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A Fuzzy Rules-Based Segmentation Method for Medical Images Analysis

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Abstract:
Medical imaging mainly manages and processes missing, ambiguous, complementary, redundant and distorted data and information has a strong structural character. This paper reports a new (semi)automated and supervised method for the segmentation of brain structures using a rule-based fuzzy system. In the field of biomedical image analysis fuzzy logic acts as a unified framework for representing and processing both numerical and symbolic information, as well as structural information constituted mainly by spatial relationships. The developed application is for the segmentation of brain structures in CT (computer tomography) images. Promising results show the superiority of this knowledge-based approach over best traditional techniques in terms of segmentation errors. The quantitative assessment of this method is made by comparing manually and automatic segmented brain structures by using some indexes evaluating the accuracy of contour detection and spatial location. Though the proposed methodology has been implemented and successfully used for model-driven in medical imaging, it is general enough and may be applied to any imagistic object that can be expressed by expert knowledge and morphological images.
Keywords: biomedical image processing, fuzzy systems, image segmentation, fuzzy rules.

1 Introduction

Within the current clinical setting, medical image segmentation is a vital component of a large number of applications, such as to: (i) study anatomical structure; (ii) identify regions of interest, i.e. locate tumor, lesion and other abnormalities; (iii) measure tissue volume to assess growth or decrease in size of tumor; (iv) help in treatment planning prior to radiation therapy and in radiation dose calculation. Contour detection for segmentation still remains a challenging problem in medical imaging, for instance in radiotherapy treatment, where both CT and MR images can be employed. The former is needed to accurately compute the radiation dose, while the latter is usually better suited for accurate delineation of tumor tissue. Any contour delineation error above 10% is considered in clinical practice that may lead to an unacceptable risk to irradiate healthy tissues instead of diseased ones. This is the main raison of our approach - to deploy a (semi)automatic and more effective segmentation procedure for CT images, based on a strong paradigm in computational intelligence: fuzzy logic. Imprecision in medical image information may be due to several factors, ranging from the observed phenomenon to the algorithms' precision. For instance, a soft transition between healthy and pathological tissues may make difficult to distinguish tumor margins from edematous normal brain.

In this context, the theory of fuzzy sets is an interesting and useful tool, as it provides a good theoretical basis to represent imprecision of the information and it constitutes a unified framework for representing and processing both numerical and symbolic information, as well as structural information. Proceeding from the grounds of artificial intelligence, soft computing, and image processing, for instance from [4], [9], [11], [18], [19] a number of authors have used these techniques to aid in the analysis of medical images, e.g. in [1], [2], [3], [5], [6]- [8], [10], [12]- [13], [20]- [22].

Our new segmentation procedure is one of supervised-type, as it requires a model image of the analyzed structure. Moreover, the adding of domain knowledge about the characteristics of objects increases the segmentation accuracy. The created fuzzy system for this application uses a rule-based linguistic description of the objects belonging to the Region of Interest, that serves to pilot the system for the edge detection-based segmentation. At the entry of the system, for each input image a symbolic representation is determined. Then, fuzzy rules are applied. Among all points of interest (candidate points for contour detection) only those satisfying the rule set are kept for further analysis, by applying some criteria of decimation. These criteria include the spatial conformity with rules and the compactness between boundary points. At the exit, the system yields the position of contour points.

2 The used fuzzy system

Figure 1 shows a block diagram of the used fuzzy system. It represents a supervised approach that converges to the contour points of the object of interest. First, a knowledge base is established going from a reference (model) image for which the contour points are manually delineated (Figure 1(a)). The written fuzzy rules include the features of the known boundary, e.g. the transitions of the brightness for neighboring pixels of the contour points.

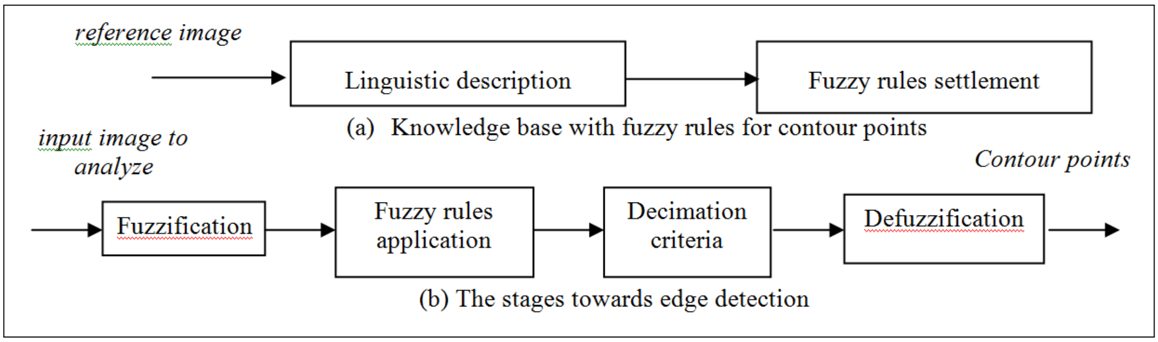

Figure 1: The block diagram of the used fuzzy system

2.1 Knowledge base settlement

Linguistic description of the image. Membership functions and fuzzification

First, for gray level images the main parameter used for their description is the brightness. In fuzzy logic we have to consider brightness as a fuzzy variable, composed by different fuzzy classes: BLACK, DARK, GRAY, BRIGHT and WHITE. Thus, for a 256 gray level image one may write the fuzzy variable (BRIGHTNESS ; [0, 255] ; { BLACK, DARK, GRAY, BRIGHT, WHITE }). We have chosen for our study trapezoidal membership functions (μ) corresponding to BRIGHTNESS, and the fuzzification process is made according to these membership functions.

Determination of a point position

The position of points in a digital image may be represented using a system of polar coordinates (θ, r) as in Figure 2. The origin is chosen as the object center, C. The number of contour points forming the knowledge base is detected by counting the intersections between different sampling rays (α_j) and the border of the (reference) object. Thus, a new fuzzy variable - POSITION - is derived from this graphical representation and it codifies the value of angle θ associated to a contour point, depending on the number of sampling rays used:

$$(POSITION; [0, 360]; \{\alpha 1, \alpha 2, ..., \alpha N\}). \tag{1}$$

For N=36 the membership functions for fuzzy variable POSITION is shown in Figure 3.

2.2 Fuzzy rules - based knowledge base

Fuzzy rules settlement

The manually traced border of the reference object is obtained using computing the average gray level respectively within two moving (outer and inner) windows situated on the two sides of the contour point (shaded area in Figure 2). This technique yields a good noise reduction and is made for every direction α_j. Thus, one establishes the existing relations between the average gray levels within the two windows and the value of angle θ. Through the fuzzification of the fuzzy variables BRIGHTNESS and POSITION the relations between these two variables are directly obtained. Then, IF...THEN fuzzy rules are derived, that show the N (N=35) relations between the two fuzzy variables. For each case when the membership value to a class α_j is maximum (1) for POSITION, i.e. $\{1/\alpha_j\}$, a new fuzzy rule may be defined. For instance, some of these fuzzy rules might be:

(1) IF the POSITION is $\{1/\alpha_1\}$ THEN the transition of the BRIGHTNESS each side of the contour varies from {1/DARK} to {1/GRAY} ;

...

(35) IF the POSITION is $\{1/\alpha_{35}\}$ THEN the transition of the BRIGHTNESS each side of the contour varies from {0.9/DARK ; 0.1/GRAY} to {1/GRAY} .

Fuzzy rules encoding

The knowledge base uses the fuzzy rules encoding, i.e. their conversion into numerical values. Indeed, for a certain direction α_j two numerical values are defined: the inner BRIGHTNESS, $g_{int}(\alpha_j)$, and the outer one, $g_{ext}(\alpha_j)$:

$$g_{int}(\alpha_j) = \frac{\sum_{i=1}^{5} \mu_{i,int}(\alpha_j) c_i}{\sum_{i=1}^{5} \mu_{i,int}(\alpha_j)} \ ; \ g_{ext}(\alpha_j) = \frac{\sum_{i=1}^{5} \mu_{i,ext}(\alpha_j) c_i}{\sum_{i=1}^{5} \mu_{i,ext}(\alpha_j)} \tag{2}$$

where c_i are the centers of the classes BRIGHTNESS, i.e. the median values of the gray levels of each class.

The values $\mu_{i,int}(\alpha_j)$ represent the membership degrees for the i-class of BRIGHTNESS, for the direction j and the inner contour. A similar definition stands for $\mu_{i,ext}(\alpha_j)$.

3 The used fuzzy system at work

The involved steps for supervised contour points detection are the image fuzzification, application of fuzzy rules, points aggregation, then applying decimation criteria, and the final stage represents the defuzzification.

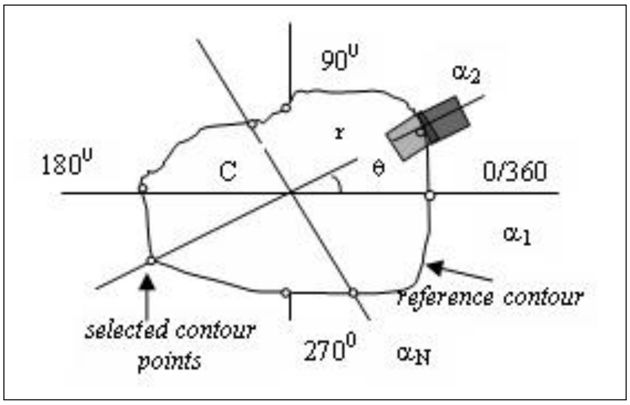

Figure 2: The block diagram of the used fuzzy system

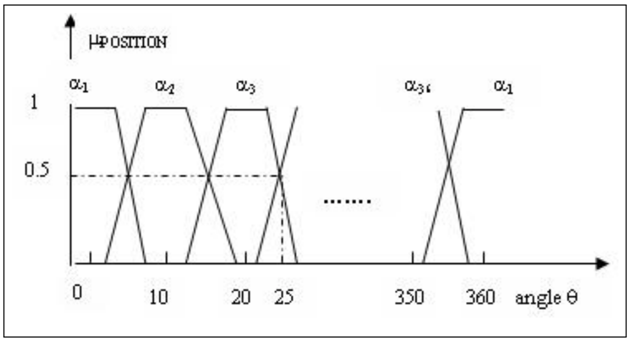

Figure 3: The block diagram of the used fuzzy system

3.1 Obtaining fuzzy image

According to our approach, when utilizing polar co-ordinates and representation from Figure 2, the angle values are fuzzified in classes α_j by the fuzzy variable POSITION. As an example, for $\theta = 25$ degrees, the membership function becomes $\mu_{POSITION}(25) = \{0.5/\alpha_3\ ;\ 0.5/\alpha_4\}$ (Figure 3). The set of points taken on N* directions constitutes the universe of discourse of a new fuzzy variable named PIXEL, whose elements are:

$$pix(\theta_j, r_i) \in PIXEL, j = 1, ..., N^*, i = 1, ..., P^*; pix(\theta_j, r_i) = [g_{int}(\theta_j, r_i); g_{ext}(\theta_j, r_i)] \quad (3)$$

3.2 Application of fuzzy rules and points aggregation

The application of fuzzy rules on the point set of the variable PIXEL yields a measure of resemblance between input image data (to be analyzed) and the non-zero values encoded in the corresponding knowledge base. The measure of resemblance with the knowledge base uses rules encoded for every class α_j, by the pair of brightness variation, e.g.:

IF the POSITION is $\{1/\alpha_1\}$ THEN the BRIGHTNESS is (50 ; 100) ;

The variable RESEMBLANCE, based on the classes INNER and OUTER, measures the "degree of similitude" between the brightness values in input image and the fuzzy rules, for a certain direction α_j. In this case the fuzzy rules are written in the following manner, in which the value of RESEMBLANCE appears:

IF the POSITION is $\{1/\alpha_1\}$ and the BRIGHTNESS is (50 ; 100) THEN one has a total RESEMBLANCE of { 1/INNER ; 1/OUTER } ;

The membership degrees to the classes INNER and OUTER of the variable RESEMBLANCE are read by means of the correspondent membership functions in Figure 4, in which we obtain, e.g., $\mu_{RESEMBLANCE}(\theta_1, r_i)$ = { 1/INNER ; 0.4/OUTER }. If the number N' of the considered directions for establishing variable PIXEL differs from the N classes of the variable POSITION, then an interpolation of fuzzy rules is needed. A contour image pixel has high values of the membership degrees to the classes INNER and OUTER, that means the use of min operator in fuzzy logic. Let's consider another class, GLOBAL, of the RESEMBLANCE series, resulting from the intersection between two membership degrees:

$$\mu_{RESEMBLANCE}(\theta_j, r_i) = \{\mu_{INNER}/INNER; \mu_{OUTER}/OUTER; min[\mu_{INNER}; \mu_{OUTER}]/GLOBAL\} \tag{4}$$

So, we may determine the CANDIDATE series, which is a subset of PIXEL series and represents a support of the GLOBAL class. In this manner, the CANDIDATE series is defined by

$$CANDIDATE = S(PIXEL) = \{pix(\theta, r_i)/\mu_{global}(\theta, r_i) > 0\} \tag{5}$$

3.3 Decimation criteria

We have two decimation criteria in order to choose the right contour points: a spatial *resemblance criterion* and a *compactness criterion*. They both allow to reduce the number of candidate pixels and these criteria measure the areas having a high pixel density and characterized by a high resemblance degree. *The spatial resemblance criterion* assesses for each candidate point, within an appropriate window, the average value of the matching to the image model. Denoting by $\mu_{spatial}$ this value, the region of interest is limited by the n directions situated on the two sides of the considered direction. On these directions we use p points surrounding the position r_i . Thus, one obtains:

$$\mu_{spatial}(\theta_j, r_i) = \frac{\sum_{u=-n}^{n} \sum_{v=-p}^{p} \mu_{global}(\theta_{j+u}, r_{i+v})}{(2n+1)(2p+1)} \tag{6}$$

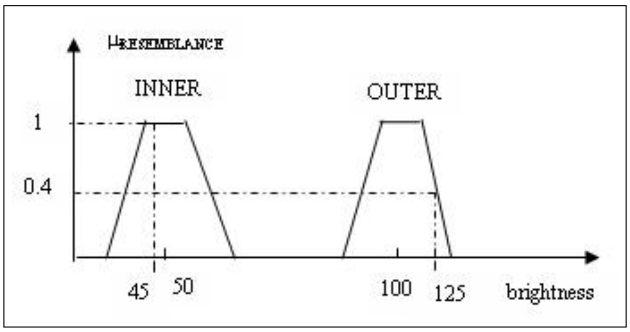

Figure 4: Membership degree of the pixel (θ_1, 1) to the PIXEL variable

The pre-segmentation points are those pixels yielding a preliminary position of the contour, on N' directions. These points must have high membership degrees μ_{GLOBAL} to the GLOBAL class and $\mu_{spatial}$ to the SPATIAL class. Thus, the pre-segmentation series contains those points having the maximal value of the combined two memberships:

$$\mu_{preseg}(\theta_j) = max_i[\mu_{spatial}(\theta_j, r_i) \cdot \mu_{global}(\theta_j, r_i)] \tag{7}$$

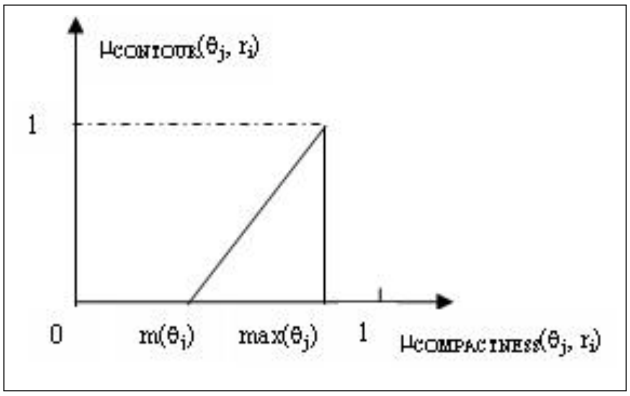

Figure 5: Membership function of the fuzzy variable CONTOUR

The compactness criterion also evaluates areas of pixels with the highest belief to be contour points. From the CANDIDATE points pix(θ_j, r_i) matching very well the image model, this criterion chooses those pixels being very "close" to the pre-segmentation points θ_j. The distance, belonging to the [0, 1] interval, between the current point pix(θ_j, r_i) and the pre-segmentation point pix(θ_{j+u}) of the θ_{j+u} direction, is computed according to the formula [1-d($\theta_{j+u}; \theta_j, r_i$)], considering n directions on both sides of the j direction. Thus, for each candidate point one computes the value

$$\mu_{compactness} = \left(\sum_{u=-n}^{n} [\mu_{global}(\theta_j, r_i) \cdot \mu_{preseg}(\theta_{j+u}) \cdot [1 - d(\theta_{j+u}; \theta_j, r_i)]] \right) / (2n+1) \tag{8}$$

3.4 Deffuzification process

The last stage of segmentation is obtaining contour points through a deffuzification process, i.e. by translating fuzzy series into real numbers. The output data offer the position of the N' contour points situated within a circular area of radius dθ_j from the considered centroide. The position of the edge pixels on a certain direction θ_j represents the median position of the points on that direction, weighted by a membership degree, $\mu_{CONTOUR}$, associated to the CONTOUR output class (Figure 5). $\mu_{CONTOUR}$ normalizes the compactness degree canceling those points with small values of the compactness. The CONTOUR series keeps those pixels having the value $\mu_{compactness}$ between an average compactness value, m(θ_j), obtained for p' points of the CANDIDATE series on the direction θ_j, and the maximum value max(θ_j):

$$m(\theta_j) = \left(\sum_{i=1}^{p\prime} \mu_{compactness}(\theta_j, r_i) \right) / p\prime \tag{9}$$

The deffuzification stage yields the contour point dθ_j for each direction θ. The value dθ_j is obtained using a weighting of the position of the points p' on that direction through their membership degree to the obtained contour.

$$d\theta_j = \left(\sum_{i=1}^{p\prime} \mu_{contour}(\theta_j, r_i) \right) / p\prime \tag{10}$$

4 Application of this method of segmentation to the cerebral images analysis

We have used this method to segment some cerebral tomographic (CT) images with a gray-level resolution of 10 bits (Figure 6). The chosen reference image is shown in Figure 7. We used a geometric system composed by 32 directions for knowledge base construction. For each direction we used 50 points on which fuzzy rules act, so a total universe of discourse of 1600 points was considered (Figure 8).

Also, we choose a (5 x 5) window for computing the average value of local gray levels. The number of pixels having a non-zero resemblance, representing CANDIDATE series, was 985 (Figure 9).

For each point of this set one averages the resemblance value to the reference image, in order to keep on every 32 directions the points having the maximum spatial resemblance (Figure 10). In this way the pre-segmentation points have been obtained. The areas involved in computing this average value are formed by two opposite directions on each analyzed point and by 20 points per directions all around that point. The computation of compactness yields areas with high pixels density having contour characteristics. The deffuzification stage offers the median point of high compactness on each direction or a set of 32 points.

The segmentation of cerebral ventricles is made by the interpolation of the 32 contour points, using a polynomial interpolating method [16], that yields contour tracing and is adapting properly to the anatomic pattern of the analyzed structure (Figures 11, 12).

Figure 6: Input image

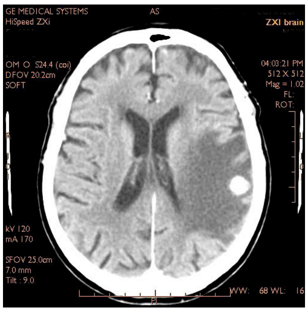

Figure 7: Reference image

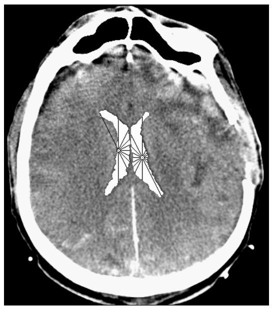

Figure 8: Universe of discourse

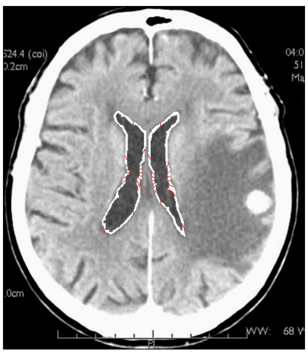

Figure 9: Candidate series

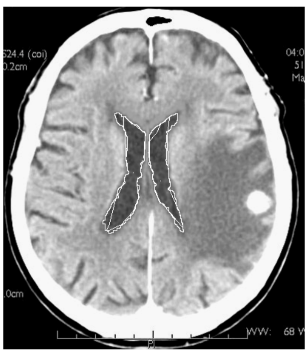

Figure 10: Pre-segmentation points

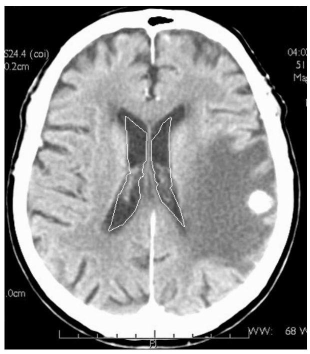

Figure 11: Interpolated points on input image

The accuracy of this segmentation method is assessed by superposing the contours detected automatically and manually, by an expert, and compute the difference between them (Figure

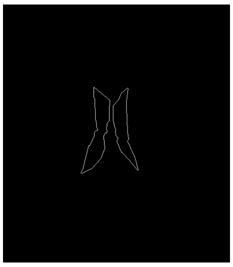

Figure 12: Interpolated points only

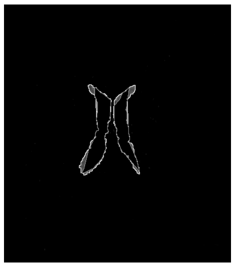

Figure 13: The difference between manually and automated traced points

Figure 14: Contours of the two ventricles over input image

13). As objective parameters of the segmentation precision we have to compute two indexes:

(1) *the relative surface difference*, ΔS, between the two contours ;

(2) *the average relative difference of ray length*, ΔD, also between the contours. The first index represents the sum of the N elementary surfaces Δs_i existing between the contours, normalized by the surface of the manually traced contour, S_{manual} :

$$\Delta S = \frac{\sum_{i=1}^{N} |\Delta S_i|}{S_{manual}} \tag{11}$$

The second parameter is computed by using the length differences Δd_i between the two contours, for a certain direction of analysis, normalized by the average ray length, Di_{manual}, of the manually traced contour, and averaged by the N considered directions:

$$\Delta D = \frac{1}{N} \sum_{i=1}^{N} \frac{|\Delta d_i|}{Di_{manual}} \tag{12}$$

We have obtained the following average values of the two indexes: $\Delta S_{average} = 5.6\%$, and $\Delta D_{average} = 4.5\%$, on 12 tomographic (CT) images used in our experiment (Figure 14 is an example). These values act as a measure of the segmentation errors, and in general are low enough for further steps of image analysis (classification, 3D reconstruction, etc.). In order to compare our results with previous ones, obtained for the same image modality (CT), we used the Fuzzy c-Means (FCM) clustering algorithm [1], [15], that yet does not address the intensity inhomogeneity artifact. Also, we have applied other traditional approach - Otsu's multithreshold segmentation method, as shown in [14] and [17]. As main software tool, Fuzzy Logic $Toolbox^{TM}$ of $Matlab^{®}$ and $Simulink^{®}$ proove to be appropriate object-oriented programming environments for our purposes. The computing time is not a critical parameter for this application of still images analysis. As shown, the proposed method doesn't rely on iterative algorithms and it is susceptible to partial parallelization. In fact, after the training stage on a reference image, that implies computing of fuzzy rules, their encoding into a data base and an interpolation procedure, the contour detection is achieved on each search direction. In this manner, the whole computation may be done almost in parallel in four main stages: image fuzzification, fuzzy rules application, decimation criteria calculus (after the end of the second stage), and defuzzification.

Table 1. Segmentation errors for the image in Figure 6

Segmentation method	**Error (%)**
Otsu's multithreshold method	12.2
Fuzzy C-means	9.4
Proposed method	5.6

5 Conclusions

The application of fuzzy logic for biomedical image segmentation proved superior results in terms of segmentation errors, in comparison with other methods developed in [14], [15], [17], taking as reference the manually contour-based segmented version. A main advantage of our method is that knowledge is directly represented in the image space by means of fuzzy sets. The automatic detection of contour points is facilitated by using a data fusion approach by combining information brought by fuzzy rules (selected after a training process) with that coming from each used searched direction. Thus, the obtained average accuracy of 5,6% was found very good by the medical neuro-surgeon who helped us during experiments, even more as the recognized variability between different medical experts when manually contouring structures in brain images is at least 10%. Moreover, this adaptive technique proves to be robust, as it may approach with good results noisy images, for which the contour area may be not well delimited even for experts. In this case, the parameters characterizing contours must be expressed by average values taken on larger research areas. This is also a working manner for increasing the robustness of the main method.

Another advantage of the method is that the computing time when implementing this non-iterative algorithm is kept at a low value and it is possible to be lowered by further parallelization.

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