Peano key rediscovery for content based retrieval of images

Youssef CHAHIR and Liming CHEN
Laboratoire HEUDIASYC UMR CNRS 6599
Université de Technologie de Compiègne
Centre de Recherches de Royallieu
BP 20529, 60205 Compiègne Cedex, France
Fax : 33. 3.44.23.44.77 - Tel : 33. 3.44.23.43.02
E-mail: {chahir,chen}@hds.utc.fr

ABSTRACT

Currently the most content-based retrieval methods of images are based on global features like histograms. Few methods have considered the spatial information for the indexing and query purpose. In this paper we present an efficient multi-dimensional spatial indexing method based on the Peano key ordering of spatial locality of regions. The Peano order gives a direct mapping between an integer (Peano key) and its corresponding element in the multidimensional space. The position in the ordering (key) of each region in an image can be simply determined by interleaving the bits of the x and y coordinates of the region. In our method, global features of the query image like histograms of colors are first used to eliminate images in the database, which are not similar. Then the query is decomposed into a quadtree in order to extract characteristics, for instance predominant colors, associated with each square. These spatial information are identified by a list of Peano keys. This list constitutes a spatial signature of the query image. This spatial signature is researched into candidate images. For a given candidate image, each Peano key of the signature precisely indicates the spatial region whose characteristics are compared to the ones associated with the Peano Key. The main advantages of our method are twofold: first its generality since it allows to associate spatial information to every kind characteristics of images, second its efficiency because there is no need to pre-extract characteristics from images in the database.

Keywords: image indexing, Peano key, spatial locality, and content-based retrieval

1. INTRODUCTION

Content based image indexing is a key technology for a large scale use of multimedia documents. The objective of content-based image query is to efficiently find and retrieve images from the database that satisfy the criteria of similarity to the user's query image[1]. Most techniques proposed in the literature for the image content based retrieval are based on simple image features, such as color histograms [2], efficient indexing structures [3], and sometimes make use of pre-filtering techniques [4]. A more sophisticated feature like color coherence vectors may also be used for the indexing purpose[5]. However, these approaches have neglected two important criteria for similarity: spatial information and spatial relationships.

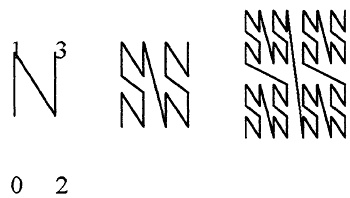
By representing images symbolically [6, 7], locations and spatial relationships of symbols have been used for the spatial queries evaluation. Unfortunately, these techniques cannot easily accommodate measures of similarity of the symbols such as visual features. Recently, there are some efforts trying to take into account the spatial information for the image retrieval purpose. For instance, VisualSEEK[8] project proposes the extraction of localized regions and features, and allows image querying by both global features and spatial information.

In this paper we present an efficient multi-dimensional spatial indexing method based on the Peano key ordering of spatial locality of regions. Our method consist of the following steps : first the query image is decomposed into a quadtree, then homogeneous regions are automatically detected according to a chosen criteria such as visual features, and they are finally framed by Minimum Bounding Rectangles which are localized by a Peano-keys. The list of these Peano-keys associated with the extracted spatial visual features gives a spatial signature of the query image which is compared with images of the base.

Section 2 gives a survey of space filling curves. Section 3 introduces our four criteria for the quadtree decomposition process. In section 4 we present our homogeneous region segmentation method according to visual features based criteria, and the way homogeneous regions are spatially localized. Experimental results and some concluding remarks are given in section 5.

2. SPACE-FILLING CURVES

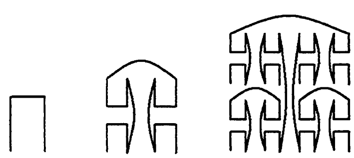
The basic Peano curve for a 2*2 grid, denoted N_1 is shown in Figure 1. The higher orders of the Peano curve are derived by replacing each vertex of the basic curve with the previous order curve. Fig. 1 also shows the Peano curves of order 2 and 3.



N_1 N_2 N_3

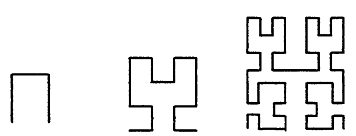
Fig. 1 Peano curves of order 1,2, and 3

Fig. 2 and Fig. 3 respectively show the reflected binary gray-code curve and the Hilbert curves of orders 1,2 and 3.



R_1 R_2 R_3

Fig.2 Reflected binary gray-code curves of order 1,2, and 3



H_1 H_2 H_3

Fig. 3 Hilbert curves of order 1,2, and 3

The basic reflected binary gray-code curve and the basic Hilbert curve of a 2*2 grid are denoted $R_1$and H_1. The path of a space-filling curve imposes a linear ordering, which may be calculated by starting at one end of the curve and following the path to the other end.

It is well known that the Hilbert curves are better than Peano curves since they require fewer clusters, generates a better distance-preserving mapping, and achieve better results than Peano curves for processing range and nearest neighbor queries [9]. Nevertheless, Peano curves are used in our work for the moment because of its simplicity.

The Peano-keys (z-values) of the two-dimensional Peano curve is simply calculated by the following algorithm :

- Read the binary representation of the x and y coordinates
- Interleave the bits of the two binary numbers into one string (key).

x = 0 0 0 1 y = 0 1 1 0 point (1,6)

key = $(0\ 0\ 0\ 1\ 0\ 1\ 1\ 0)_2 = (22)_{10}$

Fig.4 Bit interleaving

- Calculate the decimal value of the resulting binary string.

Fig.4 gives an example which illustrates the algorithm. Higher dimensions of the Peano curve are calculated in a similar way.

3. QUADTREE DECOMPOSITION

Following the quadtree literature the address space is a square, called an image, and it is represented as a $2^K \times 2^K$ array of 1 x 1 squares [10]. Each such square is called a pixel.

Each node of a quadtree corresponds to a block in the original image. Each block (node) has four edges NW, NE, SW, and SE. Figure 5 illustrates these labeling.

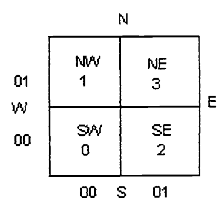


Fig. 5 – quadtree block labeling

The edges are labeled with 2-bit binary strings, where the first bit indicates the horizontal direction ('left/right', for '0/1' respectively) and the second bit indicates the vertical direction ('down/up', for '0/1' respectively). Let the directions NW, NE, SW, and SE be represented by 0, 1, 2, and 3, respectively. For example:

NE = $(0\ 0\ 1\ 1)_2 = (3)_{10}$

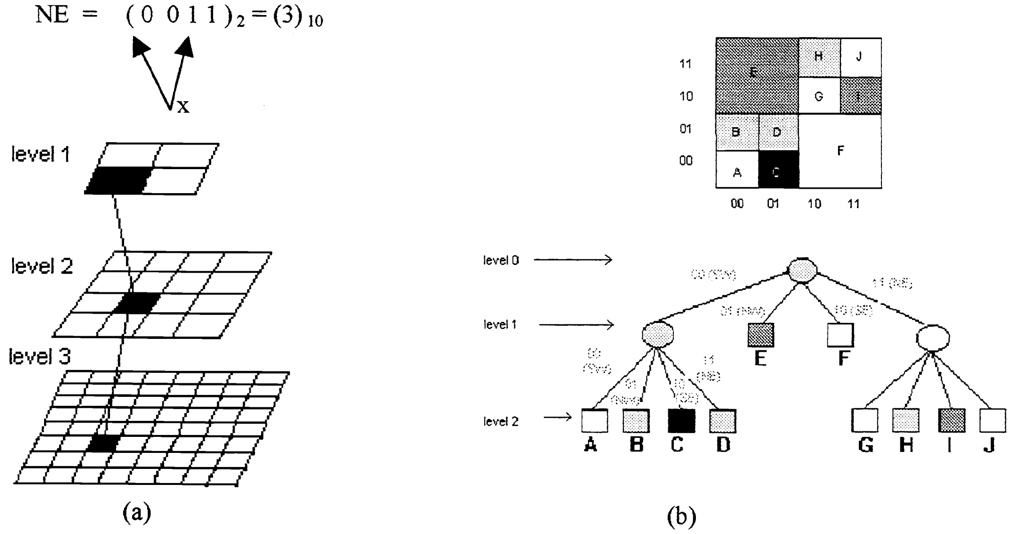


Fig.6 - An image and its quadtree

The chain code of a level-k block is the concatenation of the labels of the edges, from the root to the node of the quadtree that corresponds to this level-k block. For example, the leaf H is represented by the chain code "31" = 1101. As described above, the lengths of the chain codes indicate the level of the tree (depth). The efficient way to obtain the quadtree decomposition is by recursively dividing the image into blocks, until they are homogeneous or until we reach the pixel level. The result of such decomposition is a 4-way tree, which is termed as the region quadtree [11].

This recursive decomposition process is driven by one or several homogeneity threshold test. If the considered quadrant has a value superior than the fixed threshold, then the decomposition process is reiterated. The following four test may be used for the decomposition process :

- Radiometric test : test of difference between gray levels maxi and mini of the square. The principle consists of calculating the radiometric gap of the zone to be decomposed, to compare this gap to a fixed radiometric threshold.
- Entropy test : it allows to measure the quantity of information brought by a given color in an image. The entropy of an image is defined by the average quantity of information brought by each level on the totality of the image: $E = \sum p_i Q_i$, where: $Q_i = -\log_2(p_i)$, p_i is the probability of appearance of the level i.
- Statistical test: similar to the test of entropy, but now it is the variance of the quadrant which is used for the test.

$$V = \frac{1}{N}\sum_{i=0}^{n}(X_i - \overline{X})^2$$

- Test of the filling rate of a dominant color in the square. Actually, one compares the rest of the area with the threshold. Blocks that are full/partially filled are represented by their dominant colors in the quadtree. Thus the color of a node gives the dominant color which may be used in the retrieval purpose.

The advantage of our quadtree based approach lies in the possibility to approximate an image by its quadtree representation with a level k' largely inferior than the final decomposition. For instance, the level-1 quadtree, in Fig.6, gives an approximate image with 4 blocks : two leaves E (black) and F (white) and two nodes gray and white, or with 7 blocks: 4 leaves (A, B, C and D), 2 leaves (E and F) and white node.

4. SPATIAL IDENTIFICATION OF REGIONS

In this section, we first define visual attributes defining the similarity of colors. Then according to the color homogeneity criterion, a list of blocks having the same or close color is derived from the quadtree of an image. A minimum bounding rectangle is then associated with each such list, giving a homogeneous region. Finally each region is spatially localized by a Peano-key which corresponds to the center of gravity.

4.1 Color segmentation using perceptual attributes

The HSV color space is natural and approximately perceptually uniform. Therefore, we use a quantization of the HSV to produce a compact set of (166) colors. In practice, the dimension of the color histogram is reduced from 256 to 166 [8]. Thus each image is transformed from RGB to HSV. Let (r_i,g_i,b_i) be a color point in RGB space and (h_i,s_i,v_i) be the transformed color point in HSV color space. The similarity between two colors (h_i,s_i,v_i) and (h_j,s_j,v_j) is given by:

$$a_{ij} = 1 - 1/\sqrt{5[(v_i - v_j)^2 + (s_i \cos h_i + s_j \cos h_j)^2 + (s_i \sin h_i - s_j \sin h_j)^2]}$$

4.2 Connected component constitution

The quadtree representation of an image allows the use of split and merge techniques for the connected component identification. The metric used for this purpose between two squares (x_0,y_0,x_1,y_1) and (x'_0,y'_0,x'_1,y'_1) is the following :

$$d_{ij} = \sqrt{\left(\frac{x_0+x_1}{2} - \frac{x'_0+x'_1}{2}\right)^2 + \left(\frac{y_0+y_1}{2} - \frac{y'_0+y'_1}{2}\right)^2}$$

The construction of connected components is realized according to the following steps:

- a splitting process, which allows to divide an initial image into homogeneous blocs, and then a merging process, grouping these blocs according to criteria to obtain final homogeneous regions.
- from a square with a certain color, one visits all its neighbors in the eight directions. If the square neighbor possesses the same, or a close color then one adds it to the region.

A square is only visited once. Since the visit of a square neighbors is made in a recursive manner, we have made use of a pile for visited squares, so that they are only visited once. A square possessing the same characteristics and localized at a distances inferior to a threshold can be added to the region. Thus, a region contains all neighbors with a same or a close color.

In the beginning, each node is noticed by a key (chain code). Thus a region is defined by a list of keys of all nodes in the region. Each region is then framed by a minimum bounding rectangle (MBR) localized by a Peano key. This Peano key gives the spatial position of the center of gravity associated with the MBR. Recall that the MBR is the smallest vertically aligned rectangle that completely includes the region. Figure 7.a illustrates the MBRs for some image regions. The MBRs of the regions are indexed using an r-tree as illustrated in Figure 7.b. These MBRs overlap. The r-tree provides a dynamic structure for indexing these rectangles[12].

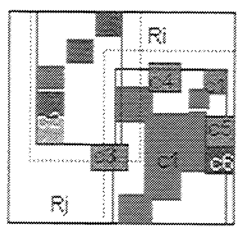


Fig.7.a Data rectangles organized in a r-tree

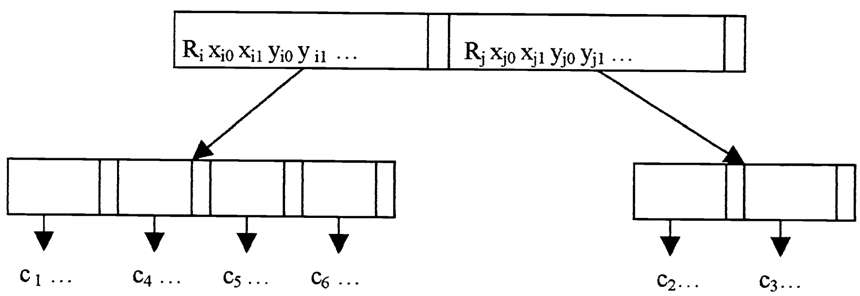


Fig. 7.b. The file structure for the previous R-tree

Figure 7

4.3 Spatial position of region

We consider two ways of representing the spatial position of regions: 2-D string[13] and spatial relations[6].

- Comparison by 2-D strings

Given a set of Peano keys V, an image is a mapping N x N, where N = {1,2,...,n}. Figure 8 shows an example of symbolic picture on V ={a,b,c,d,e,f}

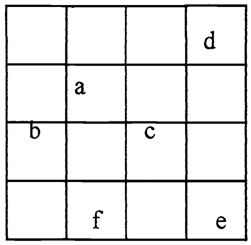


Fig.8

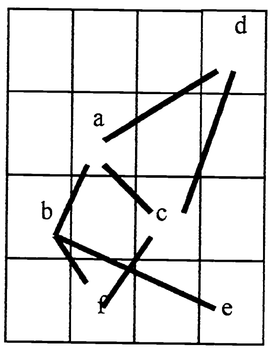
The 2-D string (u ,v) over V corresponding to this picture is:

(u ,v) = (b < f a < c < e d , f e < bc < a < d)

- Comparison by spatial relations

→	to the right
←	to the left
↑	up
↓	down

Some representations corresponding to the picture is :



b →, ↓ f

b →, ↑a

a →, ↓c

f →, ↑c

c →, ↑d

c →, ↓e

e ←, ↑b

a →, ↑d

Note that we can add others relationships.

Example : Figure 9 shows a simple image in the left and its connected components in the right.

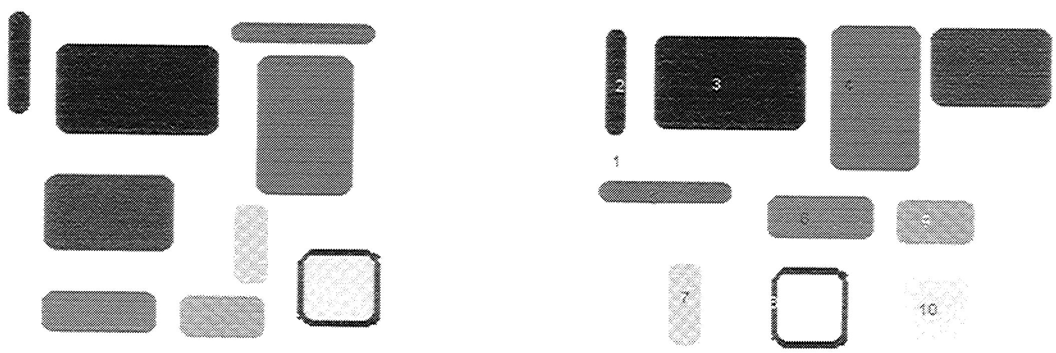


Fig.9

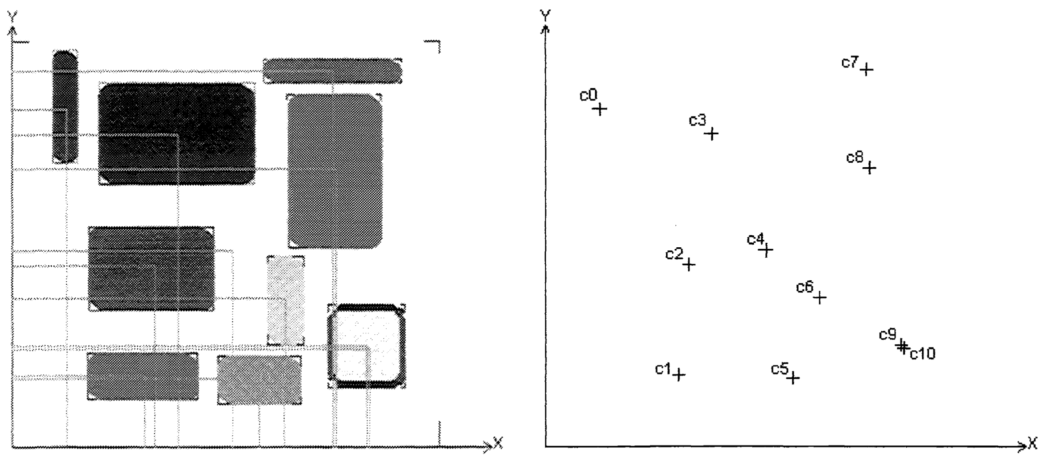


Figure 10

Figure 10 shows keys associated to each related component (minimum bounding rectangle corresponding). One can deduce this figure them these relations:

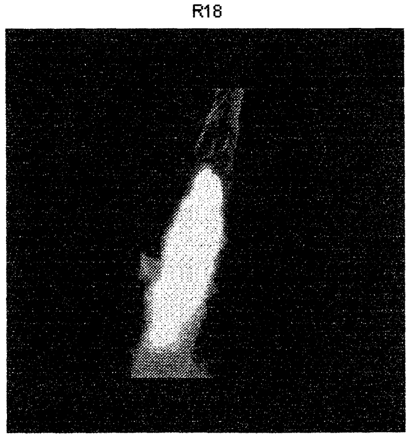
- 2-D Strings : we give in the following the 2-D string of the simple image illustrated in fig. 9

$$\begin{cases} c0 < c1 < c2 < c3 < c4 < c5 < c6 < c7 < c8 < c9 < c10 \\ c5 < c1 < c10 < c9 < c6 < c2 < c4 < c8 < c3 < c0 < c7 \end{cases}$$

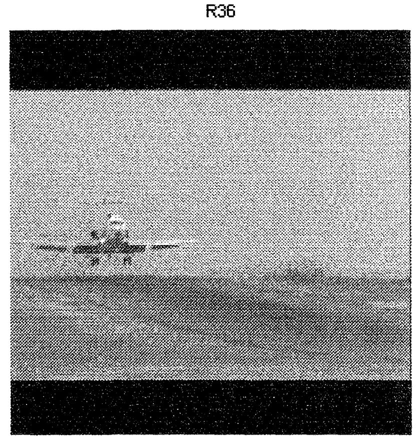
5. RESULTS AND DISCUSSION

Follow two images extracted from the movie An Indian in the city

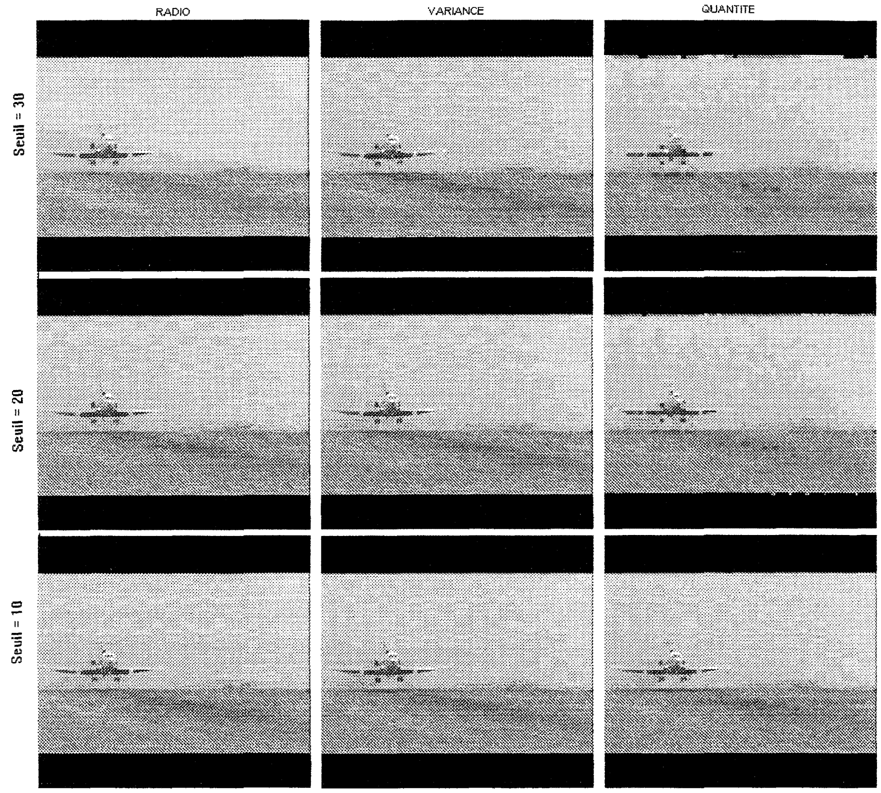
R18

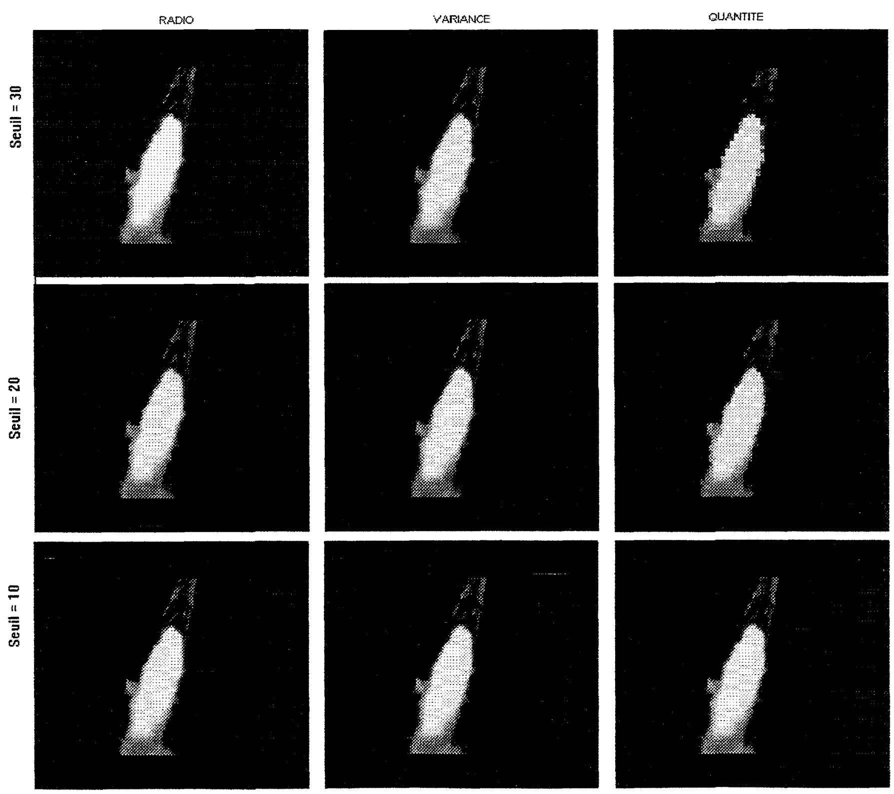


R36



Follow the quadtrees corresponding to these images with thresholds 10, 20, and 30 when RADIO, VARIANCE and QUANTITY tests are used. Radio means the radiometric test of difference between color gray maximum and the color gray minimum. Quantity means the test of the filling rate of the square.


RADIO
VARIANCE
QUANTITE
Seuil = 30
Seuil = 20
Seuil = 10


RADIO
VARIANCE
QUANTITE
Seuil = 30
Seuil = 20
Seuil = 10

RADIO

	10	20	30
I18	6718	3530	1068
I36	4211	4090	1034

QUANTITE

	10	20	30
I18	6713	5463	3133
I36	3511	448	248

VARIANCE

	10	20	30
I18	3035	1602	1274
I36	4298	4223	3958

Figure 11

RADIO

	10	20	30
I18	332	210	145
I36	182	175	79

QUANTITE

	10	20	30
I18	354	245	175
I36	145	92	54

VARIANCE

	10	20	30
I18	242	123	172
I36	187	163	101

Figure 12

Figure 11 shows the number of extracted connected components of images without taking into account neither close colors nor distances between squares. Figure 12 shows the number of related components by taking account similar colors (two first similar colors) and close squares ($<=2$ pixels). These results show the efficiency of our method which greatly reduces the number of connected components. In the most cases, isolated points i.e. connected components composed of 1element (square of 1x1 or square 2x2) are ignored.

In this paper, we have proposed a progressive regions extraction and their spatial identification method. Our techniques allow the reconstruction of initial image with or without approximation of the regions, using gray values or their dominant colors. Our method is general since it allows to associate spatial information with other features such texture for content based retrieval of images.

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