghomi et al [11]. The construction of effective criteria is an important topic which deserves further investigation.

E. Segmentation

The feature generation described above, is well suited to classification tasks. Segmentation however brings up some extra difficulties. The properties of the textured regions and even the number of different textures are not known in advance for an unsupervised problem. This becomes especially difficult for when there are many regions.

Besides this, local features are needed instead of global ones. There is an unavoidable compromise between uncertainty in position and accuracy of feature value [37]. This problem is also present with wavelet texture methods, but they are very well suited to deal with it in a convenient way. The transforms retain localization in both space and frequency, which makes it easy to compute multiscale features locally. A local estimation to get reliable feature values can be performed for all scales.

Subsampling is often omitted in segmentation tasks. One then obtains an overcomplete representation in which the redundancy improves robustness. The decomposition also becomes translation invariant and the correspondence between scales is trivial. In wavelet packet decompositions, the non-subsampled scheme is referred to as "wavelet frame decomposition". Unser [33] and Laine and Fan [20] report on this. In general, omission of subsampling will improve results, but increase computation time. Randen and Husoy [27] have made extensive studies on the effects of this.

III. Other Issues

A. Which wavelet to choose ?

Several studies have tried to answer this important question. There is however no general answer, as some wavelets will be better suited to analyse some particular textures, while other types will for others. However, most comparative studies conclude that the choice of wavelet function has only small effects on the results [11] [4].

A very reasonable requirement for a wavelet decomposition is that the same features must be obtained if an image were presented upside down. This limits the choice to symmetric wavelets (or antisymmetric ones for rectifying nonlinear features such as energy). Another general common sense argument suggests to use wavelet functions that are sufficiently compact to capture the fine details of the texture. Smoothness is not required, which points to using wavelets with small support. Other considerations like computational complexity can also determine the decision.

More powerful ways for choosing the right wavelet can be expected from work on texture matched wavelets. Constructing an "optimal" set of wavelet functions for a specific data set is commonly dealt with in signal processing. A recent study by Greiner [14] applies such a technique. He proposes orthogonal and bi-orthogonal texture matched M-channel wavelet transforms. His results show that texture-matched wavelets lead to a better description with a smaller number of features.

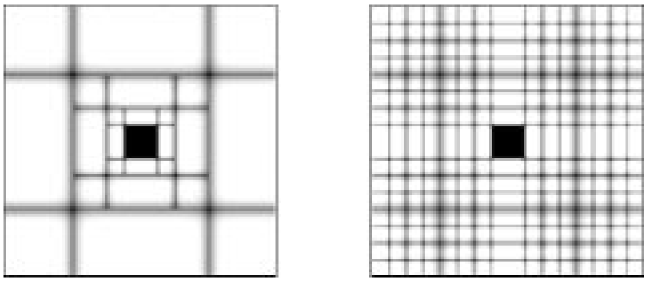

Fig. 4. frequency splitting for a 3-level wavelet (left) and wavelet packet decomposition (right).

B. Frequency Splitting

For a dyadic transform, the frequency splitting is done in octave bands, which is rather coarse. The orientational selectivity is even poorer, since it is represented with just three subimages per scale. It is instructive to observe the frequency splitting in the Fourier domain (Fig. 4).

The wavelet packet transform splits up the high and low frequencies in equal bands, so the frequency plane is tiled into equally sized squares. This can remedy the coarseness in scale and orientation splitting. However, it leads to worse spatial localization and is far from from efficient since it creates a large number of subimages.

For adaptive wavelet transforms, only some parts of the frequency plane are split up further, based on image content. One can also construct schemes in which further decomposition is given in by e.g. the need for orientational selectivity. Several intermediate schemes can be considered, which make a better compromise in splitting parts of the frequency plane (as discussed in chapter 10 of [8]). An experiment with this is found in the work of Kacker et al [17], who claim classification improvements to the level of Gabor transform results by using an additional splitting in a pyramidal wavelet scheme. A different but related solution to the coarse frequency sampling has been proposed by Wilson et al [36] in their multiresolution Fourier Transform, which incorporates Fourier analysis in a wavelet scheme.

C. Wavelet versus Gabor

The Gabor decomposition approach has been successful in texture analysis for many years [16] [21]. The newer wavelet approaches also perform well, but fail to yield significantly better results [4]. In many cases, their performance is somewhat worse. The considerable computational savings that can be made with discrete wavelet transforms are thus the main reason for their use.

In fact, the main difference lies not in the fact whether one uses Gabor or wavelet functions, but in the difference between discrete and continuous transforms. The Gabor transform is usually implemented in a continuous way using a Fourier transform. The wavelet transform has a similar implementation, called *continuous wavelet transform.* The difference between both is quite small. For example the Morlet wavelet has a corresponding Gabor function from which it only differs in a small correction term [1].

However, the wavelet transforms that are used in most cases, are discrete ones, which benefit from the efficient filtering implementation, but are much more restricted in design. These restrictions make the wavelet transform suboptimal for feature extraction purposes [26]. Most comparisons between results with wavelet and Gabor transforms should be interpreted in the light of discrete versus continuous.

D. Orientational information

An important question is: *What happens if we rotate a input image ?* If one realizes that the transform is carried out along vertical and horizontal directions, one can also expect that even a small rotation can have a large effect on the results. For all textures that are not isotropic, a rotation will result in completely different feature sets.

In general the anisotropy is an important aspect of most textures. In classification tasks, one usually wants results that are independent of the orientation of the texture. Thus rotation invariant features, which preferably still reflect the anisotropy, need to be constructed. The explicit orientation of the texture can also be of importance, e.g. for segmenting textures that are equal but oriented differently, or when one wants to detect changes in orientation. When this angular discrimination needs to be done very accurately, or when dealing with textures with high directionality, modified techniques that use directional "steerable" filters are generally better suited [12].

Some strategies have been proposed for dealing with rotation invariance. Greenspan et al. [13] try to solve the problem by employing 4 angular filters and interpolate their responses. Chen and Kundu [5] have tried to incorporate rotation-invariance in the classification strategy, by including rotated examples in the learning data. An approach by Wu and Wei [38] performs a spiral resampling of the data, to obtain a 1- dimensional signal, where rotation-invariance is reflected as translation-invariance.

The main problem of discrete schemes is that the filter outputs of one scale represent only 3 different directions, which is a very coarse representation of the directional information. Continuous transforms have a continuous representation of this, which offers far better possibilities for constructing rotation invariant features. A recent study by Vautrot et al. [35] gives a experimental confirmation of this. It also compares isotropic wavelets which showed most robust and thus favorable for classification tasks, with anisotropic wavelets, which offer a more refined texture characterisation, advantageous in segmentation.

E. Colour Texture

Wavelet texture analysis can be extended to colour texture, although this is still largely unexplored. Colour images are typically represented by RGB tristimulus values which correspond to three colour bands. A straightforward way to process colour textures is by performing a graylevel decomposition on every component image. The number of features will triple compared to the graylevel case. A recent study by Van de Wouwer et al. [34] reveals that using colour offers substantially more discriminative information and that the choice of the colour space is very important. The same work also exploits the use of correlations between colour bands. This is also being investigated by Jain and Healey [15], who use opponent features computed from Gabor filter outputs and combine information across spectral bands at different scales.

IV. Some Applications

Although many aspects are still evolving, the main methods for wavelet texture analysis are more or less established, and show good results. This was already shown in [4] and [19], where almost perfect classification is obtained on sets of 30 and 25 textures, with features from a tree structured wavelet transform.

Apart from this methodological work, which uses well controlled experiments, important experimental knowledge is coming from the application to real world problems. In a growing number of areas, wavelet based texture methods are being investigated.

Wide use is found in the analysis of medical images. The topics are 2D and 3D multiresolution image segmentation, e.g. for ultrasonic images. Other application include tissue characterisation which is also done in agricultural inspection by Kim et al [18]. Applications of texture features for searches in large image databases are shown by Smith [30] [29] and in [24]. Combined colour and texture descriptions are expected to become very important in this area.

Another successful area is remote sensing, where promising work was reported by Clausi [6]. Other applications are found in material science, where characterisation of corrosion is reported by Livens et al [22]. An application of the segmentation of marble images has been carried out by Lumbreras and Serrat [23]. The well known shape from texture problem has been tackled with wavelets by Super and Bovik [31]. Although the amount of work on applications is growing, it is still relatively small and many opportunities for new research remain.

V. Conclusion

We have given an overview of the application of wavelet multiresolution image analysis to texture. Results of recent studies prove the merits of the methods in practical segmentation and classification problems. Some aspects still need further investigation. Two were discussed: rotation invariance and colour texture.

Note. This report is part of the World Wide Web initiative *Wavelets for Texture Analysis.* (`http://www.ruca.ua.ac.be/~VisionLab/WTA.html`) The current version is 2.0 (april 1997). It largely draws upon the information gathered in this initiative and reflects a personal view on the subject, which can never be complete. It will be updated with more details, new developments and references. Comments and additions are much appreciated (email: `livens@ruca.ua.ac.be`).

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