Medical Image Segmentation Based on Fuzzy Controlled Level Set and Local Statistical Constraints

Mohamed Benzian[1,2] and Nacéra Benamrane[2]
[1]Département d'Informatique, Université Abou Bekr Belkaid-Tlemcen, Algérie
[2]Laboratoire SIMPA, Département d'Informatique, Université des Sciences et de la Technologie d'Oran Mohamed Boudiaf, Algérie

Abstract: *Image segmentation is one of the most important fields in artificial vision due to its complexity and the diversity of its application to different image cases. In this paper, a new Region of Interest (ROI) segmentation in medical images approach is proposed, based on modified level sets controlled by fuzzy rules and incorporating local statistical constraints (mean, variance) in level set evolution function, and low image resolution analysis by estimating statistical constraints and curvature of curve at low image scale. The image and curve at low resolution provide information on rough variation of respectively image intensity and curvature value. The weights of different constraints are controlled and adapted by fuzzy rules which regularize their influence. The objective of using low resolution image analysis is to avoid stopping the evolution of the level set curve at local maxima or minima of images. This method is tested on medical images. The obtained results of the technique presented are satisfying and give a good precision.*

Keywords: *Segmentation, level sets, medical images, image resolution, fuzzy rules, ROI.*

Received April 8, 2015; accepted December 23, 2015

1. Introduction

Image segmentation permits to extract distinctive objects in an image. It is classified in edge segmentation, region segmentation and segmentation by classification. Deformable models are also applied for segmentation. Explicit deformable models or snakes used in [5, 12] suffer from limitations like the difficulty to track a shape of unspecified topology.

Geodesic Active Contours proposed by Caselles *et al*. [4, 5] are based on minimizing an intrinsic weighted Euclidean length that presents correspondence with Kass *et al.* [12] classical snake model. Implicit deformable models or Level Sets [20, 22] have become very popular in segmentation over the recent years as they provide an effective tool for modelling objects of any shape or topology for the evolution of implicit curves.

The principle of Level Sets method is to move and warp temporally any kind of closed curve or surface implicitly represented [1, 20]. A closed contour C- called front or interface- represented by a function Φ evolves according to the Equation:

$$\partial\varphi/\partial t = F.N \tag{1}$$

F: propagation speed function defined in each point of the curve. N: normal to the curve.

Propagation front C is defined as:

$$C = \{(x)|\varphi(x,t) = 0\} \tag{2}$$

Φ evolves according to the equation (with time t and normal unit vector N):

$$\partial\varphi/\partial t + \vec{N}.\nabla\varphi = 0 \tag{3}$$

Theoretically, F is computed on all image positions and the curve evolves at the point having maximal value of F [7]. The narrow band principle strongly reduces time calculations and limits computing of F at pixels situated on a narrow band of width d pixels inside or outside the evolving front [1, 22].

The speed function F plays a very important role in the evolution of level set curves. There is no ideal formula that can be applied on each context or image type. Baillard *et al.* [2] proposed a speed function based on Bayes rule. They used a modified propagation term v_0 as a local force term. It is derived from probability density functions interior and exterior to the structure to segment. The Level Set function is:

$$\partial\varphi/\partial t = g(|\nabla I|)(\kappa + v_0)|\nabla\varphi| \tag{4}$$

Liu and Li [17] used a combined gradient and intensity method with level set segmentation. They used prior probability to get intensity distribution inside the region to segment $P_{in}(I(x))$ and outside the region $P_{out}(I(x))$.

In this paper, we propose a new Region of Interest (ROI) segmentation in medical images approach based on the specification of new constraints such as local statistical mean and variance to the speed evolution function of level set curves. The computation of local mean and variance was used in [9] for multiscale analysis in geomorphometry. The novelty of our approach is the use of constraints based on local statistical variation of grey level intensity (mean and variance) of a point P in both original and low resolution images, and discrete curvatures of level set curves generated at lower resolution scale with the aim of detecting rough local concavity and convexity zones.

Weights of different constraints are controlled by fuzzy rules that regularize their strength.

In section 2 we present related works to level set combined with multiresolution images, and level set with fuzzy rules and fuzzy c-means. In section 3, we give details of the proposed new Level Set ROI segmentation method based on local statistical constraints and both low Image and Curve resolution analysis, and present the fuzzy controlled evolution speed function F. In section 4, segmentation results are shown on a sample of images. Finally, we provide a conclusion with some perspectives of our approach.

2. Related Works

There are some references regarding the segmentation based on level set and image scale analysis or multiresolution. Wang *et al.* [23] proposed a local multi-scale region based level set segmentation method with presence of inhomogeneities in image intensity.

They defined the local region in circular shape to approximate non-uniform illumination and capture more local intensity information and perform a statistical analysis on intensities of local circular regions centered in each pixel with multi-scale low-pass filtering in order to extract local intensity information. The multiscale local intensity information is incorporated into the energy functional of the level set method. Min and Wang [19] integrated in their level set texture segmentation approach a multi-scale local structure operation as pixel-level feature. The global intensity information is extracted as the region-level feature and integrated with multi-scale local structure operation. Kim *et al.* [13] incorporated two evolving curves for level set evolution at two scales: at the coarse scale one curve tracked the object boundary, and at the fine scale the second curve was used to smooth the object boundary.

Chong *et al.* [6] used low resolution images to segment synthetic radar images. They execute the level set function at low resolution image in order to speed up the detection, and project the contour onto high resolution image. Gadermayr and Uhl [11] proposed a dual-resolution active contour segmentation method based on level set. They applied a shape-prior gradient descent approach to a significantly resolution-reduced image in order to find suitable initialization. Then, they used an indentation segmentation with the Chan-Vese region based technique and a local Hough transform to vertex candidate regions to optimize the accuracy of the corner detection. Fasaee *et al.* [10] proposed a segmentation approach that combines level set and super resolution images. A high resolution image is obtained from Low Resolution (LR) ones by sub-pixels shift of LR images of each other in order to enhance the image resolution and improve image segmentation.

Xu *et al.* [24] proposed also a coarse-to-fine dual scale technique for tuberculosis cavity detection on chest radiographs.

Other approaches used fuzzy logic or fuzzy C-Means combined with level set. Ciofolo and Barillot [8] proposed to segment 3D structures with competitive level sets driven by fuzzy control, by evolving simultaneously several to previously defined anatomical shapes. The fuzzy system is designed essentially to determine the directional term (expansion or contraction) of the evolution equation of each level curve in order to fit borders to their respective targets.

Kumar *et al.* [14] proposed a hybrid method for image segmentation by combining Fuzzy C-Means (FCM) and local image fitting level set method. A contour is obtained by fuzzy c-means which serves as initial contour for improved Level Set. In a similar way, Li *et al.* [15] proposed a fuzzy level set algorithm for medical image segmentation. It begins with spatial fuzzy clustering, whose results permit to initiate level set segmentation, estimate control parameters and regularize level set evolution. In another approach, Li *et al.* [16] proposed a level set method based on unsupervised fuzzy clustering that integrates image gradient, region competition and prior information estimation for CT liver tumor segmentation.

Salman [21] proposed an image segmentation and edge detection approach based on Chan Vese algorithm. He first used K-means algorithm to classify the image into different intensity regions. The level set evolution is applied to detect regions whose boundaries are not necessarily defined by the gradient but based on K-means initial results.

3. Proposed Approach

The main steps of our approach are shown below:

1) Computation of local Mean and variance and discrete curvature of the original image

↓

2) Computation of local mean, variance and discrete curvature at lower scale image

↓

3) Application of fuzzy rules to above constraints in (1) and (2)

↓

4) Computation of the speed function F in each pixel of the curve based on fuzzy rules and previous constraints in (1) and (2)

↓

5) The pixel with best value of F is candidate to evolution

↓

6) Update value F in the pixel candidate neighbourhood -in the same way as in (4)-

↓

7) Execution of the previous steps (3) to (6) until all values of F exceed a threshold or the number of iterations exceeds a limit

Figure 1. General process of our approach.

We used the following speed evolution function F of the classical level set method in comparison with our experimental results in section 5:

$$F = \alpha . g\left|\nabla I\right|\left(c + \varepsilon . \kappa\right) \tag{5}$$

c: constant, generally equal to 1. $0 < \varepsilon < 1$.

$g\left|\nabla I\right|$: Image gradient that depends on gray level intensity change. Typical formula of g is (p=1 or 2):

$$g\left(\left|\nabla I(x,y)\right|\right) = 1\Big/\left(1 + \left|\nabla G_\sigma(x,y) * I(x,y)\right|^p\right) \tag{6}$$

κ: curvature or viscosity term of the speed function F that improves smoothing of the curve φ:

$$\kappa = div\left(\nabla\varphi / \left|\nabla\varphi\right|\right) = \left(\varphi_{xx}\varphi_y^2 - 2\varphi_x\varphi_y\varphi_{xy} + \varphi_{yy}\varphi_x^2\right) \Big/ \sqrt{\left(\varphi_x^2 + \varphi_y^2\right)} \tag{7}$$

3.1. Local Statistical Constraints

Statistical Constraints based on mean and variance are applied locally in the pixel neighbourhood. First, we perform a gaussian smoothing to both original image and low resolution ones.

Given a local window F with size (mxm) at the vicinity of a point P. Generally, the evolution of a contour at a given point P implies an evolution of the pixels near P in the same direction. The local window F is centered at point P_{xy} with radius n. Radius values used in experimental results are 1 or 2 depending on both image types and resolution level.

$$F = \left\{\left(x_i, x_j\right) \middle| x - n \le x_i \le x + n, y - n \le y_j \le y + n\right\} \tag{8}$$

$$Z_1 = \left\{x_i \ \middle| x_i \in R; x_i \in F\right\},\ Z_2 = \left\{x_i \ \middle| x_i \notin R; x_i \in F\right\} = F - Z_1 \tag{9}$$

The local statistical constraints (mean and variance) are given as follows:

$$\mu_1 = \frac{\sum i(x) \in Z_1}{Card\left(Z_1\right)}, \mu_2 = \frac{\sum i(x) \in Z_2}{Card\left(Z_2\right)} \tag{10}$$

- μ_1 (resp. μ_2): local mean grey level of pixels inside the window F and belonging inside (resp. outside) the region R delimited by the evolution curve C.
- i (x): image intensity of a pixel in window F.

$$\nu = \sqrt{\left(\sum i^2(x) \in Z / Card(Z) - \mu_G^2\right)^2} \tag{11}$$

- μ_G: local mean grey level intensity of all pixels in the window F belonging both inside and outside the region R delimited by the evolution curve C.
- ν: local variance corresponding to local mean μ_G.

Statistical similarity ($|\mu_1 - \mu_2| \approx 0$) means that there is no local grey level difference inside and outside the curve C at point P, so C must evolve at P.

The second statistical similarity ($\nu \approx 0$) reinforces the previous one. It means that there is no local grey level variance disparity inside and outside curve C at point P, and implies an evolution of C at P.

The formula grouping local mean and variance intensity variation is (α_1, α_2: weighting coefficients estimated by fuzzy rules method):

$$Stat_{loc} = \alpha_1\left|\mu_1 - \mu_2\right|^{k_1} + \alpha_2 . \nu \tag{12}$$

3.2. Discrete Curvature at Lower Scale

The number of images generated at different resolution levels is not fixed. In our case, we limited resolution of images to two levels, half (1/2) and 1/4 (25%). The original curve represents a Narrow Band of a zero level set with width 1 that delimits the deforming object in segmentation. Pixels P (x, y) of the closed curve are represented by a list L of points. A curve is generated approximately at lower scale by dividing each pixel position (x, y) of L by the same scale value applied to the image. We obtain a new list L_S of points (x_S, y_S), redundant point values are removed.

Discrete Curvature at lower scale is based on the computation of the geometrical shape contour at a lower scale to obtain a coarser contour, then the computation of the discrete curvature value at a point P_S of the lower curve (Figures 2b and 2c) in order to reduce or smooth coarser concave or convex shapes. Figure 1 below shows an example of the contour and its scaling by factors 1/2 and 1/4.

a) Original curve. b) Curve obtained at scale 1/2. c) curve obtained at scale 1/4.

Figure 2. original contour and contours generated after scaling by factors 1/2 and 1/4, the points $P_{S1/2}$ and $P_{S1/4}$ after scaling correspond to the point P (red) of the original contour, so the point P_S corresponds to more than one point P of the original contour.

κ_s (discrete curvature) applied to the curve Φ_S at lower scale is the same as described in Equation (7) in order to smooth contour positions that still present convex or concave parts at a large scale. The curvature weights are also regularized by fuzzy control, $\kappa_S = div\left(\nabla\phi_S / \left|\nabla\phi_S\right|\right)$.

3.3. Local Statistical Constraints at Lower Scale

The neighbourhood zone F_S of the scaled image is centered at point Ps_{xy} with radius n.

$$F_S = \left\{(x_i, x_j) \middle| x - n \le x_i \le x + n, y - n \le y_j \le y + n\right\} \tag{13}$$

$$Z_{S1} = \left\{x \middle| x \in R_S ; x \in F_S\right\}, Z_{S2} = F_S - Z_{S1} \tag{14}$$

μ_{S1} (resp. μ_{S2}): mean gray level of pixels of the local zone F_S and belonging inside (resp. outside) the region R_S delimited by the lower scale curve Φ_S after reduction by a scale factor s (similar to Equation 10).

The local variance ν_S at lower resolution is computed similarly (Equation (11) in section 3).

The formula grouping local mean and variance at lower scale (α_3, α_4: weighting coefficients) is:

$$Stat\,Scale_{loc} = \alpha_3 \left|\mu_{S1} - \mu_{S2}\right|^{k2} + \alpha_4.\nu_S \tag{15}$$

The term $|\mu_{S1}$- $\mu_{S2}|$ means that the curve tends to evolve at the specified position, there is no coarse intensity variation in the scaled image.

3.4. Fuzzy Controlled Speed Function F

The weights corresponding to the previous constraints are regularized by a fuzzy control using a set of fuzzy rules [25] in order to have better results. This operation represents an improvement to the previous work [3].

We used fuzzy sets for comparing similarities between characteristics like mean difference value ($|\mu1$-$\mu2|$), variance (ν) and curvature (κ) of the original image and the images at lower scale (scale 1/2 and scale 1/4). Five fuzzy set types are applied (very near, near, medium, far and very far), they are of trapezoidal form with Mamdani type fuzzy controller [18] (Figure 3).

For example, very near fuzzy set for mean characteristic means that the difference ($|\mu1$-$\mu2|$) is very low and close to zero, far fuzzy set means that the difference between mean gray level values inside and outside level set curves is big, and the signification is equivalent for other fuzzy sets: very far, mead and near.

Fuzzy sets are applied to mean gray level value of the original image, mean gray value of the low resolution image at first scale (1/2) and mean value at second scale (1/4). The main idea is that the weight of the original image is attracted by the weight forces of the images at lower scale, and described in Table 1.

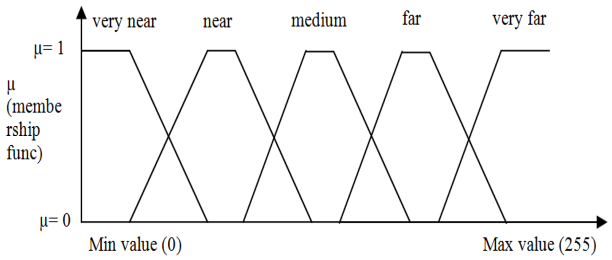


Figure 3. Fuzzy Sets indicating similarities between constraints: mean gray level (similarity between pixels inside and outside the contour), variance (near or far from zero) and curvature

Fuzzy rules applied to regularize variance and curvature constraints are similar to the mean constraint. For each resulting fuzzy set a fuzzy factor ($c_1,\ldots,c_6$) between 0 and 1 is applied to different weights α_1, α_2, α_3, α_4, α_5, α_6 corresponding respectively to the constraints mean gray level ($|\mu_1$-$\mu_2|$), variance (ν), low mean gray level ($|\mu_{s1}$- $\mu_{s2}|$), low variance (ν_s), curvature (κ) and low curvature (κ_s).

The previous constraints (section 3) are integrated into the speed function F and associated with weights calculated by fuzzy decision rules.

Table 1. Different fuzzy rules applied for decision in our approach.

Rules	Condition C1	Condition C2	Condition C3	Condition C4	Conditions Connector	Conclusion
Rule #1	mean_scale_1 is _VERY_NEAR	Mean_scale_2 is _VERY_NEAR	//	//	C1 AND C2	Mean_gray_orig is _VERY_NEAR
Rule #2	mean_scale_1 is _NEAR OR _VERY_NEAR	mean_scale_2 is _NEAR OR _VERY_NEAR	mean_gray_orig IS NOT _VERY_NEAR	Rule #1 is false	C1 AND C2 AND C3 AND C4	Mean_gray_orig is _NEAR
Rule #3	mean_scale_1 is _NEAR	mean_scale_2 is _NEAR	mean_gray_orig IS _MEDIUM		C1 AND C2 AND C3	Mean_gray_orig is _NEAR
Rule #4	mean_scale_1 is _NEAR	mean_scale_2 is _NEAR	mean_gray_orig IS _FAR	mean_gray_orig IS _VERY_FAR	C1 AND C2 AND (C3 OR C4)	Mean_gray_orig is _MEDIUM
Rule #5	mean_scale_1 is _MEDIUM	mean_scale_2 is _MEDIUM	//	//	C1 AND C2	Mean_gray_orig is _MEDIUM
Rule #6	mean_scale_1 is _MEDIUM	mean_scale_2 is _MEDIUM	mean_gray_orig IS _FAR	mean_gray_orig IS _NEAR	(C1 OR C2) AND (C3 OR C4)	Mean_gray_orig is _MEDIUM
Rule #7	mean_scale_1 is _MEDIUM	mean_scale_2 is _MEDIUM	mean_gray_orig IS _VERY_FAR		(C1 OR C2) AND C3	Mean_gray_orig is _FAR
Rule #8	mean_scale_1 is _MEDIUM	mean_scale_2 is _MEDIUM	mean_gray_orig IS _VERY_NEAR		(C1 OR C2) AND C3	Mean_gray_orig is _NEAR
Rule #9	mean_scale_1 is _VERY_FAR	mean_scale_2 is _VERY_FAR	//	//	C1 AND C2	Mean_gray_orig is VERY_FAR
Rule #10	mean_scale_1 is _VERY_FAR OR _FAR	mean_scale_2 is _VERY_FAR OR _FAR	mean_gray_orig IS NOT _VERY_FAR	Rule #9 is false	(C1 OR C2) AND C3 AND C4	Mean_gray_orig is _FAR
Rule #11	mean_scale_1 is _FAR	mean_scale_2 is _FAR	mean_gray_orig IS _MEDIUM	//	C1 AND C2 AND C3	Mean_gray_orig is _FAR
Rule #12	mean_scale_1 is _FAR	mean_scale_2 is _FAR	mean_gray_orig IS _NEAR	mean_gray_orig IS _VERY_NEAR	C1 AND C2 AND (C3 OR C4)	Mean_gray_orig is _MEDIUM

The value of F is computed at each point of curve C:

$$F = \pm \alpha . g\left(0.5 + \alpha_5 . c_5 . \kappa + \alpha_6 . c_6 . \kappa_S\right) \tag{16}$$

$g = MG_{loc} + MG\_Scal_{loc} + VAR_{loc} + VAR\_Scal_{loc}$

$$g = 1 \Big/ \begin{pmatrix} 1 + \alpha_1 . c_1 \left|\mu_1 - \mu_2\right|^{k_1} + \alpha_2 . c_2 . \nu + \\ \alpha_3 . c_3 \left|\mu_{S1} - \mu_{S2}\right|^{k_2} + \alpha_4 . c_4 . \nu_S \end{pmatrix} \tag{17}$$

Coefficients α_i, c_i are adapted and regularized according to the result of application of fuzzy rules.

- g: image intensity variation. k_1, $k_2 = 1$.
- κ : discrete curvature for curve smoothing.
- κ_S : discrete curvature of the scaled curve (this value is coarser and is computed only for points whose curvature value κ is not high).
- α_5, α_6: curvature weighting coefficients, generally lower than intensity weight coefficients α_1, α_2, α_3, α_4.

The sign of F indicates the evolution direction of the curve which means that it is in expansion or dilation, and hence limits the evolution to Fast Marching where the curve evolves only in one direction, UpWind or DownWind. In our approach, the direction is manually chosen by the user, and by default negative.

4. Experimental Results

Our approach was entirely developed with c language. We used linked lists with dynamic allocation memory for narrow bands Lin (list at the contour frontier and inside it with thickness 1) and Lout (list immediately outside the contour and adjacent to Lin). In our method we used fuzzy rules to regularize coefficient values, and these adapted coefficients give better results than the previous proposed approach [3]. Performance evaluation was done by comparing the results of our method with the classical level set method as formulated by Equation (5). Figure 4 shows coefficient values of each constraint for constructing fuzzy sets.

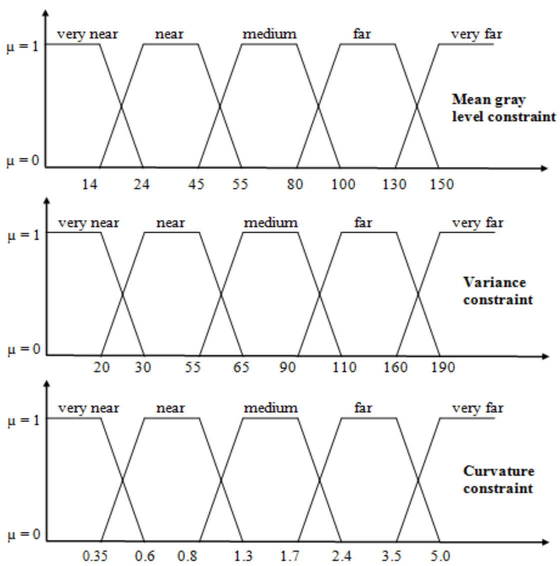
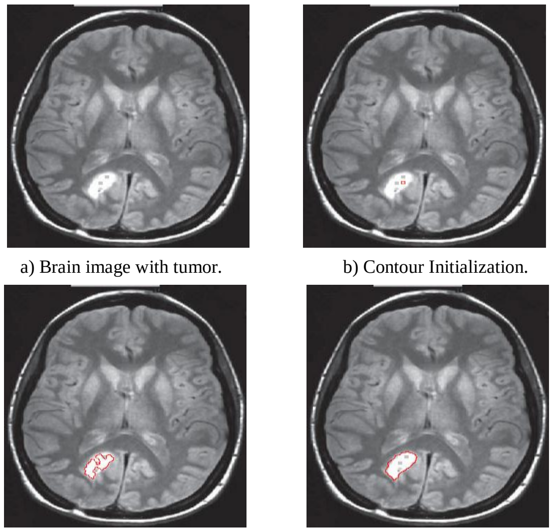


Figure 4. Interval values for constructing fuzzy sets.

In our first experiment, we applied our approach to a pathological brain image. Figure 5 shows the original image (5-a) with the initial contour (5-b), and the segmentation result with the classical level set by applying Equation (5), the local minima inside the object are not segmented (Figure 5-c). Figure 5-d shows the segmentation result with our method. The main contribution of our approach is that our method does not stop on local minima in the image.



a) Brain image with tumor. b) Contour Initialization.

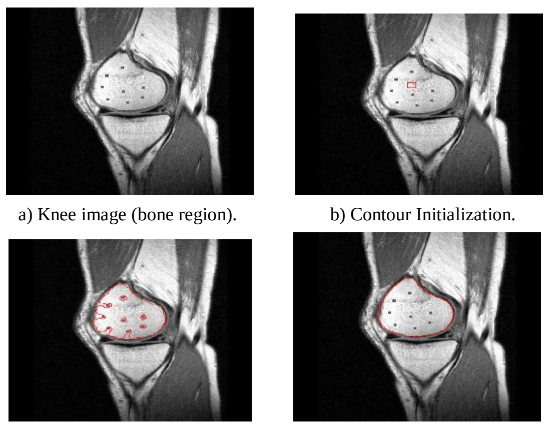
c) Result with classical level set. d) Result with our method.

Figure 5. Brain image with tumoral zone present in the image.

In Figure 6, a bone region image of the knee is presented with artificial noise –little rectangular zone- added inside the region, and the segmentation result with classical level set method (Figure 6-c) and our new approach (Figure 6-d). The third example shows segmentation result of an ultra sound carotid artery, and the artificial noise added inside the two regions that was easily resolved by our method (Figure 7).

The last example (Figure 8) shows a liver image with artificial noise added inside the tumoral zone.

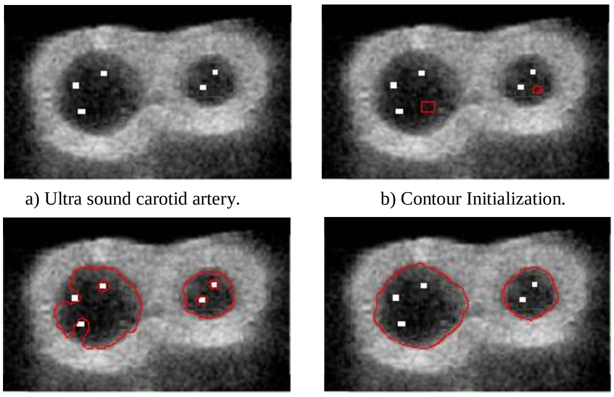
This causes segmentation defects with classical level set method, however with our method it avoids stopping at minimal zones.



a) Knee image (bone region). b) Contour Initialization.

c) Result with classical level set. d) Result with our method.

Figure 6. Bone region image of the knee with added artificial noise (6a) and segmentation results (6c) and (6d).

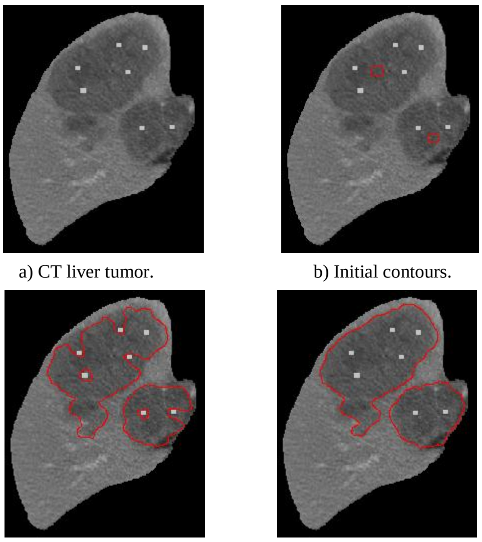


a) Ultra sound carotid artery. b) Contour Initialization.

c) Classical level set method. d) Result with our method.

Figure 7. Noisy ultra sound carotid artery image (7a) and segmentation result by classical level set method (7c) and our method (7d).

In Table 2, we list in detail the parameter values for different images used in our experiment. Mean gray level coefficient for CT liver image presenting a tumour is lightly high as in other images because the mean gray level values are nearer inside and outside the tumoral zone. By experience, variance coefficient was taken weaker than mean gray level coefficient for better results, and for the same reason curvature coefficient is weaker than gradient coefficient.



a) CT liver tumor. b) Initial contours.

c) Result with classical level set. d) Result with our method.

Figure 8. CT liver tumor with artificial noise added (8a), contour initialization (8b), and segmentation result with classical level set method (8c) and our method (8d).

The validation of segmentation results is very important, especially for medical images. The reason is because any significant difference between the obtained results and the real ones might lead to damages in medical activities. We proceed to a comparison between our segmentation result and manual segmentation result provided by a practitioner, we use comparison with classical level set method too.

The evaluation of segmentation performance is carried out quantitatively by computing undersegmented pixels (or False Negative ones (FNP), i.e., Pixels that belong to the region of manual segmentation result and do not belong to our method of segmentation result) and oversegmented pixels (or False Positive Pixels (FPP), i.e., pixels that belong to the result of our segmentation method but not to the manual one).

In Table 3, we show the approximate result and the percentage error result of both classical level set and our new approach estimated from the ratio of both false positive and false negative pixels divided by the total number of pixels from manual segmentation.

Table 2. Coefficient values used for different image results.

	Mean gray level ($\alpha 1$)	Variance ($\alpha 2$)	Mean gray at low scale ($\alpha 3$)	Variance at low scale ($\alpha 4$)	Curvatur-e ($\alpha 5$)	Curvatur-e at low scale ($\alpha 6$)	General gradient coef	Size of local rectangular zone	Local rect. Zone at low scale
Brain image	3.0	0.6	2.0	0.3	0.3	0.2	3.0	5 x5	3x3
Knee image	3.0	0.6	2.0	0.3	0.4	0.3	3.0	3 x3	3x 3
Carotid artery	3.5	0.8	2.5	0.4	0.3	0.2	3.0	7 x7	5x 5
CT liver image	3.0	0.6	2.0	0.3	0.3	0.2	3.0	5 x5	3x 3

Table 3. Validation of results between our method and manual segmentation and comparison with classical level set method.

	Manual segmentati on (pixels)	Level Set method type	Total number of pixels	True matched pixels	False positive pixels	False negative pixels	General percentage error
Brain image	1397	Classic level set	1075	1056	341	19	25.77 %
		New approach	1231	1226	171	5	12.60 %
Knee image	8060	Classic level set	7164	7116	944	48	12.31 %
		New approach	8181	7947	113	234	4.31 %
Carotid artery	5220	Classic level set	4212	4169	1051	43	20.96 %
		New approach	5004	4914	306	90	7.59 %
CT liver image	12185	Classic level set	10485	10221	1964	264	18.28 %
		New approach	11942	11613	572	329	7.39 %

5. Conclusions

In this paper, we proposed a new ROI segmentation in medical images approach that combines local statistical constraints (mean and variance) and discrete curvature estimated from the original image and low resolution images. Image resolution was fixed to two levels, half (1/2) and 1/4. These constraints are controlled and adapted by fuzzy logic rules. These rules tend to reinforce the constraint weights in low resolution images and influence the weight in the original image. The results obtained are satisfying and our new approach does not stop on local noisy regions by comparison with classical level set method. We hope that the method will be extended to motion video images and to 3D images and applied to any resolution level (1/8 or other).

References

[1] Adalsteinsson D. and Sethian J., “A Fast Level Set Method for Propagating Interfaces,” *Journal of Computational Physics*, vol. 118, no. 2, pp. 269-277, 1995.

[2] Baillard C., Barillot C., and Bouthemy P.,

"Robust Adaptive Segmentation of 3D Medical Images with Level Sets," Technical Report, 2000.

[3] Benzian Y. and Benamrane N., "Application of Scale Analysis on Level Sets for Cooperative Image Segmentation," *in Proceedings of the 4th International Conference on Computer Vision Theory and Applications*, Lisboa, pp. 224-230, 2009.

[4] Caselles V., Katte F., Coll T., and Dibos F., "A Geometric Model for Active Contours," *Numerische Mathematik*, vol. 66, no.1, pp. 1-31, 1993.

[5] Caselles V., Kimmel R., and Sapiro G., "Geodesic Active Contours," *International Journal of Computer Vision*, vol. 22, no. 1, pp. 61-79, 1997.

[6] Chong J., Ouyang Y., and Zhu M., "Two Coastline Detection Methods Based On Improved Level Set Algorithm in Synthetic Aperture Radar Images," *in Proceedings of the Dragon Symposium*, Beijing, 2008.

[7] Chopp D., "Computing Minimal Surfaces Via Level Set Curvature Flow," *Journal of Computational Physics*, vol. 106, no. 1, pp. 77-91, 1993.

[8] Ciofolo C. and Barillot C., "Brain Segmentation with Competitive Level Sets and Fuzzy Control," *in Proceedings of International Conference on Information Processing in Medical Imaging*, Glenwood Springs, pp. 333-344, 2005.

[9] Dragut L., Eisank C., and Strasser T., "Local Variance for Multi-Scale Analysis in Geomorphometry," *International Journal of Geomorphology*, vol. 130, no. 3-4, pp. 162-172, 2011.

[10] Fasaee F., Hashemi M., Avendi M., and Gu I., "An Enhanced Segmentation Method by Combining Super Resolution and Level Set," *Journal of Medical and Bioengineering*, vol. 2, no. 1, pp. 1-4, 2013.

[11] Gadermayr M. and Uhl A., "Dual-Resolution Active Contours Segmentation of Vickers Indentation Images with Shape Prior Initialization," *in Proceedings of the 5th International Conference on Image and Signal Processing*, Agadir, pp. 362-369, 2012.

[12] Kass M., Witkin A., and Terzopoulos D., "Snakes: Active Contour Models," *International Journal of Computer Vision*, vol. 1, no. 4, pp. 321-331, 1988.

[13] Kim D., Kim H., Suryanto., Choi K., and Ko S., "Multi-Scale Level Set Based Curve Evolution for Real-Time Non-Rigid Object Contour Tracking," *in Proceedings of IEEE Tencon*, Singapore, pp. 1-5, 2009.

[14] Kumar S., Ray S., and Tewari P., "A Combined Approach Using Fuzzy Clustering and Local Image Fitting Level," *Canadian Journal on Image Processing and Computer Vision*, vol. 3, no. 1, pp. 1-5, 2012.

[15] Li B., Chui C., Chang S., and Ong S., "Integrating Spatial Fuzzy Clustering with Level Set Methods for Automated Medical Image Segmentation," *Computers in Biology and Medicine*, vol. 41, no. 1, pp. 1-10, 2011.

[16] Li B., Chui C., Chang S., and Ong S., "A New Unified Level Set Method For Semi-Automatic Liver Tumor Segmentation on Contrast-Enhanced CT Images," *Expert Systems with Applications*, vol. 39, no. 10, pp. 9661-9668, 2012.

[17] Liu S. and Li J., "Automatic Medical Image Segmentation Using Gradient and Intensity Combined Level Set Method," *in Proceedings of the International Conference of the IEEE Engineering in Medicine and Biology Society*, New York, pp. 3118-3121, 2006.

[18] Mamdani E., "Application of Fuzzy Algorithms For Control of Simple Dynamic Plant," *Proceedings of the Institution of Electrical Engineers*, vol. 121, no. 12, pp. 1585-1588, 1974.

[19] Min H. and Wang X., "A Novel Level Set Model Based on Multi-Scale Local Structure Operation for Texture Image Segmentation," *Journal of Information and Computational Science*, vol. 12, no. 1, pp. 9-20, 2015.

[20] Osher S. and Sethian J., "Fronts Propagating with Curvature-Dependent Speed: Algorithms Based on Hamilton-Jacobi Formulations," *Journal of Computational Physics*, vol. 79, no. 1, pp. 12-49, 1988.

[21] Salman N., "Image Segmentation and Edge Detection Based on Chan-Vese Algorithm," *The International Arab Journal of Information Technology*, vol. 3, no. 1, pp. 69-74, 2006.

[22] Sethian J., "A Fast Marching Level Set Method for Monotonically Advancing Fronts," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 93, no. 4, pp. 1591-1595, 1996.

[23] Wang X., Min H., and Zhang Y., "Multi-Scale Local Region Based Level Set Method for Image Segmentation in The Presence of Intensity Inhomogeneity," *Journal of Neurocomputing*, vol. 151, pp. 1086-1098, 2015.

[24] Xu T., Cheng I., Long R., and Mandal M., "A Novel Coarse-To-Fine Dual Scale Technique for Tuberculosis Cavity Detection in Chest Radiographs," *EURASIP Journal on Image and Video Processing*, vol. 2013, no. 3, pp.1-18, 2013.

[25] Zadeh L., "Fuzzy Sets," *Information and Control*, vol. 8, no. 3, pp. 338-353, 1965.

Mohamed Benzian is currently an assistant professor in computer science, at Abou Bekr Belkaid University, Tlemcen, Algeria since 2001. He received his engineering degree in 1993 and his MS Degree in 2001 both from Mohamed Boudiaf University of Science and Technologyof Oran. He is now member of Laboratory SIMPA, at University of Science and Technology, of Oran, Mohamed Boudiaf since 2006. He has published many research papers in national and international conferences His research interests are image processing, 3D reconstruction and modeling.

Nacéra Benamrane is currently a full professor and a director of SIMPA laboratory in informatics department at University of Science and Technology of Oran-Mohamed Boudiaf (USTO-MB). She received her engineering degree in Computer Science from University of Oran, the M.Sc. and Ph.D. degrees from University of Valenciennes, France, in 1988 and 1994. Since 2002, she is the head of vision and medical imaging team at SIMPA laboratory. She has published more than 90 papers in journals and conference proceedings. Her main research interests include image processing, medical imaging, computer vision, biomedical engineering and pattern recognition.