Histogram and Watershed Based Segmentation of Color Images

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Abstract

A novel method for color image segmentation is proposed in this paper. The method is based on the segmentation of each color plane independently using a watershed based thresholding of the plane histograms. The segmentation maps obtained for each color plane are fused together according to a fusion operator taking into account a concordance of the labels of each segmentation map. This operator produces a fused segmentation map containing labeled and unlabeled pixels which is used as an image of seeds for a region growing method : the color watershed. The color watershed produces the final segmentation of the initial image. This segmentation scheme is experimented using several types of medical images and results in a fast and robust segmentation.

Introduction

Color image segmentation refers to the partitioning of a multi-channel image into meaningful objects. Various approaches to color image segmentation can be found in the literature and can be roughly classified into several categories: clustering methods,[1] edge-based methods,[2] region growing methods[3] and variationnal methods.[4] We propose to combine two types of methods: clustering and region growing methods. Clustering methods of the color histogram use 3D information and are time consuming, so methods based on multi-thresholding of color planes might be preferred. We propose to use the fusion of segmented color planes as an initialization for a region growing method : the color watershed. Thus, the proposed scheme consists in three stages: 1) clustering of each color planes, 2) fusion of the resulting segmentation maps, 3) color watershed growing. The paper is organized as the aforementioned segmentation scheme.

Grey-Scale Image Clustering

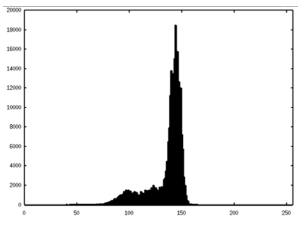
To obtain a clustering of each color plane, we propose to perform a thresholding. First, we assume that the number of class to be extracted is known and is denoted as N_c. We suppose that the decision regions of the color planes are grouped around the modes of the histogram. The clustering of the histogram can therefore be achieved by computing the watershed of the histogram complementary. The class of a pixel p of a color plane is given by the label value of the corresponding point in the clustered histogram. Since we use watershed, an initialization step is needed. We propose in a first step to simplify the histogram using a grey-scale reconstruction of height

$$h = \left|\sigma(H) - \sqrt{\max(H)}\right| \tag{1}$$

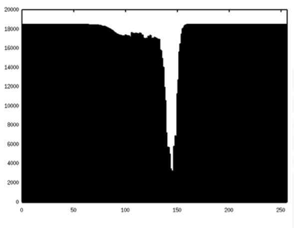
where H denotes the histogram of a given color plane, σ and *max* respectively denote the standard deviation and the maximum of the histogram. The reconstruction of the histogram H is performed with $G(n)=H(n)-h$ (for each value of the histogram, h is subtracted, if $G(n) \le 0$ then $G(n)=0$). The reconstruction of the histogram gives a simplified histogram called H_s which can be used to cluster the image since the irrelevant minima have been eliminated. In a first step, the complement of H_s is computed, providing H^c_s. From this latter, all the minima are extracted and used as seeds for the *1D* watershed. This results in a splitting of the histogram in several regions. The drawback of this method is that the number of obtained regions is generally larger than the wanted number of class N_c: an over-segmentation of the histogram is obtained. We propose to merge adjacent regions of the histogram according to a merging criterion. The *1D* adjacency graph of the obtained segmentation is constructed and the smallest region is searched. This latter region is merged with one of its two adjacent regions minimizing the following quantity:

$$\frac{\sum_{k=l(R_i)}^{u(R_i)} H(k)}{u(R_i) - l(R_i)} \tag{2}$$

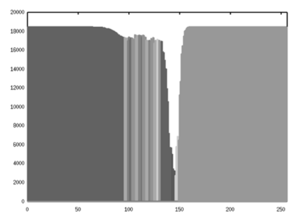
where a region R_i is described in the histogram by two values, its lower and upper bounds denoted by $l(R_i)$ and $u(R_i)$. The numerator of (2) is the number of pixels belonging to the region R_i. The adjacency graph is updated each time two regions merge and the algorithm iterates until the number of regions of the histogram is equal to the wanted number of class N_c. The quantity to be minimized (2) express that a region extracted in the histogram is considered as a relevant part of the image (in the sense that it belongs to one of the N_c clusters) if the corresponding section of the histogram is large and corresponds to a high number of pixels. The figures 1 (a) to (d) illustrates the different steps of the clustering of the histogram of a color plane in 3 regions. The histogram is computed (figure 1 (a)), it is simplified and its complement is calculated (figure 1 (b)). The watershed is performed with the minima as seeds (figure 1 (c)) and the over-clustering is eliminated by the merging step (figure 1 (d)). We can note that the three final regions extracted correspond to the main three peaks of the histogram and the influence zones of each peak are well defined. It has to be noted that the merging step is not used if the number of regions obtained after the watershed is lower than N_c. The set of regions for a given color plane C_i will be denoted by $\xi(C_i)$.



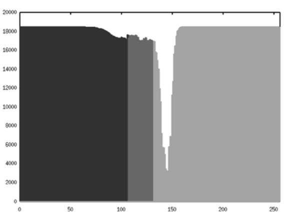
(a) H for a color plane.



(b) H^c_s, the complement of H_s.



(c) Over-clustered histogram.



(d) After the merging step.

Figure 1. An illustration of the clustering of an histogram.

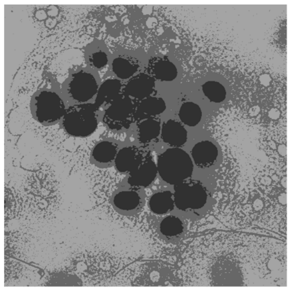
Fusion of Segmented Color Channels

Concordance of the Labels

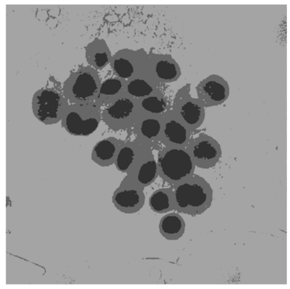
Each color plane may distinguish a number of regions which can be different from a color plane to another. According to the previous step, for each color plane C_i, $\forall\ i \in \{1,2,3\}$, we can associate a number of regions $\Theta(C_i)=Card(\xi(C_i))$. The color of a pixel is given as three values corresponding to three different tristimuli (generally R, G and B). These values correspond to different sources and do not contain the same information. In the previous clustering step, the three color planes were independently segmented and there is no guarantee that the same label would be assigned to a same type of cluster in the different segmentation maps. Without taking into account the concordance of the cluster labels in the three segmentation maps, no fusion can be considered. To achieve this aim, the set of regions ξ is deduced from the superimposition of the different regions $\xi(C_1)$, $\xi(C_2)$, $\xi(C_3)$. The superimposition produces a new image of labels (denoted by J) which is compatible with all the segmentation maps of the color planes. The number of regions of J is within

$$\left[\left(\Theta(C_1)\vee\Theta(C_2)\vee\Theta(C_3)\right), \sum_{i=1}^{3}\Theta(C_i)\right] \tag{3}$$

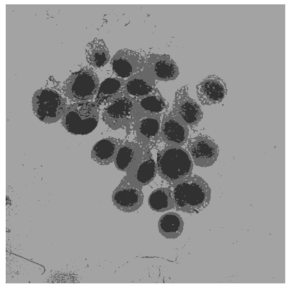
where denotes the sup. The figures 2 (a) to (d) illustrates the label concordance step on an initial color image containing $N_c = 3$ classes. For each color plane of the original color image, the segmentation maps are processed using the clustering method of the previous section. The label concordance map obtained is deduced from the three independent segmentation maps and produces a segmentation map J in compliance with all of them.



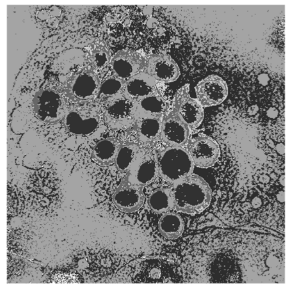
(a) Segmentation map of C_1.



(b) Segmentation map of C_2.



(c) Segmentation map of C_3.



(d) Label concordance map.

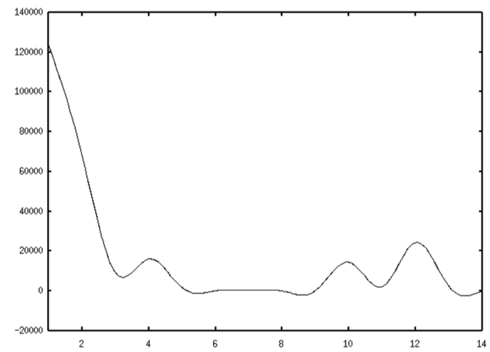
Figure 2. The segmentation maps of an image and a resulting label concordance map.

Fusion of the Segmentation Maps

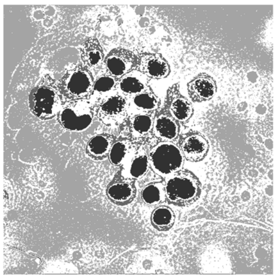
However, the number of regions of the image J might be higher than the wanted number of regions because of the superimposition. We propose to use a fusion operator to reduce this number of regions. For the image of label concordance J, the histogram is computed. Each value of the histogram corresponds therefore to the area of a region in the J image. The fusion operator is defined as follows. Let M denote the set of all the local maxima of the histogram of J denoted by H_J

$$M = \left\{\vee_{q\in V(p)} H_J(p)\right\} \tag{4}$$

with $V(p)$ the considered neighborhood of the point p (in this case the two adjacent ones in the histogram). $M(N_c)$ will denote the N_c greatest maxima belonging to M. The fusion operator is expressed by: if $J(p) \notin M(N_c)$ then $J(p) = 0$ else $J(p)$ remains identical. The fusion result in an image of $N_c + 1$ labels. Some pixels have a label corresponding to one of the clusters of the image and the other pixels are considered as unlabeled. In the image resulting from the fusion, labeled pixel are pixel which belongs to one of the N_c most representative clusters of the image. The other pixels can be considered as uncertain pixels since their label in the concordance image is not representative of the N_c clusters. This fusion operator is very appropriate for images whose color planes are correlated: the most representative clusters overlap between the three segmentation maps. Instead of using classical probability values[5] to assess the basic assignment of an unlabeled pixel to a cluster, we propose to use a region growing method. Labeled pixels are used as seeds which will propagate in the image, this enables to take into account the spatial properties of the image. The figures 3 (a) gives the histogram of the label concordance map (figure 2 (d)) from which the greatest N_c = 3 local maxima are extracted to perform the fusion of the segmentation maps. The fusion image is an image of four labels: pixels belonging to one of the wanted cluster and unlabeled pixels (white pixels on the figure 3 (b)).



(a) Concordance map histogram.



(b) Result of the fusion.

Figure 3. The fusion of the segmented maps.

Color Watershed

The color watershed is done in two steps:

- Marker Extraction which corresponds to the extraction of the seeds of the watershed growing,
- Growing which uses previously extracted seeds to propagate the labels in the image according to an aggregation function.

The marker image is provided by the fusion of the segmented maps, therefore only the definition of the color watershed has to be detailed.

Aggregation Function

The color watershed used in this paper is defined according to a specific aggregation function. The aggregation function defines the aggregating probability of a pixel to a region. It is based on two main information describing the spatial information of the image: local information expressed by the color gradient and global information expressed by the color mean of the regions describing their color homogeneity. This aggregation function can be formally defined6. Let $\overline{I(R)}$ denote the mean color vector of the region *R* for the image *I* in the color space $C_1C_2C_3$, the *I(p)* vector giving the color of a pixel *p* and $\nabla I(p)$ the color gradient. The aggregation function is expressed as[6]:

$$f(p,R) = (1-\alpha)\left\|\overline{I(R)} - I)p)\right\| + \alpha\left\|\nabla I(p)\right\| \qquad (5)$$

This function combines local information (modulus of the color gradient) and global information (a statistical comparison between the color of a pixel *p* and a neighbor region *R* performed with the Euclidean distance). During the growing process, each time a pixel is added to a region *R*, the mean color of the region is updated. The color image and the gradient image are both normalized before the watershed growing to have values in the same range. α is a blending coefficient which allows to modify the influence of the local and global criteria during the growing process. The gradient is processed using Di Zenzo's definition.[7]

Estimation of α

The parameter α was introduced to control the influence of each global and local criteria. Usually, α is fixed according to *a priori* knowledge on the images. However, an adaptable segmentation which modifies the value of α along the iterations seems more suitable. The initial value of α is 0 and the value of α evolves during the growing. At each iteration *k*, the following quantity is computed: $V_k = \Sigma f(p,R)$ for all the processed unlabeled pixels *p*. V_0 gives the initial value for all the unlabeled pixels of the image. At a given iteration *k* and after the processing of all the considered unlabeled pixels, V_k is computed and a new value for α is given by $\alpha = V_k/V_0$. However, it is not desirable to have high variations of α between each iterations, so the value retained for the next iteration *k* + 1, is considered to be the mean of all the previous values of α, including the new computed one. This enables a more smoothed evolution of α.

Experimental Results

The watershed was performed using the result of the fusion as a marker function. The figure 4 presents the final regions obtained after the growing process in the *RGB* color space with the estimation of α. All the unlabeled pixels have been assigned to a cluster of the image, the spatial information provided by the color watershed algorithm enables the refining of the segmentation.

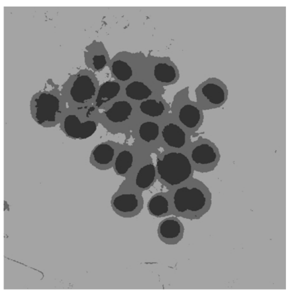
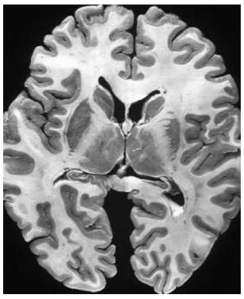
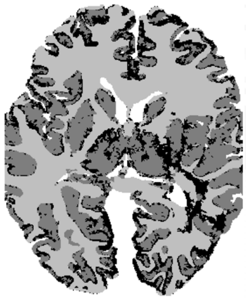


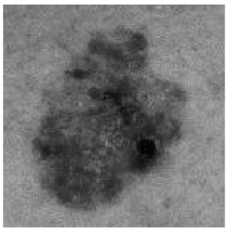
Figure 4. The regions obtained after the watershed growing on the fusion result image (figure 3 (b)).



(a) brain image.

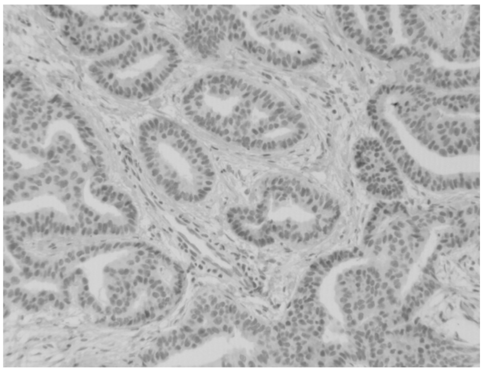


(b) segmentation of brain.

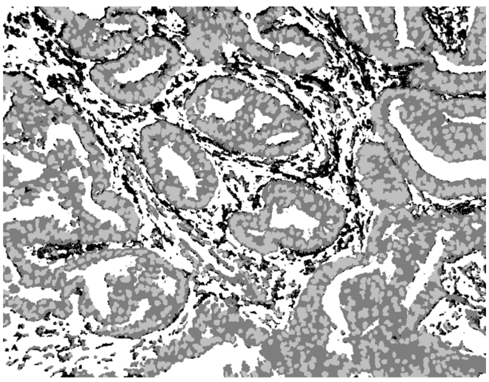


(c) Skin image

(d) Segmentation of Skin



(e) Histology image.



(f) Segmentation of histology

Figure 5. Medical images and their segmentation.

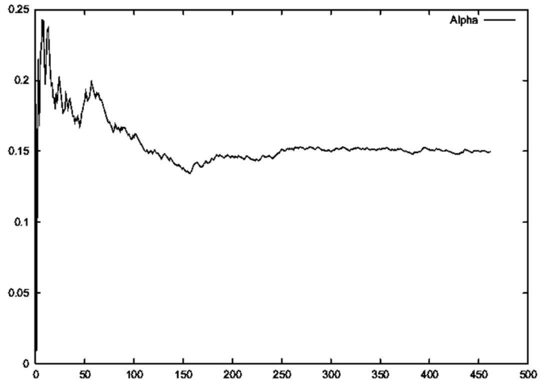


Figure 6. An example of variation of the 〈 parameter.

Table 1. Mean value of α for several medical images.

Image	α	N_c
I_1	0.054	2
I_2	0.037	2
I_3	0.212	2
I_4	0.191	2
I_5	0.207	2
I_6	0.078	3
I_7	0.051	3
I_8	0.216	4
I_9	0.188	4
I_{10}	0.216	4

To illustrate the fact that the evolution of α during the growing is necessary, the table 1 gives the mean value of α during the growing for 10 different medical images (microscopy, hematology, skin, brain, histology, ...) segmented in several classes (see figure 5). Medical images generally have correlated color planes, therefore they correspond to segmentation scheme. Whatever the images, small values of α are obtained, this states that for these images, the edge (local) information seems less important than the global information. The figure 6 gives a plot of the variation of α along the different iterations of the watershed region growing process. Visual evaluations of the segmented images proved that the self-adaptable segmentation gives more accurate results than with a fixed value of α according to *a priori* knowledge.

Conclusion

A new supervised method for segmenting color images was suggested. In a first step, for each color plane, distinct segmentation maps are extracted and fused together according to a fusion operator. Some pixels remain unlabeled and a self-adaptable region growing method is performed to obtain the final regions. The proposed method is reliable, fast and can be used with images having correlated color planes. Further researches focus on a new fusion operator appropriated for images with uncorrelated channels and on the automatic determination of the number of classes to use the segmentation for indexing color medical images.

References

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Biography

Olivier Lezoray received a Ph.D in computer Science from the University of Caen, France in 2000. Since 2000, he is an assistant professor at the University of Caen in the Saint-Lô Institute of Technology. His work is primarily focused on color image segmentation and classification methods such as neural networks for pattern recognition.

Hubert Cardot received a Ph.D in computer Science from the University of Caen in 1993. He is head of the Image group of the LUSAC research laboratory. His work is focused on image analysis and neural networks.