

A Review on Image Segmentation Techniques and Performance Measures

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Abstract—Image segmentation is a method to extract regions of interest from an image. It remains a fundamental problem in computer vision. The increasing diversity and the complexity of segmentation algorithms have led us firstly, to make a review and classify segmentation techniques, secondly to identify the most used measures of segmentation performance and thirdly, discuss deeply on segmentation philosophy in order to help the choice of adequate segmentation techniques for some applications. To justify the relevance of our analysis, recent algorithms of segmentation are presented through the proposed classification.

Keywords—Classification, image segmentation, measures of performance.

I. INTRODUCTION

IMAGE segmentation is the basis for applications such as objects recognition, medical diagnosis, image analysis and understanding, detecting and locating objects in an image. It refers to partitioning an image into several disjoint subsets such that each subset corresponds to a meaningful part of the image [1].

A rich amount of literature on image segmentation has been published over the past decades. Conventionally, image segmentation is grouped into five main categories [2]. The first category is edge-based segmentation scheme. This method assumes that the grey levels of the pixels connecting foreground and background are very distinct, thus discontinuities are usually detected by the first or second order derivatives method, despite the fact that, they were usually found sensitive to the image noise. Post-processing operations are usually required to remove noise. The second category is threshold-based segmentation scheme [3]. This approach is able to detect different objects in the image by using threshold value based on classification rules. When we need only one object in an image, the rest of image is called background. When the intensity of the pixels is found to be larger/smaller than a predefined threshold, those pixels are classified as foreground. Otherwise, they will be viewed as background. However, the challenge on this is to find an appropriate threshold. The third category is region-based segmentation [4],

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where we generally have region growing and split-and-merge algorithms. As the fourth category we have watershed-based segmentation [5], where image is viewed as a topological surface and the intensity value as height. The local minimal height is assigned to a region and the maximal one to edge. However, a direct application of watershed algorithm will generally lead to over-segmentation problem due to noise generation. The fifth category is clustering-based segmentation. This method tries to establish clusters or collection of data points held together because of the predefined criteria. To answer the question “how good is a given segmentation algorithm?” and to cope with shortcomings of segmentation algorithms, the researcher's ingenuity led them to propose performance measurements and to explore other potentially effective tools for good segmentation.

The goal of this paper is to present adequate segmentation techniques for some applications and that, through presentation of segmentation methods and the most widely used measures of evaluation. This is to inform researchers about the increasing complexities of image segmentation and at the same time to equip users of segmentation.

The outline of the paper is as follows. Section II will be of particular interest to see our classification method of the segmentation. In Section III, we list performance measures of segmentation. In Section IV, we present recent segmentation techniques as classified by our method. Performance analysis of segmentation is presented in Section V. Conclusion is given finally in Section VI.

II. METHODOLOGY

Image segmentation is the process by which an original image is partitioned into homogeneous regions [6]. The segmentation aims to localize objects among many others. Many image segmentation techniques have been proposed. Some of the most important and widely used image segmentation techniques can be classified based on three steps as shown in Fig. 1.

Each region in segmentation process is generally identified by its inside or its boundary. A good knowledge of one of those two elements is often suitable for a good segmentation. Some processes look within regions without necessarily being concerned with the borders. These segmentation techniques can be considered as region inside approach. Some other segmentation processes give priority to good knowledge of region boundary. We consider them as approach region boundary. While considering those two approaches, segmentation process considers at least one of three

elementary properties in a 2D or 3D image, namely color, gray level and texture. Color images are represented by three intensity components. Color uniformity is one of the most significant low-level features that can be used to extract homogeneous regions that are most of the time related to objects or part of objects [7]. The gray level or brightness denoted as $f(x, y)$, represents a set of positive integers $G = \{0, 1, \dots, L-1\}$, where (x, y) is the spatial coordinate of a digitized image. By convention, the gray level 0 is the darkest and the gray level $L-1$ is the lightest. The brightness variation is another far-reaching low-level feature used to extract objects [8]. Texture is a field of the image which seems to be a coherent and homogeneous field. It is this property of

coherence which is generally required to recognize regions. In each segmentation algorithm, once image elementary properties and segmentation approach have been chosen, we need to find appropriate tools. The state of the art in segmentation abounds a multitude of tools used to enhance, denoise and properly segment. The most recent tools used are: Canny edge detection, clustering algorithms, Contrast stretching, Decision trees, Descriptors, Dynamic Programming, Filters, Firework algorithm, Flood fill, Fuzzy tools, Graph theory, Local search, Morphological Operators, Neutrosophy, Partial Differential Equations, Statistical tools and Support Vector Machine.

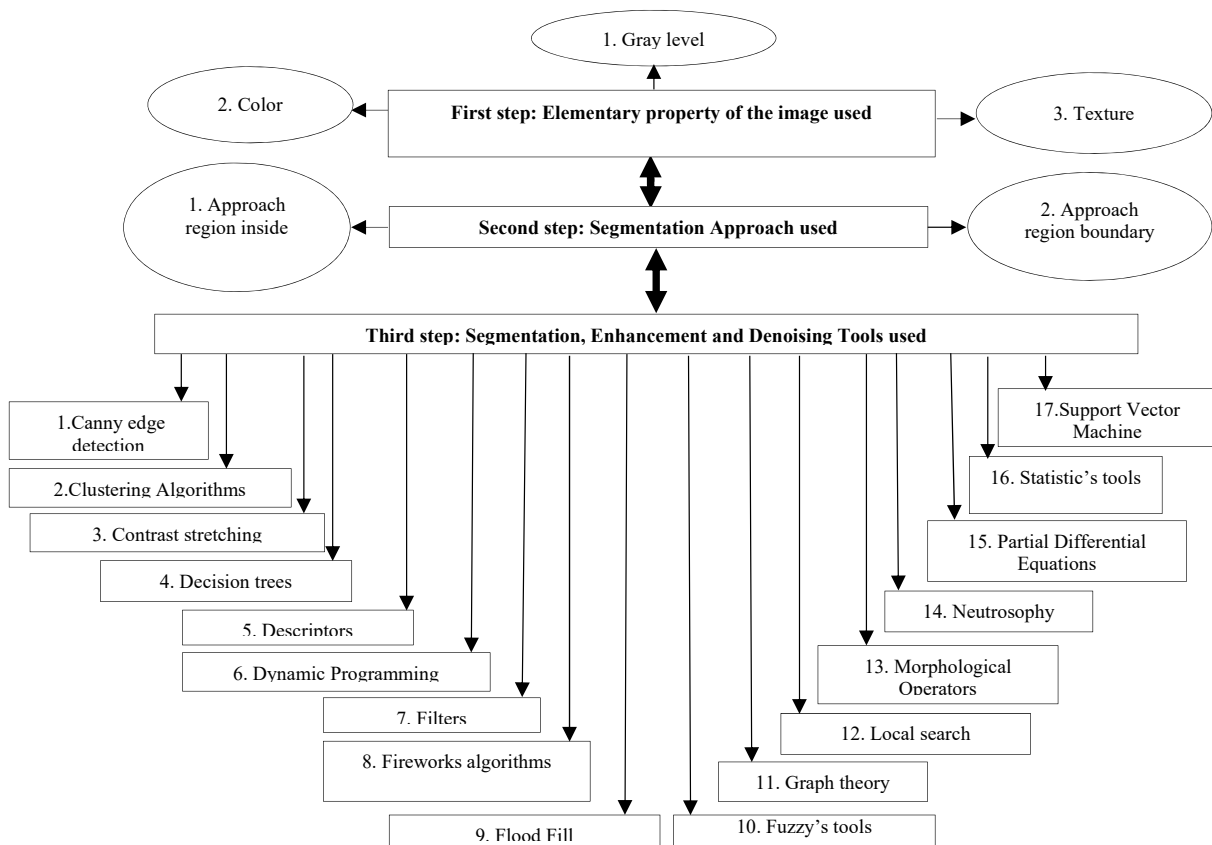


Fig. 1 Characterization of segmentation methods

A. Canny Edge Detection

It is a multi-step algorithm that can detect edges with noise suppressed at the same time [9]. It aimed to build an edge detector that satisfied three criteria: there should be no response where edges do not exist (a low error rate), edge points should be well localized and there should be only one response to a single edge [6].

B. Clustering Algorithms

The clustering algorithm extracts the region as a cluster, and is suited to the partitioning of larger parts. They have features which are robust to noise, but are not suited to extract small

regions [10]. Those algorithms are: Artificial neural networks, deep learning, connectivity-based algorithm, Centroid-based algorithm, density-based algorithm, dimensionality reduction.

C. Contrast Stretching

It is a tool which operates by stretching the range of pixel intensities of the input image to take a larger dynamic range in the output image [6].

D. Decision Trees

It is a type of supervised learning algorithm used in classification process which represents graphically, specific decision situations that are used when complex branching

occurs in a structured decision process [11].

E. Descriptors

Image is considered as a matrix information where we can extract some information. Descriptors are some transformations used to extract this information. Among these transformations we have, the histogram equalization generally uses to enhance the contrast in regions where pixels have similar intensities [12], the Discrete Wavelet Transform (DWT), Discrete Cosine Transform (DCT), Hough Transform, Co-occurrence matrix, Chromaticity, the dominant color (color that is most prevalent in image).

F. Dynamic Programming

Dynamic programming or dynamic optimization is a method for solving a complex problem by breaking it down into a collection of simpler sub-problems. Each sub-problem is considered as a stage and the possible alternatives available at each stage are regarded as its states. Associated with each stage is the return function of a decision variable which evaluates each feasible decision [13].

G. Filters

Filters are used to improve contrast, remove noises, detect known patterns. They transform pixel intensity values to reveal certain image characteristics [6]. Among them, we have matched filter (an optimal linear filter for maximizing the signal to noise ratio in the presence of additive stochastic noise), Gabor filter, rank filter, steerable filter, Gaussian filter, Prewitt filter, Sobel filter, line detection filters.

H. Firework Algorithm

Inspired by firework explosion process, firework algorithm is an optimisation of subtle functions. Four steps define the process of fireworks algorithm namely, explosion operation, mutation operation, mapping rule and selection strategy. It explores a very large solution space by choosing a set of random points confined by some distance metric. Reference [14] used it as a tool for image segmentation.

I. Flood Fill

Flood fill or seed fill, is an algorithm that determines the areas that are connected to a given node in a multi-dimensional array. It's used for region filling when all the pixels in the region have same features [15].

J. Fuzzy Tools

Fuzzy set theory and fuzzy logic are strength tools to describe human language rules, in form of fuzzy if-then rules [16]. They have four main algorithms used in image segmentation: fuzzy thresholding, fuzzy rule-based inferencing scheme, fuzzy C-mean clustering and fuzzy integral-based decision [17].

K. Graph Theory

Image segmentation can be interpreted as partitioning the image elements into different categories; a cut of a graph is a partition of the vertices in the graph into two disjoint subsets. Constructing a graph with an image can solve the

segmentation problem by using techniques for graph cuts in graph theory [18].

L. Local Search

Local search is a method for solving computationally hard optimization problems. It is based on the concept of a neighborhood which generates function that may be able to generate the optimal solution [19]. Local search algorithms generally used in image segmentation are Hill climbing and genetic algorithms.

M. Morphological Operators

There are many applications for morphological operators, like texture analysis, noise elimination, and boundary extraction. Their goal is to eliminate all defects and maintain structure of image [20]. Key Morphological Operators are called *erosion* and *dilation*.

N. Neutrosophy

It is a general framework for unification of many existing logics (philosophy, set theory, probability and statistics) and can be used in segmentation image [21].

O. Partial Differential Equations (PDE)

Using PDE-based methods and solving the PDE by a numerical scheme, can segment an image. The central idea is changing an initial curve towards the lowest potential of a cost function, where its definition reflects the task to be addressed. Active contours and level sets are some approaches. Active contour model or snake is a tool for delineating an object outline from a possibly 2D noise image. It is popular in computer vision, and greatly used in segmentation, edge detection and stereo matching. A snake is an energy minimizing, deformable spline influenced by constraints [22]. The segmentation problem can be reduced to finding curves to enclose regions of interest. Intuitively, these issues can also be alleviated using the level set method [23]. One of the level set algorithms used is the Chan-Vese algorithm [24].

P. Statistical Tools

Among statistical tools, we can mention, the Markov random field (MRF), Otsu thresholding, Bayesian parameter estimation (BPE), iterative conditional estimation (ICE), expectation maximization algorithm (EMA), regression analysis, likelihood, region merging (growing/splitting). Segmentation is formulated to assign labels to pixels. MRF is a probabilistic approach to build label/pixel dependencies [25]. BPE is a powerful probabilistic graphical model that has been applied in computer vision. It can group low-level edge segments for high-level image understanding, for the interpretation of complex scenes [26]. Region merging is a robust algorithm to segment an image into regions with similar intensity or color. It starts with one region per pixel and then applying a statistical test on neighboring regions (in ascending order of intensity differences) to find out whether the mean intensities are sufficiently similar enough to be merged [27].

Q. Support Vector Machines (SVM)

SVM is primarily a classification method that performs classification tasks by constructing hyperplanes in a multidimensional space that separates cases of different class labels and thus, segmentation can be done using SVM [28].

III. ACCURACY MEASUREMENT OF IMAGE SEGMENTATION

In order to gain a better understanding of a good image segmentation, extensive research have been carried out by creating many different approaches and algorithms, but it is still difficult to assess whether one algorithm produces more accurate segmentation than another [29]. Designing a good measure for segmentation quality is a known hard problem [30]. Image segmentation partitions the entire image region R into many sub regions, with some rules, as follows: Every region is spatially connected, every pixel belongs to only one region, all pixels in a region satisfy a specified similarity predicate [31].

In this section, we choose to classify existing performance measures in two main sets: those using ground truth and those not using ground truth. However, it should be stressed that, authors [5], [7], often use two criteria independent of ground truth, namely time complexity of algorithm (the total time required by the algorithm to run to completion) and human visual system (HVS) or visual quality, through the judgment relates to images segmented. The following notations are used for the presentation of evaluation metrics.

- Let I_0 the original image, I be the segmented image and I_{Ref} the ground truth image all with the height I_H and width I_W .
- Let S_I be the area (the number of pixels) of the full image (i.e. $S_I = I_H \cdot I_W$). We define segmentation as a division of an image into N arbitrarily-shaped regions in I , and M specifically-shaped regions in I_{Ref} .
- We use R_j and V_i to denote the set of pixels in region "j" of I and region "i" of I_{Ref} respectively, and use $S_j = |R_j|$ to denote the area of region j . We use $C(p)$ to denote the value of pixel p . We define the average value in region j by

$$\hat{C}(R_j) = \sum_{p \in R_j} C(p) / S_j \quad (1)$$

- The squared color error of region j is defined as,

$$e^2(R_j) = \sum_{p \in R_j} [C(p) - \hat{C}(R_j)]^2 \quad (2)$$

- $E_{NG} = \{1, 2, \dots, L\}$ is used as the set of image gray level. We use $N(\alpha)$ to denote the number of regions in the segmented image having an area of exactly α .
- Let "MaxArea", be the number of pixels of the biggest region. The subscript "gl" denotes gray-level, subscript "o" means those measures for object or foreground, and subscript "b" means those for background. We use "Card(A)" as cardinality or the number of elements in A-set and $d(\cdot)$ the Euclidean distance.

A. In the Case of Ground-Truth Image

Ground truth images are "true" or "accurate" segmentations that are typically made by one or more human experts. There are performance metrics which measure the amount of overlap between the ground truth segmentation I_{Ref} and the automated segmentation produced I . We present the most used.

1) Dissimilarity of Vinet's Measure (M_v)

Reference [32] proposed a dissimilarity criterion between I and I_{Ref} . For any pair of regions (V_i, R_j) with $V_i \subset I_{Ref}$ and $R_j \subset I$, let's have $t_{ij} = Card(V_i, R_j)$ the number of pixels occurring simultaneously in the two regions. Let's also have C_1, C_2, \dots, C_k the values t_{ij} of each possible pair of regions. The target of a good segmentation, is to have a maximum value of $C_{i, 1 \leq i \leq k}$. The sum of this values can be normalized by the total area of the image S_I . Thus, the Vinet's measure M_v presented in (3), is efficient for low values. This dissimilarity value was used by [33] & [34].

$$M_v = 1 - \frac{1}{S_I} \cdot \sum_{i=1}^k C_i \quad (3)$$

2) Yasoff's Measure (M_Y)

It is a measure that considers pixels misclassified and their distance from the region to which they belong [35]. Let's have "s", a misclassified pixel and $d(s)$: the distance of s to the nearest pixel of the region of which it belongs. The purpose of a good segmentation, is to have a minimal value of the distance $d(s)$. So, Yasoff's measure M_Y presented in (4), is efficient for low values. This measure was used by [36] & [37].

$$M_Y = \frac{100}{S_I} \cdot \sqrt{\sum_s d^2(s)} \quad (4)$$

3) Local and Global Consistency Error

For any pixel "s", simultaneously belonging to the regions V_i and R_j , it presents two relative errors E and E' shown in (5) [38] where the operator $/$, means subtraction of the sets. Using both two relative errors, Local Consistency Error (LCE) and Global Consistency Error (GCE) are presented in (6) and (7) respectively. They are in the range $[0, 1]$ and, they are efficient for low values. They were used by [39] & [40]

$$E(s) = \frac{Card(V_j/R_i)}{Card(V_j)} ; E'(s) = \frac{Card(R_j/V_i)}{Card(R_j)} \quad (5)$$

$$LCE(I, I_{Ref}) = \frac{1}{S_I} \sum_{s \in I} \min\{E(s), E'(s)\} \quad (6)$$

$$GCE(I, I_{Ref}) = \frac{1}{S_I} \min\{\sum_{s \in I} E(s), \sum_{s \in I} E'(s)\} \quad (7)$$

4) Precision, Recall and Their Dependent Functions

For classification tasks in image segmentation with ground-truth, [41] and [42] used precision, recall and their dependent functions presented in Table I.

The terms, true positive (TP), true negative (TN), false

positive (FP), false negative (FN) mean:

- TP: pixels that are detected as an object and also labeled as so on the ground truth image.
- TN: pixels that are detected as a background and also labeled as so on the ground truth image.
- FP: pixels that are detected as an object and labeled as background on the ground truth image.
- FN: pixels that are detected as background and labeled as an object region in the ground truth image.

TABLE I
PRECISION, RECALL AND THEIR DEPENDENT FUNCTIONS

Parameter name	Expression
Positive prediction value or precision (PPV)	$PPV = \frac{TP}{FP+TP}$
True positive rate or sensitivity or Recall (TPR)	$TPR = \frac{TP}{FN+TP}$
True negative rate or specificity (TNR)	$TNR = \frac{TN}{FP+TN}$
Negative predictive value (NPV)	$NPV = \frac{TN}{TN+FN}$
Accuracy (ACC)	$ACC = \frac{TN+TP}{FN+FP+TN+TP}$
Type-I error	$Type_I = \frac{FP}{FN+FP+TN+TP}$
Type-II error	$Type_{II} = \frac{FN}{FN+FP+TN+TP}$
F_β -measure: with β a natural number	$F_\beta = (1 + \beta^2) \frac{TP}{\beta^2 \cdot (PPV + TPR)}$
Dice similarity coefficient (DSC)	$DSC = \frac{2TP}{FN+TP+FP}$
Receiver operating characteristic (ROC)	ROC: a curve created by plotting the TPR against the 1-TNR at various threshold settings.
Miss rate or false negative rate (FNR)	$FNR = 1 - TNR$
False discovery rate (FDR)	$FDR = 1 - PPV$
False omission rate (FOR)	$FOR = 1 - NPV$
Book maker informedness (BM)	$BM = TPR + TNR - 1$
Markedness (MK)	$MK = PPV + NPV - 1$

PPV, TNR, TPR, NPV, ACC, F_β , ROC and DSC are in the range [0, 1] and, they are efficient for high values. Type-I and Type-II errors are efficient for small values.

5) Modified Hausdorff distance (MHD)

This measure can be used to match two sets of edge points extracted from any two objects. MHD, shown in (8), has the following desirable properties: Its value increases monotonically as the amount of difference between the two sets of edge points increases; it is robust to outliers that might result from segmentation errors [43].

$$MHD(I, I_{Ref}) = \text{Max}\{g(I, I_{Ref}); g(I_{Ref}, I)\} \quad (8)$$

with

$$g(I, I_{Ref}) = \frac{1}{|S_I|} \sum_{p \in I} \text{Min}_{q \in T} \{d(p, q)\} \quad (9)$$

6) Two measures of similarity (JIM, MS)

The Intersection-over-Union (IOU) or Jaccard Index measure (JIM) in (10), computed between the binary masks of a predicted segmentation and ground-truth, averaged over all categories. This measure was used by [44]. It is efficient for high value.

$$JIM(R_i, V_i) = \frac{\text{Card}(R_i \cap V_i)}{\text{Card}(R_i \cup V_i)} \quad (10)$$

Another measure of similarity sometimes used [45] in the case of ground-truth image is MS shown in (11). It is a measure that evaluates the level of overlap between the region resulting from the segmentation and its reference. It is also efficient for high values.

$$MS = 100 \cdot \frac{\text{Card}(R_i \cap V_i)}{\text{Max}(\text{Card}(R_i); \text{Card}(V_i))} \quad (11)$$

B. Without Reference Image

Unsupervised evaluation methods, also known as empirical goodness methods do not require a reference image, but instead evaluate a segmented image based on how well the homogeneity attributes of regions have been reached.

1) A Discrepancy Measure (Dis)

Reference [46] presented a gray-level measure which computes the difference between the original image I and the foreground object of segmented image I_0 after thresholding. It was proposed to evaluate thresholding-based segmentation techniques that separate the foreground object from the background. It is efficient for low values.

$$Dis = \sum_{i=1}^{I_H} \sum_{j=1}^{I_W} (I_0(i, j) - I(i, j))^2 \quad (12)$$

2) Otsu Measures (η , σ_W^2)

Reference [47] proposed a measure which allows to choose a suitable threshold k , or verify if a selected threshold k , is the best of a thresholding segmentation. The appropriate threshold is the one that maximizes the function $\eta(k)$ presented in (13). For $i \in E_{NG}$, $n_1 + n_2 + \dots + n_L = S_I$, with n_i the number of pixels which have "i" value, we have Otsu measure in (13):

$$\eta(k) = \frac{w(k)[1-w(k)] \left[\frac{\mu_T - \mu(k)}{1-w(k)} - \frac{\mu(k)}{w(k)} \right]^2}{\sigma_T^2} \quad (13)$$

where,

$$k \in E_{NG}; w(k) = \sum_{i=1}^k \frac{n_i}{S_I} \mu(k) = \sum_{i=1}^k i \frac{n_i}{S_I} \mu_T = \sum_{i=1}^L i \frac{n_i}{S_I} \sigma_T^2 = \sum_{i=1}^L (i - \mu_T)^2 \frac{n_i}{S_I} \quad (14)$$

The variance σ_W^2 of Otsu measure in (15), is presented by [28] and it is efficient for low values.

$$\sigma_W^2 = \frac{S_b}{S_I} e_{gl}^2(R_b) + \frac{S_o}{S_I} e_{gl}^2(R_o) \quad (15)$$

3) U, C, LC, DR_α and DL_α

- Region Uniformity (U)

It is a metric proportional to the squared color error of regions, efficient for high values [48].

$$U = 1 - \frac{1}{Z} \sum_{j=1}^N w_j e_{gl}^2(R_j) \quad (16)$$

where $w_j = \frac{1}{S_j}$, $Z = \frac{(C_{max} - C_{min})^2}{2}$ are respectively the weight associated with the contribution of the region and the maximum variance.

- Region Contrast (C)

It is a function of contrast, which is efficient for high value [48].

$$C = \frac{\sum_{j=1}^N v_j \sum_{Adj R_j} p_{ij} \frac{|\hat{c}(R_i) - \hat{c}(R_j)|}{\hat{c}(R_i) + \hat{c}(R_j)}}{\sum_{j=1}^N v_j} \quad (17)$$

where

$$p_{ij} = \frac{\text{Length of the border between } R_i \text{ and } R_j}{\text{perimeter of } R_j}$$

and v_j a weight assigned to region R_j

- Line Connectivity (LC)

A line is considered as a set of pixels which define an edge. The number of lines that have one or both ends opened is an indication of the degree of discontinuity in the lines. Let t_j be the number of closed ends of the lines L_j , which can have three quantitative values (0, 1, or 2). Let l_j be the length of the line. The line connectivity (LC) shown in (18) is efficient for high value [48].

$$LC = \frac{\sum_{j=1}^N l_j t_j / 2}{\sum_{j=1}^N l_j} \quad LC \in [0, 1] \quad (18)$$

- Density of Region in α -Area (DR_α and DL_α)

In a segmented image, it may be necessary to look for the density of the regions in an area [48]. Thus, we can calculate DR_α or DL_α as:

$$DR_\alpha = \frac{NR_\alpha / S_\alpha}{NR_I / S_I}; \quad DL_\alpha = \frac{NL_\alpha / S_\alpha}{NL_I / S_I} \quad (19)$$

where NR_α and NR_I are the number of regions in α -area and in the whole image respectively. NL_α and NL_I are the number of close lines in α -area and in the whole image respectively. If $DR_\alpha > 1$, the density of regions in α -area will be greater than the average density for the whole image.

4) Functions of the Squared Error: F, F' and Q

References [49] & [50] proposed three measures built with the squared error to appreciate the segmentation and which are efficient for small values.

$$F = \sqrt{N} \sum_{j=1}^N \frac{e^2(R_j)}{\sqrt{S_j}} \quad (20)$$

$$F' = \frac{\sqrt{\sum_{a=1}^{Maxarea} [N(a)]^{1+\frac{1}{a}}}}{1000 \cdot S_I} \sum_{j=1}^N \frac{e^2(R_j)}{\sqrt{S_j}} \quad (21)$$

$$Q = \frac{\sqrt{N}}{1000 \cdot S_I} \sum_{j=1}^N \left[\frac{e_j^2}{1 + \log S_j} + \left(\frac{N(S_j)}{S_j} \right)^2 \right] \quad (22)$$

5) Intra and Inter Region Disparity (\underline{D} , \bar{D})

Reference [51] proposed two measures shown in (23) and (25), to evaluate how much homogeneity is preserved from a region, or which disparity we can observe between regions.

- The Intra-region disparity (\underline{D}): which is efficient for small values.

$$\underline{D}(I) = \frac{1}{N} \sum_{j=1}^N \frac{S_j}{S_I} \underline{D}(R_j) \quad (23)$$

where,

$$\underline{D}(R_j) = \frac{1}{\frac{(c_{jmax} - c_{jmin})}{2}} \sum_{p=1}^{S_j} \frac{1}{S_j} [C(p) - \hat{c}(R_j)]^2 \quad (24)$$

- The Inter-region disparity (\bar{D}): which is efficient for high values.

$$\bar{D}(I) = \frac{1}{N} \sum_{j=1}^N \frac{S_j}{S_I} \bar{D}(R_j) \quad (25)$$

with

$$\bar{D}(R_j) = \frac{1}{N_{ej}} \sum_{j=1}^{N_{ej}} D(R_j, R_i) \quad (26)$$

Rosenberger et al. [51] presented two possible cases of $D(R_j, R_i)$ values:

$$D(R_j, R_i) = \frac{|\hat{c}(R_i) - \hat{c}(R_j)|}{L} \quad \text{and} \quad D(R_j, R_i) = \frac{d(B_i, B_j)}{\|B_i\| + \|B_j\|} \quad (27)$$

where N_{ej} is the number of regions adjacent to R_j ; $d(B_i, B_j)$ the Euclidean distance between barycenter of regions R_i and R_j .

6) Disparity of a Region (ZEB)

It is a measure which combines concepts of maximum inter-regions disparity (CI) and minimal intra-region disparity (CE) measured on a pixel neighborhood [52].

$$CI(R_j) = \frac{1}{S_j} \sum_{p \in R_j} \text{Max} \left\{ \frac{|c(p) - c(t)|}{L-1}, t \in w(p) \cap R_j \right\} \quad (28)$$

$$CE(R_j) = \frac{1}{N_b(R_j)} \sum_{p \in \eta(R_j)} \text{Max} \left\{ \frac{|c(p) - c(t)|}{L-1}, t \in w(p), t \notin R_j \right\} \quad (29)$$

where $w(p)$ is a neighborhood of the pixel p ; $N_b(R_j)$ the R_j perimeter; $\eta(R_j)$ the pixels set of $N_b(R_j)$

Let

$$C_{EI}(R_j) = \begin{cases} 1 - \frac{CI(R_j)}{CE(R_j)} & \text{if } 0 < CI(R_j) < CE(R_j) \\ CE(R_j) & \text{if } CI(R_j) = 0 \\ 0 & \text{otherwise} \end{cases} \quad (30)$$

The disparity of a region (ZEB) presented at (31) is efficient for high values.

$$ZEB(I) = \frac{1}{S_I} \sum_{i=1}^N S_i \cdot C_{EI}(R_i); \quad ZEB(I) \in [0, 1] \quad (31)$$

7) Error Measurements (E_{intra} , E_{inter})

It is a composite evaluation method for color images, which uses intra-region visual error shown in (33) to know the

degree of under-segmentation and uses inter-region shown in (34) to evaluate the degree of over-segmentation [53].

Let's have the step function $\mu(t)$ as shown in (32),

$$\mu(t) = \begin{cases} 1 & \text{if } t > 0 \\ 0 & \text{otherwise} \end{cases} \quad (32)$$

The threshold $th = 6$, fixed by authors [53], for a visible color difference.

Let $\|\cdot\|_{L^*a^*b^*}$ be the Euclidean norm in Lab-Space color and w_{ij} the joined pixels length between regions R_i and R_j . We have,

$$E_{intra} = \frac{1}{S_I} \sum_{p \in I} \mu(\|I_O(p) - I(p)\|_{L^*a^*b^*} - th) \quad (33)$$

$$E_{inter} = \frac{1}{6 \cdot S_I} \sum_{i=1}^N \sum_{j=1}^N w_{ij} \mu(th - \|I_O(p) - I(p)\|_{L^*a^*b^*}) \quad (34)$$

E_{inter} is high for an over-segmentation and E_{intra} is high for an under-segmentation.

8) Weighted Disorder Function (H_w) and Entropy-Based Evaluation Function (E)

Since entropy measures the disarray within a region, it is a natural characteristic to incorporate into a segmentation evaluation method.

Let $i \in E_{NG}$; $N_j(i)$ the number of pixels in region R_j which has i -value [53]. We have,

Entropy for region R_j :

$$H(R_j) = - \sum_{i=1}^{L_j} \frac{N_j(i)}{S_j} \log \left(\frac{N_j(i)}{S_j} \right) \quad (35)$$

Expected region entropy:

$$H_r(I) = \sum_{j=1}^N \left(\frac{S_j}{S_I} \right) \cdot H(R_j) \quad (36)$$

Layout entropy:

$$H_l(I) = - \sum_{i=1}^L \frac{S_j}{S_I} \log \left(\frac{S_j}{S_I} \right) \quad (37)$$

By using those functions, we have the weighted disorder and entropy-based functions in (38), which are efficient for small values.

$$H_w = \sqrt{N} \cdot H_r(I); \quad E = H_r(I) + H_l(I) \quad (38)$$

9) Multi-Scale Criterion (E_M)

A good segmentation is considered as a process which minimizes a total energy (E_M),

$$E_M(k, I) = \sum_{R_i \in I} E_D(R_i) + k \sum_{R_i \in I} E_C(R_i) \quad (39)$$

where, $E_D(R_i)$ is the energy of attachment to data, which promotes the over-segmentation, for example, $E_D(R_i) = e^2(R_i)$. The energy of complexity $E_C(R_i)$ penalizes the under-segmentation, for example the perimeter of the regions. The natural number "k" is used to adjust the relative contribution of the two previous energies [54].

10) Dunn's index (DI_m)

Let R_i a region considered as being a cluster; x and y be two features assigned to the same cluster R_i . Let us define Δ_i (maximum distance) in (40), as the size of the region R_i according to x and y .

$$\Delta_i = \text{Max}_{x, y \in R_i} d(x, y) \quad (40)$$

Let $\delta(R_i, R_j)$ be an inter-cluster distance metric between R_i and R_j . If there are m clusters, the Dunn's index is DI_m [55].

$$DI_m = \frac{\text{Min}_{1 \leq i < j \leq m} \delta(R_i, R_j)}{\text{Max}_{1 \leq k \leq m} \Delta_k} \quad (41)$$

The Dunn Index is the ratio of the smallest distance between observations not in the same cluster to the largest intra-cluster distance. The Dunn Index has a value between zero and infinity, and should be maximized for a better segmentation [56].

IV. NON-EXHAUSTIVE EXAMPLES OF SEGMENTATION TECHNIQUES

In Table II, 21 recent segmentation techniques are presented according to the classification of segmentation methods shown in Section II. We can observe that, gray levels seem to be the most used elementary property in image segmentation. Clustering algorithms generally use this elementary property with the region inside approach. Tools like, active contours, level sets, morphological operators and Canny edge detection are mostly used in the case of region boundary research. Something really important to underline is the general habits of combining many tools in one segmentation approach. Another important observation is the fact that one metric would not be enough to judge all properties of segmentation algorithms. Different methods, especially different evaluation metrics are therefore used. Among them, HSV is the most used.

TABLE II
CLASSIFICATION OF 21 SEGMENTATION TECHNIQUES

No	References	Elementary Property used	Approach used	Tools used	Performance measure used
1	[57]	Gray level	Region inside	firework algorithm (with an adaptive transfer function)	- Dunn's index - HVS
2	[58]	Gray level	Region inside	-Enhancement with a Clustering algorithm (Feed Forward Neural Network) and a Descriptor (Hessian Matrix) - Segmentation with a Fuzzy tool (Fuzzy Local Information C-means)	- DSC - HVS
3	[59]	Gray level	Region inside	Clustering algorithm (Convolutional Neural Network)	- Accuracy - Sensitivity - Specificity - IOU (or JIM) - DSC - HVS
4	[60]	Gray level	Region inside	Clustering algorithm (Convolutional Neural Network)	- Accuracy - Sensitivity - Specificity - ROC - HVS
5	[61]	Gray level	Region boundary	-Descriptor (Adaptive Histogram Equalization) - Filter (Steerable Filters)	- Accuracy - Type-I error - Type-II error - HVS
6	[62]	Gray level	Region inside	-Fuzzy tool's (FCM) -Descriptor (Histogram) - Contrast Stretching (intensity transformation)	- Accuracy - Computational time
7	[63]	Gray level	Region inside/ boundary	-Morphologic Operators -Flood Filling -Contrast Stretching	- Accuracy - HVS
8	[64]	Color	Region inside	-SVM -Descriptor (DCT, Chromacity)	- Accuracy - Sensitivity - Specificity - HVS
9	[65]	Gray level	Region boundary	-Active contour	- Computational time - HVS
10	[66]	Color	Region inside/ boundary	-Descriptor (Dominant Color) - Fuzzy Tool (Fuzzy-C-Means) -Level set	- HVS
11	[67]	Color	Region inside	-Descriptor (Histogram) -local search algorithm (Hill climbing) -fuzzy tool (fuzzy-C-Means).	- HVS
12	[68]	Color	Region inside	-Filter (rank filter) -Morphologic operator (opening)	- Precision - Recall - F_1 -measure - Computational time - HVS
13	[69]	Color, Texture	Region inside	-SVM (improve with self-organizing data analysis techniques algorithm) -local search algorithm (Genetic Algorithm)	- Accuracy - HVS
14	[70]	Gray level	Region inside	-Morphologic operator (opening) -fuzzy tool (fuzzy C-Means Clustering).	- Accuracy - HVS
15	[71]	Gray level	Region inside	-Decision tree	- HVS - DSC
16	[72]	Gray level	Region inside	-PDE -Level set -Filter (Gaussian filter)	- HVS
17	[73]	Color	Region inside/ boundary	-Canny edge detection -statistic's tool (Otsu method, Region growing)	- HVS - Precision - Sensitivity - F_1 -measure - HVS
18	[74]	Gray level	Region boundary	-Graph theory -Dynamic Programming - Neutrosophy	- Computational time - Computational time
19	[75]	Color	Region inside	- Statistical tools (Merging Region)	- HVS
20	[76]	Gray level	Region boundary	- Neutrosophy - Morphologic operator (Watershed)	- HVS
21	[77]	Gray level	Region boundary	- Morphologic operator (Watershed)	- DSC - HVS - Sensitivity - Specificity

V. DISCUSSION

Image segmentation is an important step in image analysis, and performance measures of segmentation algorithms play a key role both in developing efficient algorithms and in selecting suitable methods for the given tasks. A range of publications have appeared on segmentation methodology and segmentation performance evaluation. Generally, two categories of segmentation algorithms are presented; supervised and unsupervised methods. Supervised segmentation algorithms need human presence to select better orientation in the process contrary to unsupervised segmentation algorithms, which is an automatic process. Supervised evaluation criteria use some a priori knowledge such as ground truth. They generally compute a global dissimilarity measure between the ground truth and the segmentation result; however the overriding concern is objectivity and variability of experts. While unsupervised ones compute some statistics in the segmentation result according to the original image such as the gray-level standard deviation or the contrast of each region in the segmentation result. Another point of view [2] grouped segmentation algorithms in five categories: edge-based segmentation, threshold-based segmentation, region-based segmentation, watershed-based segmentation and clustering based segmentation. Reference [78] classified segmentation methods in eight groups: region-based, edge-based, histogram thresholding, clustering, morphological, model-based, active contours and soft computing. However, the increasingly diversity and the complexity of operators such as Neutrosophy, Fireworks algorithms used in segmentation algorithms led us to propose a classification of segmentation techniques and to identify the most used measures of segmentation performance. With this classification, an important attention has been paid to be able to identify key process of each segmentation method as presented in Table I. The performance of segmentation algorithms is influenced by many factors. Since one metric would not be enough to judge all properties of segmentation algorithms, different methods, especially different evaluation metrics, should be combined. The multi-scale criterion presented in Section III B 9 has this possibility to evaluate both under and over segmentation between two segmentation methods by plotting their total energy (E_M) according to the scale number "k" and observe positions of curves obtained. Two substantial challenges for image segmentation are image intensity inhomogeneity and low contrast. Another critical issue in image segmentation is how to explore the information in both feature and image space and incorporate them together. Segmentation with clustering technique is one of the most efficient techniques and shows better results than other segmentation methods [79]. However, clustering methods depend on initial number of clusters, setting of central values of the initial clusters. MRF is widely applied because of many reasons. It uses few model parameters and is easy to deal with; it has a strong ability of space constraints; it is easy to combine it with other methods and it is stable. When we face the problem of image segmentation, we can regard the class

label in random field as different areas. Watershed algorithm is traditionally applied on image domain but it fails to capture the global colour distribution information. There is neither a general image segmentation method, nor an objective criterion judgment: segmentation method is chosen for the most appropriate given application.

VI. CONCLUSION

In this paper, we have proposed a classification for image segmentation. Our model considers three elements to define a segmentation, namely, the elementary property of the image, the portion of the region sought and the chosen tools. We have thus identified a large number of operators widely used in image segmentation. We have also presented the most used performance measures in segmentation. Several recent segmentation algorithms have also been classified by our method. A thorough discussion has been carried out to highlight the difficulties and solutions generally met in segmentation process. The target of this work was to guide the researchers to understand segmentation algorithms and progress in this field, and to provide useful measures of segmentation performance for the follow-up research work.

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