Adaptive spatio-colorimetric classification

M. Gouiffès
Laboratory IEF, University of Paris XI, CNRS UMR 8622
AXIS, Bat. 220 Campus Scientifique d'Orsay
91405 ORSAY Cedex, France.
michele.gouiffes@ief.u-psud.fr

Abstract

Unlike most color classification methods, which consist in partitioning the image according to the pixels color attributes exclusively, spatio-colorimetric techniques bring some spatial information directly among the data to classify. However, they usually involve some heavy data structures and a large amount of trichromatic data.

To answer this issue, this article proposes a color spatio-classification method performing two successive stages. First of all, the number of colors is lowered through an analysis of the connectedness degrees on the three marginal components independently. Since the number of colors is significantly reduced, it becomes reasonable, in a complexity point of view, to analyze the vectorial connectedness degrees of the trichromatic intervals. Several experimental results will be shown on different images and the method parameters will be discussed.

Keywords : color connectedness degree, unsupervised spatio-colorimetric classification.

Introduction

The *color classification* consists in partitioning the image exclusively upon the pixels color attributes, without any spatial information. Therefore, the criteria involved in the formal definition of the segmentation [9] are not respected, in particular concerning the connectedness. In order to answer to the segmentation problem, the classification is usually followed by a labeling procedure.

Using color classification to achieve a color partition assume either :

- that the pixels of a same region have similar colorimetric components, which cluster in the 3D color space. These methods are called *clustering* ;
- or that the color distribution in the color histogram show several modes of high density corresponding to pixels classes.

In a different way, Markovian processes can be used to iteratively maximize the membership probabilities of the pixels to a class according to their neighborhood in the image. The use of a maximization procedure is usually time-expensive, in particular for color.

In spatio-colorimetric methods, spatial or structural information is introduced upstream. These methods can be viewed as an improvement of color classification by use of spatial information extracted from the images structure.

For example, Ferri *et al.* [3] introduce shape and surface information in the data. They use a vector which directly include the components of the four neighbors pixels around the pixel to be treated. In a different way, neural networks strategies [6] can help favoring the assignation of adjacent pixels to the same cluster while avoiding the classification of one pixel to several clusters. Campadelli *et al.* [1] have extended this approach to color images. Let us also notice that the geometrical information can be introduced in fuzzy classification systems [8].

The spatio-colorimetric methods usually involve heavy data structures. As an example, the computation of 3D histograms requires a large memory (2^{3n} bins for an image coded on n bits), what explains that few techniques propose to analyze them. The pyramid of color connectedness degrees [5] provides a multi-scale analysis by computing a connectedness degree based on the cooccurrence probabilities for all possible color intervals in a bichromatic image. From a similar principle, Cheng *et al.* [2] define the *homogram* which considers a fuzzy homogeneity vector involving each pixel and its 8 neighbors. The classes are extracted through successive thresholdings of this data structure. Recently, a segmentation procedure based on spatial color compactness degree [7] has been proposed to get a bijective one-to-one relationship between color clusters and regions.

Our classification method is based on the connectedness degree defined by [5], which has been extended to color in [4]. Unlike this latter technique, our procedure does not involve any heavy 3D data structures, while carrying out a vectorial unsupervised classification. First, the number of colors is reduced by analyzing successively the connectedness degree of each color component, in a multi-scale approach. Once the distinguishable colors have been extracted, a second step computes all the possible combinations of color components (all of them do not necessarily occur in the image) and analyzes the trichromatic space in order to define the meaningful 3D color intervals.

This article is structured as follows. The first section focuses on the definition of the connectedness degree. Then, our procedure is detailed in the second section. To finish, some experimental results on the Kodak color images data base are reported in the third section.

The connectedness degree

Let us consider a trichromatic image of components $c_i = (c_1, c_2, c_3)$.

For each image channel histogram, we define the monochromatic color intervals $I(c_i, w) = [c_i - w, c_i + w]$ of size $2w+1$ centered on each value c_i.

The first order probability $P_1(I(c_i, w))$ is the probability that a pixel of color a belongs to the interval $I(c_i, w)$. It is computed as the sum of the first order probabilities $P_1(a)$ of the components a belonging to the considered interval :

$$P_1(I(c_i, w)) = \sum_{a \in I(c_i, w)} P_1(a) \tag{1}$$

We define the co-occurrence probability of two colors a, b as

$$P_{cc}(a, b) = \frac{1}{8} \sum_{a \in \mathcal{N}(b)} P_{oc}(a, b) \tag{2}$$

where $P_{oc}(a,b)$ is the probability that a and b are the colors of two neighbor pixels in the sense of 8-connectedness, the neighborhood being noted as $\mathcal{N}$. The second order probability $P_2(I(c_i,w))$ of the color interval $I(c_i,w)$ is computed as the sum of the co-occurrence probabilities of all color couples (a,b) belonging to $I(c_i,w)$.

$$P_2(I(c_i,w)) = \sum_{a\in I(c_i,w)} \sum_{b\in I(c_i,w)} P_{cc}(a,b) \quad (3)$$

Therefore, the connectedness degree [5] of a color interval $\mathcal{D}(I(c_i,w))$ is given as :

$$\mathcal{D}(I(c_i,w)) = \frac{P_2(I(c_i,w)}{P_1(I(c_i,w))} \quad (4)$$

This degree is assumed to be maximal when the interval $I(c_i,w)$ corresponds to one or several connected components in the image, *i.e* to a meaningful class in the sense of connectedness. In the seminal work [5], the connexity degree is analyzed through a multi-level data structure. The characteristics of the most relevant intensity classes are computed by extracting specific signatures in this representation. The extension to color has been published in [4], where a multi-level pyramid of connexity is computed for each bichromatic histogram. Three pyramids are then necessary to extract each meaningful color interval, which is not time-effective.

In order to reduce those limitations, our method operates through two stages : first of all, a marginal classification ; secondly, a vectorial classification carried out on a reduced amount of data.

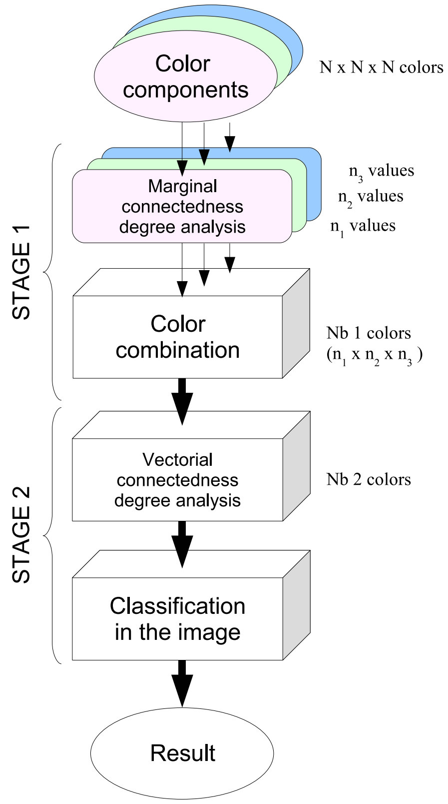


FIG. 1. *Flowchart of the procedure.*

The procedure

The flowchart of the algorithm is sketched on Fig. 1. Our procedure first reduces the number of distinguishable monochromatic colors for each color component c_i, by analyzing the monochromatic connectedness degrees separately on each color channel. The coordinates are then combined together in order to define the new set of colors. Once the number of colors have been reduced, the connectedness degree of the trichromatic intervals can be reasonably computed. This stage outputs the 3D color intervals which are the most relevant in the image. Of course, an additional stage can consist in labeling the resulting image in order to output a segmentation, where the smallest regions, usually associated to noise, can be removed if necessary.

1. First stage : marginal classification

1.1 Analysis of the monochromatic connectedness degree

First, an unsupervised classification is achieved independently on each color component c_i, by searching for local *maxima* of connectedness degree. For increasing values of w, more precisely from 1 to w_{max}, the connectedness degree $\mathcal{D}(I(c_i,w))$ is computed for each interval $I(c_i,w)$. When the connectness degree $\mathcal{D}(I(c_i,w+1))$ at a level $w+1$ becomes lower than the degree $\mathcal{D}(I(c_i,w))$ at the previous level then we can reasonably assume that the color interval $I(c_i,w)$ is a local maximum of connectedness. The corresponding size w_i is then given as :

$$w_i = \{w/\mathcal{D}(I(c_i,w+1)) < \mathcal{D}(I(c_i,w)), w < w_{max}\}$$

Therefore, the resulting interval $I_i = I(c_i,w_i) = [c_i - w_i, c_i + w_i]$ of connectedness degree $\mathcal{D}(I_i)$ is likely to correspond to the color range of a set of connected components in the image. As soon as this maximum is reached, the procedure is stopped for the actual color component c_i, and the corresponding color interval and degree are saved. The procedure continue since all the *maxima* $\mathcal{D}(I_i)$ for each c_i have been computed.

At that stage, a reasonably low value of w_{max} is required in order to avoid the appearance of two large clusters, leading to an over-clustering. This parameter value will be discussed in the experiments.

Fig. 2 illustrates this stage of the algorithm. Fig. 2(a) shows the values $\mathcal{D}(I_i)$ (in gray levels) with respect to the color component c_i and the size of interval w. The white corresponds to a high value, and the black corresponds to zero. For each bin c_i, the algorithm proceeds from the bottom to the top (increasing w) and stops when a local maximum (in white) has been reached or when $w = w_{max}$. Fig. 2(b) sketches in red points the local *maxima* finally extracted.

Once the intervals have been extracted separately on each image channel, they have to be combined in order to get a reduced number of vectorial values.

1.2. Reduction and combination of the colors

At that stage, each monochromatic interval I_i have inherited three values : the central color component c_i, the length w_i and the degree $\mathcal{D}(I_i)$.

a) Reduction of the monochromatic components

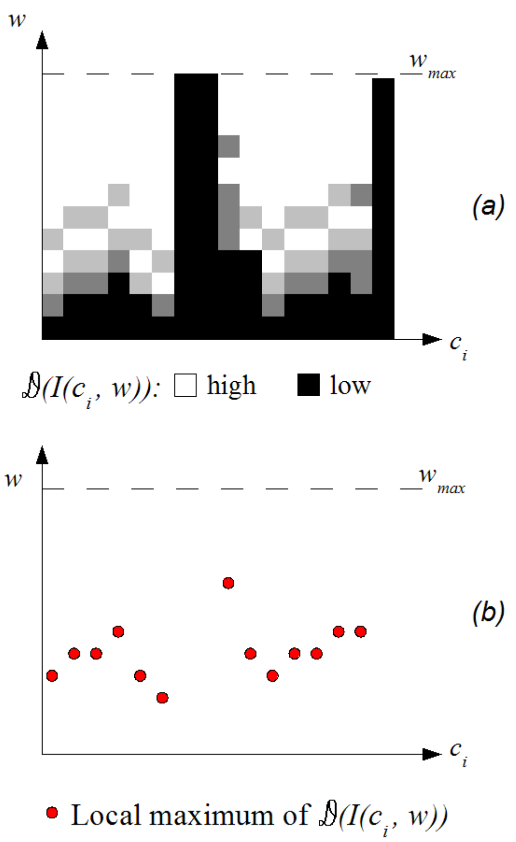


FIG. 2. *First reduction of the amount of colors. (a) Monochromatic connectedness degree. (b) Detection of the local maxima.*

These intervals are sorted in decreasing values of degree, in order to to be processed from the most relevant one (probably associated to some meaningful regions in the image) up to the least relevant one (probably associated to noise). In Fig. 3, the interval $I_a = [a - w_a, a + w_a]$ is assumed to be more relevant than I_b and I_c.

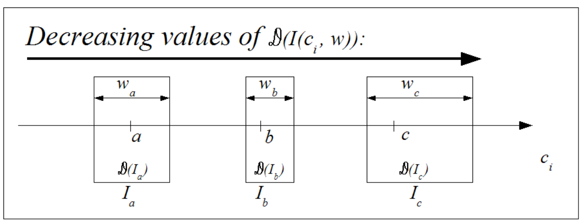


FIG. 3. *Intervals are sorted in decreasing order of connectedness degrees.*

Successively, each color component belonging to the interval I_i inherits the color of its centroid c_i, the most relevant interval being analyzed first. In Fig. 3, I_a is processed before I_b and I_c. Of course, since the color intervals of two contiguous intervals can overlap, a color component previously labeled in a more relevant interval can not be changed by a less relevant interval. In Fig. 3, if color $d \in I_a$ and $d \in I_b$, d will get the value a.

At that stage, the number of colors is reduced independently on each channel. They have to be combined together in order to define the new vectorial values.

b) Combination and computation of the vectorial values

The marginal components are combined together in order to extract all the possible vectorial values. Each color combination $\boldsymbol{c}_n$, for $n = 1..N$ gets the color value $\boldsymbol{c}(n) = (c_1(n), c_2(n), c_3(n))$ and the sizes of the corresponding marginal intervals.

2. Second stage : vectorial classification

2.1. Analysis of the trichromatic connectedness degrees

The second stage of the method analyzes the colors $\boldsymbol{c}_n$ in a similar fashion to the first stage of the algorithm, except that $3D$ intervals are now considered.

a) Connectedness degree of colors

Let us define a cubic color interval $\boldsymbol{I}(\boldsymbol{c}_n, d)$ in the color space, centered around the color $\boldsymbol{c}(n)$ and of size $(2d+1, 2d+1, 2d+1)$:

$$\begin{aligned} \boldsymbol{I}(\boldsymbol{c}_n, d) \quad = \quad & ([c_1(n) - d, c_1(n) + d], \\ & [c_2(n) - d, c_2(n) + d], \\ & [c_3(n) - d, c_3(n) + d]) \text{ for } n = 1..N \end{aligned} \tag{5}$$

A spherical interval around the central color $\boldsymbol{c}_n$ of the interval should allow an isotropic distribution of the distances to the centroid color. On the other hand, the use of cubic intervals ensure a total and straightforward partition of the RGB cube.

The first order probabilities $P_1(\boldsymbol{I}(\boldsymbol{c}_n, d))$ of the colors intervals $\boldsymbol{I}(\boldsymbol{c}_n, d)$ are expressed as :

$$P_1(\boldsymbol{I}(\boldsymbol{c}_n, d)) = \sum_{\boldsymbol{a} \in \boldsymbol{I}(\boldsymbol{c}_n, d)} P_1(\boldsymbol{a}) \tag{6}$$

where $P_1(\boldsymbol{a})$ is the occurrence probability of the color $\boldsymbol{a}$.

The second order probabilities $P_2(\boldsymbol{I}(\boldsymbol{c}_n, d))$ of the colors intervals $\boldsymbol{I}(\boldsymbol{c}_n, d)$ are computed as :

$$P_2(\boldsymbol{I}(\boldsymbol{c}_n, d)) = \sum_{\boldsymbol{a} \in \boldsymbol{I}(\boldsymbol{c}_n, d)} \sum_{\boldsymbol{b} \in \boldsymbol{I}(\boldsymbol{c}_n, d)} P_{cc}(\boldsymbol{a}, \boldsymbol{b}) \tag{7}$$

where the co-occurrence probabilities $P_{cc}(\boldsymbol{a}, \boldsymbol{b})$ of two colors $\boldsymbol{a}$ and $\boldsymbol{b}$ are computed as :

$$P_{cc}(\boldsymbol{a}, \boldsymbol{b}) = \frac{1}{8} \sum_{\boldsymbol{a} \in \mathcal{N}(\boldsymbol{b})} P_{oc}(\boldsymbol{a}, \boldsymbol{b}) \tag{8}$$

considering the 8-connexity and a neighborhood $\mathcal{N}$ around $\boldsymbol{b}$.

Finally, the connectedness degree $\mathcal{D}(\boldsymbol{I}(\boldsymbol{c}_n, d))$ of the interval $\boldsymbol{I}(\boldsymbol{c}_n, d)$ is defined as :

$$\mathcal{D}(\boldsymbol{I}(\boldsymbol{c}_n, d)) = \frac{P_2(\boldsymbol{I}(\boldsymbol{c}_n, d))}{P_1(\boldsymbol{I}(\boldsymbol{c}_n, d))} \tag{9}$$

b) Analysis of the connectedness degrees of colors

The analysis of the connectedness degrees is similar to the analysis carried out in the first stage of the procedure. The degrees are analyzed in a similar structure as Fig. 2, but with abscissa $\boldsymbol{c}_n$ and ordinates d.

For each color $\boldsymbol{c}_n$, increasing sizes of cubic intervals $d = 1$ to d_{max} are successively considered. The optimal color interval size

d_n associated to the color $\boldsymbol{c}_n$ is obtained when the connectedness degree reaches the first local maximum :

$$d_n = \{d / \mathscr{D}(\boldsymbol{I}(\boldsymbol{c}_n,(d+1))) < \mathscr{D}(\boldsymbol{I}(\boldsymbol{c}_n,d)), d \leq d_{max}\}$$

The procedure stops when the values d_n has been computed for all the colors $\boldsymbol{c}_n$.

Each outputted color interval $\boldsymbol{I}_n = \boldsymbol{I}(\boldsymbol{c}_n, d_n)$ inherits three values : the centroid color $\boldsymbol{c}_n$, the size of the interval d_n and the connectedness degree $\mathscr{D}(\boldsymbol{I}_n)$.

2.2 Final classification

Similarly to the stage 1, the colors belonging to an interval $\boldsymbol{I}_n$ successively gets the centroid color value of this interval, *i.e* $[c_1(n), c_2(n), c_3(n)]$. Beforehand, the colors $\boldsymbol{c}_n$ are sorted in the decreasing order of connectedness degree $\mathscr{D}(\boldsymbol{I}_n)$, in order to cluster the colors from the most relevant color interval to the less relevant one. This stage is illustrated on Fig. 4. Interval $\boldsymbol{I}_a$ will be classified before $\boldsymbol{I}_b$ and $\boldsymbol{I}_c$. Therefore if a color $\boldsymbol{c}$ is clustered in $\boldsymbol{I}_a$, it will not be treated anymore.

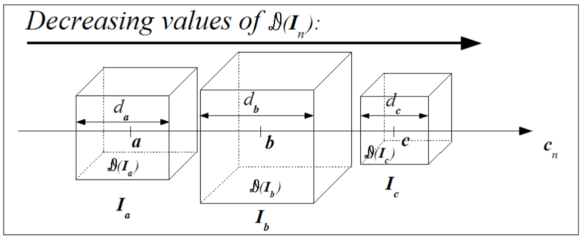


FIG. 4. *3D intervals are sorted in decreasing order of connectedness degrees.*

Results

In this section, the classification proposed in this article is analyzed qualitatively on the images *Window*, *Parrots* and *Caps* of Fig. 6. These images belong to the Kodak image data base available on the web [1]. In the experiments, their size has been reduced twice.

First of all, let us consider the RGB representation of the images. In the first stage of the algorithm, the monochromatic histograms and the associated first order probabilities $P_1(c_i)$ are computed. As an example, the first row of Fig. 5 sketches the three monochromatic R, G and B histograms of the image *Window*. Second, we compute the local *maxima* of monochromatic connectedness degrees $\mathscr{D}(I_i)$ for each color component (see the bottom row of Fig. 5). Each maximum corresponds to a given relevant monochromatic interval I_i.

In these experiments, the parameters used for maximum sizes of intervals are fixed around ten percent of the image dynamic, *i.e* $w_{max} = d_{max} = 25$. We can notice on Fig. 5 that a high probability $P_1(c_i)$ usually involves a high $\mathscr{D}(I_i)$ value. Indeed, the peaks in the histograms mostly correspond to a set of connected components in the image. Inversely, a high $\mathscr{D}(I_i)$ does not always correspond to a mode in the histogram. Indeed, this degree stresses the amount of connectedness independently from the amount of pixels. When no local maximum is extracted, the final size is w_{max} or 0 depending on the connectedness degree.

[1]http ://r0k.us/graphics/kodak/index.html

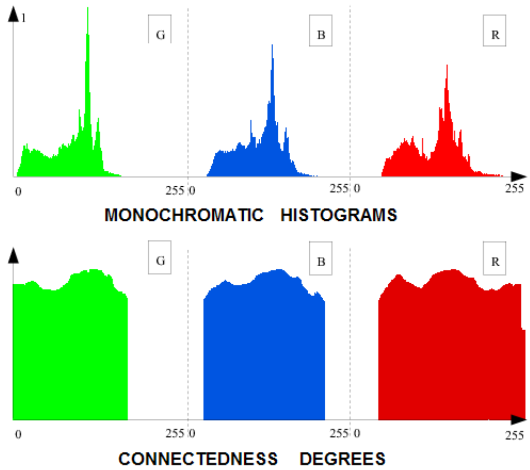


FIG. 5. *Monochromatic histograms $P_1(c_i)$ and connectedness degrees $\mathscr{D}(I_i)$ computed on image Window in the RGB space.*

At that stage, the number of colors of the image *Window* is reduced to 576 trichromatic values $\boldsymbol{c}_n$ after combination. Indeed, $n_1 = 9$ classes have been extracted on R, $n_2 = 8$ on G, $n_3 = 8$ on B. The resulting classification image is shown on Fig. 8(a). On image *Parrots*, $n_1 = n_2 = 9$ and $n_3 = 8$, leading to the combination of 648 possible colors $\boldsymbol{c}_n$. This result is shown on Fig. 8(b).

The trichromatic connectedness degree is then analyzed on the components $\boldsymbol{c}_n$. As an example, the first row of Fig. 7(b) shows the local *maxima* of the trichromatic connectedness degrees $\mathscr{D}(\boldsymbol{I}_n)$, computed on *Window*. The corresponding sizes d_n are shown on the second row. Note that no result appears for a few values $\boldsymbol{c}_n$. Indeed, these colors have been computed by combination at the stage 1, but they do not occur in the image. At that final stage, 27 classes have been extracted on *Window* and 35 classes on *Parrots*. Fig. 8(c) and 8(d) (second row) show respectively the classification results obtained on these two images. Besides, Fig. 8(e) and 8(f) (third row) show the contours (in white) of the connected components. Note that the classification procedure leads to the appearance of wide spatial homogeneities in the image.

The procedure has been executed on the whole Kodak image data base (23 images), with different values w_{max} and d_{max}, in order to evaluate the impact of these parameters on the classification results. For comparison criteria, we consider the number of colors computed at the first and second stage, respectively Nb 1 and Nb 2, and the execution times in seconds. The average, minimum and maximum values of these comparison criteria are collected in Table 1. Concerning the computation times, they are indicated for comparison purpose. No specific algorithmic optimization has been carried out and the computer used has one processor Intel(R) T2300 1.66 Ghz with a 1Go RAM memory. The first three tables correspond to the results computed from the RGB images. First of all, let us compare the first two tables, obtained respectively with $d_{max} = 25$ and 50 and $w_{max} = 25$. Note that the execution times increase with a high value d_{max}, since a large number of 3D intervals have to be analyzed. However, the classification results are not significantly improved, according to the number of classes Nb 2.

The second stage of the procedure reduces 18 times the number of color in average with $w_{max} = 25$ and $d_{max} = 50$ and

Window Parrots Caps

FIG. 6. *Initial RGB images from the Kodak color image data base.*

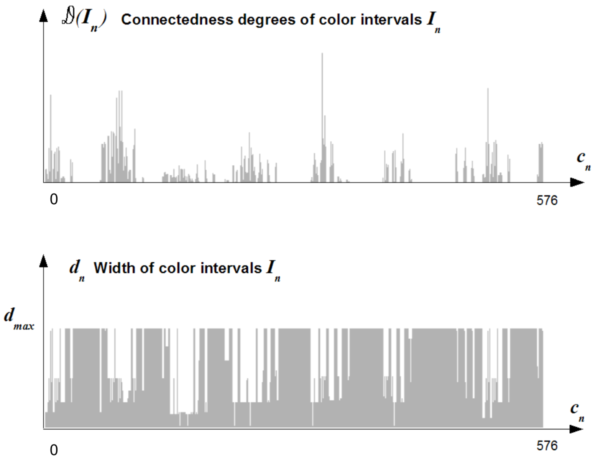


FIG. 7. *Connectedness degrees of 3D intervals $\mathcal{D}(I_n)$ and their associated sizes of interval.*

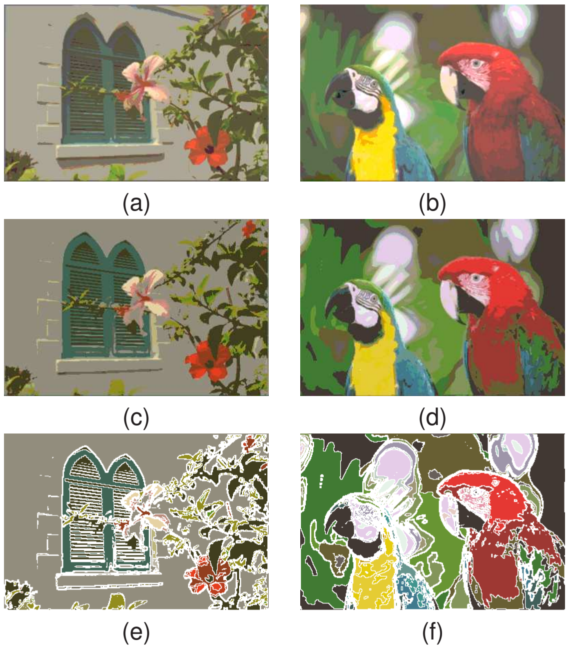


FIG. 8. *Classification results for the images Window (left column) and Parrots (right column) in the RGB space.*

17 times with $w_{max} = 25$ and $d_{max} = 25$.

The third table collects the results for $w_{max} = 15$ and $d_{max} = 50$. Obviously, a large number of color combinations is extracted at the first stage. Consequently, the total computation times increase significantly. The second stage of the algorithm decrease the number of colors 30 times in average, but it finally leads to a large number of classes (see Nb 2).

Fig. 9 illustrates the results outputted for the different values w_{max} and d_{max} on *Caps*. Obviously, the results for $d_{max} = 25$ and $d_{max} = 50$ are qualitatively similar ($w_{max} = 25$), while the computation time is twice lower with $d_{max} = 25$. The values $w_{max} = 15$ and $d_{max} = 50$ lead to an over-classification (132 classes).

Thus, to ensure a good trade-off between effectiveness and computation times, w_{max} and d_{max} can be fixed reasonably around 10 % of the initial range.

The last results of Table 1 are computed in the HSV representation, for w_{max} and d_{max} around 10 % of the range. The execution times are significantly reduced compared to the RGB space. Indeed, the analysis of the connectedness degrees provides a lower number of marginal classes. It is well known that the HSV space some more homogeneous regions than in RGB space, especially on the hue component (material homogeneity, independent from shadows and specular reflection). Therefore less data have to be processed at the second stage. However, because of the non-correlated HSV components, the stage 2 is less effective than in the RGB space. Fig. 10 illustrates some results obtained from the HSV representation of *Caps*. For display purpose, the Hue, Saturation and Value components are represented on the R, G and B channels respectively. Note on Fig. 10(c), that with $w_{max} = 40$ and $d_{max} = 40$, the classification provides both the subtraction of most shadows and the extraction of material homogeneities.

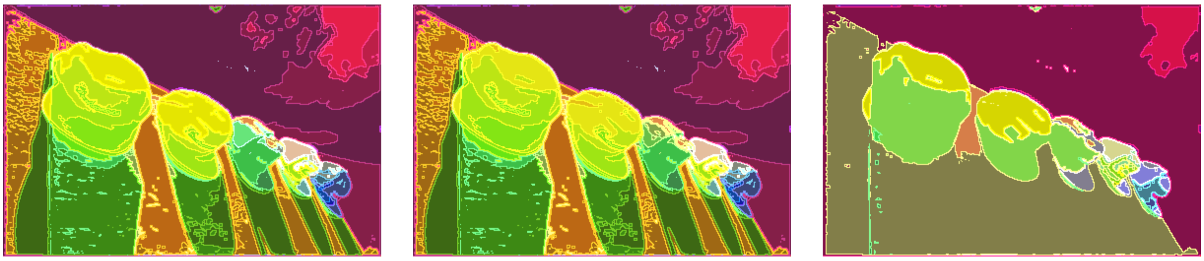
Conclusion

We have designed a two-stages classification procedure based on the color connectedness degrees. It first reduces the number of distinguishable monochromatic colors for each color channel by analyzing the marginal connectedness degree. Then, the resulting color components are combined together in order to define the new set of colors, significantly reduced compared to the initial set (in general 255^3 possible colors). Once the number of colors have been reduced, the connectedness degree of the trichromatic intervals can be reasonably computed. This method has been evaluated qualitatively and quantitatively on the Kodack image data base. It provides the extraction of homogeneous regions in the image. Besides, the parameters involved are not critical, they can be reasonably fixed to 10 % of the color range.

In future works, it will be applied to road segmentation for a car driven-assistance application.In addition, this approach can be extended to other type of data, such as velocity components

(a) (b) (c)

FIG. 9. *Evaluation of the parameters on the image Kodim04 in RGB space. (a)* $w_{max} = 25$, $d_{max} = 50$*, 45 classes, 7.3 sec. (b)* $w_{max} = 25$, $d_{max} = 25$*, 46 classes, 3.02 sec. (c)* $w_{max} = 15$, $d_{max} = 50$*, 132 classes, 24.8 sec.*



(a) (b) (c)

FIG. 10. *Evaluation of the parameters on the image Kodim04 in HSV space. (a)* $w_{max} = 25$, $d_{max} = 50$*, 58 classes, 3.92 sec. (b)* $w_{max} = 25$, $d_{max} = 25$*, 58 classes, 6.25 sec. (c)* $w_{max} = 40$, $d_{max} = 40$*, 24 classes, 3.82 sec.*

for motion analysis.

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(a) Results on the Kodak images in the RGB space with parameters $w_{max} = 25$ and $d_{max} = 50$.

	Nb 1	Nb 2	Mean time (in sec.)
Minimum	336	15	6,73
Maximum	968	64	24,81
Mean	598,7	32,8	12,70

(b) Results on the Kodak images in the RGB space with parameters $w_{max} = 25$ and $d_{max} = 25$.

	Nb 1	Nb 2	Mean time (in sec.)
Minimum	336	15	3,02
Maximum	968	69	21,08
Mean	598,7	35,4	7, 20

(c) Results on the Kodak images in the RGB space with parameters $w_{max} = 15$ and $d_{max} = 50$.

	Nb 1	Nb 2	Mean time (in sec.)
Minimum	1560	28	21,09
Maximum	3136	153	49,30
Mean	2178,3	71,18	35,15

(d) Results on the Kodak images in the HSV space with parameters $w_{max} = 25$ and $d_{max} = 25$.

	Nb 1	Nb 2	Mean time (in sec.)
Minimum	160	20	2,72
Maximum	567	66	10,07
Mean	377,5	50,77	4,3

Table 1. Classification results computed on the Kodak color image data base (23 images). The tables collects the minimum, maximum and average values of three criteria : the total number of combined colors computed by the marginal analysis of the connectedness degrees (Nb 1), the final number of classes available in output of the analysis of the vectorial connectedness degree (Nb 2), and the executing times.