Spectral Characterization of Orientation Data along Curvilinear Structures

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Abstract

This paper lies within the scope of texture analysis. We focus on anisotropic textures and propose an approach to measure the ripple of texture patterns. It assumes that the patterns are represented by some characteristic curves called generatrices (i.e. edges, level curves). Two steps are involved. The first one deals with the estimation of the orientation along the generatrices. The second step consists in computing the power spectrum of the generatrix orientation. The global texture ripple is captured by the ripple spectrum which is computed by cumulating the orientation spectra of all individual generatrices. The approach is exercised on synthetic textures and on composite material images.

1. Introduction

Texture is often defined as being composed of primitives the shape and the layout of which are specified by some deterministic or stochastic laws. Although this structural definition is widely accepted, most of texture analysis methods do not take into account the structural dimension of texture. According to the typology made by Haralick [4], these methods fall into the statistical method category. They restrict to the statistical characterization of pixels using their grey level distribution and their spatial layout. On the contrary, structural methods [4] attempt to identify textural primitives, to get a description of their shape and to capture the laws that govern their spatial arrangement. The main difficulty of structural approaches comes from the need of some a priori information about the primitives. As a result structural approaches are often bounded to specific classes of texture.

In this paper, we focus on directional textures i.e. on textures made of elongated patterns. Such textures can be found in various fields as seismic imagery, fingerprint identification [8] or composite material characterization [3][4]. Directional textures have been addressed by various methods based on spatial grey level statistics [1][2] or on statistics of orientation tokens [10][11][5].

The approach we propose is also based on orientations but is embedded in a general framework which aims at a structural description of texture. This framework consists in two stages: the identification of the patterns and the description of their ripple properties. In this paper, we address the second stage. We assume that the patterns have been previously identified and are represented by some characteristic features (e.g. ridges). These features are called generatrices. The present work aims at characterizing the ripple properties of the generatrices.

Our approach involves two steps: first, the estimation of the orientation along generatrices provides with an orientation curve for each generatrix. In the second step, we describe the pattern ripple in the frequency domain by using the spectra of orientation curves. More exactly, we compute a ripple spectrum by cumulating the orientation spectra of all individual generatrices. Assuming that the generatrices are relevant descriptors of the patterns, the ripple spectrum accurately captures the ripple properties.

In section 2, we address the estimation of orientation along the generatrices. In section 3, we present the ripple spectrum and evaluate its ability to capture texture ripple on synthetic images. Finally in section 4, our approach is applied to the characterization of composite material images observed by transmission electronic microscopy.

2. Measuring orientation along patterns

2.1. On the nature of the generatrices

The first step of any structural approach is primitive extraction [6]. In the case of directional textures, primitives are elongated patterns. The characterization of their shape can be done using specific topographic features. For instance, one can use ridges or valleys for which a great number of extraction methods are available (e.g. [5][9]). In previous works [3][4], we suggested to use image level curves instead. Assuming that the image has not undergone any significant photometric distortion, level curves are relevant descriptors of the pattern shape.

The experiments we show in this paper have been carried out using the algorithm presented in [3]. It consists in tracking the level curves which go through a set of
seeds. It results in a set of sub-pixel parametric curves connecting the extremities of the patterns. Figure 1 represents a composite material image on which the pattern generatrices have been superimposed. Level curves interrupted by the border are not represented.

Anyway, even if the choice of the generatrices is application dependant, our approach applies to any kind of generatrices. It just assumes that a set of generatrices is available in the form of parametric curves.

Figure 1. Example of a composite material image: level curves are superimposed.

2.2. Orientation operator

Assuming that the generatrices are available, the first step of our approach consists in measuring their local orientation. For this purpose, some authors [10][11][14] use the angle between two \( m \)-distant points of the generatrix. The orientation accuracy then directly depends on the sampling and on the resolution of the generatrix. For this reason, we chose to estimate the orientation directly from the underlying texture. Approaches based on the gradient estimate [9][12] are well adapted to orientation estimation on pixels located on high slope areas, where the generatrix extraction algorithm performs. In the present paper, we use the approach presented in [12]. It results in an orientation map which provides with an orientation \( \theta(i,j) \) in each pixel of integer coordinates \((i,j)\).

2.3. Curvilinear orientation

A generatrix \( G \) can be considered as an application which associates a spatial location \((x_s,y_s)\) with any curvilinear coordinate \( s \) between 0 and the length \( L \) of the generatrix. For the sake of generality, we will consider that \( x_s \) and \( y_s \) have real values:

\[
G: [0,L] \rightarrow \mathbb{R}^2 \\
\quad s \rightarrow (x_s,y_s)
\]

In order to be processed numerically, the generatrix is regularly sampled so that \( s \) is an integer belonging to \{0,1,...,\( N_L \)\}. \( N_L \) is the entire part of \( L \).

The curvilinear orientation curve \( \theta_c \) is obtained by interpolating the local orientation \( \theta \) for any position \((x_s,y_s)\). Let \( x_l \) and \( y_l \) be respectively the entire parts of \( x_s \) and \( y_s \). Let \( x_2 = x_1 + 1 \) and \( y_2 = y_1 + 1 \) (see Figure 2).

Figure 2. Orientation interpolation principle: neighborhood of a real coordinate point.

The orientation \( \theta_c(s) \) is interpolated as follows:

\[
\theta_c(s) = \frac{1}{2} \arg V,
\]

where \( V \) is the complex number defined by:

\[
V = \sum_{k,l\in[1,2]} w_{kl} e^{2 \pi i (k,l)}.
\]

This formula computes a bilinear interpolation of the orientation field \( \theta \). The weighting coefficients \( w_{kl} \) associated with each neighbor \((x_k,y_l)\) of \((x_s,y_s)\) are given by:

\[
w_{kl} = \left(1-|x_s-x_k|\right)\left(1-|y_s-y_l|\right).
\]

Figures 3 and 4 show four generatrices and their corresponding curvilinear orientation curves.

Figure 3. A composite material image and four of its generatrices.

Figure 4. Curvilinear orientation curves of the generatrices a, b, c and d of figure 3.
3. The ripple spectrum

3.1. Principle

The spectral representation of a signal has the advantage of highlighting its frequential properties. In order to get a description of the ripple properties of directional patterns, we choose to use the spectra of the orientation curves $\theta_c(s)$. The Fourier transform of $\theta_c(s)$ is computed for discrete frequencies:

$$\Theta(n) = \sum_{i=0}^{N_L} \theta_c(i)e^{-j2\pi N n/N},$$

with $N_L \leq N$. $N$ is the size of the window used to compute the Fourier transforms.

The ripple energy by unit of length for an individual generatrix is then given by the ripple spectrum $S$:

$$S(n) = \frac{1}{(N_L)^2} \sum_{i=0}^{N_L} \theta_c(i)e^{-j2\pi N n/N},$$

3.2. Cumulated spectra

Let $G_k, k = 1...M$ be of a set of generatrices, $N_k$ their lengths and $S_k$ their spectra. For instance, these generatrices could represent all the patterns within an image or a set of images. Let define the cumulated spectrum $S_{cum}$ as the whole ripple energy of the set of generatrices:

$$S_{cum}(n) = \sum_k N_k S_k(n).$$

In order to get a measure of the ripple energy by unit of length for the whole set of generatrices, $S_{cum}$ is normalized as follows:

$$S_{norm}(n) = \frac{1}{\sum_k N_k} \sum_k N_k S_k(n).$$

$S_{norm}$ is a frequential representation of the ripple phenomena within the patterns. It depends neither on the number of generatrices nor on their length.

3.3. Evaluation on synthetic textures

In order to validate the ability of the ripple spectrum to describe directional textures, we have first applied it to the discrimination of simple synthetic textures. Four texture sets of eight 512x512 images were used. Each image is a mosaic of 20 regions with rippling directional patterns of different orientations and contrasts (Figure 5).

Locally, the texture is defined by:

$$f(i, j) = A \sin \left( \frac{2\pi}{T} (i \sin \theta - y \cos \theta + \phi) \right),$$

where the $\phi$ expresses the ripple of the patterns:

$$\phi = \sum_r A_r \sin \left( \frac{2\pi}{T_r} (j \sin \theta + i \cos \theta) \right).$$

$A$ and $\theta$ are constant within a homogenous region but vary within an image. $T=12$ is constant for all regions, all images and all sets. The number and the values of the ripple components $(A_r, T_r)$ depend on the texture set. They are given in Table 1.

![Figure 5. Synthetic texture mosaic: original texture (left), superimposed generatrices (right).](image)

![Figure 6. PCA Score plot (axes 1 and 2) for the 32 textures divided into 4 sets i.e. groups.](image)

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We have exercised the level curve tracking algorithm and computed the curvilinear orientation curve for each extracted generatrix on each image. All the individual generatrix ripple spectra were processed and cumulated within an image to get the 32 cumulated ripple spectra corresponding to the 32 images.

In order to show how the ripple spectrum is able to discriminate the four sets of textures, we used all the energy coefficients – corresponding to the different frequencies – in a Principal Component Analysis. The representation of the 32 images on the first two factorial axes is given in figure 6.
The PCA score plot shows a clear discrimination, without any ambiguity, between the four sets in spite of the very small amount of ripple. This experiment shows the ability of the approach to capture fine frequential phenomena in the pattern ripple.

4. Application to the characterization of composite material images

We also exercised our approach to the characterization of composite material images. The images are obtained by electronic microscopy and correspond to materials from two different fabrication processes A and B which have been treated by temperature or not. It results in four image sets on which the normalized cumulated ripple spectra have been computed. The results are shown on figure 8. They bring out a lot of information about the effects of the thermic treatment and also about the microscopic material structure. For instance, they show a very good discrimination between treated and non treated materials: the thermic treatment proves to reduce texture ripple and thus change the physical properties of the material. These spectra also show that the difference between the two processes vanishes with the thermic treatment. Finally, in a structural point of view, we can see that the pattern ripple on such materials do not correspond to a unique frequential component. It was shown that the ripple energy decreases exponentially for high frequencies and that the materials could be characterized by the location of the spectral peak and by the speed of decrease.

5. Conclusion

In this paper we have proposed a new structural approach for the characterization of directional textures. This approach results in the computation of the ripple spectrum which captures the ripple properties of the directional patterns. It has been successfully exercised in a validation framework to discriminate textures with very low levels of ripple. Finally, the relevance of the approach was also proved in the applied context of composite material characterization.

6. Acknowledgements

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7. References