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# Fractal Coding of Textural Images

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# 텍스처 영상의 프락탈 코딩

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New very low bit rate segmentation image coding technique is proposed by segmenting image into textually homogeneous regions. Regions are classified into one of three perceptually distinct texture classes (perceived constant intensity (class Ⅰ), smooth texture (class Ⅱ), and rough texture (class Ⅲ)) using the Human Visual System (HVS) and the fractals. To design very low bit rate image coder, it is very important to determine nonoverlap and overlap segmentation method for each texture class. Good quality reconstructed images are obtained with about 0.10 to 0.21 bit per pixel (bpp) for many different types of imagery.

영상을 텍스처의 같은 성질의 영역으로 세그멘트함으로써 새로운 very low bit rate 세그멘테이션 영상코딩 기술을 제안한다. 영역은 Human Visual System(HVS) 과 프락탈 특성을 이용하여 3 가지의 다른 텍스처 크래스(인간이 인지한 상 인텐셔티 (크라스 Ⅰ), 부드러운 텍스처 (크라스 Ⅱ) 및 거칠은 텍스처(크리스 Ⅲ)) 중 1 가지로 구분한다. Very low bit rate 영상코더를 설계하기 위해 각각의 텍스처 크라스에 대해 nonoverlap과 overlap 세그멘테이션 방법을 결정하는 것이 중요하다. 좋은 화질을 갖는 재생영상은 여러 종류의 영상에 대해서 약 0.10 에서 0.21비트/피셀에서 얻는다.

**Key words** : texture, image coder, fractal coding, perceptual

## 1. Introduction

Toward very low bit rate environment,[10,12] new image compression techniques are strongly required for various applications such as in the areas of digital video codecs for desktop multimedia computers, electronic publishing, and video teleconferencing etc. Symbolically based image compression technique which is a promising solution[2,5,7-9] employs properties of the HVS and tools of image analysis to achieve good image quality at very low bit rates. One approach to symbolically based image compression techniques is segmentation based image compression. In segmentation based image compression, the image to be compressed is segmented, i.e. the pixels in the image are separated into regions having widely differing perceptual importance. The importance of a region corresponds to the amount of informatoin it conveys to the viewer. Typically, the amount of local detail or high frequency content, is considered a reasonable measure of this importance; however, this by itself is an inadequate measure for efficient very low bit rate image compression. It is also desirable to consider other significant characteristics, such as texture and the global context of the local region, in order to assess the local informatoin content. Certain regions are critical to our subjective evaluation of quality, and relatively small errors can perceptually have a major degrading effect on the overall reproduction quality. Such regions tend to dominate the viewer's attention and are intrinsically less compressible than background segments. Consequently, when the overall bit rate is low, a uniform allocation of bits across image implies that the spatial distribution of perceptual degradation is highly nonuniform; some regions have a starvation diet of bits, causing a significant degrataion, while other regions have been coded with far more bits than needed for perceptaully transparent quality.

In the proposed new technique, we overcome the texture representation problem and determine the best block size for estimating the fractal dimension and the thresholding of the fractal dimenion. The segmentation technique we present segments image into texturally homogeneous regions with respect to the degree of perceived rouhgness using the HVS and the fractals. After segmentation, the image can be viewed as being composed of region boundaries and texturally homogeneous regions. As image coding system with high compression and good image quality is achieved by developing an efficient coding technique for the region boundaries and the three textural classes. The proposed algorithm is applied to different types of imagery.

In section 2, determination of nonoverlap and overlap segmentation methods for each texture class is presented. In section 3, we describe the proposed texture image segmentation. Finally, conclusions are provided in section 4.

## 2. Nonoverlap and Overlap Segmentation Method

During image segmentation, the image is segmented into three texture classes.[4,6,11] The number of pixels belonging to each class in an image affects the overall compression ratio. In general, the more regions belonging to the class I, the higher the compression ratio. An approach to obtain higher compression ratio and maintain high image quality is considered. It is referred to as the overlap method. In the non-overlap method, an image is divided into mutually exclusive blocks. In the overlap method, the block subimages are allowed to overlap at their perimeters. The pixels at the perimeter are computed in two or more blocks. If the pixels at the perimeter represent perceived constant intensity, the overlap method produces more regions which belong to the perceived constant intensity. Thus, the compression ratio is increased while the image quality is maintained or improved.

A $8\times8$ image consists of three strips of textures. The block size is $4\times4$. Pixels in the first and second columns represent texture which corresponds to the class II. Pixels from the third through the sixth columns represent texture which corresponds to the class I. Pixels in the last two column represents texture which corresponds to the class III. The 50 percent overlap method characterizes the texture in the middle four columns while the non-overlap method does not characterize the texture exactly. However, some pixels are computed more than once, and this increases the computation load. When an image of $256\times256$ pixels is divided into $8\times8$ blocks,the number of blocks with 0, 50, and 75 percent overlaps are $32\times32$, $4\times32\times32$, and $16\times32\times32$, respectively. There must be a trade-off between the overlap and compression ratio. Experimental results are given in the next subsection.

### 2.1 The Experimental Results for the Nonoverlap and Overlap Segmentation

In paper,[8] we discussed how to determine the thresholds $D_1$ and $D_2$ of the fractal dimension. It was shown that the curve of the fractal dimensions belonging to the perceived constant intensity are approximately semi bell-shaped around the zero and the curves of the fractal dimensions belonging to class Ⅱ and class Ⅲ are approximatedly bell-shaped around their mean respectively. In addition, there are gaps between the curves of the fractal dimensions for each class. By these experiments, the value of $D_1$ should not be greater than the minimum of the fractal dimensions belonging to class Ⅱ and the value of $D_2$ should lie between the means of class Ⅱ and class Ⅲ. Therefore, it is reasonable that the value of $D_1$ is chosen to be half of the sum of the maximum fractal dimension corresponding to the perceived constant intensity and the minimum fractal dimension corresponding to the smooth texture. The value of $D_2$ is chosen to be half of the sum of the maximum fractal dimension corresponding to the smooth texture and the minimum fractal dimension corresponding to the rough texture. The class type images for the test images with 0%, 50%, and 75% overlap are obtained. Blocks with fractal dimension less than $D_1$, between $D_1$ and $D_2$ and greater than $D_2$ are represented with an intensity value of 0, 127, and 255 respectively at all pixels in their blocks for visual purposes. In Miss USA, almost all of the blocks in the large background and some blocks on the sweater correspond to class I, some blocks around the neck correspond to class Ⅱ, and blocks around the eyes, noses, and mouth correspond to class Ⅲ. In Lena, most blocks on the background and many blocks on the black frame of the mirror and the within mirror correspond to class I, blocks on the cap, the chin, and the shoulder class Ⅱ, and all the blocks on the feather correspond to class Ⅲ. In House, all the blocks on the sky on the top and some blocks on the wall on the bottom correspond to class I. Some of the blocks on the lawn correspond to class I and Ⅱ. Almost all of the blocks on the trees on the left and right, and the bushes, correspond to class Ⅲ. In addition, blocks on the windows of the house correspond to class Ⅲ since shadows of trees are on the house. The percentage of pixels within each class in the test images is given in Tables 1, 2 and 3 with the different overlaps. When the overlap is 50 percent, the percentage of pixels belonging to class I is greatly increased. This means that the compression ratio for 50 percent overlap will be much higher than that for a zero percent overlap. When the overlap is 75 percent, the percentage of pixels belonging to class I is almost the same as for 50 percent overlap. Since the number of computation is increased for the 75 overlap method and computation rate is not significantly decreased, we determined that the best overlap is 50 percent.

Table 1. Pixel percentage of each class in Miss USA

| overlap | class I | class Ⅱ | class Ⅲ |
|---|---|---|---|
| 0 % | 73.24 | 20.11 | 6.65 |
| 50 % | 85.49 | 10.29 | 4.22 |
| 75% | 88.59 | 7.56 | 3.85 |

Table 2. Pixel percentage of each class in Lena

| overlap | class I | class Ⅱ | class Ⅲ |
|---|---|---|---|
| 0 % | 25.49 | 45.89 | 24.62 |
| 50 % | 52.05 | 26.14 | 21.81 |
| 75% | 59.79 | 20.08 | 20.13 |

Table 3. Pixel percentage of each class in House

| overlap | class I | class Ⅱ | class Ⅲ |
|---|---|---|---|
| 0 % | 16.99 | 37.89 | 45.12 |
| 50 % | 24.26 | 30.26 | 45.48 |
| 75% | 29.48 | 26.37 | 44.15 |

## 2.2 Variability of $D_1$ and $D_2$

In this subsection, we examine the percentage of pixels within each class as a function of $D_1$ and $D_2$. Higher values of $D_1$ force more pixels into the perceived constant intensity class and generally there will be both a larger number of regions belonging to the perceived constant intensity class and more pixels per region. Lower values of $D_2$ produce more regions belonging to the rough texture class. We investigate the changes of the percentage in pixels within each class for the following values of $D_1$ and $D_2$. $D_1$ is the half of the sum of the maximum of the curve corresponding to the perceived constant intensity, $D_2$ is the half of the sum of the maximum of the curve corresponding to the smooth texture and the minimum of the curve corresponding to the rough texture, 2.021 is the maximum of the curve corresponding to the perceived constant intensity, 2.049 is the minimum of the curve corresponding to the smooth texture, 2.324 is the maximum of the curve corresponding to the smooth texture, and 2.408 are the minimum of the curve corresponding to the rough texture in our experiment. We examined the changes of the pixels of each class with 50% overlap since the 50% overlap was used for the proposed coding algorithm. The percentage of the pixels within each class with variation in $D_1$ and $D_2$ are given in Tables 4-9, and 6. These results show that higher values of $D_1$ produce more pixels belonging to the perceived constant intensity and lower values of $D_2$ produces more pixels belonging to the rough texture.

Table 4. Percentage of the pixels in each class in Miss USA with 50% overlap, $D_1$ variable and $D_2$ = 2.363.

| $D_1$ | class I | class II | class III |
|---|---|---|---|
| 2.021 | 76.70 | 18.40 | 4.88 |
| 2.035 | 85.49 | 10.27 | 4.22 |
| 2.049 | 90.62 | 5.88 | 3.49 |

Table 5. Percentage of the pixels in each class in Miss USA with 50% overlap, $D_1$ = 2.035 and $D_2$ = variable.

| $D_1$ | class I | class II | class III |
|---|---|---|---|
| 2.324 | 85.49 | 10.27 | 4.22 |
| 2.363 | 85.49 | 10.27 | 4.22 |
| 2.408 | 85.49 | 10.40 | 4.10 |

Table 6. Percentage of the pixels in each class in Lena with 50% overlap, $D_1$ variable and $D_2$ = 2.363.

| $D_1$ | class I | class II | class III |
|---|---|---|---|
| 2.021 | 30.51 | 44.79 | 24.68 |
| 2.035 | 52.05 | 26.14 | 21.80 |
| 2.049 | 65.89 | 15.23 | 18.87 |

Table 7. Percentage of the pixels in each class in Lena with 50% overlap, $D_1$ = 2.035 and $D_2$ = variable.

| $D_1$ | class I | class II | class III |
|---|---|---|---|
| 2.324 | 52.05 | 26.14 | 21.80 |
| 2.363 | 52.05 | 26.14 | 21.80 |
| 2.408 | 52.05 | 26.63 | 21.31 |

Table 8. Percentage of the pixels in each class in House with 50% cverlap, $D_1$ variable and $D_2$ = 2.363.

| $D_1$ | class I | class II | class III |
|---|---|---|---|
| 2.021 | 17.45 | 35.05 | 47.48 |
| 2.035 | 22.58 | 31.42 | 45.99 |
| 2.049 | 35.18 | 21.72 | 43.09 |

Table 9. Percentage of the pixels in each class in House with 50% overlap, $D_1$ = 2.035 and $D_2$ = variable.

| $D_1$ | class Ⅰ | class Ⅱ | class Ⅲ |
|---|---|---|---|
| 2.324 | 22.58 | 31.03 | 46.38 |
| 2.363 | 22.58 | 31.42 | 45.99 |
| 2.408 | 22.58 | 31.88 | 45.53 |

# 3. The proposed texture image segmentation

The definition fo of $D$ is a set for which the Hausdorff-Besicovich dimension is strictly greater than the topological dimension.[1,3] We consider object $X$ in an $E$-dimensional space. $N(\varepsilon)$ is the number of $E$-dimensional sphere of diameter $\varepsilon$ needed to cover $X$, where $E$ is an integer and the $E$-dimensional space is the minimum integer dimensional space among all possible integer dimensional spaces which can envelop $X$. Thus, if $N(\varepsilon)$ is given by

$$N(\varepsilon) = K \cdot \left(\frac{1}{\varepsilon}\right)^D, \quad as\ \varepsilon \to 0, \tag{1}$$

where $K$ is a constant and $X$ has Hausdorff dimension $D$. If $D$ is fractional, $D$ is also called the fractal dimension. For fractal objects, $D_1$ is independent of $\varepsilon$.

The goal of the image segmentation process is to decompose an image into texturally homogeneous regions with respect to the degree of roughness as perceived by the HVS. Textural regions are classified into three classes; class Ⅰ, class Ⅱ, and class Ⅲ. For example, the background in a head and shoulder image or the sky in a natural image is considered as class Ⅰ, the face or the shoulder is considered as class Ⅱ, and the trees and the bushes in a natural image are considered as class Ⅲ. To extract texture information for accomplishing textural-based image segmentation, the fractal dimension $(D)$, mean, and just noticealbe difference (JND) are used in the segmentation algorithm. The segmentation algorithm is based on a region growing technique. A unique of feature of the region growing process used in this research is that it is directed by the texture feature distance between image blocks. The region growing is achieved through a merging test condition between texturally homogeneous neighboring blocks. If the condition for merging is satisfied, an observing block can be merged into a neighbor block. Otherwise, a new region is declared.

For our segmentation, we have used a centroid linkage region growing method because it is gauranteed to produce disjoint segments with close boundaries and provides a sequential algorithm for growing region. The controid linkage region growing method is illustrated in paper.[4] The texture features are used the mean, JND, and the class type based on $D$ of the image block.

Incorporating the HVS and the fractal model, the proposed texture-based image segmentation algorithm for image coder is defined as follows.

Step 1) Divide the image into $NR \times NC$ blocks ( $NR$ and $NC$ are the numbers of row and column blocks, respectively).

Step 2) Calculate the feature set: the mean and the class type for each block and the JND lookup table.

Step 3) Calculate the distance between an observing block and its 4-connected neighboring blocks. The distance is given by

$$D(OB,NB) = \begin{cases} 0 & \text{if} \begin{cases} F(OB) < D_1,\ C(OB) = C(NB), \\ \mid M(OB) - M(NB) \mid < JND(OB,NB) \\ \text{or} \\ D_1 \le F(OB) < D_2,\ C(OB) = C(NB) \\ \text{or} \\ F(OB) \ge D_2,\ C(OB) = C(NB) \end{cases} \\ 1 & \text{otherwise} \end{cases}$$

where $F(OB)$ is $D$ of an observing block. $C(OB)$ and $C(NB)$ are the class types of an observing block and its neighboring block respectively. $M(OB)$ and $M(NB)$ are the means for an observing block and its neighboring block respectively. $JND(OB,NB)$

is JND between an observing block and its neighboring block.

Step 4) If there is a neighboring block with distance 0, then merge the observing block into it; else declare a new region. If there are more than two good neighboring blocks, merge the observing block into a neighboring block whose mean value is closest to the mean value of the observing block.

Step 5) Repeat step 3 to step 4 until all blocks are segmented and stop.

The proposed texture segmentation-based image coder system for the very low bit rate is given in detail in paper.[7,8]

## 4. Conclusions

Decoded images are obtained with $D_1$, $D_2$, and block size 8×8 for the proposed texture segmentation compression technique. The compression ratios for the two test images Miss USA and House are 0.11 and 0.21 bpp respectively.

These results indicate that, using the new texture-based segmentation image compression system, compression ratios in the neighborhood of 0.11 to 0.21 bpp are attainable with good image quality for the various imagery in very low bit rate.

One advantage of the proposed block by block method is that it allows more readily for compression ratio and image quality trade-offs. By varying parameter, the compression ratios can be easily controlled.

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