Segmentation of head by geometrical active contour method

[1,2]**F. DERRAZ,** [1] **A. TALEB-AHMED**, [2]**A. CHIKH,** [2]**F. BEREKSI,** [1]**A. PINTI**
[2]Genie Biomedical Laboratory Abou Bekr Belkaid University
B.P 230, TLEMCEN (13 000), ALGERIA
[1]LAMIH UMR-CNRS 8530 Valenciennes Mont-Houy University
59313, Valenciennes, Francia
taleb@univ-valenciennes.fr

Abstract: *A new measure of quality is proposed for evaluating the performance of geometrical active segmentation based on Level-set method's. The technique is intended for the evaluation of the segmented image and features objective assessment of discrepancy with the theoretical contours, in tandem with subjective visual evaluation using F-measure criteria. The proposed mathematical model is extremely simple, even from the perspective of computational cost. Encouraging results were obtained for a selection of test images, especially in relation to other recently proposed and/or currently employed quality measures in medical image segmentation area.*

Index Terms-Segmentation, geometrical active contour, level-set, F-measure

1. Introduction

Segmentation of medical images is an important step in various applications such as visualization, quantitative analysis and image-guided surgery. Numerous segmentation methods have been developed in the past two decades for extraction of organ contours on medical images. Furthermore the subsequent analysis of segmented objects is hampered by the primitive, pixel level representations from those region-based segmentation [1]. Deformable models, on the other hand, provide an explicit representation of the boundary and the shape of the object. They combine several desirable features such as inherent connectivity and smoothness, which counteract noise and boundary irregularities, as well as the ability to incorporate knowledge about the object of interest [2]. However, parametric deformable models have two main limitations. First, in situations where the initial model and desired object boundary differ greatly in size and shape, the model must be re-parameterized dynamically to faithfully recover the object boundary. The second limitation is that it has difficulty dealing with topological adaptation such as splitting or merging model parts, a useful property for recovering either multiple objects or objects with unknown topology. This difficulty is caused by the fact that a new parameterization must be constructed whenever topology change occurs, which requires sophisticated schemes. Level set deformable models [3], also referred to as geometric deformable models, provide an elegant solution to address the primary limitations of parametric deformable models. These methods have drawn a great deal of attention since their introduction in 1987 [1]. Advantages of the geometrical active contour model over parametric active contour include: (i) no parameterization of the contour, (ii) topological flexibility, (iii) numerical stability, (iv) segmentation quality.

Recent reviews on the subject include papers from [4, 5]. In this paper, we give a general overview of the geometric active contour based on level set segmentation methods and their application in medical imaging area. Mainly these methods are controlled and final segmentation is strongly affected by intrinsic and extrinsic image parameters. ***In the present work, we are interested to found optimal parameter for a good segmentation***. In medical image it to difficult to found a referenced image, so we propose in this work to evaluate the segmentation method based on level-set by measuring three cues, the brightness, texture and contrast. The paper is organized as follow, in the next section we give an overview of the segmentation based on level-set method, where geometrical active contours is detailed and discussed in third section. In the forth section we present an overview evaluation framework for geometrical active contour segmentation. In the last section, the main results obtained and mainly the segmentation quality measure where the optimal parameter for level-set method segmentation are relatively determined.

2. Background

Segmentation of an image I via active contours, also referred to as snakes [1], operates through an energy functional controlling the deformation of an initial contour curve $C(s), s \in [0,1]$ under the influence of internal and external forces achieving a minimum energy state at high-gradient locations. The energy functional for active contour models is expressed as:

$$E(C) = \alpha \int_0^1 \left| C'(s) \right|^2 ds + \beta \int_0^1 \left| C''(s) \right|^2 ds - \lambda \int_0^1 \left| \nabla I(C(s)) \right|^2 ds \quad (1)$$

The first positive parameters (α, β) defines the internal energy of the deformable object, controlling the rigidity and elasticity of the contour while the last term define the external energy, attracting the model to high-gradient locations in the image *I*. Active contour segmentation via minimization of the energy functional in equation (1) is typically implemented with a parametric active contour models which is explicitly formulated as a parameterized contour on a regular spatial grid, tracking its point positions in a Lagrangian formulation [7]. In their paper [2], introduced the concept of geometric active contour models, which provide an implicit formulation of the active contour in a level set approach. To introduce the concepts of the level set approach, we focus on the boundary value problem of a close contour C deforming with a speed F along its normal direction:

$$|\nabla C| F = 1 \qquad (2)$$

Their fundamental idea is, instead of tracking in time the positions of the front on a regular grid as:

$$\Gamma(t) = \{ s = (x, y) | C(s) = t \} \qquad (3)$$

to embed the curve into a higher dimension function $\phi(s,t)$ such that:

1. the set $\{ s / \phi(s, t = 0) = 0 \}$ defines the initial contour .
2. the function ϕ evolves with the dynamic equation:

$$\frac{\partial \phi}{\partial t} + \vec{N} \nabla \phi = 0 \qquad (5)$$

where $\vec{N}$ is the unit normal vector to the curve expressed as:

$$\vec{N} = -\frac{\nabla \phi}{|\nabla \phi|} \qquad (6)$$

The front implicitly defined as:

$$\Gamma(t) = \{ s | \phi(s,t) = 0 \} \qquad (7)$$

corresponds to the solution of the initial boundary value problem defined parametrically in equation (3). In their paper [13, 14], focused on motion under mean curvature flow where the speed term is expressed as:

$$F = div\left(\frac{\nabla \phi}{|\nabla \phi|} \right) \qquad (8)$$

Since its introduction, the concept of deformable models for image segmentation defined with a level set approach has motivated the development of several families of method that include: geometric active contours based on mean curvature flow, gradient-based implicit active contours and geodesic active contours.

3. Segmentation methods

3.1. Level Set speed regularizers functions

The main issue of geometrical active contours segmentation methods is related to contour leakage at locations of weak or missing boundary data information. This phenomenon is provided for segmentation of a high-resolution Magnetic resonance image: (MRI) slice. Several efforts have been performed to add stopping criteria on the entire front, and local pixel freezing rules, or combine gradient with region information to make the segmentation process more robust to poor edge definition [8, 9]. When dealing with weak boundaries the most radical solution to leaking problems is to remove the expansion term at the cost of requiring an initialization close to the final solution. An alternative to this approach was proposed by [10] initially keeping the expansion term for pushing the model and turning it off as it approaches the object boundary. Detection of the boundary location was performed using a homogeneity map derived from scale-based fuzzy connectivity. [11] discussed the problem of segmentation of an object with missing boundaries and introduced a new geometric model for subjective surfaces. Starting from a reference point inside the object to segment, the ‘point of view’, a geometric deformable model is evolved with mean curvature flow and image-derived speed terms until a piecewise constant solution is reached. This piecewise constant solution, is the subjective surface defined by the segmentation process that is flat inside the object and has boundaries defined by geodesic curves. The authors also introduced the notion of “modal” contours which are contours that are perceived in the visual context and “amodal” contours which are associated with partially occluded objects.

All the level set segmentation methods presented above are based on image gradient intensity making them prone to leaking problems in areas with low contrast. A second problem related to the use of the image gradient as the only image-derived speed term is that it makes the segmentation process very sensitive to the initial position of the level set function as the model is prone to converge to false edges that correspond to local minima of the functional. Medical images typically suffer from insufficient and spurious edges inherent to physics of acquisition and machine noise from different modalities. To address these limitations, one approach can be followed is to fuse regularizer terms in the speed function as detailed in [9]. Recent works on the fusion of classical geometric and geodesic active contours models speed terms with regularizers, *i.e.* regional statistics information from the image. Regularization of the level set speed term is desirable to add prior information on the object to segment and prevent segmentation errors when using only gradient-based information in the definition of the speed. Three main types of regularizers were identified as: (a) Clustering-based regularizers, (b) Bayesian-based regularizers and (c) Shape-based regularizers.

In this paper, we give a brief overview of each regularizer’s method.

a. Clustering-Based Regularizers: In [12] the following energy functional for level set segmentation:

$$\frac{\partial \phi}{\partial t} = (\varepsilon k + V_p) |\nabla \phi| - V_{ext} \nabla \phi \qquad (9)$$

Where V_p is a regional force term expressed as a combination of the inside and outside regional area of the propagating curve. This term is proportional to a region indicator taking value between 0 and 1, derived from a fuzzy membership measure as described in [12].

b. Bayesian-Based Regularizers: Recent work [13] proposed an approach similar to the previous one where the level set energy functional expressed as:

$$\frac{\partial\phi}{\partial t} = g(|\nabla I|)(k + V_0)|\nabla\phi| \qquad (10)$$

uses a modified propagation term V_0 as a local force term. This term was derived from the probability density functions inside and outside the structure to segment. The data consistency term $g(|\nabla I|)$ is modified using a transitional probability from going inside to outside the object to be segmented.

c. Shape-Based Regularizers: [14] introduced shape-based regularizers where curvature profiles act as boundary regularization terms more specific to the shape to extract than standard curvature terms. A shape model is built from a set of segmented exemplars using principle component analysis applied to the signed-distance level-set functions derived from the training shapes. The principal modes of variation around a mean shape are computed. Projection coefficients of a shape on the identified principal vectors are referred to as shape parameters. Rigid transformation parameters aligning the evolving curve and the shape model are referred to as pose parameters. To be able to include a global shape constraint in the level set speed term, shape and pose parameters of the final curve $\phi^{\mu}(t)$ are estimated using maximum *a posteriori* estimation. The new functional is derived with a geodesic formulation with solution for the evolving surface expressed as:

$$\phi^{t+1} = \phi^t + \lambda_1\left(g(|\nabla I|)(\nu + k)\left|\nabla\phi^t\right| + \nabla g(|\nabla I|)\nabla\phi^t\right) + \lambda_2\left(\phi^{*t} - \phi^t\right) \qquad (11)$$

where λ_1 and λ_2, are two parameters that balance the influence of the gradient-curvature term and the shape-model term. In more recent work, [15] introduced further refinements of their method by introducing prior intensity and curvature models using statistical image-surface relationships in the regularizer terms. Limited clinical validation have been reported using this method but some illustrations on various applications including segmentation of the femur bone, the corpus callosum and vertebral bodies of the spine showed efficient and robust performance of the method.

3.2. Level-Set implementation:

In [16], introduced a reformulation of the Hamilton-Jacobi equation of (5) underlying the level-set initial formulation from [7] to eliminate problems related to reinitialization of the distance function and the need to extend the velocity field away from the level zero. The fact that the solution to Hamilton-Jacobi equations of the form in (5) is not distance functions has been demonstrated formally in [16]. [13] provide two simple examples illustrating this result. There are both theoretical and practical reasons pointed out motivate the preservation of the signed distance function during the segmentation process. Theoretically, the signed distance function gives a unique equivalence to the implicit description of the moving front. From a practical point of view, the use of a signed distance function enables to directly extract from the level-set function geometrical properties of the front and guarantees bounded values of the level-set function gradient, ensuring numerical stability of the segmentation iterative process. To derive the new dynamic equation, the level-set function is initialized as $\phi^0 = \phi(s, t = 0)$ as the signed distance function from the initial front. The goal is to redefine a speed function such that ϕ is preserved as the signed distance function from the level zero and ensures that the level-zero of ϕ evolves as in equation (2). These constraints are formulated as:

$$\begin{cases} \frac{\partial\phi}{\partial t} + F|\nabla\phi| = 0 \\ \nabla F \nabla\phi = 0 \\ \phi(s, t = 0) = dist(s, S_0) \\ |\nabla\phi| = 1 \\ F_{\{s/\phi(s,t)=0\}} = -k \end{cases} \qquad (12)$$

where S_0 is a given closed hypersurface and $dist(s, S_0)$ is signed distance function from s to S_0, for s to S_0, for s outside S_0 positive and otherwise negative. The restriction on level-set function $|\nabla\phi| = 1$, lead to derive the following dynamic equation as a solution of system described in (24). For Narrow-band algorithm the complexity to update level-set function have a global cost $O(mN^2)$. In the three last year the narrow band method has is intensively applied in medical imaging area. The aim of our work is give a new application with optimal parameter's where the initial level-set function is proposed.

4. Segmentation evaluation

An effective evaluation of segmentation is important for optimally setting its parameters. However, evaluation of segmented medical images is difficult, and there is no standard method for evaluating automatically the segmentation quality. Common practice for evaluating segmentation results are based clinician judgment and consist in ad hoc subjective assessment by representative group of observers. A significant number of observers is required to produce statistically relevant results, thus making subjective evaluation expensive process. To avoid systematic subjective evaluation, an automatic procedure is desired to evaluate objectively either segmentation algorithm and segmentation results. For the first, the evaluation can be done by evaluating the complexity of the algorithms, and second can achieved by evaluating accordingly two classes proposed in [6,17]:

1) Objective standalone evaluation: achieved when no reference of segmented images is available.
2) Objective relative evaluation: achieved when reference segmentation, playing the role of ground truth, is available.

One of the important issues of segmentation with geometrical active contour based on a level set method were image is segmented accordingly to edge–stop function $g(|\nabla I|)$. The edge stop map is single reference for comparing the segmentation results were g is closely related to variance of Gaussian kernel. Another important parameter for evaluating the segmentation, optimal ε parameter and the choice of a good initial level set function is need to ensure the fast convergence. As in [17], a way to match segmentation to a reference image and calculating precision and recall for the match is proposed. Thinned edges are matched to those of referenced image and based on this match; precision (P) and recall (R) are calculated. To assess the precesion and recall, the F-measure is selected as an optimal evaluation parameter as fellows:

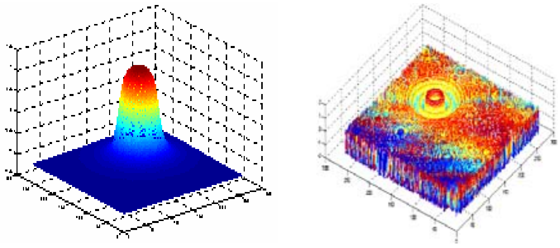
$$\hat{F} = \frac{RP}{\theta P + (1-\theta)R} \qquad (13)$$

Where θ defines the tradeoff between precision and recall. As detailed in [37, 39], θ is selected as 0.5, which we also followed in this work. For a better resolution, successive samples of are interpolated and P and R are estimated by linear interpolation using the P and R values for a range of ε between 0 and 1 and for F between 0 and 1. Finally, the value of ε, F with the highest F-measure is selected as the optimum for variance of the Gaussian kernel. This process is repeated for a range of σ, ε and the scale with the highest F-measure is selected as the optimum g. The location of the maximum value F-measure along a precision–recall curve provide the optimal segmentation. In the next section we described the most important segmentation results and we give an evaluation of geometrical active based on level-set method.

Experiment results:

We consider in the first of all some images from BERKELY dataset of image. The images are selected to be significante in grayscale mode and nearly to those of MRI. To applied successfully the geometrical active contour. The parameter of edge stop function must be evaluated. This can be done subjectively by choosing iteratively the goodness edge-stopping image by fixing a set value for σ. After this images are compared via the F-measure. ***For this, we have found that for geometrical active contour the goodness values are between [0.4.. 08].*** This first result is very helpful to objectively evaluate the segmentation quality. In the second steep, we remark that the choice the initial level set function affects significantly the convergence speed for algorithm 1 and 2.

For this we have to design a initial level set function with help the two algorithms to converge quickly to their final results accordingly to (12). The first idea is to find an oscillatory damping spatial function for with the condition of distance is respected in Fig 1. We give an example of the two initial level-set functions.

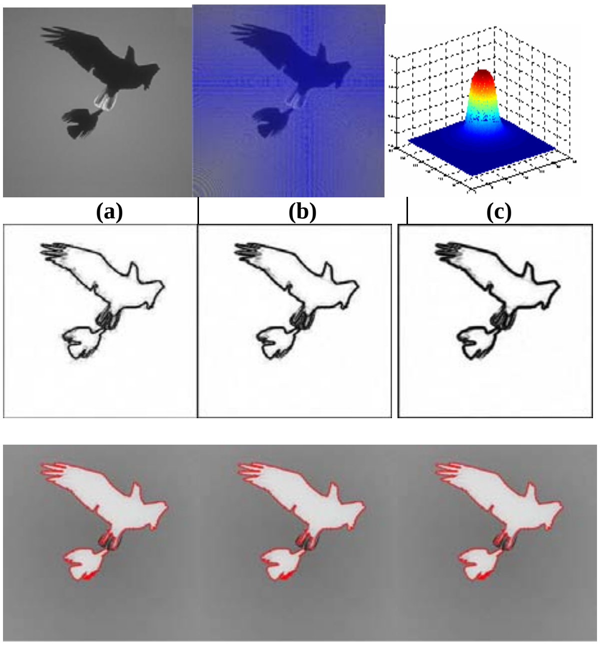


(a) **(b)**

Figure 1: Initial level-set function.

For each of these function the algorithm converge more rapidly and with the same accuracy as the function proposed in [8, 9]. To segment an image, we have choose the parameter's for $\Delta t = 0.005$ and for a set: σ =[0,4..0,8], F=[0..1] and the control parameter ε in range of [0..1]. In this steep the image were considered affected by Gaussian noise of zero mean and a range of variance [0 0,001 0,01]. We realized a Matlab software on Linux for our simulation (Pentuim IV, 2,7Ghz, 512 Moct).
Applied the geometrical active contour, the segmentation results is closely related to stop edge function were the image resulting form this is narrowly affected by noise, so a good choice of the stop edge function parameter lead to a good segmentation. To evaluate the segmentation quality. we calculate the three optimal values of $\hat{F}$, P, R for the image with different values of σ, as shown in Fig .2 and with noised image in Fig 3.
An evaluation of the relative objective quality segmentation is described in Fig.3. The segmentation quality is relatively less good for noised image and the quality can be modified for others noise (Poisson, Bernoulli) kind.
In the second steep we considered MRI brain image and particulary T1-weighted MRIs were interface between white matter and gray matter is clearly visible were the purpose is segment the anatomical structure. Difficulties of MRI segmentation arise from imaging noise, inhomogeneities, partial volume effects and the highly convoluted geometry of the cortex. Regarding quantitative measurements of the brain anatomy using MRI, cortical gray matter surface, white matter surface, cortical surface area, cortical shape characteristics are among the most interesting to study brain anatomy. Such measurements can typically assist in characterizing, predicting or assessing neurological and psychiatric disorders via correlation to abnormality in the measurements. These measurements are all easily derived from the final level set function in a distance preserving (ensured by reinitialization of the level set function during the iterative deformation process). Image is considered for two cases, for the first the image is not affected with a noise were the stop edge-map is selected for three values of σ. After the segmentation parameters are fixed we compare the segmented images in term of F-measure. The F-measure curve as shown in Fig. 7 confirmed.
An evaluation of F-measure shows that for F=1 and ε =0.2 the segmentation is better than the other cases. In presence of noise, the F-measure decreases significantly for the

values of variance noise of 0.01 to 0.001. For this, we have evaluated F-measure for different value of σ. As shown in Fig .7, the optimal segmentation is realized for σ =0.70. For three cases were the noise is present. As shown in Fig .4 F-measure increase and decrease rapidly after 0.7.



(d) $\sigma = 0.2$ **(e)** $\sigma = 0.7$ **(f)** $\sigma = 1$

Figure 2: Image stop edge function g for variance (d) $\sigma = 0.5$ (e) $\sigma = 0.7$ (f) $\sigma = 1$ and their resulting segmentation.

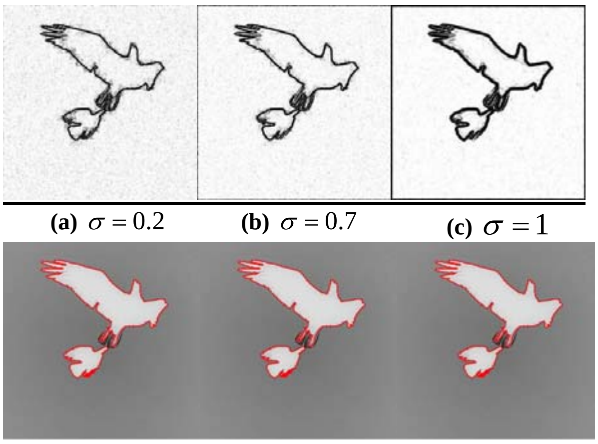


Figure 3: Image stop edge function g for noised image with an artificial Gaussian noise ($\sigma_b = 10^{-3}$) and edge stop function generated for g where the variance of kernel Gaussian is (a) 0.2 (b) 0.7 (c) 1.

Through the F-measure curve as shown in Fig.4, we show that the segmentation is optimal for $\varepsilon = 0.1$ and $F = 1$ this optimum in term of F-measure is reached for $\sigma = 0.7$. The second curve (blue color), shows the action of noise on the images traduced on the stop-edge function of geometrical active contour. To keep the robustness of the geometrical active contour method, the statistical properties of g must be performed.

Relatively, the optimal segmentation is realized for low level-noise and for a good choice of σ, ε, F. In this work we have shown that obtained for $\sigma = 0{,}70, \varepsilon = 0.1$ and $F = 1$. The geometrical active contour have been tested on MRI image acquired from CHRU of LILLE (Fig 5)

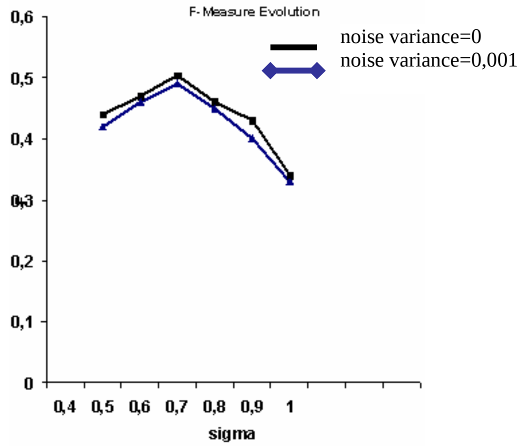


Figure4: Evaluation of F-measure for different values of σ for optimal value of $\varepsilon = 0.1$ $F = 1$

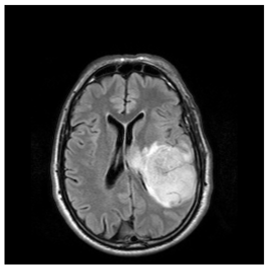
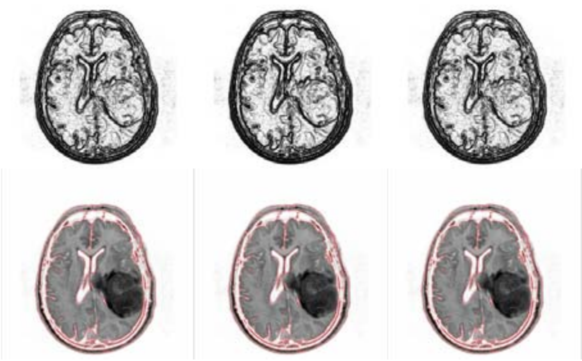


Figure 5: MRI Axial slice T1 of 256x256 pixels

5. Conclusion:

Level set methods for segmentation of medical images have been the focus of intense research for the past decade producing very promising results. Major advantages of the method include its robustness to noisy conditions, its aptitude in extracting curved objects with complex topology and its clean numerical method of multi-dimensional implementation. Despite their success, these methods still need to be refined to address two limitations. The first limitation is the complexity of algorithm needs to be further reduced, for viability of the method in clinical application where interactivity and therefore close to real time computation is critical. This optimization will have to handle the constant increase in data size observed in medical imaging applications with improvements of spatial resolution.



(a) $\sigma = 0.2$ **(b)** $\sigma = 0.70$ **(c)** $\sigma = 1$

Figuire 6: Image stop edge function g for noised image with an artificial Gaussian noise ($\sigma_b = 10^{-3}$) and edge stop function generated for g where the

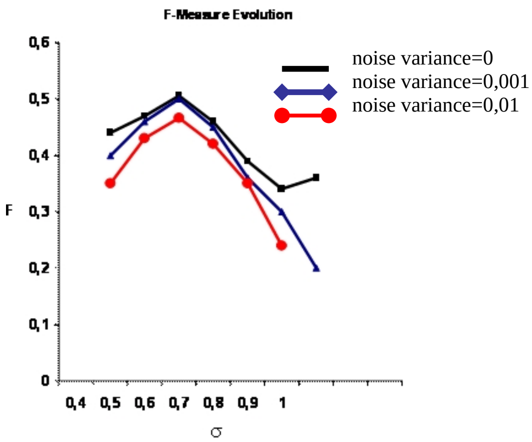


Figure 7: Evaluation of F-measure for different values of σ for optimal value of $\varepsilon = 0.1$ $F = 1$

The second is its robustness to variation in image quality and organ anatomy needs to be studied. Unfortunately, the geometrical active contour model is rarely validated in clinical studies. On the other hand it is well known that these methods require tuning of their parameters to adapt to the nature of the image data to segment. In that optic, it is therefore critical to evaluate robustness of the performance on a set of data that covers the range of quality encountered in clinical practice for a particular examination. For geometrical active contour models, it is also critical to test the method on a variety of abnormal (e.g. disease) cases that differ from the average anatomy that they typically represent

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