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Texture Analysis by a Perceptual Model

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Abstract

A hierarchical set of operators for texture analysis is presented. Our method is to code the local frequency resonance of these operators but not their simple responses. Therefore, the texture features obtained are stable. The operators fulfill the conditions described by J.P. Crettez in his work on the visual system model. The procedure is used to automatically determine the resolution of homogeneous texture, the resolution being the minimum window size capable of giving stationary features. All the samples of suitable size then have the same signature coding the local feature of texture.

Keywords: texture, resolution, texture discrimination.

1 Introduction

Texture is the term generally used to characterize a region in an image, corresponding to a homogeneous local spatial organization. Texture is a perceptual concept for which there is no mathematical definition [5]. Perceptually, texture gives the same visual impression for any position of a small window of observation inside the corresponding region [4]. For any position of the visual axis, the neuronal responses of cortical cells must be the same. Each cortical cell is characterized by its receptive field which corresponds to a small window in the visual field. Consequently, a texture must be analysed by small local samples. Samples of a homogeneous texture should give the same response. A sample corresponds to a pixel neighborhood. A number of analytical methods, which all try to characterize pixel neighborhood relationships, have been proposed during last decade. Recently, Unser developed the use of textural measures based on the average of some local properties [7]. Local textural properties are extracted in two stages: a local linear process followed by a non-linear process. The statistics of the individual transform coefficients are then used as texture descriptors. By analogy with the receptive field models for simple or complex cells in the visual areas, we present, in this paper, a set of texture operators [2] [3]. These operators can be efficiently applied to textures by the aid of Hadamard Transform and by an operation which makes results of operators invariant by translation on homogeneous textures.

2 Texture Feature Extraction

2-1 The Set of Operators

An operator or a filter simulates a single cell of a visual system. So the neighborhood geometry, on which the operator is applied, models the reception field of the cell, while the coefficients of the operator or filter simulate the cell responses to given visual stimuli. Due to hierarchy, the first order operators are simply quadruplets in hexagonal tessellation. The coefficients are obtained from Hadamard matrices H_4 : every line of the matrix gives the coefficients of one filter. We have then four filters, called first-order operators or first-order filters, represented in figure 1. The neighborhood structure of the second-order is obtained from that of the first order: dilating twice the first order's structure and replacing each point by the structure of the first order. So a second-order structure includes 16 pixels and is represented in figure 2. More generally, an n -th order structure can be obtained by dilating twice the $(n-1)$ -st order structure and replacing each point by the structure of the first order. A

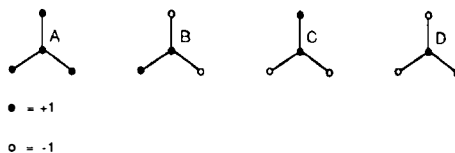


Figure 1: first-order operators

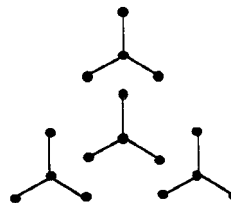


Figure 2: structure of second-order operator

second order operator corresponds to a line of the Hadamard matrix H_{16} , and a n -th order operator corresponds to a line of the Hadamard matrix H_{4^n} . So the connection process between the different order structures can be modelled by the Hadamard Transform H_4 in the natural order.

2-2 Properties of the Operators

We suppose that our operators model the simple cells of the striate cortex. As shown in figure 3, the first-order operators are oriented filters. We want to know if the operators of higher order can also analyse the orientations and frequencies. This can be determined from the operators orientation-frequency properties by use of the Fourier Spectrum.

We consider every operator as an image and periodize it in the image space. We then apply the Fourier Transform and look for the maxima of the power spectrum.

We can make a drawing of the Fourier plane for every order and note the positions of the maxima:

- for the first and second order we obtain an uniform sampling of the Fourier space
- for higher orders we must use the secondary maxima

From the second order it is possible to see that some operators have the same power spectrum. They differ only by phase. They

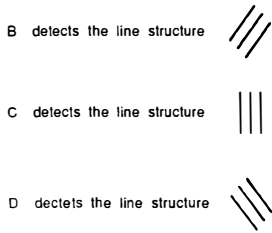


Figure 3: first-order operators are oriented filters

are written on the same places in the Fourier plane. By combining these operators we obtain a new set of operators, that are characteristic of the different orientation-frequencies in the Fourier plane. So by combining the second order operators, we obtain ten operators.

Each point in the Fourier plane corresponds to only one of these new operators. We obtain a regular sampling of the Fourier plane. The operators can be used to detect all orientations and frequencies.

2-3 Local Analysis of Texture

A discrete texture image is defined on a $K \times K$ grid with a pseudo hexagonal sampling. The image is denoted $(Y_{k,l})$ ($k = 1 \dots K, l = 1 \dots K$).

According to the study of A. Gagalowicz, texture analysis should be fulfilled, when the texture is locally analysed with a 9° solid angle [4]. Because the position of the camera is free, we can choose the distance between the camera and the image, such which the width of a second-order neighborhood corresponds to a 4° solid angle. Thus, we choose to analyse textures with the second-order operators. At any localization in the image, we consider the pixels in a second-order neighborhood and apply the ten new operators. The responses are represented in the angular frequency plane since each operator corresponds to a special orientation in the Fourier plane. The set of local maxima of this frequential representation is considered to characterize the texture neighborhood at location (k, l) . This set is reordered to obtain a nine binary components vector $U_{k,l} = (u^2, u^3, \dots, u^{10})$ where :

- $u^i = 1$ if the operator, τ_i , gives a response that is a local maximum of the frequency representation
- $u^i = 0$ otherwise.

The first operator is not considered, because the response (summation of the grey levels) is always a maximum in the frequency representation. We decided to consider only the geometry of the frequency representation to be coherent with the perceptual data. By comparing the responses of the operators in the Fourier representation, we model the excitation-inhibition phenomena between visual cells of same order.

2-4 Texture Signature

We consider that a texture sample is a $N \times N$ subimage. For every location (k, l) in the sample, we calculate the nine binary components vector $U_{k,l}$. We sum up $U_{k,l}$ over the subimage to obtain the sample signature Z .

$$Z = \sum_{k=1}^N \sum_{l=1}^N U_{k,l}$$

If Z is denoted: $Z = (z^2, \dots, z^{10})$ we obtain:

$$z^i = \sum_{k=1}^N \sum_{l=1}^N u_{k,l}^i$$

z^i is the summation of the geometrical response of the operator τ_i . This summation permits us to avoid local noise and to extract global properties of texture.

3 Resolution and Invariance

Our procedure is used to automatically determine the resolution of a homogeneous texture: the minimum window size giving an invariant translation perception. A number of textures are considered.

j denotes the window

τ_i denotes the operator

p denotes the width of the window

m_i^p and σ_i^p are the mean and the standard deviation of the results of operator τ_i for windows of width p .

We define the following criterion :

$$C(p) = \sum_{i=2}^{10} \sigma_i / m_i$$

When p increases, $C(p)$ tends to a limit:

$$\lim_{p \rightarrow \infty} C(p) = const$$

We choose the value where the criterium is stable enough :

$$\left| \frac{C(p)}{C(p+1)} - 1 \right| < \varepsilon$$

This value, denoted P , is called the mathematical resolution of the texture.

Experimentals results show that this corresponds to the perceptual resolution of the texture. The perceptual resolution of the texture is the window width that gives a translation-invariant perception. By considering for one texture a number of samples with the correct width P , we have shown that the numerical sample signatures are very stable and permit a good classification rate [6].

A second phase, described below, permits us to obtain constant signature vectors.

For every operator, τ_i , we consider the mean m_i of the results of that operator for windows of suitable width. We represent the m_i graphically by ordering them in decreasing order.

Two cases are possible

The first case is represented in figure 4. The curve presents an

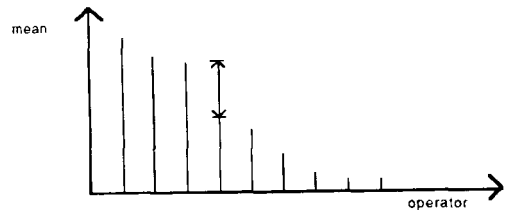


Figure 4: first type of means curve

important variation after the k -th number (in figure $k=3$). We say that the texture presents k important frequential resonances.

Then we code the signature vector Z^j with the following method

the k greatest components of Z^j are coded by 1 and the other values are coded by 0

We obtain a new vector Y^j .

Y^j is called the signature vector of the sample j .

The second case is represented in figure 5. The mean curve

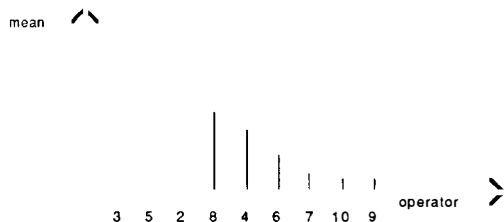


Figure 5: second type of means curve

presents a continuum of values. We consider

$$M = \frac{\sum_{j=1}^9 |m_j|}{9}$$

We say that an operator i presents an important resonance on the studied texture if $m_i - \sigma_i > M$ where m_i and σ_i are respectively the mean and the standard deviation resulting from the application of the operator i .

If k operators satisfy this property we say that the texture presents k important frequential resonances. The final signature vector Y^j associated to the vector Z^j is defined as above. Our experiments have shown that this new signature vector is constant with translation.

4 Application and Results

This global procedure has been used on different natural textures extracted from Brodatz's textures. For every texture we have first determined the resolution.

We have then observed 100 samples of suitable width for every texture and examined the signature vectors. The results are expressed in the following table.

The first line gives the name of the texture. The second line gives the mathematical resolution of the texture. The lines three to eleven give the results of the operators for the different textures. The operator 1 is not considered because its response is always a maximum and its value is always 1.

The vector formed by the responses of the operators (rows three to eleven), is the signature of each texture. Almost all the samples have the same signature. The last line gives the number of errors for the different textures.

texture	wood	jute	wool	crepe	lichen
windowwidth	88	64	56	56	80
operator 2	1	0	1	1	0
operator 3	0	1	1	1	1
operator 4	1	0	1	1	0
operator 5	0	0	0	0	0
operator 6	0	1	0	1	0
operator 7	0	0	0	0	0
operator 8	1	0	0	0	0
operator 9	0	0	0	0	0
operator 10	0	1	0	0	0
errors	0	5	0	4	0

5 Stability of the Results

The signature vector that we obtain is very stable. The property of translation-invariance requires large window width to calculate signature vectors, but in fact we need only a few points inside the window.

The study of stability was done with two textures : wood and woven. We have computed the number of errors to translation-invariance when we calculate the local characterization of texture only at N points inside the window. The choice of the N points inside the window is done with a random procedure. The results are expressed by the following tables. The first line gives the number of points inside the window, where the texture characterization is done.

The second line gives the number of errors.

This study is done with 100 samples for every texture.

WOOD TEXTURE					
number of points	10	20	30	40	50
number of errors	29	10	4	1	0

WOOL TEXTURE					
number of points	100	160	220	280	340
number of errors	11	13	4	4	0

These two textures were chosen because they exhibit different behaviors when we perform the texture characterization on a few points inside the window. The stability converges faster with the wood texture. The conclusion is identical: we don't need to calculate the texture characterization at every point, but at most at 25 percent of points.

6 Conclusion

By using a linear transform over a neighborhood and a non-linear process, we obtain a texture signature that can be used to define the resolution of an homogeneous texture image. This process can be used to find the homogeneous textured regions in an image and, more generally, for segmentation.

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