COLOR SEGMENTATION BY ORDERED MERGINGS

Jesús Angulo, Jean Serra

Centre de Morphologie Mathématique - Ecole des Mines de Paris
35, rue Saint-Honoré, 77305 Fontainebleau, France
{angulo,serra}@cmm.ensmp.fr

ABSTRACT

The paper deals with the use of the various color pieces of information for segmenting color images and sequences with mathematical morphology operators. It is divided in four parts. The first one is concerning the choice of the color space suitable for morphological processing. The choice of a connection which induces a specific segmentation is discussed in section 2. Section 3 presents the color segmentation approach which is based on a non-parametric pyramid of watersheds, with a comparative study of different color gradients. In section 4 is introduced another multi-scale color segmentation algorithm, relying on the merging of chromatic-achromatic partitions ordered by the saturation component.

1. CHOICE OF A COLOR SPACE

A recent study [7] has shown that many color spaces (HLS, HSV,...) having been developed for computer graphic applications, are unsuited to image processing. A convenient representation must yield distances, or norms, and provide independence between chromatic and achromatic components. We adopt here an improved family of HLS systems that satisfy these prerequisites, and compare it with other spaces, such as Lab. This space is named: *Improved HLS* (IHLS). There are three versions of IHLS: using the norm L_1, the norm L_2 or the norm $max - min$. The equations of transformation between RGB and the new HLS systems are given in [7] [13]. For the sake of simplicity, all the examples of the paper were obtained according to the equations: $L = 0.212R + 0.715G + 0.072B$, $S = \max(R,G,B) - \min(R,G,B)$, $H' = \arccos\left[\frac{R-\frac{1}{2}G-\frac{1}{2}B}{(R^2+G^2+B^2-RG-RB-GB)^{1/2}}\right]$, $\Rightarrow H = 360^\circ - H' \ if \ B > G, H = H' \ otherwise.$

2. CHOICE OF CONNECTIONS

Another recent study [12] proposes a theory where the segmentation of an image is defined as the maximal partition of its space of definition, according to a given criterion. See also Serra's paper in this conference [14]. The criterion cannot be arbitrary and permits to maximize the partition if and only if the obtained classes are connected components of some connection (*connective criterion*). Therefore, the choice of a connection induces specific segmentation. In this paper, four connections are investigated, namely flat-zones, quasi-flat zones, jump connection and watershed connection.

3. NON-PARAMETRIC PYRAMID OF WATERSHEDS

The *watershed transformation*, a pathwise connection, is one of the most powerful tools for segmenting images. The watershed lines associate a catchment basin to each minimum of the function [1]. Typically, the function to flood is a gradient function which catches the transitions between the regions. Using the watershed on a grey tone image without any preparation leads to a strong over-segmentation (large number of minima). There are two alternatives in order to solve the over-segmentation. The first one consists in initially determining markers for each region of interest: using the homotopy modification, the gradient function has as local minima only the region markers. The need of a criterion for defining the markers can make difficult the generalisation. The second alternative involves a non-parametric approach which is based on merging the catchment basins of the watershed image belonging to almost homogenous regions; this technique known as *waterfall algorithm* [2] is discussed below. Both strategies can be performed in a hierarchical framework which levels yield different degrees of partition of the images structures. The watershed method is meaningful only for grey tone images (is based on the existence of a total ordering relation in a complete lattice). However, it can be easily used for segmenting color images by defining a scalar gradient function corresponding to the color image.

3.1. Color gradients

The color gradient function at the point x is associated to a measure of color disimilarity or distance between the point and the set of neighbours at distance one from x, $K(x)$. For our purposes, three definitions of gradient have been used,

- Morphological gradient, $\nabla f(x)$: This is the standard morphological (Beucher algorithm) gradient for grey level images ($f : E \rightarrow T$, where E is an Euclidean or digital space and T is an ordered set of grey-levels) [10], $\nabla f = \delta_K(f) - \varepsilon_K(f)$.

- Circular centred gradient, $\nabla_c a(x)$: If $a(x)$ is a function containing angular values ($a : E \rightarrow C$, where C is the unit circle), the circular gradient is calculated by the expression [6], $\nabla_c a(x) = \vee[a(x) \div a(y), y \in K(x)] - \wedge[a(x) \div a(y), y \in K(x)]$ where $a \div a' = \mid a - a' \mid$ iff $\mid a - a' \mid \leq 90^o$ and $a \div a' = 180^o - \mid a - a' \mid$ iff $\mid a - a' \mid \leq 90^o$.

- Euclidean gradient, $\nabla_E f(x)$: Very interesting for vectorial functions ($\mathbf{f}(x) = (f_1(x), ..., f_n(x))$), it is based on computing the Euclidean distance d_E [9], $\nabla_E \mathbf{f}(x) = \vee[d_E(x,y), y \in K(x)] - \wedge[d_E(x,y), y \in K(x)]$.

Let f be a color image, its components in the IHLS color space are (f_H, f_L, f_S) and let (f_L, f_a, f_b) be the components for the Lab color space. We define a series of gradients for $\mathbf{f}$: (1) *Luminance gradient*: $\nabla^L \mathbf{f}(x) = \nabla f_L(x)$; (2) *Hue circular gradient*: $\nabla^H \mathbf{f}(x) = \nabla_c f_H(x)$; (3) *Saturation weighing-based color gradient*: $\nabla^S \mathbf{f}(x) = f_S(x) \times \nabla_c f_H(x) + f_S^c(x) \times \nabla f_L(x)$ (where f_S^c is the negative of the saturation component); (4) *Supremum-based color gradient*: $\nabla^{sup} \mathbf{f}(x) = \vee[\nabla f_S(x), \nabla f_L(x), \nabla_c f_H(x)]$; (5) *Chromatic gradient*: $\nabla^C \mathbf{f}(x) = \nabla_E(f_a, f_b)(x)$; (6) *Perceptual gradient*: $\nabla^P \mathbf{f}(x) = \nabla_E(f_L, f_a, f_b)(x)$. In Figure 1 is depicted a comparative of the gradients of a color image.

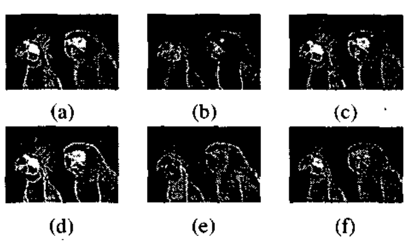

Fig. 1. Examples of color gradients: (a) $\nabla^L \mathbf{f}$, (b) $\nabla^H \mathbf{f}$, (c) $\nabla^S \mathbf{f}$, (d) $\nabla^{sup} \mathbf{f}$, (e) $\nabla^C \mathbf{f}$ and (f) $\nabla^P \mathbf{f}$.

3.2. Waterfall algorithm for color images

Let g be a positive and bounded function ($0 \leq g(x) \leq M$) and let $W(g)$ be its watershed. An efficient algorithm for implementing the waterfalls is based on building a new function h: $h(x) = g(x)$ iff $x \in W(g)$ and $h(x) = M$ iff $x \in W^c(g)$ (h is obviously greater than g) and then, g is reconstructed by geodesic erosions from h [1], i.e. $\widehat{g} = R^*(g, h)$. The minima of the resulting function $\widehat{g}$ correspond to the significant markers of the original g, moreover, the watershed transform of $\widehat{g}$ produces the catchment basins associated with these significant markers. In practice, the initial image g is the gradient of the mosaic image m (after a watershed transformation, m is obtained by calculating the average value of the function in each catchment basin). By iterating the procedure described above, a hierarchy of segmentations is obtained. Dealing with color images has the drawback of the method for obtaining the mosaic color image $\mathbf{m}_i$ of the level i. We propose to calculate the average values (associated to the catchment basins) in the RGB components, i.e. $\mathbf{m} = (m_R, m_G, m_B)$. The gradient of level $i+1$ is obtained from $\mathbf{m}_i$, i.e. $g_{i+1} = \nabla \mathbf{m}_i$. In practice, all the presented gradient functions can be applied on $\mathbf{m}$. It is possible to consider a contradiction the fact that, for the mosaic image, the values are averaged in the RGB color components and then, the gradients (and consequently the watersheds) are computed using other color components. However, this procedure of data merging allows to obtain good results and on the other hand, the calculation of the mean of angular values (Hue, a, b components) is not trivial. The example of Figure 2 illustrates this hierarchical technique (using $\nabla^S \mathbf{f}$).

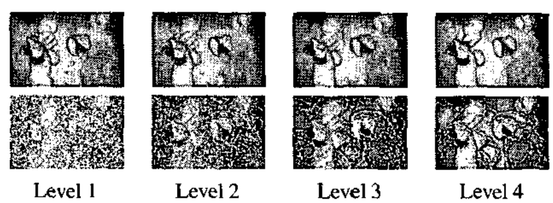

Fig. 2. Pyramid of segmentation by waterfall algorithm. First row, mosaic images and second row, watershed lines.

3.3. Segmentation results

The segmentation results corresponding to the different gradients are given in Figure 3. Other tests have been performed on a representative selection of color images and the results have been similar. The use of only the brightness (∇^L) or only the color (∇^H and ∇^C) information produces very poor results. We can observe in Figure 1 that the *supremum-based color gradient* is the most contrasted and obviously achieves to good results of segmentation. The *perceptual gradient*, which has very interesting properties for colorimetric measures in perceptually relevant units [9], leads to better results for the dark regions. However, the best partitions have been obtained with the proposed *saturation weighing-based color gradient*. The rationale behind this operator is the fact that the chromatic image regions correspond to high values of saturation and the achromatic regions (grey, black or white) have low values in f_S (or high values in f_S^c). According to the expression of ∇^S, for the chromatic regions the priority is given to the transitions of ∇^H and for the achromatic regions the contours of ∇^L are taken.

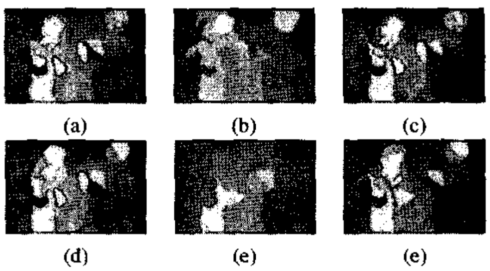

Fig. 3. Examples of color segmentation (level 4 of pyramid): (a) $\nabla^L\mathbf{f}$, (b) $\nabla^H\mathbf{f}$, (c) $\nabla^S\mathbf{f}$, (d) $\nabla^{sup}\mathbf{f}$, (e) $\nabla^C\mathbf{f}$ and (f) $\nabla^P\mathbf{f}$.

4. ORDERED PARTITION MERGING

Now, we propose the way for applying other connections: *jump connection* [11], *flat zones* [3] and *quasi-flat zones* [8], to color images. The examples are illustrated with jump connection, but the flat or quasi-flat zones can be also used. Let σ be a connective criterion which segments the function f obtaining a partition P, i.e. $\sigma[f] \to P_\sigma(f)$. The connective criteria are typically defined for functions $f : E \to T$ where T is a totally ordered lattice. As for the watershed, the application to color images involves special considerations. The simplest way lies in associating a grey level image f to the color image $\mathbf{f}$, and after segmenting f by σ, the partition is applied to $\mathbf{f}$. This image f can be obtained as a linear combination of the color components (luminance, principal components, etc. have the drawback that the RGB components are strongly correlated) or using other techniques. Following the idea of putting together the hue and the brightness, we have initially tested the interest of the function $f(x) = f_S(x) \times f_H(x) + f_S^c(x) \times f_L(x)$, however, the results were unsatisfactory, Figure 4(a).

There is another way of doing it. In the IHLS color systems, the σ is applied to each grey level component (it is also possible to use a σ for each component), obtaining a partition for each component, i.e. $\sigma[f_L] \to P_\sigma(f_L)$, $\sigma[f_S] \to P_\sigma(f_S)$, $\sigma[f_H] \to P_\sigma(f_H)$. In Figure 4(b)-(d) are shown the partitions by jump connection. Remark that we must fix a color origin for the hue component in order to have a totally ordered set which involves some disadvantages [6]. Remark also that non-significant small regions appear in the partitions (over-segmentation).

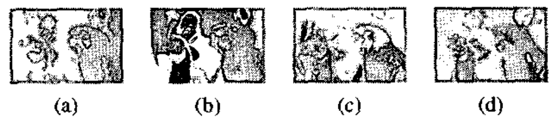

Fig. 4. Examples of segmentation by using a jump connection of $k = 20$ on: (a) $f = f_S \times f_H + f_S^c \times f_L$, (b) f_L, (c) f_S, (d) f_H.

4.1. Region growing in partition lattice

There are several possible alternatives to reduce the over-segmentation (taking a higher k can lead to lose important contours). The segmentation may be refined by the classical *region growing algorithm*, based on merging initial regions according to a similarity measure between them. An efficient implementation of the merging process uses a hierarchical queue and a Region Adjacency Graph structure, see [5]. In our approach, the jump connection (or quasi-flat zones) partition is considered as the finest partition. For the region merging process, each region is defined by the mean of grey levels and the merging criterion is the *area* a of the region. Note that the iteration of the area operator is idempotent and moreover it is another connective criterion.

4.2. Combination of chromatic-achromatic partitions

Now, the question is how the obtained partitions can be combined. As we can see in the examples, the partition $P_\sigma(f_H)$ represents well the chromatic regions, as well as $P_\sigma(f_L)$ the achromatic ones. We propose the following strategy. Starting from the mosaic image associated to $P_\sigma(f_S)$, we can threshold the saturation at u_S in order to obtain a binary key, X_S which classifies all the pixels as chromatic or achromatic. Using X_S, the chromatic and achromatic partitions are again merged by the saturation information, i.e. $P_\sigma(\mathbf{f}) = (P_\sigma(f_H) \wedge X_S) \vee (P_\sigma(f_L) \wedge \overline{X}_S)$. This idea of using a thresholded saturation was introduced in [4], where a method is also proposed to obtain the optimal u_S. Figure 5 illustrates the technique, showing the final segmentation by jump connection and quasi-flat zones, refined by region merging. The performance of segmentation is very good using both approaches.

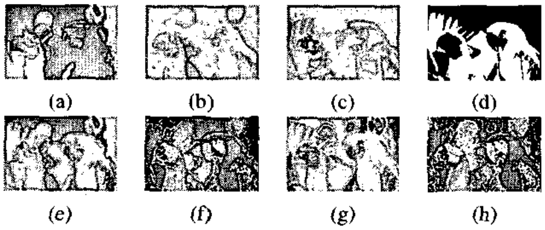

Fig. 5. Jump connection $k = 20$ + region merging $a < 50$: (a) $P_\sigma(f_L)$, (b) $P_\sigma(f_H)$, (c) $P_\sigma(f_S)$, (d) X_S at $u_S = 45$, (e) combined partitions $P_\sigma(\mathbf{f})$, (f) segmentation. Quasi-flat zones $\lambda = 15$ + region merging $a < 50$ + $u_S = 45$: (g) $P_\sigma(\mathbf{f})$, (h) segmentation.

5. CONCLUSIONS

We discuss two multiscale algorithms which incorporates concepts of mathematical morphology in color image segmentation. Both approaches involve a color space representation of type "hue-luminance-saturation", where the saturation component plays an important role in order to merge the chromatic and the achromatic information during the segmentation procedure. The present methods are both good and fast.

6. REFERENCES

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