A color morphological segmentation

Olivier Lezoray, Abderrahim Elmoataz, Hubert Cardot, Marinette Revenu

A COLOR MORPHOLOGICAL SEGMENTATION

O. Lezoray[1], A. Elmoataz[1,2], H. Cardot[1] and M. Revenu[2]

[1]: LUSAC,
EIC, B.P 78,
Site Universitaire,
50130 Octeville, FRANCE
Olivier.Lezoray@info.unicaen.fr
Hubert.Cardot@greyc.ismra.fr

[2]: GREYC-ISMRA,
6 Bd. du marechal Juin,
14050 Caen Cedex, FRANCE
Abder.Elmoataz@greyc.ismra.fr
Marinette.Revenu@greyc.ismra.fr

ABSTRACT

In this paper we propose to use the classic framework of a morphological segmentation. Each step of the framework involves the utilization of image analysis operators. We propose some new operators operating on the color of the image (the simplification, the gradient, the watershed and the region fusion). The segmentation method is illustrated by experimental results.

Keywords: *Color, Segmentation, Mathematical Morphology, Watershed, Fusion.*

1. INTRODUCTION

Color image processing has become a very active field of research during the last years. But the literature is not as important as for gray-scale image. Color being directly and naturally attached to the regions of an image, a color segmentation method might give better results than monochromatic segmentation methods [9]. Color segmentation addresses problems related to the representation and the processing of color. Many color segmentation algorithms can be found in the literature. One can mention the histogram analysis [4], the pixel classification [7] and the region growing methods [12]. A more precise review is given in [2]. In this article, we are interested in color morphological segmentation. Mathematical morphology methods are very appropriated for complex images, which is the case of color images in general. In the next section we present a color morphological segmentation which is based on four steps. Finally, we give experimental results on real images.

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2. COLOR MORPHOLOGICAL SEGMENTATION

The structure of a morphological segmentation is given in four steps [11]:

① Simplification. Simplification of an image consists in a pre-treatment phase which aim is to simplify the image. Simplification can consist in a smoothing of the image using filtered regularization. Connected operators based on morphological reconstruction can eliminate details or objects according to size, shape or color criteria.

② Marker extraction. Marker extraction is the growing initialization step and is dedicated to a imprecise extraction of the objects. Operators allows to partially extract the objects without a precise localization at the location of the boundaries. This step marks up the seeds, i.e. the points at which the growing will begin.

③ Watershed growing. Using the markers previously extracted, the watershed [14] performs a growing using color information. This enables the obtaining of regions corresponding to the objects in the image.

④ Region fusion. In the case of over-segmentation, regions are merged according to a merging criterion. This latter can be based on size, shape or color and can be performed by an energy minimization or a recursive step.

We propose to use this classic framework to segment color images. The innovation of this paper relies in the the operators used : the image simplification, the new color aggregation function for the watershed.

2.1. Simplification

The simplification of a color image has to increase the global contrast. We propose to use a recursive contrast filter to simplify the images (as in [3]). The aim is to sharpen the color transitions. For a pixel p, V_p denotes the adjacent pixels for a B neighborhood. We define two morphological operators S_1 and S_2 by :

$$S_1(p) = Sup_{\theta \in [0,\pi]}(Min_{B_\theta}(V_p))$$

$$S_2(p) = Inf_{\theta \in [0,\pi]}(Max_{B_\theta}(V_p))$$

in each direction θ of the B filter (3×3 for us). S_1 is the minimum of dilatations by linear structuring element B in the directions of 0, 45, 90 and 135 degrees. S_2 is the maximum of erosions by linear structuring element B in the same directions. The simplification operator S is defined as follows :

$$S(p) = \frac{S_1(p) + S_2(p)}{2} \quad \text{if} \quad \|S_1 - S_2\| < K$$

$$S(p) = p \quad \text{otherwise}$$

with K a contrast value corresponding to the contrast not to preserve. The filter S is recursively applied for n iterations. This simplification increases the global contrast of the color image and smooth it.

However, since we are working with color images, the order used to compare pixel vectors (for the calculation of the max and the min) has to be defined. We propose to use the lexicographical order (denoted by $\ll$). This ordering is a total ordering : an ordering on a set E defined by the relation $\ll$ is total if two vectors of E are always comparable :

$$\forall (X, Y) \in E^3$$

$$\text{one has } X \ll Y \text{ or } Y \ll X \text{ or both if } X = Y$$

The lexicographical order is defined (for color vectors) by :

$$\forall (X,Y) \in E^3 \times E^3, X \ll Y \Leftrightarrow$$

$$\exists k \in \{1,2,3\} / \quad X_i = Y_i \quad \forall i \in \{1,2,3\}$$

$$X_k < Y_k$$

with $E = \{0, ..., 255\}$.

2.2. Color Gradient

The computing of the gradient in a color space can be performed on one, two or three color components. However a color gradient taking into account the three color channels will give finer results corresponding more precisely to the color dispersion. Di Zenzo [5] has shown how to extend the gradient concept to multispectral images. This latter can be used under two assumptions : the different channels have to be correlated and the level of noise has to be equivalent in each one of them. The first assumption is an important limitation since a change of color space allows, according to the color space, to uncorrelate the channels. We therefore propose to use a color gradient which can be performed whatever the color space is. The gradient is computed as follows :

$$\|\nabla I_{C_1C_2C_3}(x,y)\|^2 =$$

$$(\|\nabla I^{C_1}_{C_1C_2C_3}(x)\| + \|\nabla I^{C_2}_{C_1C_2C_3}(x)\| + \|\nabla I^{C_3}_{C_1C_2C_3}(x)\|)^2 +$$

$$(\|\nabla I^{C_1}_{C_1C_2C_3}(y)\| + \|\nabla I^{C_2}_{C_1C_2C_3}(y)\| + \|\nabla I^{C_3}_{C_1C_2C_3}(y)\|)^2$$

where $I_{C_1C_2C_3}$ denotes a color image I in the $C_1C_2C_3$ color space and $I^{C_1}_{C_1C_2C_3}$ denotes the C_1 component of the $I_{C_1C_2C_3}$ image.

The filters used to compute the color gradient are, according to the X and Y directions, respectively FX and FY (in a 3×3 neighborhood) :

$$FX = \frac{1}{12}\begin{pmatrix} 1 & 4 & 1 \\ 0 & 0 & 0 \\ -1 & -4 & -1 \end{pmatrix} \quad FY = \frac{1}{12}\begin{pmatrix} 1 & 0 & -1 \\ 4 & 0 & -4 \\ 1 & 0 & -1 \end{pmatrix}$$

To ensure the rotation independence, filter convolutions are made with all the rotations of the filter FX and FY. For each direction θ, $\nabla_\theta I_{C_1C_2C_3}(p)$ is obtained and the gradient is defined as :

$$\nabla I_{C_1C_2C_3}(p) = \|sup(\nabla_\theta I_{C_1C_2C_3}(p))\|.$$

Since this gradient is noise sensitive, the gradient is computed on the simplified image.

2.3. Marker Extraction

To extract the markers, the h-minima are calculated (the minima in the image of height h). This is performed using a morphological reconstruction of the gradient image [13]. h defines the height of the minima to extract. The reconstruction of a function f by g (with $g \leq f$ for every pixel p) is obtained by iterating the following operation until stability is reached :

$$g^0(p) = g(p)$$

$$g^{k+1}(p) = max(f(p), g^k(p) \ominus B).$$

where $\ominus$ stands for the erosion. The h-minima are extracted by a reconstruction of f by $f - h$. For a color image the number of minima can be high for certain values of h. The main difficulty relies in the choice of the h value. The figure 1 gives a plot of the number of minima for the gradient of the image 2(a). In order to have an accurate number of markers, which is not to low or to high in order to avoid severe over or under segmentation, the value of h is fixed to 5. This gives a good compromise and extracts all the reliable minima. The ordering used to compute the min is again the lexicographical order.

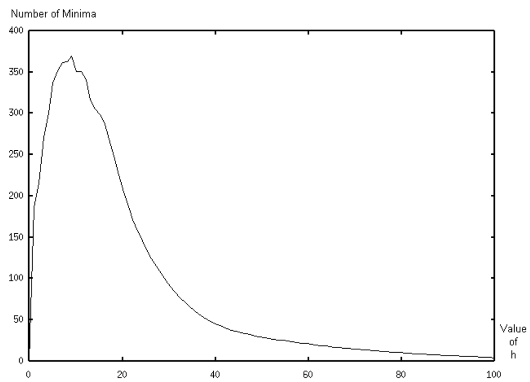


Figure 1: Variation of the number of minima according to their height.

2.4. Color Watershed

Color watersheds have been introduced by [8]. The growing formula is defined as a potential function that is the aggregation probability of a pixel. The main research studies have focused on the elaboration of this function [1]. The integration of local and global color criteria allows the extraction of more reliable regions. The color of the objects in an image can be expressed by a statistical measure of their color mean and the transitions between the regions are easily given by the color gradient. The use of color according to these two criteria can lead to results corresponding to significant color changes in the images. We propose to use these two criteria [6] (local for the gradient and global for the color mean) to define a new potential function by :

$$f(p, R) =$$

$$(1-\alpha)\|\overline{I_{C_1C_3C_3}(R)} - I_{C_1C_2C_3}(p)\| + \alpha\|\nabla I_{C_1C_2C_3}(p)\|$$

where $\overline{I_{C_1C_2C_3}(R)}$ denotes the color mean of a region R, $I_{C_1C_2C_3}(p)$ denotes the color vector and $\nabla I_{C_1C_2C_3}(p)$ is the color gradient at the point p. α is a blending coefficient which allows to modify the influence of each criterion.

This potential function blends together local information (color gradient modulus) and global information (obtained from a statistical comparison between the color of a point p and a neighbor region R). The gradient is computed as previously defined and the statistical comparison (which defines a similarity measure) is based on the distance between $\overline{I_{C_1C_2C_3}(R)}$ and $I_{C_1C_2C_3}(p)$. During the growing process, each time a point is added to a region R, the region mean color is updated. The color image and the gradient image are both normalizated before the watershed growing to have values in the same range. In this paper the distance measure used is the Euclidean distance. The α parameter is settled according to the image : for sharp transitions, it should be close to 1, for less sharp transitions and non homogeneous regions it should be close to $0,5$ and for blurred transitions and homogeneous regions it should be close to 0.

2.5. Adjacency Graph

The adjacency graph of the regions is constructed after the watershed process [10]. In order to avoid over-segmentation, regions are merged according to a color difference measure. For two adjacent regions R_i and R_j, we can associate the Fisher distance expressed by

$$d^2(R_i, R_j) = \frac{(n_i + n_j)\|\overline{I_{C_1C_2C_3}(R_i)} - \overline{I_{C_1C_2C_3}(R_j)}\|^2}{n_i\sigma_i^2 + n_j\sigma_j^2}$$

where $\overline{I_{C_1C_2C_3}(R_i)}$ denotes the mean color of a region, n_i is the number of pixels of the region R_i and σ_i^2 is the variance of the color in the region R_i. We propose to merge adjacent regions in order to reduce the possible over-segmentation. The fusion of two adjacent regions is based on a similarity measure : adjacent regions are merged according to a fusion criterion expressed by the Fisher distance. For each different adjacent nodes in the adjacency graph, the Fisher distance is computed. These adjacent nodes are then sorted according to this distance. The first two nodes minimizing the distance are merged if $d^2(R_i, R_j) < \frac{K}{2}$ (K is a contrast value defined in the simplification step). If the two candidate nodes are merged, the adjacency graph is updated and the algorithm iterates. The merging step ends when no candidate for merging are obtained i.e. the two adjacent nodes i and j minimizing the distance verify $d^2(R_i, R_j) > \frac{K}{2}$.

The variance is defined by $\sigma^2(R_i) = \frac{\sum_{j=1}^{3} \sigma^2_{C_j}(R_i)}{3}$ where $\sigma^2_{C_j}(R_i)$ denotes the grey-level variance of the C_j channel for the region R_i.

3. EXPERIMENTAL RESULTS

We have applied our morphological segmentation on two images (Figures 2(a) et 2(b)).

(a) House Image. (b) Table tennis image.

Figure 2: Images to segment.

The figure 3 illustrates the influence of the number of iterations and of the value of contrast K for the segmentation of color images. The three curves give the number of final regions obtained after the watershed process. The number of iterations n is the x axis and the values of K are 10, 20 and 30 (respectively the red, green and blue curves). The more the number of iterations increases, the less the number of final regions is. This is the the morphological scale-space principle :

$$n_R(k_1) \leq n_R(k_2) \quad \text{if } k_1 \leq k_2$$

where $n_R(k_1)$ denotes the number of regions after the watershed process with a contrast value if k_1. The number of iterations has not to be high and is usually set to 20. The contrast value is the most important parameter of the method : for complex images it is set to 40 and for the other to 20 (in a scale from 0 to 255).

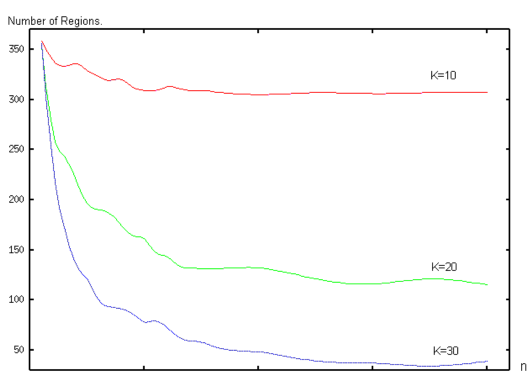
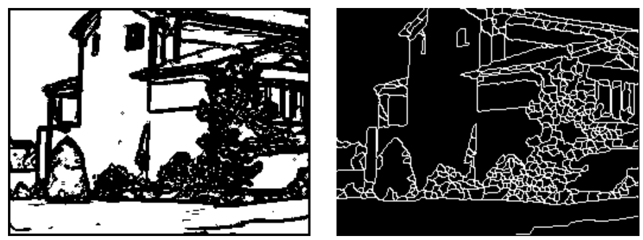


Figure 3: Variation of the number of regions according to the number of iterations of the simplification.

The figure 4 illustrates the h-minima and the regions obtained after the watershed process for the Figure 2(a) ($n = 20$, $K = 20$ and $\alpha = 0,5$). As it can be seen, there is some over segmentation. To illustrate the utility of the merging step to eliminate this latter, we use the Figure 2(b). The Figure 5(a) gives the regions after the watershed process : in the background there is a lot of small regions. The parameters were set to : $n = 20$, $K = 40$ and $\alpha = 0,5$. The graph of the regions is very complex (Figure 5(b)) and the merging step simplifies it (Figure 5(c)). All the little regions in the background are merged and the final segmentation is more accurate (Figure 5(d)).

A complete example of segmentation is given by the figures 6 and 7 with $n = 20$, $K = 40$ and $\alpha = 0,5$. The region extracted correspond to the main regions in the original image. One can see that the merging step has reduced the number of regions.

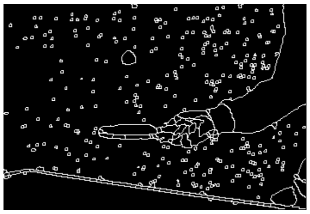


(a) The h-minima (h=5). (b) The boundaries of the regions obtained.

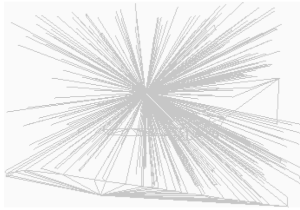
Figure 4: h-minima and boundaries of the house image regions (Figure 2(a)).

4. CONCLUSION

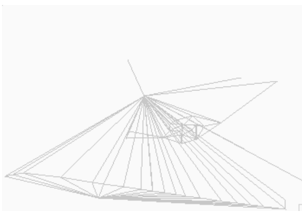
A morphological color segmentation was proposed. It is based on four steps. The simplification step uses a recursive morphologic filter based on a total ordering (the lexicographical order) of the color vectors. The markers are extracted using an accurate morphological transformation : the reconstruction which extracts all the reliable minima in the image. From these seeds, a growing is performed. The watershed growing process combines local and global information and this allows an accurate definition of the boundaries of the regions. A merging step based on a similarity measure expressed by the Fisher distance was proposed. This final enables the elimination of some over-segmentation. The experimentations give promising results. The proposed scheme is sufficiently general to be applied to a wide class of images by using different tuning of the parameters n, K and α.



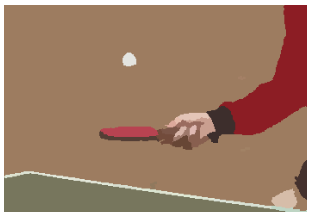
(a) The boundaries of the regions of the Figure 2(b).



(b) Region adjacency graph (Rag).



(c) Rag after fusion.



(d) Colorized image of the final regions.

Figure 5: The fusion of regions using the region adjacency graph.

5. REFERENCES

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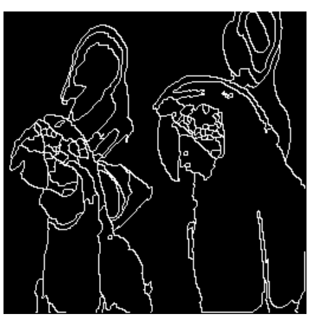
(a) Initial parrot image.

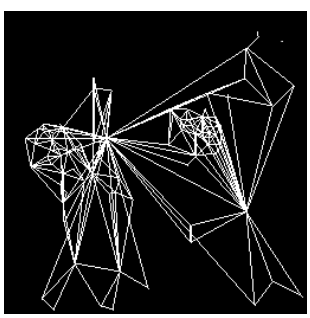
(b) Simplified image of the figure 6(a).

(c) Color gradient of the figure 6(b).

(d) h-Minima for the figure 6(c).



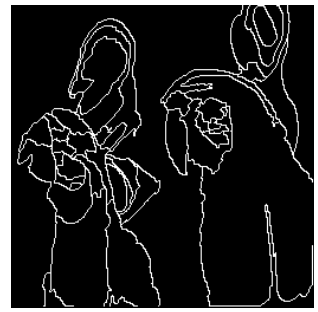
(e) Boundaries of the regions after the watershed growing process.



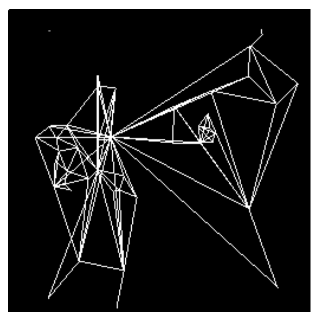
(f) Adjacency graph of the regions before fusion.

Figure 6: Segmentation of a parrot image.

(a) Colorized image of the regions after the watershed growing process.



(b) Boundaries of the regions after the merging step.



(c) Adjacency graph after the merging step.

(d) Colorized image of the regions after the merging step.

Figure 7: Segmentation of a parrot image (continued).