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Analysis of the Relevance of Evaluation Criteria for Multicomponent Image Segmentation

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ABSTRACT

Image segmentation is an important stage in many applications such as image, video and computer processing. Generally image interpretation depends on it. The materials and methods used to demonstrate are described. The results are presented and analyzed. Several approaches and algorithms for image segmentation have been developed, but it is difficult to evaluate the efficiency and to make an objective comparison of different segmentation methods. This general problem has been addressed for the evaluation of a segmentation result and the results are available in the literature. In this work, we first presented some criteria of evaluation of segmentation commonly used in image processing with reviews of their models. Then multicomponent synthetic images of known composition are applied to these criteria to explore the operation and evaluate its relevance. The results show that choosing an assessment method depends on the purpose, however the criterion of Zeboudj appears powerful for the evaluation of region segmentations for properly separated classes, on the contrary the criteria of Levine-Nazif and Borsotti are adapted to the methods of classification and permit to build homogeneous regions or classes. The values of the Rosenbeger criterion are generally low and similar, so hard to make a comparison of segmentations with this criterion.

1. Introduction

Segmentation is an essential step in image processing to the extent that it affects the interpretation which will be made of these images in many application areas [1-4]. They are based on different approaches, such as contour, region and texture. Many algorithms have been proposed in recent decades. Given the multitude of proposed methods, the problem of assessing the quality of segmentation becomes paramount.

Originally, the first criteria for evaluating the quality of segmentation were purely subjective: the observer merely to examine different results of segmentation, to decide which the best was according to the objective. It soon becomes necessary to replace this qualitative method by quantitative methods, defining appropriate quality criteria. The first quantitative criteria date from the Nineties (90), but the field remains open, and new criteria appear regularly in literature [5-7].

These criteria are not intended to provide the abso-

lute quality of a segmentation: they serve just to compare, using a given criterion, different segmentation algorithms applied to the same image, or to set up an algorithm to adjust its parameters to provide the best result.

It should be noted that classification with a particular criterion, different algorithms of segmentation can be changed if we change the criterion. Similarly, a choice of parameters optimizes a segmentation algorithm, with respect to a given criterion it may be changed if we change the evaluation criterion.

Throughout this paper, the image segment will be denoted I. After segmentation, we get an image I_s, formed with N_s regions S_i, where $i \in \{1, \cdots, N_s\}$, checking the properties:

$$\begin{cases} S_i \bigcap S_j = \phi \\ \bigcup_1^{N_s} S_i = I \end{cases} \quad (1)$$

Denoting by A the number of pixels in the image and by A_i that of the region S_i, properties 1 can be written:

$$A = Card(I) = \sum_{1}^{N_s} S_i \qquad (2)$$

One generally agrees to classify the methods of assessing the quality of a segmentation in two categories, corresponding respectively to a supervised evaluation and an unsupervised evaluation [6,8].

2. Criteria for Evaluating the Region Segmentation

2.1. Supervised Evaluation

The assessment is known as supervised when a reference segmentation I_v (also called ground-truth) is defined. This one can be established on a natural image, by one (or more) operator human expert of application domain, using drawing software. A more comfortable case is that of the synthetic images whose ground truth is rigorously accessible.

The evaluation of a segmentation algorithm is then performed by comparing the segmented image I_s with the ground-truth I_v. Denoted by V_j, where $j \in \{1, \cdots, N_v\}$, the N_v regions of the reference image. The question which is asked is that of the measurement of the similarity (or dissimilarity) between the reference segmentation and the algorithmic segmentation.

One possible answer is provided by the method of Vinet, search recursively the pairs of regions (S_i, V_j) with the highest recovery [9]. T_{ij} recovery regions S_i and V_j is defined by:

$$T_{ij} = Card\left(S_i \cap V_j\right) \qquad (3)$$

It makes it possible to build a table of covering $T(I_s, I_v)$, whose elements are the t_{ij}. One initially selects in the table the cell corresponding to the maximum t_{ij}. The two corresponding regions are then paired. Then one removes in the table the corresponding line and column, and we iterate the operation until all the cells are treated. K couples thus are obtained:

$$K = \min(N_s, N_v) \qquad (4)$$

Each couple presents a covering t_k, where $k \in \{1, \cdots, K\}$. The measurement of Vinet is then defined by:

$$VIN(I_s, I_v) = 1 - \frac{1}{A} \sum_{k=1}^{K} t_k \qquad (5)$$

Assuming a perfect recovery, (1) and (5) show that Vinet's criterion takes the value 0. It tends to 0.5 for minimal recoveries. The method iteratively chosen to match regions is suboptimal; it does not guarantee maximum recovery across all regions.

Other supervised evaluation criteria can be defined [8], taking into account the number and position of the evil segmented pixels, or even their color. They will not be used in this article.

2.2. Unsupervised Evaluation

In most cases, we do not have a ground-truth. It is thus necessary to develop calculable evaluation criteria only on the image I_s, segmented by algorithm. Many criteria, more or less discriminating, have been proposed. They are based on inter-region variability and (or) intra-region uniformity.

Variability or uniformity is measured from the colors of pixels in the image. The color of the pixel p will be denoted $C(p)$, and the average color of a region R of the image will be denoted $\bar{C}(R)$. In the particular case of textured images, texture attributes may also be implemented. They will form the vectors that we denote $G(R)$ when characterized in a region R of the image.

2.2.1. Intra-Region Uniformity Criterion of Levine and Nazif

The intra-region uniformity is translated here by the normalized variance of colors inside each region [10]. The colors' average of the region S_i is written:

$$\bar{C}(S_i) = \frac{1}{A_i} \sum_{p \in S_i} C(p) \qquad (6)$$

The normalized color variance of the component C_q, on the region S_i, is expressed:

$$\sigma_q^2(S_i) = 4 \frac{\frac{1}{A_i} \sum_{p \in S_i} \left(C_q^2(p) - \bar{C}_q^2(S_i)\right)}{\left(\max_{p \in S_i}\left[C_q(p)\right] - \min_{p \in S_i}\left[C_q(p)\right]\right)^2} \qquad (7)$$

where $\bar{C}_q$ denotes the q-th component of $\bar{C}$. The total variance of the color on the region S_i is written:

$$\sigma^2(S_i) = \sum_{q=1}^{n} \sigma_q^2(S_i) \qquad (8)$$

Assuming an image with n components.
The criterion of Levine and Nazif is defined by:

$$LEV(I_s) = 1 - \sum_{i=1}^{N_s} \sigma^2(S_i) \qquad (9)$$

Assuming that all regions are perfectly homogeneous, the test is 1 since the variance of each region (the numerator of the fraction in the (7)) is zero. The criterion decreases in presence of inhomogeneity. An alternative is to weight in the sum on i, each region by the number of pixels.

2.2.2. Dissimilarity Measure of Liu and Yang

Let us consider e_i the sum of Euclidean distances (*dist*) between the colors of pixels in the region S_i and the average color of S_i:

$$e_i = \sum_{p \in S_i} dist\left[C(p), \overline{C}(S_i)\right] \qquad (10)$$

The criterion of Liu and Yang is defined by [11]:

$$LIU\left(I_s\right) = \frac{1}{1000 \times A} \sqrt{N_s} \sum_{i=1}^{N_s} \frac{e_i^2}{\sqrt{A_i}} \qquad (11)$$

If all regions are perfectly homogeneous, the criterion is 0 because of e_i. Contrary to Levine and Nazif's criterion, that of Liu and Yang does not just evaluate intra-region variance: it penalizes the over-segmentation by the presence of many regions in numerator and the area of regions in denominator.

2.2.3. Criterion of Borsotti

The criterion of Liu and Yang strives only partially against the over-segmentation. Suppose that it leads to a large number of small regions, all homogeneous: the presence of the factor e_i in the (11) gives then $LIU\left(I_s\right) = 0$, which is characteristic of a "good" segmentation, this is in contradiction with the decision of over-segmentation as starting hypothesis.

To overcome this drawback, Borsotti proposed a neighboring criterion, penalizing small regions even in the case where they are homogeneous [12]

$$BOR\left(I_s\right) = \frac{1}{1000 \times A} \sqrt{N_s} \sum_{i=1}^{N_s} \left[\frac{e_i^2}{1 + \log A_i} + \frac{v^2\left(A_i\right)}{A_i^2}\right]$$

$$(12)$$

where $v\left(A_i\right)$ is the number of regions comprising A_i pixels. The first term under the summation sign penalizes large inhomogeneous regions, while the second penalizes small regions of the same size, even if they are homogeneous. A "successful" segmentation will be characterized by the criterion of Borsotti close to 0.

2.2.4. Inter-Region and Intra-Region Contrast of Zeboudj

The above criteria are only interested in the intra-region homogeneity. The criterion of Zeboudj takes into account not only the intra-region homogeneity, but also the inter-region contrast, in a neighborhood $W(p)$ of the pixel p [13].

The contrast $\Delta(p, s)$ between two pixels p and s of an image is proportional to the distance separating the colors of these pixels:

$$\Delta\left(p, s\right) = \frac{dist\left[C(p), C(s)\right]}{d_{max}} \qquad (13)$$

where d_{max} is the maximum distance possible in the multicomponent space used.

The contrast $\Delta_I\left(S_i\right)$ within the region S_i, and the contrast $\Delta_E\left(S_i\right)$ between the region S_i and the neighboring regions are respectively defined by:

$$\Delta_I\left(S_i\right) = \frac{1}{A_j} \sum_{p \in S_i} \max\left[\Delta(p, s), s \in W(p) \cap S_i\right] \quad (14)$$

$$\Delta_E\left(S_i\right) = \frac{1}{L_i} \sum_{p \in F_i} \max\left[\Delta(p, s), s \in W(p) \cap S_i, s \notin S_i\right]$$

$$(15)$$

where L_i is the length of the boundary F_i delimiting the region S_i. The global contrast $\Delta\left(S_i\right)$ of the region S_i is defined by:

$$\Delta\left(S_i\right) = \begin{cases} 1 - \dfrac{\Delta_I\left(S_i\right)}{\Delta_E\left(S_i\right)} & if \ 0 < \Delta_I\left(S_i\right) < \Delta_E\left(S_i\right) \\ \Delta_E\left(S_i\right) & if \ \Delta_I\left(S_i\right) = 0 \\ 0 & else \ if \end{cases} \qquad (16)$$

Zeboudj's criterion is deduced by:

$$ZEB\left(I_s\right) = \frac{1}{A} \sum_{i=1}^{N_s} A_i \times \Delta\left(S_i\right) \qquad (17)$$

This criterion increases with the quality of segmentation. It is not suitable for images too noisy or textured.

2.2.5. Criterion of Rosenberger

To take into account the possible presence of textured regions in the segmented image, while addressing the inter-region disparity, Rosenberger offers a different treatment of textured regions and non-textured regions in the defining of the evaluation criterion of the segmentation [14]. The textured character or not of a region is established using the co-occurrence matrices (thus performing the pre-processing of multicomponent images into scalar images, which is simplified by a process of multiple thresholding in order to reduce the size of co-occurrence matrices). The non-textured regions are characterized by their colors $C\left(p \in S_i\right)$, and textured regions by a vector of 29 texture attributes, noted G, chosen, because of their discriminating power among the classic attributes of co-occurrence, lengths of intervals, and local histograms of local extremas.

- *Intra-region disparity*

The disparity of non-textured regions is characterized by the intra-region variance of pixel colors in a manner analogous to that used by Levine and Nazif. In the region S_i attributed the disparity coefficient:

$$D(S_i) = \sigma(S_i) \qquad (18)$$

calculated using Equations (6) to (8).

For the textured regions, the attributes used are not any more the colors, but the vectors of texture $G(S_i)$. Their calculation of the coefficient of disparity $D_I(S_i)$ associated with textured regions is more complex, and will not be detailed here, because all the images used in the continuation of this work will be considered non-textured. The interested reader may however see reference [14].

The global intra-region disparity is given by:

$$D_I(I_s) = \frac{1}{N_s} \sum_{i=1}^{N_s} \frac{A_i}{A} D_I(S_i) \qquad (19)$$

• *Inter-region disparity*

Between two non-textured regions, the disparity is proportional to the distance separating the average colors of the two regions:

$$D(S_i, S_j) = \frac{dist\left[\bar{C}(S_i), \bar{C}(S_j)\right]}{d_{max}} \qquad (20)$$

where d_{max} is the maximum distance possible in the multicomponent space used.

Between two textured regions, disparity takes into account the textural distance vectors, and their norm.

$$D(S_i, S_j) = \frac{d\left[G(S_i), G(S_j)\right]}{\|G(S_i)\| + \|G(S_j)\|} \qquad (21)$$

Between two regions one of which is textured and the other not, the disparity is set to:

$$D(S_i, S_j) = 1 \qquad (22)$$

If we denote $\{S_{i1}, \cdots, S_{iq_i}\}$ the set of q_i neighboring regions of S_i. The inter-region disparity of the region S_i is written:

$$D_E(S_i) = \frac{1}{q_i} \sum_{j=i1}^{iq_i} D(S_i, S_j) \qquad (23)$$

and the global inter-region disparity of the image I_s is given by:

$$D_E(I_s) = \frac{1}{N_s} \sum_{i=1}^{N_s} \frac{A_i}{A} D_E(S_i) \qquad (24)$$

• *Criterion of Rosenberger*

Finally, the criterion of Rosenberger is defined by:

$$ROS(I_s) = \frac{D_I(I_s) + 1 - D_E(I_s)}{2} \qquad (25)$$

This criterion decreases when the segmentation quality increases. A sub-segmentation is penalized through an intra-region disparity D_I strong, and over-segmentation will be through an inter-region disparity D_E low.

3. Analysis of Unsupervised Evaluation Criteria, Results and Discussion

The behavior of the above criteria will be studied using synthetic images constituted of regions of uniform color, perfectly controlled: their segmentation in region is thus known. The segmented image and the ground-truth being rigorously similar, it is unnecessary to examine the behavior of Vinet's criterion, which will systematically give a result equal to 0 (perfect overlap). Only then we will study the unsupervised evaluation criteria (except that of Liu and Yang: we have preferred to him that of Borsotti, which is an improvement). The window *W* used to calculate Zeboudj's criterion here is a window of size 3 × 3 (neighboring order 8). To calculate Rosenberger's criterion, all regions will be considered non-textured.

3.1. Characteristics of Synthetic Images Used

The test images are 4 synthetic images shown in **Figure 1** and whose detailed composition is described in **Table 1**. Their segmentation (shown in false color to better highlight the regions) is shown in **Figure 2**.

The first two images (Synt1a_Lisa and Synt1b_Lisa) present two uniform regions, of different sizes. The colors of these regions are clearly separated for the image Synt1a_Lisa, and otherwise very similar (and indistinguishable to the eye) for the image Synt1b_Lisa. The last two images (Synt2a_Lisa and Synt2b_Lisa) present three
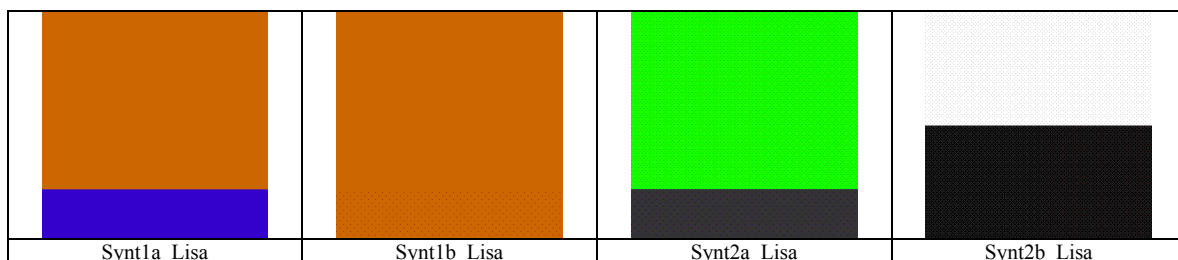

| Synt1a_Lisa | Synt1b_Lisa | Synt2a_Lisa | Synt2b_Lisa |

Figure 1. Synthetic images.

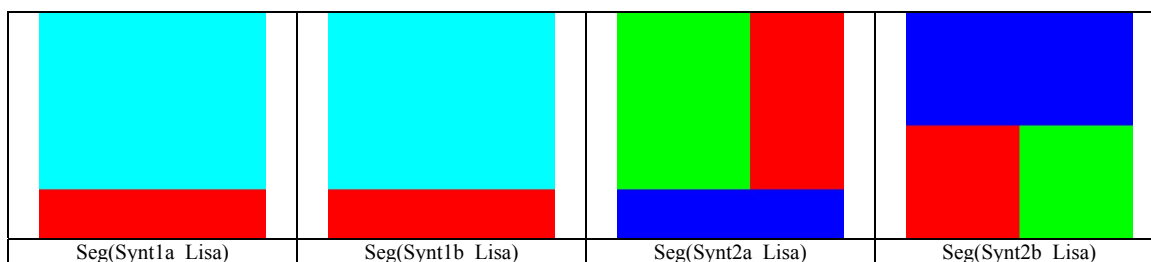| Seg(Synt1a_Lisa) | Seg(Synt1b_Lisa) | Seg(Synt2a_Lisa) | Seg(Synt2b_Lisa) |

Figure 2. Result (in arbitrary colors) of the segmentation.

Table 1. Building of synthetic images of Figure 1.

(a)

Building of synthetic images							
Synt1a_Lisa				Synt1b_Lisa			
R	G	B	Population	R	V	B	Population
51	0	204	51200	203	101	0	14336
204	102	0	14336	204	102	0	51200

(b)

Building of synthetic images							
Synt2a_Lisa				Synt2b_Lisa			
R	G	B	Population	R	V	B	Population
21	250	0	21200	20	20	20	16384
23	250	0	30000	22	20	20	16384
51	50	54	14336	250	250	250	32768

Table 2. Value of evaluation criteria for unsupervised segmentation for synthetic images of Figure 1.

Image	Criterion			
	Levine and Nazif	Borsotti	Zeboudj	Rosenberger
Synt1a_Lisa	1	$1,13.10^{-16}$	0,6000	0,3500
Synt1b_Lisa	1	$1,13.10^{-16}$	0,0026	0,4993
Synt2a_Lisa	1	$2,17.10^{-16}$	0,1957	0,4584
Synt2b_Lisa	1	$8,12.10^{-16}$	0,6753	0,3873

uniform regions.

On the Synt2a_Lisa image, two regions have neighboring colors (and indistinguishable with the eye) and Different sizes, higher than that of the third region, from which the color is distant. On the Synt2b_Lisa image, two regions are identical in size, equal to half of that of the third region: the colors of the two regions of identical size are very close one to the other (indiscernible to the eye), and far away from the color of the third.

3.2. Calculation and Analysis of Criteria Evaluation for Segmentation

The evaluation criteria for unsupervised segmentation, computed for these images, take the values reported in **Table 2**.

Each region is of uniform color, Levine's criterion returns the possible maximum value 1, as expected.

For the same reason, Borsotti's test is sensitive only to the size of regions and the number of regions with the same size (second term under the summation sign in (12)). Segmentation provides a partition exactly the same for the first two images, and consequently, the criteria of Borsotti are identical in both cases. Compared to the first two images, the latter two are penalized by the criterion of Borsotti (which increases), because the number of regions increases from 2 to 3. The fourth image is most penalized than the third because it has two regions of identical size (parameter ν of Borsotti's criterion).

As each region is uniform in color, the internal contrast of regions Δ_I is zero, and Zeboudj criterion no longer considers the contrast between a region and its neighbors. It penalizes the image Synt1b_Lisa (*ZEB* = 0.0026) compared to the image Synt1a_Lisa (*ZEB* = 0.6000). The same reasoning, with the same conclusions can be made with the criterion of Rosenberger.

3.3. Influence of Inter-Class Colorimetric Distance and the Population of Regions

Consider a square image of *a* hand consisting of two homogeneous regions of color respective C_1 and C_2 which *n* components are coded from levels 0 to $2^q - 1$. The position of the boundary between the two regions is marked by a variable *x* (**Figure 3**) proportional to the population of both regions.

We find generalize the model of images Synt1a_Lisa and Synt1b_Lisa of **Figure 1**. The calculation of the evaluation criteria for segmentation provides here the following results:

$$LEV = 1 \qquad (26)$$

$$BOR = \begin{cases} \dfrac{\sqrt{2}}{1000a^6}\left[\dfrac{1}{x^2} + \dfrac{1}{(1-x)^2}\right] & if \quad x \neq \dfrac{1}{2} \\ \dfrac{32\sqrt{2}}{1000a^6} & if \quad x = \dfrac{1}{2} \end{cases} \qquad (27)$$

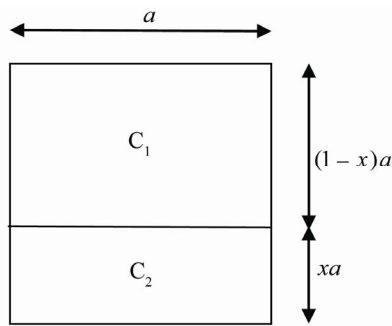$$ZEB = \frac{1}{a}\frac{dist(C_1, C_2)}{d_{max}} \qquad (28)$$

Figure 3. Square image consisting of two regions of color C_1 and C_2.

$$ROS = \frac{2 - \dfrac{dist(C_1, C_2)}{d_{max}}}{8} \tag{29}$$

The Equation (26) shows that Levine's criterion values the segmentation into homogeneous regions, regardless of their sizes and colors. Segmented into two neighboring regions of nearly identical color will be as good as if the colors were distant, which may be irrelevant for the intended application.

The function between brackets in (27) is decreasing in the interval [0, 0.5] and increasing in the interval [0.5, 1]. This shows that Borsotti's criterion values the segmentation in homogeneous regions of similar size, regardless of their spacing colors. A segmentation into two neighboring regions of very different sizes will be considered bad, even if the application is to detect a small homogeneous region within a greater one.

Equations (28) and (29) show that Zeboudj's and Rosenberger's criteria value the segmentations into two neighboring homogeneous regions in proportion to their color difference, and this result holds true regardless of the sizes of the two regions.

3.4. Influence of the Metric on Zeboudj's and Rosenberger's Criteria

Denote ZEB_{min} and ZEB_{max} (respectively ROS_{mini} and ROS_{max}) limits of variation of Zeboudj parameter (respectively that of Rosenberger) for an image which model is that of **Figure 3**. The minimum distance between two colors is equal to 1, whether we use the Euclidean metric, that of Manhattan, or that of Chebychev. Since the n components of the image are each coded on q bits, the maximum distance between two colors is written:

$$d_{max} = \begin{cases} \sqrt{n \times 2^{2q}} & \text{in Euclidian metric} \\ n \times 2^q & \text{in Manhattan metric} \\ 2^q & \text{in Chebychev metric} \end{cases} \tag{30}$$

The range of variation of Zeboudj and Rosenberger criteria that results is summarized in **Table 3**, for grayscale images ($n = 1$), color images ($n = 3$) and multicomponent images ($n = 10$), the tonal resolution q can vary from 1 to 8 bits per component. ZEB_{max} and ROS_{mini}, who write the best segmentations, are not listed in the table because they are respectively 1 and 0.125 for all configurations.

For scalar images ($n = 1$), the values of ZEB_{min} and ROS_{max} repeated identically whatever the type of metric, which is not surprising since the distances are d_{max} identical.

For all metrics, the value of $2 \times ZEB_{min}$ characteristic of bad segmentation is less than 0.1 regardless of the number of components, provided that the tonal resolution is greater than or equal to 4 bits. This provides ranges of variation in a width at least equal to 0.9 (for 4 bits per pixel), which approaches the limit 1 when the tonal resolution increases. It is therefore possible in this case to use the metric of choice, without significant impact on the available scale of classification of segmentation algorithms.

We will have an incentive to choose Chebychev's metric, which induces less computation. At lower tonal resolutions, the range of possible values for $2 \times ZEB$ shrinks, until a width equal to 0.5 for binary images. But again this difference remains the same whatever the metric used.

For Chebychev's metric, the maximum distance between two colors do not depend on the number of components (see (30)). This explains the identical repetition of values of ZEB_{min} and ROS_{max}, whatever the number of components (two last columns of **Table 3**).

For all metrics, the value of ROS_{max} characteristic of poor segmentation is between 0.240 and 0.250 regardless of the number of components, as long as the tonal resolution is greater than 4 bits. This provides ranges of variation in a width at least equal to 0.115 (for 4 bits per pixel), which tends to the limit 0.125 when increases tonal resolution. Again it will be possible to use the metric of choice. At lower tonal resolutions, the range of possible values for ROS narrows to a width equal to 0.0625 for binary images. But again this difference remains the same whatever the metric used.

4. Conclusions

This work has enabled us to study the unsupervised evaluation methods of segmentation to understand their relevance. We showed that their relevance is related to the metric used, the distance between color regions or classes, classes or regions size, the tonal resolution of images and the number of components n of the images without forgetting the homogeneity of the regions. We

Table 3. Value of evaluation Variation range of Zeboudj and Rosenberger criteria, for images consistent with the model in Figure 3 ($a/2$ was assumed equal to 1 for the calculation of the Zeboudj criterion).

n	q	Euclidean distance		Manhattan distance		Chebychev distance	
		$2*ZEB_{min}$	ROS_{max}	$2*ZEB_{min}$	ROS_{max}	$2*ZEB_{min}$	ROS_{max}
1	1	0.500	0.188	0.500	0.188	0.500	0.188
	2	0.250	0.219	0.250	0.219	0.250	0.219
	3	0.125	0.234	0.125	0.234	0.125	0.23
	4	0.063	0.242	0.063	0.242	0.063	0.242
	5	0.031	0.246	0.031	0.246	0.031	0.246
	6	0.016	0.248	0.016	0.248	0.016	0.248
	7	0.008	0.249	0.008	0.249	0.008	0.249
	8	0.004	0.250	0.004	0.250	0.004	0.250
3	1	0.289	0.214	0.167	0.229	0.500	0.188
	2	0.144	0.232	0.083	0.240	0.250	0.219
	3	0.072	0.241	0.042	0.245	0.125	0.234
	4	0.036	0.245	0.021	0.247	0.063	0.242
	5	0.018	0.248	0.010	0.249	0.031	0.246
	6	0.009	0.249	0.005	0.249	0.016	0.248
	7	0.005	0.249	0.003	0.250	0.008	0.249
	8	0.002	0.250	0.001	0.250	0.004	0.250
10	1	0.158	0.230	0.050	0.244	0.500	0.188
	2	0.079	0.240	0.025	0.247	0.250	0.219
	3	0.040	0.245	0.013	0.248	0.125	0.234
	4	0.020	0.248	0.006	0.249	0.063	0.242
	5	0.010	0.249	0.003	0.250	0.031	0.246
	6	0.005	0.249	0.002	0.250	0.016	0.248
	7	0.002	0.250	0.001	0.250	0.008	0.249
	8	0.001	0.250	0.000	0.250	0.004	0.250

also showed what ranges of evaluation criteria were good or bad.

Knowing that the study of the relevance of a segmentation algorithm requires choosing an evaluation criterion of segmentation, therefore to realize the goal of the segmentation in homogeneous regions and well separated, we recommend an appropriate combination of Zeboudj's and Borsotti's criteria.

In Perspectives, an experiment with models of synthetic multi-region images will achieve a comprehensive study of the relevance of unsupervised evaluation methods of segmentation.

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