# NEW APPROACHES TO TEXTURE CODING IN SEGMENTATION AND FEATURE-BASED IMAGE CODING SCHEMES

**L.Torres J. R. Casas**

**Dept. of Signal Theory and Communications**

**Universitat Politècnica de Catalunya**

**08034 Barcelona, SPAIN**

**E.mail: Torres@tsc.upc.es**

## 1. INTRODUCTION

A major objective of image coding is to represent an image with as few bits as possible while preserving the level of quality and intelligibility required for the given application. A major breakthrough in image coding should rely on the use of segmentation-based techniques (second generation image coding techniques) and not on the classical pixel-based approach. In segmentation-based techniques, the image is decomposed in contours and textures. A dual representation, such as contour/texture, is very useful for very low bit rate video coding applications but, on the other hand, the contour/texture approach may occasionally present some limitations. Objects can be found in an image that do not correspond to the basic idea of region employed in segmentation-based schemes. In addition, there can be very significant contours that not need to be closed. The fact of considering them as closed contours, makes the coding inefficient and may introduce false contours. These considerations have led to the proposal of alternative second generation image coding schemes that have been given the name of feature-based coding schemes. These schemes describe the image as sets of lines and points from which the texture information is recovered. In this context, there is a need to develop new and efficient texture representations for both kind of schemes, segmentation and feature-based, that could provide good visual rendering of the decoded image. The objective of this paper is to present a summary of two independent image coding techniques highly suitable to the encoding of texture in segmentation and feature-based coding schemes. Examples of computer simulated coded images using both approaches are presented.

## 2. CODING OF TEXTURE IN SEGMENTATION-BASED IMAGE CODING TECHNIQUES

In segmentation-based image compression techniques the image to be compressed is first segmented [1]. The pixels are divided into mutually exclusive spatial regions based on some criteria. After segmentation, the image consists of regions separated by contours. Then, the information is coded describing the shapes and interiors of the regions. The interior of the regions are represented by encoding, for example, the coefficients in the polynomial models describing each region, or for flat regions the average gray level of the pixels in each region. These coding schemes are currently being introduced in the coding of video sequences with very good results [2]. Almost all the effort in inside coding (texture coding) has been devoted to orthogonal polynomial coding or transform coding [3], what has to some extent limited the improvement of these schemes. The quality of the encoded textures is in some cases acceptable, but there is a need to develop more powerful schemes that may provide better visual quality results still giving very high compression. A new technique, called Stochastic Vector Quantization (SVQ), for encoding homogeneous textures was introduced in [4] and further improvements were proposed in [5] and [6]. We will discuss the integration of a particular SVQ scheme, called Stochastic Vector Quantization Linear Prediction, (SVQLP), in segmentation-based image coding schemes that provides very good rendering of textures.

### 2. 1 Stochastic Vector Quantization (SVQ)

The vector quantization scheme has proven to be very effective in speech and image coding but has not been extensively applied to segmented images because, among other reasons, not an easy method was available for the generation of the codebook. In order to overcome the intrinsic problem concerning the design of the codebook when using the LBG algorithm [7], a new simple fixed-rate VQ image coding scheme, called Stochastic Vector Quantization (SVQ), was proposed and successfully applied to non-segmented images in [4] and then to segmented images in [5]. A completely new SVQ scheme, called SVQLP, was presented in [6] where the new approach showed very good visual performance for homogeneous textures for compression ratios in the range of 0.04 - 0.16 bits/pixel. The SVQLP scheme generates a codebook following a prediction error model of the texture to be encoded and it is the prediction error what is encoded using VQ. To decode the image, the entire error image is decoded first and then filtered as a whole, using a Linear Predictor Filter. With this approach, the “block effect” problem found in all block-based image coding schemes is eliminated what produces a very pleasant reproduction of the decoded image. We will present next the SVQLP scheme applied to segmentation-based image coding schemes.

### 2. 2 Stochastic Vector Quantization Linear Prediction (SVQLP)

If the segmentation process has been well defined and the obtained regions are homogeneous, then it is possible to design a specific codebook suited to the statistics of each region. The approach is to design the codebook according to some previously defined prediction error model for the regions of the image found in the segmentation process. That is, to generate the codebook according to the model obtained for each region and not according to some specific data sequence as it is usually done in non-segmented images. The SVQLP presented in [6] has been modified to cope with the arbitrary shape of the regions resulting of the segmented process. Besides, specific techniques have been developed to minimize the number of codewords used to encode each region. Also, and in order to improve the efficiency of the overall segmentation-based coding scheme, several methods have been investigated to adequately code each region. Thus, a strategy has been developed to know if a region has to be encoded using SVQLP, as is the case for highly textured regions, or if the mean value of the region or low order polynomials are enough to represent a region, as is the case of very flat spatial regions or slow gray level varying regions. With this approach the performance of the encoding system increases greatly.

### 2. 3 Results using Stochastic Vector Quantization Linear Prediction (SVQLP)

We have performed a variety of experiments to show the goodness of the proposed algorithm. The well known 256x256 Cameraman image has been selected as test image. A previously reported segmentation scheme based on Mathematical Morphology has been used to segment the image [8]. Contour coding has been done using a modified lossless version of the chain code technique where 1.34 bits/contour pixel have been used [9]. Good visual results have been obtained for compression ratios between 20 and 30 for still black and white images although the algorithm can be easily extended to color images. As an example Image 1 shows the original image and Image 2 shows the coded image with the SVQLP for a compression ratio of 25. All regions in image 2 have been encoded with the technique we present. If more compression is desired, then each region may be coded with a different strategy as explained above (mean value of the region or low order polynomials for very flat spatial regions or slow gray level varying regions).


Image 1: Original image


Image 2: Segmented image encoded with SVQLP

Let us explain now a second coding technique independent of the SVQLP approach presented above. As will be seen, the combination of the two may prove to be a powerful scheme for texture coding.

### 3. CODING OF TEXTURE IN FEATURE-BASED IMAGE CODING TECHNIQUES

The objective of feature-based coding is to provide some alternate representation to the basic contour/texture model of the image. When analyzing the problems encountered in segmentation-based techniques, it is seen that the coding of the contours represents a bottle-neck in terms of bits. Most of the bits are assigned to the contours, and in fact, many times there exist contours that do not need a precise representation or even do not need to be represented. This concept allows to introduce a relaxation in the notion of closed-contour and to seek for more flexible representations leading to open contours. One possible alternative to find open contours is to extract important sets of points and lines of the image which we will called features. The fact of finding open contours leads naturally to open regions what presents new perspectives in texture coding. One approach to encode texture from open contours is given by interpolation. In feature-based schemes, interpolation techniques are applied such that allow the representation of the texture information.

For addressing the problem of the extraction of significant features from digital images, a processing technique strongly related to the physical image structure is required. Such a technique, should deal with the "shapes" contained in the video signal, in order to match the perception process of the visual system. Mathematical Morphology provides tools that give a good insight into the structure of the image for processing purposes. Geodesic interpolation approaches coming also from Mathematical Morphology, will be presented for interpolation purposes. The interpolation technique will be presented first and then according to this interpolation strategy a set of adequate points from which the interpolation is performed will be found. Some previous results have already been presented in [10].

### 3.1 Morphological interpolation

The target of the morphological interpolation algorithm is to approximate the amplitudes of unknown pixels of the image by fitting a surface on a subset of pixels of known values. Such surface is constrained to be maximally smooth between the known pixels in the sense that pixel to pixel variations should be minimized. A suitable strategy for the 2D interpolation is to compute at each point the average of the amplitudes of the initial pixels weighted by the inverse of the distances to each of them [11]. The nearest pixels have stronger influence than the distant ones and the interpolated amplitudes change slowly in the areas in between. The distance measure is taken as the geodesic distance within the set of unknown pixels because the use of the geodesic distance allows the preservation of the transitions indicated by the set of initial pixels. The interpolation technique may be efficiently implemented by an iterative algorithm based on geodesic dilation. This is performed using FIFO queues, so that each pixel is treated only once in a complete propagation process. After a few number of iterations, the algorithm quickly converges to the final interpolated image. Figure 3 illustrates some steps of the morphological interpolation algorithm.

### 3.2 Image coding by maximum and minimum curvature lines

Given that the interpolation algorithm only generates smooth surfaces (both flat and sloping ones) between the initial pixels, such pixels should be selected so that the main transitions between these surfaces are kept. The set of points with largest curvature values characterize the upper and lower edges of important transitions. Thus, these points taken as the initial set can lead to a good restoration of the image by means of the morphological interpolation process. In order to extract lines of maximum and minimum curvatures the following steps are carried out. First, the original image is prefiltered by a dynamics prefilter, which removes low contrasted components while preserving the gray level shape of the remaining components. Secondly, the morphological Laplacian is computed. Thirdly, the watershed of the Laplacian extracts a network of lines identifying the lines of maximum curvature. The dual process extracts the lines of minimum curvatures. This process is illustrated in Fig. 4. The upper row shows the original and prefiltered images and the Laplacian. In left image of the lower row, the set of markers are in dark gray, and the networks of maximum and minimum curvature lines (resulting of the two watershed processes) are drawn in white and black respectively. The position of the networks' pixels and the gray level values of these pixels in the original image have to be coded and transmitted to the receiver. Since the networks are composed of connected pixels, a derivative chain code is used to code the pixels' positions and the starting points. The gray level values are coded by polynomial approximation. More precisely, the network is broken at each triple point (points with more than two branches) and the gray level values of the resulting curves are approximated by a second order polynomial. The resulting three coefficients are quantized, entropy coded and transmitted. At the receiver, the networks of lines with the approximated gray levels are used as initial pixels for the interpolation. These values and the restored image are presented in last two images of the lower row in Fig 4.

### 3.3 Results of the feature-based morphological interpolation

The compression ratio achieved with the above strategy is equal to 40 for the interpolation result shown in Fig. 4. As can be seen, most of the smooth texture component has been nicely reconstructed. Smooth variations as well as transitions of the signal have been coded along with the positional (contour) information in the networks. The proposed algorithm is general in the sense that it is able to perform interpolation from any set of given pixels, i.e. a set of isolated points or isolated lines of open contours [10].

## 4. GENERAL CONCLUSIONS

We have presented two different texture coding techniques well suited for segmentation and feature-based image coding. Although the techniques have been presented independently, they are intended to be used in combination. SVQLP has been shown to provide good results for homogeneous textures as is the case for segmentation-based schemes. Morphological interpolation has been shown to produce good results for smooth textures and sharp transitions of the image. Then, the morphological interpolation approach can be used to represent a low pass version of the image along with sharp transitions and the SVQLP technique can be used to code what is left in the image. Current work is being performed to combine these two different approaches that may prove very useful for advanced feature-based coding schemes.

## 5. REFERENCES


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