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**Coding textures by means of a
multiresolution selective deconvolution
scheme**

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1 Introduction

For many years transform techniques have proven to be efficient for picture coding. Several standardization groups have produced algorithms which include a transform operator. The goal of the transform is to decorrelate the original signal, and this decorrelation generally results in the signal energy being redistributed among only a small set of transform coefficients. These techniques always process blocks.

The next generation of algorithms uses a different approach, namely an object based approach. The picture is no longer cut in blocks but in objects characterized by their shape and their aspect respectively called *contour* and *texture*. As a consequence, to be competitive with older algorithms, contour-texture schemes need efficient methods for both contour and texture coding. The intention of this report is to propose new ideas for the coding of texture.

Up to now, only a few papers have considered the task of coding the texture of arbitrarily shaped regions. Authors propose polynomial representations often computed on small rectangular regions. Gilge et al. [2] develop a scheme which decomposes the texture signal into an orthogonal basis adapted to each region whatever its shape. Unfortunately the receiver has to compute the basis functions; this burden is not suitable for real time applications. Gilge's work consists in adapting basis functions to a segment shape.

For coding purposes, transforms lead to an interesting interpretation in terms of frequency. Moreover, some textures have a spatial organization corresponding to a given frequency. For this kind of textures it is sufficient to transmit a very small amount of coefficient amplitudes. However for any spectral analysis, and subsequent high compression ratios, the signal support has to be regular (rectangular, ...). In order to remove the window effect—the window being the spatial domain covered by the texture—the idea is to extrapolate the spatial window content to a rectangular net. After extrapolation no further window information is present and the final signal spectrum reflects only the texture spectrum.

In 1987, Franke[1] has introduced an algorithm for the extrapolation of discrete signals. This method is called the *selective deconvolution* and acts as an iterative process using the Fourier transform and its inverse. The algorithm detects the dominant spectral lines of a texture and removes insignificant spectral information. To speed up the computation, the selective deconvolution has been integrated into a subband decomposition [4, 5]. Extrapolating a texture signal is useful in many situations:

- Decorrelation between contours and textures. Contours and textures are two separate kinds of information about regions. In an object coding scheme it is important to assure an excellent decorrelation between contours and textures. When

Coefficient amount	No extrapolation	After extrapolation
50	10.5	7.1
100	9.3	5.7
200	7.7	4
300	6.7	3.1
400	6.1	2.3
500	5.5	1.9
1000	3.6	0.3

Table 1: Mean values of absolute errors for several amounts of selected coefficients.

the signal is “regular”, a spectral extrapolation generates a new signal free of any information about the contour and therefore easier coded with a small amount of spectral coefficients -this extended signal is the input of a transform coder. Figure 1 is an illustration. The upper left picture is the original texture; it is a 8-bit picture enclosed in a square of size 64x64. A possible texture extrapolation is drawn on its right. Figure (c) is the original texture reconstructed with only 50 coefficients of the Fourier transform; the other coefficients are equal to zero. The last picture represents the reconstruction with 50 Fourier coefficients after the original texture has been extrapolated. As it can be seen, if we fix the amount of coefficients or the compression ratio, the extrapolated texture is closer to the original than the reconstructed texture with no extrapolation. The explanation for this is that the texture spectrum is corrupted by the region shape spectrum. After the extrapolation process, the region shape influence has disappeared. The last picture of figure 1 is built with 50 Fourier coefficients only. It means that the compression ratio -more precisely, it is a *selection ratio* - is about 72 before quantization and entropy coding. To complete the example, we compile in table 1 the mean values of the absolute error between the original and the reconstructed signals for different amounts of selected coefficients, without or with extrapolation (respectively row 2 and 3). The table clearly indicates that texture extrapolation drastically reduces the reconstruction error whatever the amount of conserved coefficients.

- Texture synthesis and compression.

The aim of texture analysis is to determine parameters which describe exactly the signal. The associated compression technique consists in transmitting the parameter values only. At the transmission channel output, the receiver synthesizes the texture with respect to the parameter values. The extrapolation mechanism is also a type of texture synthesis, but this time, the transmitted information is not a set of parameter values; just a small sample of the original texture is sufficient for the synthesis of the whole texture. The synthesis principle by means of a texture extrapolation is illustrated in figure 1. The left picture is the original texture. The right picture results from the extrapolation of the texture initially confined in the white square. As a consequence of the texture extrapolation, the associated compression ratio is directly related to the area of the transmitted texture sample. In this particular example, the compression ratio lays eight times higher than any other coding technique.

- Texture prediction.

In image sequences the receiver computes a prediction for the next image with the help of the previous ones; the better the prediction the higher the compression ratio. In object based motion

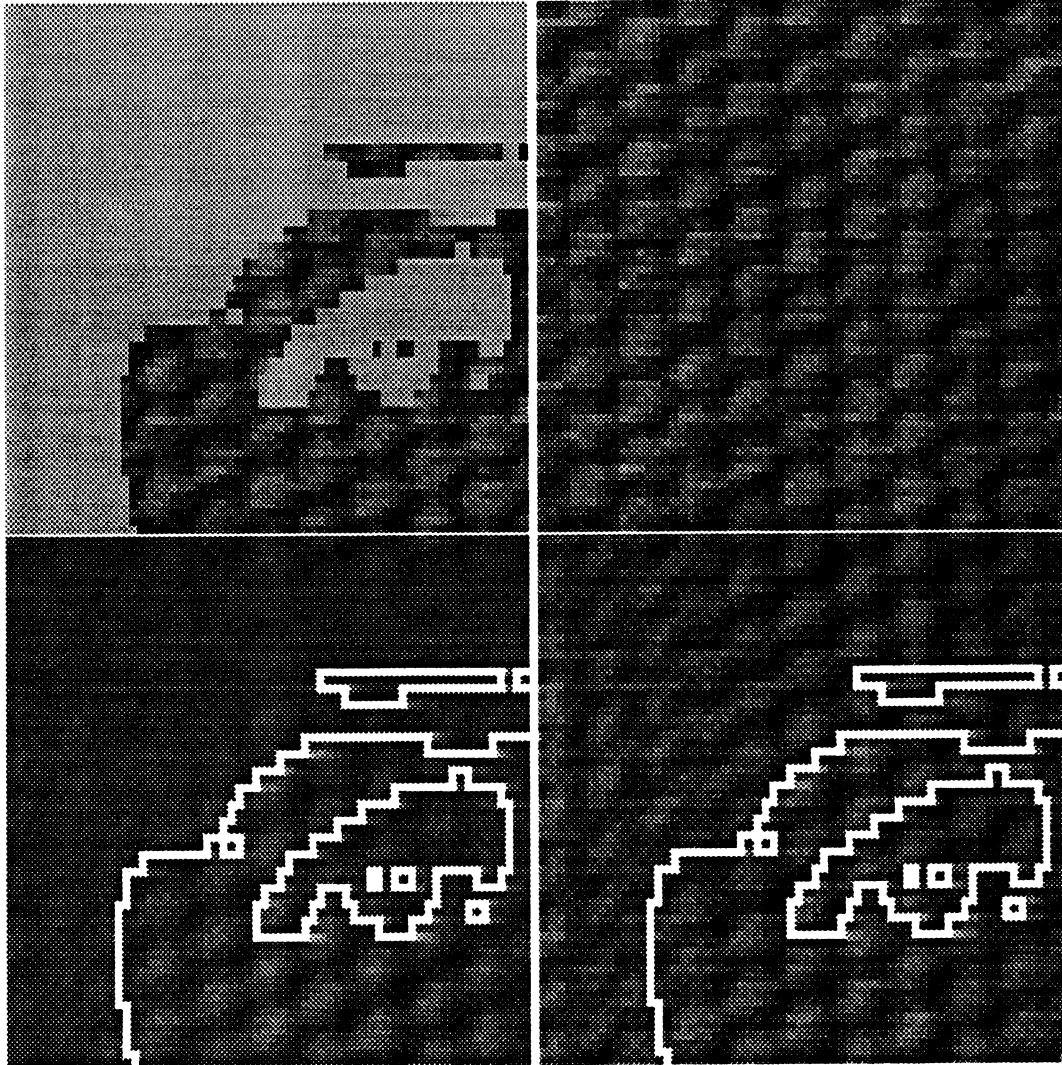


Figure 1: Extrapolation of a regular texture to a square. The first signal represents the texture on an arbitrarily shaped region. Picture (b) is a possible extension of the texture which contains no information about the shape. (c) is the signal reconstructed with 2% of the total amount of Fourier coefficients without extrapolation. (d) is the same as (c) but after extrapolation.

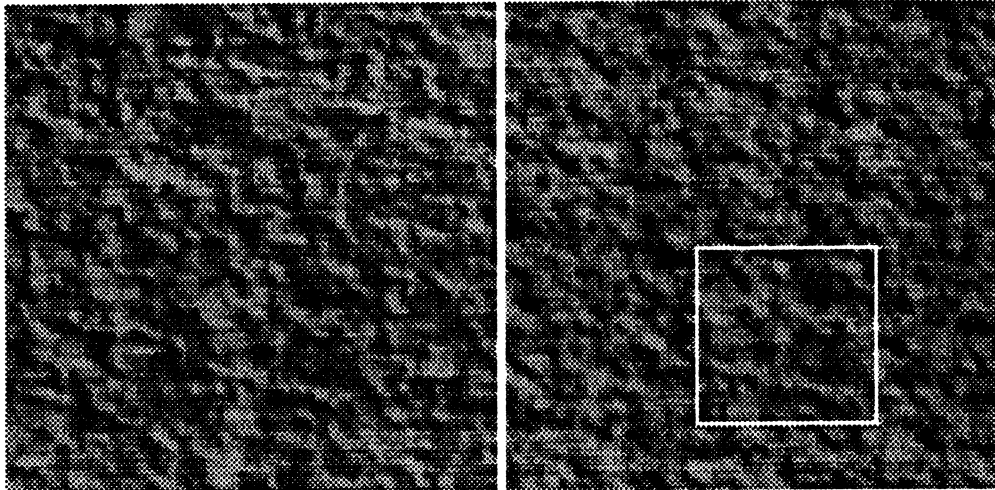


Figure 2: Texture synthesis starting from the white square content.

compensation techniques, objects moving for the first time show a background area which is not predictable a priori. But in videophone like sequences, the extrapolation of the background can serve as a first *prediction for all new regions* resulting from a head movement.

Formulation of the extrapolation problem

For commodity we adopt a one-dimensional formulation; the formal extension to picture (or other 2D signals) introduces no particular difficulty. Let $f(n)$ be the function to extrapolate and $y(n)$ the luminance values over the region having a shape D_w . The functions $f(n)$ and $y(n)$ are related through the following expression:

$$y(n) = w(n)f(n) \quad 0 \leq n \leq N - 1 \quad (1)$$

where

$$w(n) = \begin{cases} 1 & \text{for } n \in D_w \subseteq \{0, \dots, N - 1\} \\ 0 & \text{if } n \notin D_w \end{cases} \quad (2)$$

is the window.

With the transform formalism, the equation is equivalent to the following convolution:

$$\mathcal{Y}(k) = \mathcal{W}(k) \otimes \mathcal{F}(k) \quad 0 \leq k \leq N - 1 \quad (3)$$

As clearly indicated by this last equation, the desired spectrum $\mathcal{F}(k)$ for coding purposes is affected by the window spectrum $\mathcal{W}(k)$; it is why a spatial extrapolation technique is also called a “deconvolution” technique.

2 Basic principles

2.1 Iterative extrapolation algorithm

The only way to solve the extrapolation problem with respect to the spectrum analysis is to proceed iteratively. With a consistent operator \mathcal{O} , we may form a list of successive values $\dots, f_i(n), f_{i+1}(n), \dots$ resulting from

$$f_{i+1}(n) = \mathcal{O}[f_i(n)] \quad (4)$$

The classical solutions to the extrapolation problem consider different operators with the associated questions of convergence and unicity. The question is discussed in [3].

The extrapolation efficiency is completely conditioned by the choice of the iterative operator \mathcal{O} . Next we describe a simple operator constituted of a transform, its inverse and an adaptive selection filter. To avoid excessive computation time we can decompose the texture in smaller signals (by a subband transform for example). In such a situation the following algorithm is applied on each component.

2.2 Selective deconvolution of a texture by means of spectral transform

The iterative process acts as an adaptive filter $\mathcal{S}(k)$. At the beginning, the function is equal to zero for every k . The complete initialization step is then:

$$\begin{aligned} f_0(n) &= y(n) \\ \mathcal{S}(k) &= 0 \quad \forall k \end{aligned}$$

The block diagram of the algorithm is shown in figure 3. At step $i + 1$, the algorithm detects the

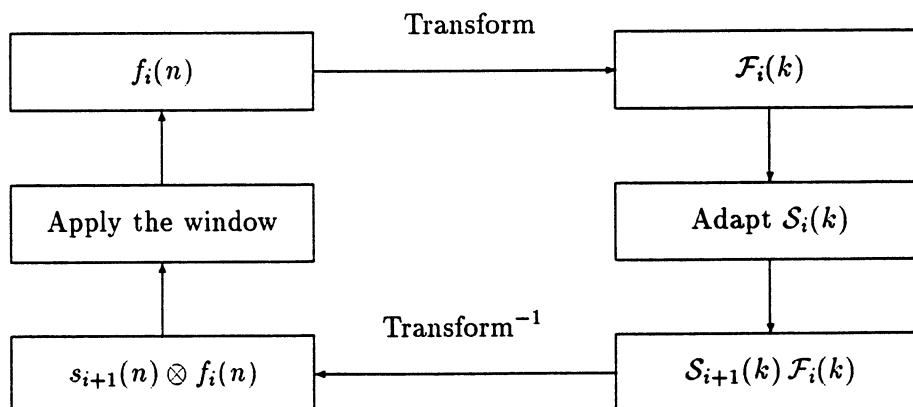


Figure 3: Block diagram of a transform based selective deconvolution algorithm

spectral line of $\mathcal{F}_i(k)$ having the largest magnitude and not considered in an earlier step. In accordance with Parseval's theorem, one then expects the error to be minimal. Let k_s be the selected line (with the symmetrical position when working with real functions). The filter is modified by

$$\mathcal{S}_{i+1}(k) = \begin{cases} \delta(k - k_s) & \text{if } k = k_s \\ \mathcal{S}_i(k) & \text{elsewhere} \end{cases} \quad (5)$$

So, a supplementary spectral coefficient is added at each iteration. The corresponding estimation $f_{i+1}(n)$ results from the inverse transform of $\mathcal{S}(k)\mathcal{F}(k)$. If the spectral content of $f_{i+1}(n)$ is enriched, the values of $f_{i+1}(n)$ on the D_w segment differ from the observed samples. To achieve the iteration, it is necessary to apply the window by $f_{i+1}(n) - [1 - w(n)]f_{i+1}(n) + w(n)y(n)$, after what the function is ready for a further step.