Color space selection for unsupervised color image segmentation by analysis of connectedness properties

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ABSTRACT
In this paper, we propose a new color image segmentation algorithm by unsupervised classification of pixels. This procedure iteratively constructs the classes by histogram multithresholding. For this purpose, the procedure selects different color spaces in which the pixels belonging to the modes of the 1D-histograms present remarkable connectedness properties, so that each mode corresponds effectively to a region in the image.

KEY WORDS
Color image segmentation, classification, Histogram multithresholding, Color spaces, Connectedness properties

1 Introduction

One of the most important problems in color image analysis is that of segmentation. In this paper, we consider color uniformity and connectedness properties of pixels for partitioning an image into disjoint regions. The color image segmentation techniques described in the literature can be categorized into two main classes, depending on the distribution of the pixel colors is analyzed either in the image plane or in a color space [1].

The methods which analyze the distribution of the pixel colors in a color space consider that each pixel in the color image is represented by a color point in a color space. The most widely used is the (R,G,B) color space, where a color point is characterized by the color component levels of the corresponding pixel, namely the red (R), the green (G) and the blue (B). Other color spaces can be used and the performance of an image segmentation procedure is known to depend on the choice of the color space [2]. Many authors have tried to determine the color spaces which are the most appropriate for their specific color image segmentation problems [1]. Unfortunately, there does not exist a color space which provides satisfying results for the segmentation of all kinds of images. Vandenbroucke proposes a color image segmentation approach by pixel classification in an hybrid color space which is adapted to the analyzed image [2]. This space, determined by means of a supervised learning scheme, is constituted of several color components which can belong to any of different classical color spaces.

It is generally assumed that homogeneous regions in the image plane give rise to clusters of color points in the color space, each cluster defining a class of pixels which share similar color properties. The classes can be constructed by means of a cluster analysis procedure which requires the desired number of classes [3], by the analysis of the color 3D-histogram which requires a large amount of memory [4], or by the analysis of the 1D-histograms of the three color components [5]. When the classes are constructed, the pixels are assigned to one of them by means of a decision rule and are mapped back to the original image plane to produce the segmentation. It is important to underline that a class can represent one or several disjoint regions with the same colors.

The analysis of the 1D-histograms of the three color components assumes that the color component levels of the pixels which belong to the regions give rise to modes in each of the three 1D-histograms. The detection of these modes consists in determining the thresholds which delimit them. As a 1D-histogram is the result of the projection of the color 3D-histogram on one single color component, a mode may represent several regions with different colors. The ideal case would be to detect the modes which correspond to regions with the same colors.

As the classes constructed by a classification procedure depend on the used color space, it would be interesting to select the color space which is the most relevant for detecting the modes which correspond to regions. For this purpose, we assume that the higher the discriminating power of the 1D-histogram is, the more probably the detected modes correspond to regions with the same colors. So, among several color spaces, the proposed procedure selects the most relevant, which is the one for which the discriminating powers of the 1D-histograms are the highest.

The discriminating power of a 1D-histogram depends on the number of detected modes and on the connectedness properties of pixels whose color component levels fall into these detected modes.

In this paper, we propose an original color image segmentation procedure based on an iterative analysis of the 1D-histograms of the color components. At each iteration step, this procedure constructs one class of pixels. For this purpose, the procedure looks for the most relevant color space among several ones. It detects the modes of each of the 1D-histograms of the three color components constituting this most relevant color space. The connectedness properties of pixels represented by these modes are analyzed to construct one class. The pixels assigned to this class are not taken into account for constructing the classes at the next steps. The iterative procedure stops when there remain only a few pixels which are not assigned to any constructed classes.

The main originality of the proposed unsupervised procedure is the selection of the most relevant color space for constructing each class of pixels at each iteration step. The selection takes simultaneously into account the color and spatial connectedness properties of the pixels in the image.

The second section presents the classical color spaces which are used by the proposed method. The third section describes the proposed color image segmentation algorithm. The fourth section shows the segmentation results obtained by this algorithm.

2 Color spaces

In order to classify color spaces into a few categories with respect to their definitions and their properties, Vandenbroucke proposes to group the classical color spaces into four main families [2] as shown in figure 1:

- The ***primary spaces***, which are based on the thrichromatic theory, assuming that is possible to match any color by mixing appropriate amounts of the three primary colors. The primary spaces used by the proposed method are (R,G,B), (r,g,b), (X,Y,Z) and (x,y,z).

- The ***luminance-chrominance spaces*** where one component represents the luminance and the two others the chrominance. The luminance-chrominance spaces used by the proposed method are (Y,I,Q), (Y,U,V), (wb,rg,by), (Y,C_1,C_2), (L^*,a^*,b^*) and (L^*,u^*,v^*).

- The ***perceptual spaces*** which try to quantify the subjective human color perception by means of the intensity, the hue and the saturation. The perceptual spaces are not used by the proposed method because of the instability and non-removable singularities of the hue component.

- The ***statistical independent component spaces*** resulting from different statistical methods which provide as less correlated components as possible. The statistical independent component space used by the proposed method is the Ohta's color space (I_1,I_2,I_3).

The dotted rectangles within the principle rectangles correspond to sub-families of color color spaces. In general, color images are acquired through a (R,G,B) color space that we call the image acquisition color space. So, all color spaces are defined by an equation whose inputs are R, G and B. In the figure 1, we can see how is determined any color space by following the arrows starting from the (R,G,B) color space. When the conditions of the image acquisition are not controlled, the chosen transformations from the (R,G,B) color space to the device-dependent color spaces use default parameters [2].

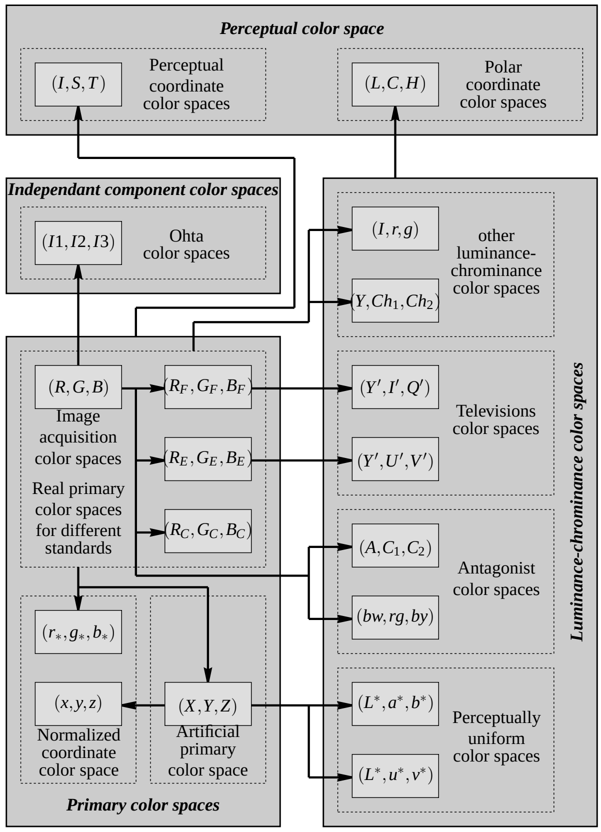


Figure 1. Color space families

3 Segmentation

Each stage of our iterative method is shown by figure 2 and is detailed in the next sub-sections.

3.1 1D-histograms determination

At each iteration step, the color vectors of the pixels submitted to the analysis are represented into the N_S color spaces ($N_S = 11$) presented in the second section. In the i^{th} color space, we determine each of the three 1D-histograms $h^{i,j}(x)$ of each color component numbered j, $j = 1,2,3$, where x is the color component level. The 1D-histograms of the red, green and blue component of the image "Hand" of figure 3(a) are represented in figures 3(b), 3(c), and 3(d) respectively.

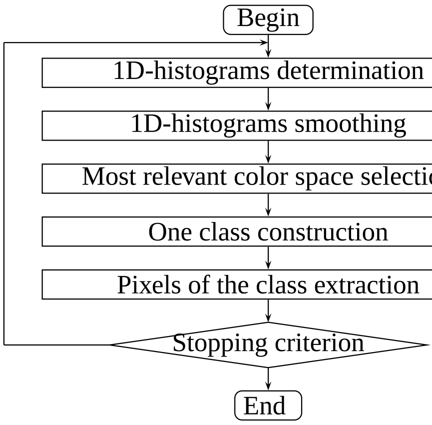
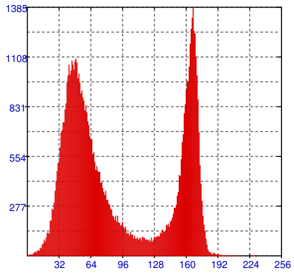
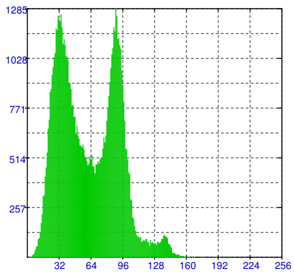


Figure 2. Color image segmentation flowchart.

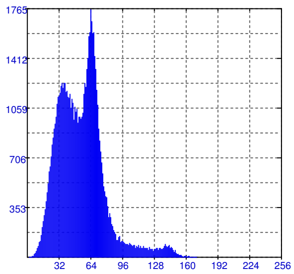
(a) Original image



(b) red 1D-histogram $h^{1,1}$



(c) green 1D-histogram $h^{1,2}$



(d) blue 1D-histogram $h^{1,3}$

Figure 3. 1D-histograms of the image "Hand" in the (R,G,B) color space ($i=1$)

3.2 1D-histograms smoothing

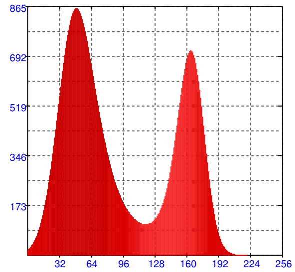
It is difficult to detect the modes when the 1D-histograms are corrupted by noise. Hence, we propose to smooth them by means of an adaptive filtering. A smoothed histogram $h^{i,j}_{\sigma}(x)$ is computed by the convolution between the 1D-histogram $h^{i,j}(x)$ and a Gaussian kernel $g_{\sigma}(x)$ where σ is the standard deviation:

$$h^{i,j}_{\sigma}(x) = h^{i,j}(x) * g_{\sigma}(x) \tag{1}$$

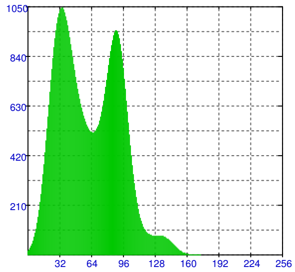
where "$*$" denotes the convolution operator and $g_{\sigma}(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(\frac{-x^2}{2\sigma^2}\right)$.

The effect of the smoothing depends on the standard deviation σ used to define the Gaussian kernel. For each 1D-histogram, σ is automatically adjusted by means of the procedure proposed by Lin [6], so that the smoothed 1D-histogram reveals its modes. Figures 4 shows the smoothed 1D-histograms of the image "Hand" of figure 3(a).

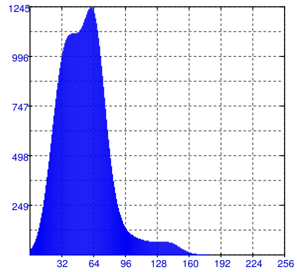
(a) Original image



(b) Smoothed red 1D-histogram $h^{1,1}_{\sigma}$ with $\sigma = 11$



(c) Smoothed green 1D-histogram $h^{1,2}_{\sigma}$ with $\sigma = 7$



(d) Smoothed blue 1D-histogram $h^{1,3}_{\sigma}$ with $\sigma = 8$

Figure 4. Smoothed 1D-histograms by Lin's method

3.3 Most relevant color space selection

3.3.1 Modes detection

The thresholds which delimit the modes of each smoothed histogram $h^{i,j}_{\sigma}(x)$ are determined by the analysis of the zero-crossings of its first derivative function. A threshold is detected by a zero-crossing of the first derivate function of $h^{i,j}_{\sigma}(x)$ whose sign changes from minus to plus (local minimum). A mode is detected by a zero-crossing of the first derivate function of $h^{i,j}_{\sigma}(x)$ whose sign changes from plus to minus (local maximum). The number of these so-detected modes is denoted $N^{i,j}$.

Three features characterize the k^{th} ($k = 1,\ldots,N^{i,j}$) detected mode of the 1D-histogram $h^{i,j}_{\sigma}(x)$:

- the left and right detected thresholds $T^{i,j,k}_{left}$ and $T^{i,j,k}_{right}$,
- the amplitude $A^{i,j,k} = \max\limits_{l=T^{i,j,k}_{left}}^{l\leq T^{i,j,k}_{right}} h^{i,j}_{\sigma}(l)$.

For each 1D-histogram $h^{i,j}_{\sigma}(x)$, we denote $K(i,j)$ the rank order of its mode with the highest amplitude.

j	1		2		3
$N^{i,j}$	2		2		1
k	1	2	1	2	1
$T_{left}^{1,j,k}$	0	120	0	67	0
$T_{right}^{1,j,k}$	119	220	66	173	179
$A^{1,j,k}$	861	713	1048	952	1243
$CD(S)$	0.98	0.97	0.91	0.90	0.99
$R^{1,j}$	1.95		1.81		0.99

Table 1. Features of the detected modes in the 1D-histograms of figures 4(b), 4(c), 4(d).

In order to illustrate the procedure, table 1 shows the features of the detected modes in the smoothed histograms of figures 4(b), 4(c), 4(d) with only the (R,G,B) color space ($i=1$).

3.3.2 Connectedness pixels properties

The main problem of the schemes which analyze the 1D-histograms is that they only analyze the similarities between the colors of the pixels and ignore their spatial arrangement in the image. However, when a subset of pixels corresponds to a region in the image, they have similar colors and they are strongly connected. So, in order to select the most relevant color space, we propose to use the connectedness degree [7].

Let us denote the subset $S[T_{left}^{i,j,k}, T_{right}^{i,j,k}]$, of the pixels whose levels of the color component j range between $T_{left}^{i,j,k}$ and $T_{right}^{i,j,k}$ in the considered image. For the sake of simplicity, the subset $S[T_{left}^{i,j,k}, T_{right}^{i,j,k}]$ will be denoted hereafter S.

Let $N_S(P)$ be the subset of pixels Q which are the 8-neighbors of P and which belong to S. The connectedness between P and the color-subset S, denoted $\gamma_S(P)$, depends on the number of pixels which belong to $N_S(P)$. It is estimated as:

$$\gamma_S(P) = \frac{\text{Card}\{Q \in N_S(P)\}}{8}, \qquad (2)$$

where the normalizing factor 8 corresponds to the number of considered neighbors of a pixel in the image.

In order to define a connectedness measure of a non empty subset of pixels which does not depend on its cardinal number, we introduce the connectedness degree of a subset S, denoted $CD(S)$, which is defined as:

$$CD(S) = \frac{\sum_{P \in S} \gamma_S(P)}{\text{Card}\{P \in S\}}. \qquad (3)$$

The connectedness degree of an empty subset of pixels is set to 0. The connectedness degree $CD(S)$ depends on the mean number of neighbors of a pixel of S which belong also to S. More precisely, it is the mean cardinal number of the subsets $N_S(P)$ of the pixels P which belong to S. A low connectedness degree of a subset S, close to zero, means that its pixels are sparsely scattered through the image. On the other hand, a high connectedness degree, close to one, indicates that its pixels are strongly connected in the image.

Table 1 shows the connectedness degrees $CD(S)$ of the detected modes of the smoothed histograms shown in figures 4(b), 4(c), 4(d).

3.3.3 Most discriminating 1D-histogram

Among the three smoothed 1D-histograms of each color space, we determine the *most discriminating 1D-histogram*. For each smoothed 1D-histogram $h_\sigma^{i,j}(x)$, we evaluate the discriminating power, denoted $R^{i,j}$, which is the sum of the connectedness degrees of the subsets $S\left[T_{left}^{i,j,k}, T_{right}^{i,j,k}\right]$ associated with the histogram:

$$R^{i,j} = \sum_{k=1}^{N^{i,j}} CD\left(S\left[T_{left}^{i,j,k}, T_{right}^{i,j,k}\right]\right) \qquad (4)$$

As the Gaussian smoothing eliminates the non significant modes, we assume that a 1D-histogram allows to discriminate the classes if the number of the detected modes is high and if the sum of their connectedness degrees is high.

Thus, the higher the discriminating power $R^{i,j}$, the more probably the modes correspond to regions with same colors in the image. So, the most discriminating 1D-histogram of the i^{th} color space is the 1D-histogram with the highest discriminating power $R^{i,j}$ value.

We denote $J(i)$ the rank order of the color component which corresponds to the most discriminating 1D-histogram of the i^{th} color space.

Table 1 shows that, in our example, among the three 1D-histograms of figure 4, the most discriminating histogram of the (R,G,B) color space is the histogram of the component R, so $J(1)$ is set to 1.

3.3.4 Color space selection

The most relevant color space is the color space with the most discriminating 1D-histogram.

If the discriminating powers $R^{i,j}$ of several 1D-histograms are equal, the most relevant color space is the color space with the 1D-histogram with the second highest value of $R^{i,j}$.

We denote I the rank order of the color space which is selected as the most relevant one. For the image "hand", the most relevant color space which is selected at the first step is the (L^*, u^*, v^*) color space ($I=11$). The most discriminating 1D-histogram of the selected color space is the $u*$ component ($J(11)=2$) with $R^{11,2}=2.90$.

3.4 One class construction

One class of pixels is constructed by analyzing the most relevant color space with rank order I which is determined at each iteration step of the algorithm. This class of pixels is defined by a parallelipedic box in the most relevant color space. This box is delimited by two thresholds defined along each color component of the most relevant color space.

Along the color component with rank order $J(I)$ which corresponds to the most discriminating 1D-histogram, the two thresholds $T_{left}^{I,J(I),K(I,J(I))}$ and $T_{right}^{I,J(I),K(I,J(I))}$ are those which delimit the mode with the highest amplitude.

The thresholds along the two other color components are selected among the thresholds $T_{left}^{I,j,k}$ and $T_{right}^{I,j,k}$, $j \neq J(I)$, determined in the mode detection stage. The selected thresholds delimit the box in which fall into the color vectors of pixels with the highest population. The pixels whose color vectors fall into this box constitute the class of pixels constructed at the iteration step.

3.5 Pixels of the class extraction

The pixels which are assigned to the so-constructed class, are extracted from the color image so that they are not taken into account at the next iteration steps of the procedure. The pixels which are assigned to this class and which are connected in the image, constitute one of the reconstructed regions in the segmented image. We assume that each constructed class corresponds to regions with the same colors.

3.6 Stopping criterion

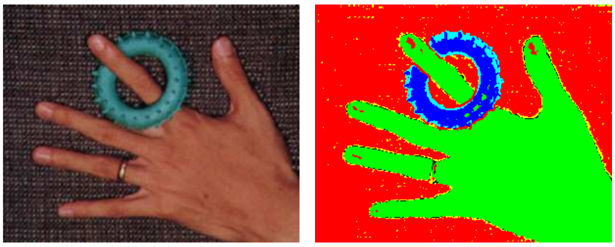
The iterative procedure stops when a percentage p of pixels of the image have not been assigned to any of the previously constructed classes. The parameter p, adjusted by the analyst, allows to tune the desired coarseness of the segmentation.

When the iterative procedure stops, the pixels which have not been assigned to any class, could be assigned to one of the constructed classes by means of a specific decision rule.

4 Results

The class construction scheme presented in this paper is based on the analysis of both the connectedness and the color homogeneity properties of the subsets of pixels. In order to demonstrate the interest of this new approach, we propose to segment three benchmark images, the "hand" image (see the images 5(a)), the "Peppers" image (see the image of figure 6(a)) and the "Lena" image (see the image of figure 7(a)) by means of the presented procedure.

Tables 2, 3 and 4 show the discriminating powers of the color spaces selected at each step of the procedure applied to the images 5(a), 6(a) and 7(a), respectively. The extracted pixels of a constructed class at each iteration step



(a) Original image "Hand" (b) Segmented image "Hand"

Figure 5. Segmention of the image "hand" $(303 \times 243$ pixels$)$ by the proposed method (time processing on a PC 730 Mhz: 1’55”)

(a) Original image "Peppers" (b) Segmented image "Peppers"

Figure 6. Segmention of the image "peppers" $(512 \times 512$ pixels$)$ by the proposed method (time processing on a PC 730 Mhz: 4’18”)

(a) Original image "Lena" (b) Segmented image "Lena"

Figure 7. Segmention of the image "Lena" $(512 \times 512$ pixels$)$ by the proposed method (time processing on a PC 730 Mhz: 5’20”)

of the algorithm are labelled with a false color in the segmented images 5(b), 6(b) and 7(b). These labels are represented in the fisrt column of the tables 2, 3 and 4 respectively. These tables show that there does not exist one single color space which is the most relevant at all the iteration steps of the procedure.

The discriminating power of the color space selected at each step number tends to decrease with the iteration step number. Indeed, the number of pixels to analyze decreases

Class	I	$J(I)$	$N^{I,J(I)}$	$R^{I,J(I)}$
1	(L^*,u^*,v^*)	2	3	2.90
2	(R,G,B)	1	2	1.95
3	(A,C_1,C_2)	2	3	2.11
4	(A,C_1,C_2)	2	3	1.83
5	(r,g,b)	1	2	1.16

Table 2. Number of modes $N^{I,J(I)}$ and discriminating power $R^{I,J(I)}$ of the most discriminating 1D-histogram $J(I)$ of the color space I selected at each step of the procedure applied to the image "hand".

Class	I	$J(I)$	$N^{I,J(I)}$	$R^{I,J(I)}$
1	(Y,U,V)	1	3	2.79
2	(R,G,B)	2	2	1.94
3	(X,Y,Z)	3	3	2.69
4	(A,C_1,C_2)	2	3	2.60
5	(I_1,I_2,I_3)	1	2	1.84
6	(R,G,B)	3	2	1.42

Table 3. Color space I selected at each step of the procedure to the image "peppers".

with the iteration step number. So, the number of detected modes in the 1D-histograms tends to decrease too.

However, the number of modes may increase whereas the number of pixels decreases, (see class 3 of table 3 by example). In this case, the discriminating power may increase in a single iteration step.

Images of figures 5(b), 6(b) and 7(b) show that this procedure provides satisfying segmentation results in terms of pixel classification. Indeed, the regions which represent the different objects in the images are well-reconstructed.

The results show that the selection of different color spaces at the iteration steps of the procedure, which is designed to discriminate the considered pixel classes, is a relevant solution for the construction of the regions.

5 Conclusion

In this paper, we have proposed a color image segmentation algorithm by unsupervised pixel classification. This iterative method determines one class of pixels at each iteration step. For this purpose, it selects the most relevant color space in which the 1D-histogram allows to discriminate as well as possible the pixels classes. The discriminating power is based on the connectedness properties of pixels whose color component levels range in the modes of the 1D-histograms. The criterion used for selecting the most relevant color space is based on the analysis of the color distribution and the connectedness properties of the pixels in the image.

Class	I	$j(I)$	$R^{I,J(I)}$	$N^{I,J(I)}$
1	(X,Y,Z)	2	5	4.26
2	(X,Y,Z)	1	4	3.42
3	(R,G,B)	1	3	2.66
4	(R,G,B)	2	2	1.90
5	(A,C_1,C_2)	3	3	2.27
6	(A,C_1,C_2)	1	3	2.02
7	(A,C_1,C_2)	3	3	1.93
8	(A,C_1,C_2)	3	3	1.66
9	(A,C_1,C_2)	2	2	1.64

Table 4. Color space I selected at each step of the procedure applied to the image "Lena".

The segmentation results strongly depend on the mode detection stage, and more precisely on the localizations of the determined thresholds. Presently, we are working for improving this stage.

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