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

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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.

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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 \( \Phi \) evolves according to the Equation:

\[
\frac{\partial \Phi}{\partial t} = F . N
\]  

(1)

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

Propagation front \( C \) is defined as:

\[
C = \{ x | \Phi(x,t) = 0 \}
\]  

(2)

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

\[
\frac{\partial \Phi}{\partial t} + \vec{N} . \nabla \Phi = 0
\]  

(3)

Theoretically, \( \Phi \) 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 \( \nu_0 \) 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:

\[
\frac{\partial \Phi}{\partial t} = \kappa [\nabla \Phi] \nabla \Phi
\]  

(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 \( P_{\text{int}}(I(x)) \) and outside the region \( P_{\text{ext}}(I(x)) \).
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 multisresolution 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 multisresolution. 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. Gadernayr 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:
We used the following speed evolution function F of the classical level set method in comparison with our experimental results in section 5:

\[ F = \alpha \cdot g \left( \nabla I \right) \left( c + \varepsilon \kappa \right) \]  

\( c: \) 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 \( (p=1 \text{ or } 2): \)

\[ g\left( \nabla I \left( x, y \right) \right) = \left[ 1 + \left| \nabla G \left( x, y \right) \ast I \left( x, y \right) \right| \right] ^{p} \]  

\( \kappa: \) curvature or viscosity term of the speed function \( F \) that improves smoothing of the curve \( \phi \):

\[ \kappa = \text{div} \left( \nabla \phi \right) = \left( \phi \cdot \nabla \phi , -2 \phi \cdot \nabla \phi + \phi \cdot \phi \right) \left( \sqrt{\phi \cdot \phi + \phi \cdot \phi} \right) \]  

\[ 3.1. \text{Local Statistical Constraints} \]

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 \( (m \times m) \) 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 \( P_{s} \) with radius \( n \). Radius values used in experimental results are 1 or 2 depending on both image types and resolution level.

\[ F = \left\{ \left( x, y \right) \big| x - n \leq x \leq x + n, y - n \leq y \leq y + n \right\} \]  

\[ Z_{s} = \left\{ x \big| x \in F \right\}, Z_{t} = \left\{ x \big| x \notin F \right\} = F - Z_{s} \]  

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

\[ \mu_{i} = \frac{\sum_{(x) \in Z_{i}} \phi (x)}{\text{Card} \left( Z_{i} \right)}, \mu_{t} = \frac{\sum_{(x) \in Z_{t}} \phi (x)}{\text{Card} \left( Z_{t} \right)} \]  

\[ \mu_{l} (\text{resp. } \mu_{2}): \] local mean grey level of pixels inside the window \( F \) and belonging inside (resp. outside) the region \( R \) delimited by the evolution curve \( C \).

\[ i \left( x \right): \] image intensity of a pixel in window \( F \).

\[ \mu_{G}: \] 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 \( C \).

\[ \nu: \] local variance corresponding to local mean \( \mu_{G} \).

Statistical similarity \( \left( \mu_{1} - \mu_{2} \right) \approx 0 \) 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 \( \left( a_{1}, a_{2}; \right) \) weighting coefficients estimated by fuzzy rules method:

\[ \text{Stat}_{w} = a_{1} \left| \mu_{l} - \mu_{2} \right| + a_{2} \nu \]  

\[ 3.2. \text{Discrete Curvature at Lower Scale} \]

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 \( x, y \) 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 \( 1/4 \).
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, κ_s = div(∇ φ_s /|∇ φ_s|).

3.3. Local Statistical Constraints at Lower Scale

The neighbourhood zone F_s of the scaled image is centered at point p_s with radius n.

\[ F_s = \{(x, y) | -n \leq x, y \leq n \} \]
\[ Z_s = \{x \in R_s, x \in F_s \}, Z_s = F_s - Z_s \]

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, ν; weighting coefficients) is:

\[ \text{Start Scale}_a = \alpha_1 \mu_1 - \mu_2 |^{1/4} + \alpha_2 \nu_2 \]

The term [%μ_s1 - μ_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 (|μ1 - μ2|), 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 (|μ1 - μ2|) 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, near and medium.

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.

Fuzzy rules applied to regularize variance and curvature constraints are similar to the mean constraint. For each resulting fuzzy set a fuzzy factor (c1,...,c6) between 0 and 1 is applied to different weights α1, α2, α3, α4, α5, α6 corresponding respectively to the constraints mean gray level (|μ1 - μ2|), variance (ν), low mean gray level (|μ1 - μ2|), low variance (ν), curvature (κ) and low curvature (κ).

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.

<table>
<thead>
<tr>
<th>Rules</th>
<th>Condition C1</th>
<th>Condition C2</th>
<th>Condition C3</th>
<th>Condition C4</th>
<th>Conditions Connector</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule #1</td>
<td>mean_scale_1 is _VERY_NEAR</td>
<td>mean_scale_2 is _VERY_NEAR</td>
<td>//</td>
<td>//</td>
<td>C1 AND C2</td>
<td>Mean_gray_orig is _VERY_NEAR</td>
</tr>
<tr>
<td>Rule #2</td>
<td>mean_scale_1 is _NEAR OR _VERY_NEAR</td>
<td>mean_scale_2 is _NEAR OR _VERY_NEAR</td>
<td>mean_gray_orig IS NOT _VERY_NEAR</td>
<td>Rule #1 is false</td>
<td>C1 AND C2 AND C3 AND C4</td>
<td>Mean_gray_orig is _NEAR</td>
</tr>
<tr>
<td>Rule #3</td>
<td>mean_scale_1 is _NEAR</td>
<td>mean_scale_2 is _NEAR</td>
<td>mean_gray_orig IS _MEDIUM</td>
<td>C1 AND C2 AND C3</td>
<td>Mean_gray_orig is _NEAR</td>
<td></td>
</tr>
<tr>
<td>Rule #4</td>
<td>mean_scale_1 is _NEAR</td>
<td>mean_scale_2 is _NEAR</td>
<td>mean_gray_orig IS _FAR</td>
<td>C1 AND C2 AND C3 OR C4</td>
<td>Mean_gray_orig is _MEDIUM</td>
<td></td>
</tr>
<tr>
<td>Rule #5</td>
<td>mean_scale_1 is _MEDIUM</td>
<td>mean_scale_2 is _MEDIUM</td>
<td>//</td>
<td>//</td>
<td>C1 AND C2</td>
<td>Mean_gray_orig is _MEDIUM</td>
</tr>
<tr>
<td>Rule #6</td>
<td>mean_scale_1 is _MEDIUM</td>
<td>mean_scale_2 is _MEDIUM</td>
<td>mean_gray_orig IS _FAR</td>
<td>C1 OR C2</td>
<td>Mean_gray_orig is _MEDIUM</td>
<td></td>
</tr>
<tr>
<td>Rule #7</td>
<td>mean_scale_1 is _MEDIUM</td>
<td>mean_scale_2 is _MEDIUM</td>
<td>mean_gray_orig IS _NEAR</td>
<td>(C1 OR C2) AND C3</td>
<td>Mean_gray_orig is _FAR</td>
<td></td>
</tr>
<tr>
<td>Rule #8</td>
<td>mean_scale_1 is _MEDIUM</td>
<td>mean_scale_2 is _MEDIUM</td>
<td>mean_gray_orig IS _VERY_FAR</td>
<td>(C1 OR C2) AND C3</td>
<td>Mean_gray_orig is _NEAR</td>
<td></td>
</tr>
<tr>
<td>Rule #9</td>
<td>mean_scale_1 is _VERY_FAR</td>
<td>mean_scale_2 is _VERY_FAR</td>
<td>//</td>
<td>//</td>
<td>C1 AND C2</td>
<td>Mean_gray_orig is _VERY_FAR</td>
</tr>
<tr>
<td>Rule #10</td>
<td>mean_scale_1 is _VERY_FAR OR _FAR</td>
<td>mean_scale_2 is _VERY_FAR OR _FAR</td>
<td>mean_gray_orig IS NOT _VERY_FAR</td>
<td>Rule #9 is false</td>
<td>C1 OR C2 AND C3 AND C4</td>
<td>Mean_gray_orig is _MEDIUM</td>
</tr>
<tr>
<td>Rule #11</td>
<td>mean_scale_1 is _FAR</td>
<td>mean_scale_2 is _FAR</td>
<td>mean_gray_orig IS _FAR</td>
<td>C1 AND C2 AND C3</td>
<td>Mean_gray_orig is _FAR</td>
<td></td>
</tr>
<tr>
<td>Rule #12</td>
<td>mean_scale_1 is _FAR</td>
<td>mean_scale_2 is _FAR</td>
<td>mean_gray_orig IS _NEAR</td>
<td>C1 AND C2 AND C3 OR C4</td>
<td>Mean_gray_orig is _MEDIUM</td>
<td></td>
</tr>
</tbody>
</table>
The value of $F$ is computed at each point of curve $C$:

$$
F = \pm \alpha_c \left( 0.5 + \alpha_s \cdot c_s \cdot \kappa + \alpha_\kappa \cdot c_\kappa \cdot \kappa_s \right)
$$

(16)

$$
g = MG_{loc} + MG_{Scal_{loc}} + VAR_{loc} + VAR_{Scal_{loc}}
$$

(17)

Coefficients $\alpha_c$, $c_s$ are adapted and regularized according to the result of application of fuzzy rules.

- $g$: image intensity variation. $k_1$, $k_2 = 1$.
- $\kappa$: discrete curvature for curve smoothing.
- $\kappa_S$: discrete curvature of the scaled curve (this value is coarser and is computed only for points whose curvature value $\kappa$ is not high).
- $\alpha_s$, $\alpha_\kappa$: curvature weighting coefficients, generally lower than intensity weight coefficients $\alpha_1$, $\alpha_2$, $\alpha_3$, $\alpha_4$.

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 Lou (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.](image)

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.

![Figure 5. Brain image with tumoral zone present in the image.](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.

![Figure 6. Bone region image of the knee with added artificial noise (6a) and segmentation results (6c) and (6d).](image)
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>
<thead>
<tr>
<th>Brain image</th>
<th>Manual segmentation (pixels)</th>
<th>Level Set method</th>
<th>Total number of pixels</th>
<th>True matched pixels</th>
<th>False positive pixels</th>
<th>False negative pixels</th>
<th>General percentage error</th>
</tr>
</thead>
<tbody>
<tr>
<td>1397</td>
<td>Classic level set</td>
<td>1075</td>
<td>1056</td>
<td>341</td>
<td>19</td>
<td>25.77 %</td>
<td></td>
</tr>
<tr>
<td></td>
<td>New approach</td>
<td>1231</td>
<td>1226</td>
<td>171</td>
<td>5</td>
<td>12.60 %</td>
<td></td>
</tr>
<tr>
<td>Knee image</td>
<td>Classic level set</td>
<td>7164</td>
<td>7116</td>
<td>944</td>
<td>48</td>
<td>12.31 %</td>
<td></td>
</tr>
<tr>
<td>8060</td>
<td>New approach</td>
<td>8181</td>
<td>7947</td>
<td>113</td>
<td>234</td>
<td>4.31 %</td>
<td></td>
</tr>
<tr>
<td>Carotid artery</td>
<td>Classic level set</td>
<td>4212</td>
<td>4169</td>
<td>1051</td>
<td>43</td>
<td>20.96 %</td>
<td></td>
</tr>
<tr>
<td>5220</td>
<td>New approach</td>
<td>5004</td>
<td>4914</td>
<td>306</td>
<td>90</td>
<td>7.59 %</td>
<td></td>
</tr>
<tr>
<td>CT Liver image</td>
<td>Classic level set</td>
<td>10485</td>
<td>10221</td>
<td>1964</td>
<td>264</td>
<td>18.28 %</td>
<td></td>
</tr>
<tr>
<td>12185</td>
<td>New approach</td>
<td>11942</td>
<td>11613</td>
<td>572</td>
<td>329</td>
<td>7.39 %</td>
<td></td>
</tr>
</tbody>
</table>

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

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


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