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DIGITAL PICTURE GENERATION BY TEXTURE AND CONTOUR MODELLING

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Abstract

This paper describes some efficient techniques for visual stochastic field generation, based on statistical models of textures and contours. Computer simulation of these techniques yields pictures which show controllable properties of granularity, clustering and symmetry depending on the specified model parameters.

1. INTRODUCTION

Efficient designing of picture processors and coders requires a thorough understanding of the structure of pictures and of the human visual discrimination capabilities. Therefore, generating synthetic pictures can be a useful step toward a close analysis of the stochastic structure of real images. Moreover, since texture discrimination and contour extraction are believed to be important means of scene analysis by human viewers, the use of synthetic pictures can prove to be helpful when performing visual discrimination experiments.

This paper describes somes efficient techniques for visual stochastic field generation, based on statistical models of textures and contours. Two texture generation techniques are first described and some results presented. It is shown that a controllable amount of granularity and clustering can be put in this generated fields by varying the shape of the texture autocorrelation function. A random contour generation procedure is then presented; its combination with the texture generation techniques yields digital pictures which show a controllable degree of structure and complexity.

2. STOCHASTIC TEXTURE GENERATION

A stochastic texture is defined as a discrete visual field, devoid of sharp edges and having multiple grey levels. Two techniques are presented for generating textures of controllable spatial correlation: the first one works on the two-dimensional Fourier transform of the visual field(1), while the second one is a direct generation technique using two-dimensional digital filters.(5)

2.1 TEXTURE GENERATION IN THE FOURIER TRANSFORM DOMAIN

Let a discrete two-dimensional field be represented by

$$s_p(m,n) \qquad \begin{matrix} m = 0,1,\dots N_x-1 \\ n = 0,1,\dots N_y-1 \end{matrix} \qquad (1)$$

where $s_p(m,n)$ designates the grey level value of element (m,n). Considering such a field as spatially periodic with period (N_x,N_y), one can define its two dimensional discrete Fourier Transform $S_p(k,\ell)$ and $s(m,n)$ can be obtained from $S_p(k,\ell)$ using the relation:

$$s_p(m,n) = \frac{1}{N_xN_y}\sum_{k=0}^{N_x-1}\sum_{\ell=0}^{N_y-1} S_p(k,\ell)\ \exp\ j2\pi\left[\frac{mk}{N_x}+\frac{n\ell}{N_y}\right] \qquad (2)$$

If $R_p(t_x,t_y)$ designates the autocorrelation of the periodic signal associated with $s_p(m,n)$, the following relation can be established:

$$R_p(t_x,t_y) = \text{IDFT}\left[(|S_p(k,\ell)|^2/N_xN_y)\right] \qquad (3)$$

where IDFT denotes the Inverse Discrete Fourier Transform operator.

In expression (3), $R_p(t_x,t_y)$ represents the autocorrelation of a particular field $s_p(m,n)$. Then, if $s_p(m,n)$ designates only a sample from a two-dimensional stochastic process, the autocorrelation function $R(t_x,t_y)$ of this process can be expressed as:

$$R(t_x,t_y)=E\left[R_p(t_x,t_y)\right]= \text{IDFT}\left[E(|S_p(k,\ell)|^2)/N_x,N_y\right] \quad (4)$$

where E [.] denotes the expected value operator. Finally, assuming $|S_p(k,\ell)|$ to be a zero-mean process of variance var[$S_p(k,\ell)$] , expression (4) can be rewritten as

$$\text{var}\left[|S_p(k,\ell)|\right]= E(|S_p(k,\ell)|^2)= N_xN_y\text{DFT}\left[R(t_x,t_y)\right] \quad (5)$$

where DFT denotes the Discrete Fourier Transform operator.

Consequently, the generation of stochastic textures, of multiple grey levels, having a specified autocorrelation function $R(t_x,t_y)$ can be performed by choosing elements $S_p(k,\ell)$ in the following way:

(1) express $S_p(k,\ell)$ as:

$$S_p(k,\ell) = H(K,\ell) \cdot W_p(k,\ell) \qquad k = 0,1\ldots N_x-1, \quad \ell = 0,1\ldots N_y-1 \quad (6)$$

where

$$|H(k,\ell)|^2 = \text{DFT } R(t_x,t_y)$$

(2) choose $W_p(k,\ell)$ as complex-valued independant numbers of the form:

$$W_p(k,\ell) = r_p(k,\ell) + j\ i_p(k,\ell) \quad (7)$$

where $r_p(k,\ell)$ et $i_p(k,\ell)$ are mutually independant, Gaussian random variables of zero-mean and of variance equal to $\frac{1}{2} N_xN_y$.

(3) ensure that for every (k,ℓ)

$$S_p(k,\ell) = \text{conjugate of } S_p(N_x-k,\ N_y-\ell) \quad (8)$$

in order to get real-valued elements $s_p(m,n)$

(4) take the inverse discrete Fourier transform of the field $S_p(k,\ell)$ thus generated

Such a texture generation techniques leaves a complete freedom of choice for the autocorrelation function $R(t_x,t_y)$. Consequently, a controllable amount of structure can be put in the generated texture fields by varying the nature of the autocorrelation function.

2.2 TEXTURE GENERATION BY MEANS OF 2-D DIGITAL FILTERING

This technique consists in applying equation (6) in the spatial domain, thus leading to

$$s_p(m,n)=h(m,n)*w_p(m,n) \qquad m= 0,1,\ldots N_x-1, \quad n= 0,1,\ldots N_y-1 \quad (9)$$

with

$$h(m,n) = \text{IDFT } H(k,\ell)$$

$$w_p(m,n) = \text{IDFT } W_p(k,\ell)$$

and where * denotes the convolution operator.

Given the nature of elements $W_p(k,\ell)$, as defined in the previous section, the elements $w_p(m,n)$ are real-valued, uncorrelated gaussian random variables of zero-mean and unit variance. It must also be noted that the phase of $H(k,\ell)$ can be chosen arbitrarily, since it has no effect as regards to the generation technique.

A simple realization of equation(9) can be obtained by means of a two-dimensional linear filter(5), the only difficulty of this technique lying in the computation of the filter coefficient. In fact, the number of coefficients and the filter structure (F.I.R. or I.I.R) put some limitations on the achievable autocorrelation function of the fields. Consequently, standard optimization techniques must be used in the computation of the filter coefficients, in order to approximate a pre-specified autocorrelation function $R(t_x,t_y)$.

The use of recursive IIR filters, is particularly attractive since it leads to a small number of filter coefficients. Denoting $b_{i,j}$ and G the filter coefficients, the generation technique is then expressed by:

$$s_p(m,n) = \sum_{(i,j)\in D} b_{i,j}\, s_p(m-i,n-j) + G\, w(m,n) \quad (10)$$

where $w(m,n)$ are independant random variables, and D represents the domain over which the values $s_p(m-i,n-j)$ are considered in the computation of element $s_p(m,n)$.

The computation of the actual autocorrelation function $R_f(t_x,t_y)$ achieved with such a filter, can be performed iteratively as:

$$R_f^{(n+1)}(t_x,t_y) = \sum_{(i,j)\in D} b_{i,j}\, R_f^{(n)}(t_x-i,t_y-j) \quad (11)$$

It must be noted that this generation technique does not allow, like the previous one, a complete freedom in the choice of the autocorrelation function $R(t_x,t_y)$. In fact, one can only approximate a given autocorrelation function, and the approximation can be improved only at the expense of a greater number of filter coefficients.

2.3 RESULTS

Figures 1, 2, 3 and 4 illustrate some visual textures of specified autocorrelation function, as obtained with the first generation technique (in the Fourier Transform domain) in the case $N_x = N_y = 256$. Figure 1 corresponds to the autocorrelation function.

$$R_1(t_x,t_y) = \mathrm{Exp}\left\{-0.1\left[\mathrm{Max}(|t_x|,|t_y|)+3\mathrm{Min}(|t_x|,|t_y|)\right]\right\} \quad (12)$$

As it can be seen on Figure 1, such an autocorrelation function has been chosen in order to obtain a strong correlation along the horizontal and vertical directions.

This effect is attenuated, while still visible, in Figure 2, where the autocorrelation function is of the form:

$$R_2(t_x,t_y) = \mathrm{Exp}\left\{-0.1\left[|t_x| + |t_y|\right]\right\} \quad (13)$$

As opposed to the previous ones, Figure 3 illustrate a texture field in which the correlation is devoid of any privileged direction. This case corresponds to a circularly symmetric autocorrelation function:

$$R_3(t_x,t_y) = \mathrm{Exp}\left\{-0.1\left[t_x^2 + t_y^2\right]\right\} \quad (14)$$

Finally, Figure 4 illustrates a texture field having strong correlation along the diagonal directions and corresponds to the autocorrelation function:

$$R_4(t_x,t_y) = \mathrm{Exp}\left\{-0.1\,\mathrm{Max}(|t_x|,|t_y|)\right\} \quad (15)$$

In all the examples illustrated here, an exponentially decreasing law has been chosen for the autocorrelation function. However, one can vary the granularity of the texture fields by changing the type of decreasing law. Moreover, a certain periodical structure can be added by considering autocorrelation functions of periodic form.

3. CONTOUR MODELLING AND DIGITAL PICTURE GENERATION

This section describes first a method for random contour generation where each contour is a closed polygonal figure. This method is then combined with the previously described texture generation techniques in order to produce synthetic digital pictures.

3.1 RANDOM CONTOUR GENERATION

In the generation method described here, a contour is defined as a closed polygonal figure of N sides. Each side is defined by its initial point, its length and its orientation. Since the contour is closed, the initial point is identical to the previous side final point. Given the important number of sides (N=200), the length of each side, is maintained constant. As for the orientation of each side, it is assumed to follow a first order Gauss-Markov process of zero mean and controllable variance.

Figure 5 shows some examples of closed contours thus generated. For the purpose of presentation, these contours have all be normalized in order to get identical dimensions.

3.2 DIGITAL PICTURE GENERATION

A combination of the texture and contour generation techniques previously described is performed in order to get synthetic digital pictures of controllable aspect.

As a first step, closed contours are randomly generated and positioned in the picture. Each contour defines an inner region which can be partly hidden by the inner regions of previously generated contours. In order to illustrate the effect thus obtained, Figure 6 shows a synthetic picture where each region has been assigned a constant, randomly chosen luminance value. Finally, instead of a constant luminance value, each region is assigned a random texture, as obtained by means of the digital filter technique described in section 2.2. The resulting picture is shown in Figure 7. This picture shows a definite amount of structure in terms of granularity, clustering and symmetry. Moreover the amount and the nature of this structure can be controlled by varying the parameters of the texture and contour generation techniques.

4. DISCUSSION AND CONCLUSIONS

This paper had described a technique for random digital picture generation, based on texture and contour modelling. The pictures thus produced appear to have a controllable amount of structure. Generating such pictures can be useful in the area of picture coding, since it can help understand the stochastic structure of real pictures. Moreover, such synthetic pictures can be successfully used in subjective testing of human vision capabilities, since they can display a variable amount of complexity. (6)

In the texture generation procedure, only first and second-order statistics have been used for texture characterization. However it has been shown, (4), that, in general, textures having the same first and second-order statistics, but different higher order statistics, look extremely similar to human viewers.

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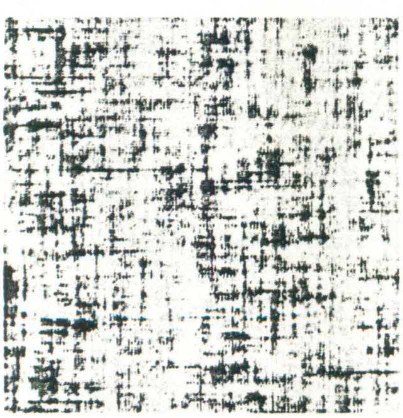

Figure 1: Texture field corresponding to autocorrelation function $R_1(t_x,t_y)$ (equation 12)

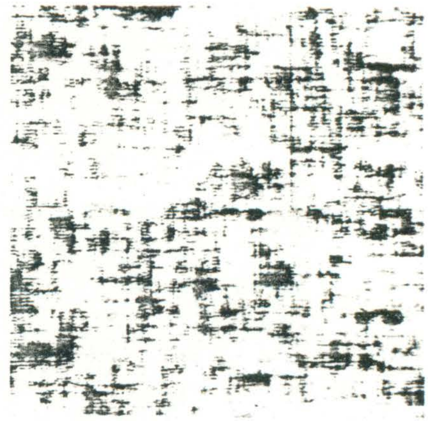

Figure 2: Texture field corresponding to autocorrelation function $R_2(t_x,t_y)$ (equation 13)

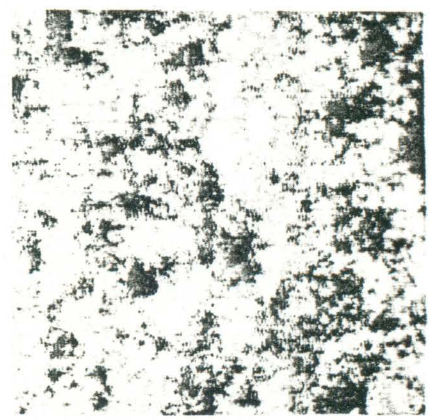

Figure 3: Texture field corresponding to autocorrelation function $R_3(t_x,t_y)$ (equation 14)

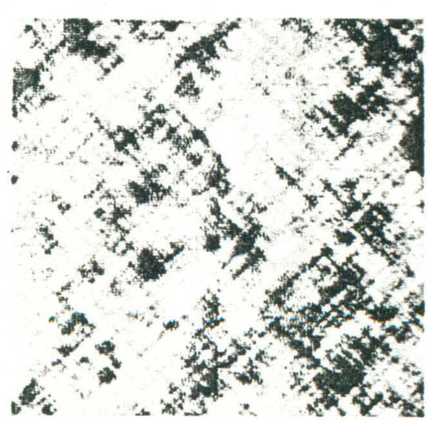

Figure 4: Texture field corresponding to autocorrelation function $R_4(t_x,t_y)$ (equation 15)

Figure 7: Synthetic picture with random contours and textures

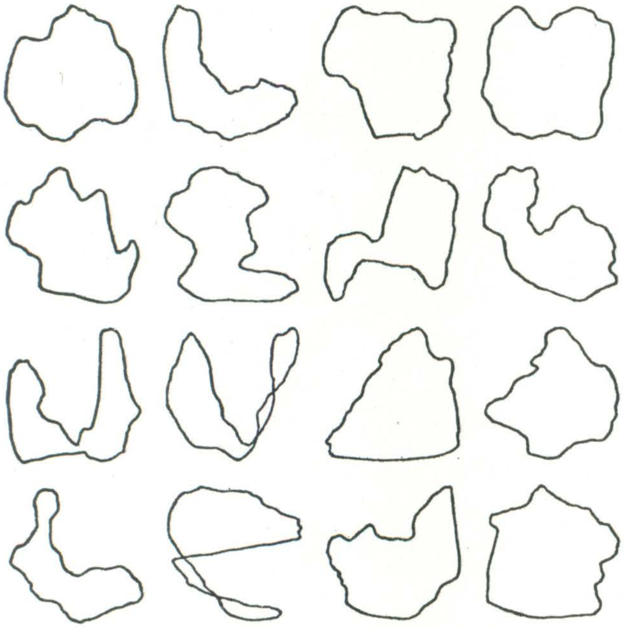

Figure 5: Randomly generated closed contours

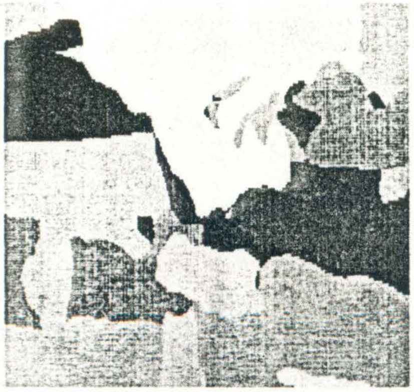

Figure 6: Synthetic picture with constant amplitude regions