Segmentation of Lung Tumor in Cone Beam CT Images Based on Level-Sets

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Abstract

Automatic segmentation of tumor in low dose scans like the Cone Beam Computed Tomography (CBCT) is quite challenging. We use a semi-automatic approach to segment tumor from non tumor using the classical level-set formulation.

- A pipeline of techniques, mainly involving gradient-based level-sets (GB) and Local Rank Transform (LRT) is used to achieve the tumor segmentation.
- To improve the edge strength in the CBCT image at tumor and non-tumor interface, we propose to use the edges obtained from the LRT-attractor of the image.
- The gradient-based level-sets with LRT-attractor (GBLA) is a non-linear technique that helps in strengthening the latent tumor and non-tumor boundary.

We compare the GBLA level-sets with the GB level-sets technique, and report our results on 307 volumes of 45 patients. It was found that average precision is improved by 10% when using GBLA.

Introduction

- CBCT images are prone to noise, the edge strength at the tumor and non-tumor boundary is very low.
- Supervised and automatic segmentation or classification techniques perform poorly in noisy conditions.

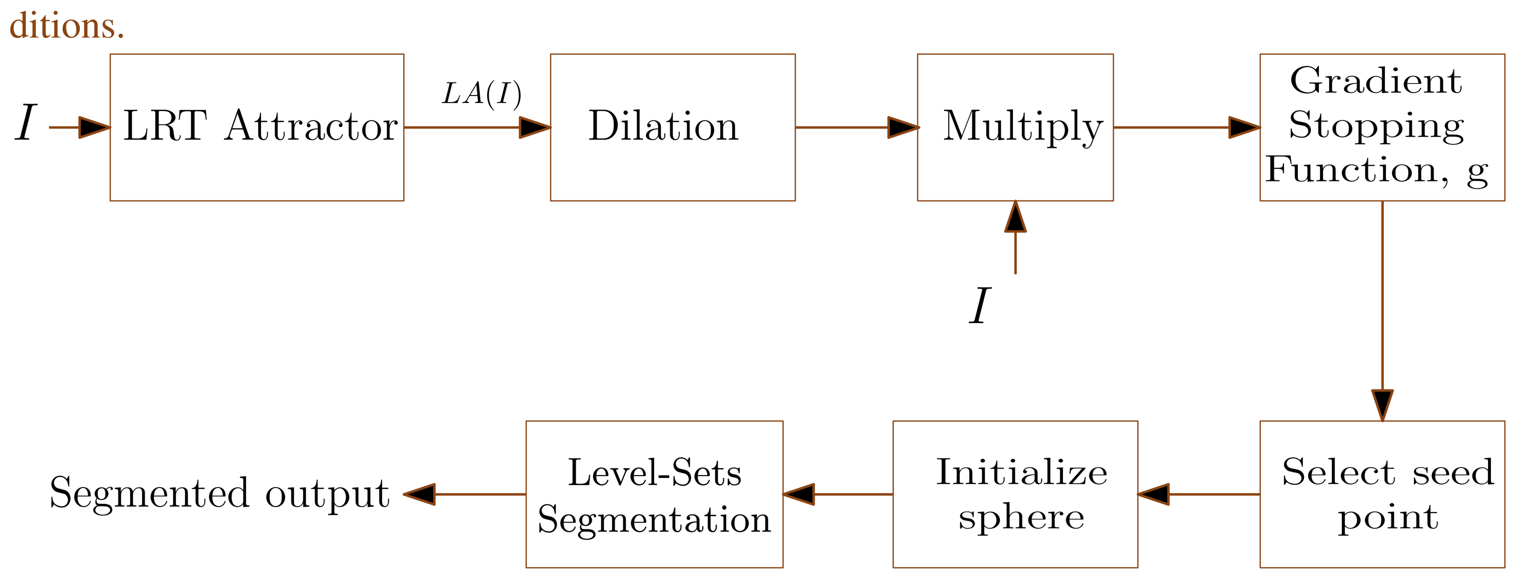

Figure 1: Block diagram of the GBLA Level-Sets segmentation of CBCT images.

Main Objectives

- To segment the Gross Tumor Volume (GTV) from CBCT images of lung cancer patients.

Methodology

- A curve (C) represented by level-set (ϕ) satisfies:
  - $\phi = 0$; at the curve
  - $\phi > 0$; interior of the curve
  - $\phi < 0$; exterior of the curve

  $C = \{(x, y) \quad | \quad \phi(x, y) = 0\}$
- The normal $\vec{N} = -\frac{\nabla\phi}{|\nabla\phi|}$; $\nabla\phi = (\frac{\partial\phi}{\partial x}, \frac{\partial\phi}{\partial y})$
- Curvature of a level-set : $k = div(\frac{\nabla\phi}{|\nabla\phi|})$

Curve Evolution using Level-Sets

Curve evolution is in the direction of the normal at a curve. An example flow:

- $C_t = v\vec{N}$; v is a constant
- $\frac{d\phi(x,y,t)}{dt} = 0 \Rightarrow \phi_x x_t + \phi_y y_t + \phi_t = 0 \Rightarrow \phi_t = -\langle\nabla\phi, C_t\rangle \Rightarrow \phi_t = v|\nabla\phi|$
- Other flows: $C_t = k\vec{N}$; k is curvature

Level-Sets Segmentation

- Curve evolution based on image properties
- Gradient stopping function $\propto \frac{1}{gradient}$
- Gradient stopping function is given as:

$$g = \frac{1}{1 + \alpha\nabla(G_\sigma * I)} \quad (1)$$

- The evolving level-set(ϕ) [3] is given as:

$$\frac{\partial\phi}{\partial t} = \{|\nabla\phi_n|(gk + \langle\nabla g, \widehat{N}\rangle)\widehat{N}\} + \frac{\gamma}{3}div\left[\begin{pmatrix} x \\ y \\ z \end{pmatrix} g\right]|\nabla\phi_n| \quad (2)$$

Local Rank Transform (LRT)

- Rank of an element x in a sequence S is the number of elements less than x.
- LRT [2] of the sequence $\{2, 1, 4, 2, 3, 2, 0\}$ is: $\{1, 0, 2, 0, 1, 1, 0\}$
- LRT_δ of a sequence is the number of elements less than by at least δ amount.
- $LRT_\delta(\{2, 1, 4, 2, 3, 2, 0\})$ with $delta = 2$ is: $\{0, 0, 2, 0, 0, 1, 0\}$
- The LRT attractor is defined as :

$$LA(I) = \lim_{m\to\infty} LRT^m(LRT_\delta(I)) \quad (3)$$

- Positive delta increases the edge strength.
- Negative delta makes the smooth regions more homogeneous.
- Found to improve edge strength at the tumor and non-tumor boundary.

Results

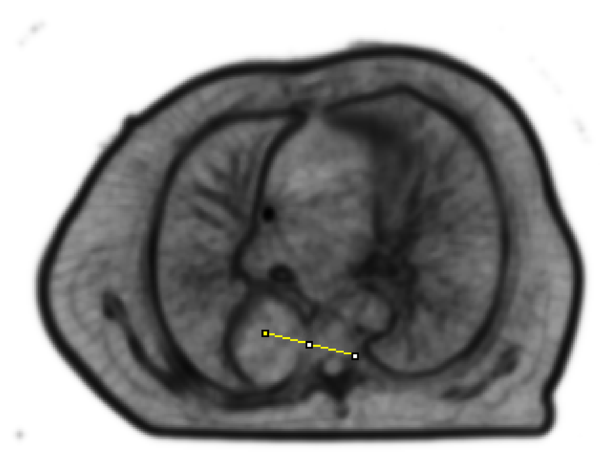

Figure 3: Gradient Stopping Function in the typical Gradient Based Level-Sets.

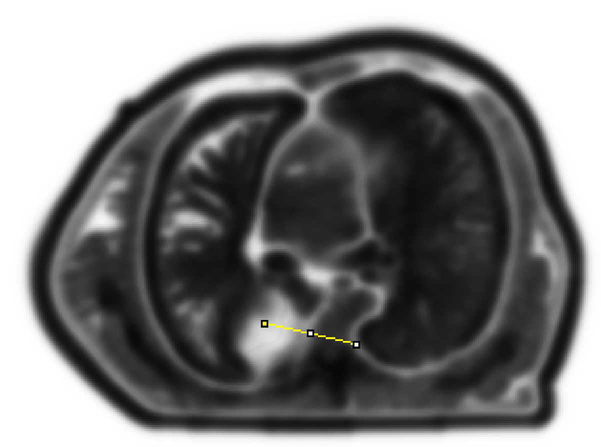

Figure 4: Gradient Stopping Function in the typical Gradient Based LRT Attractor Level-Sets.

Parameter	Value	Significance
δ_+	250	Positive δ for the δ_{ext}-LRT
ext	7	Extension in x, y, z directions
ϵ	$1e-8$	Convergence hyper-parameter
Δt	6.0	Initial time stepping parameter
s_t	0.95	Time stepping scale parameter

Table 1: Parameters used in GB and GBLA segmentation

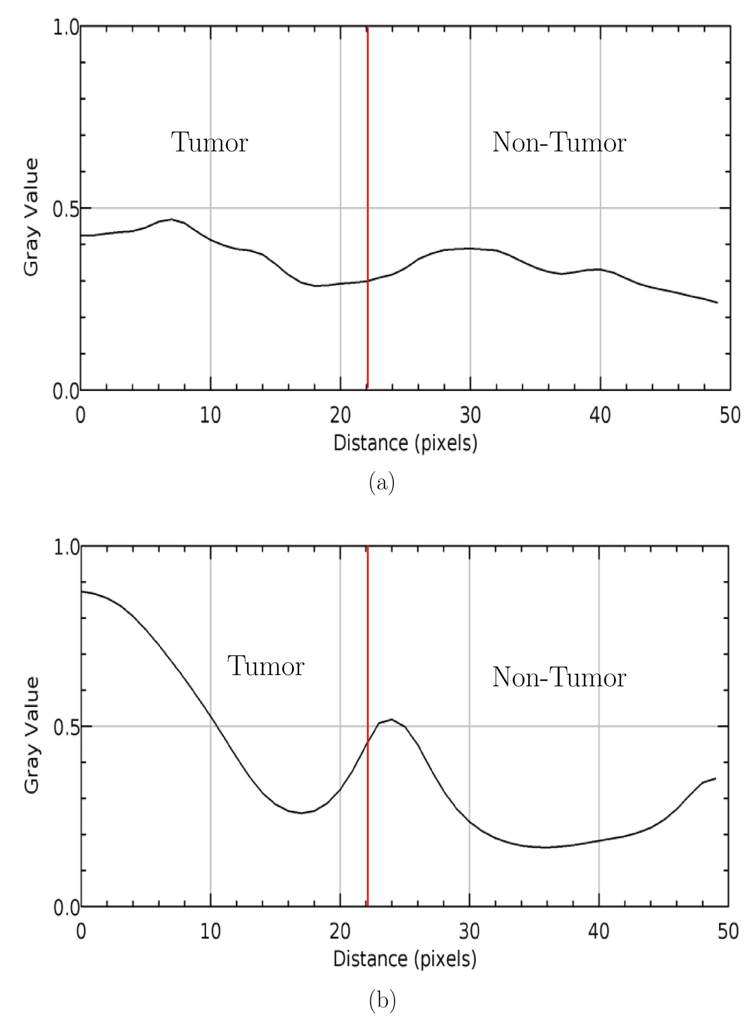

Figure 5: Profile of the gray level values of the gradient stopping function (g), at the tumor and non-tumor interface.

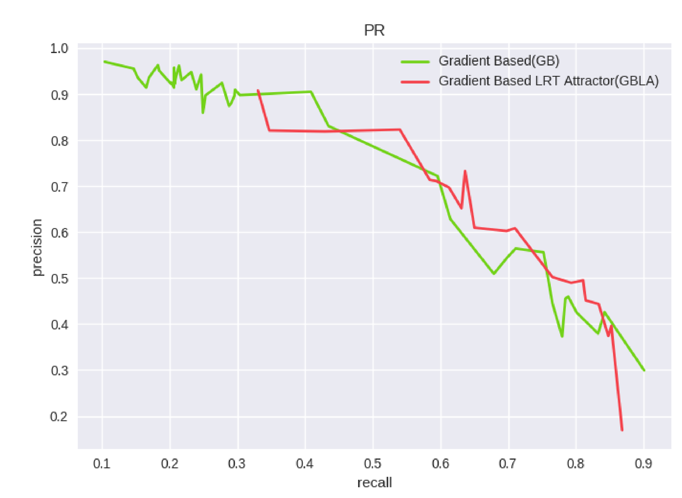

Figure 6: Precision-Recall curve of the GB level-sets and GBLA level-sets is shown.

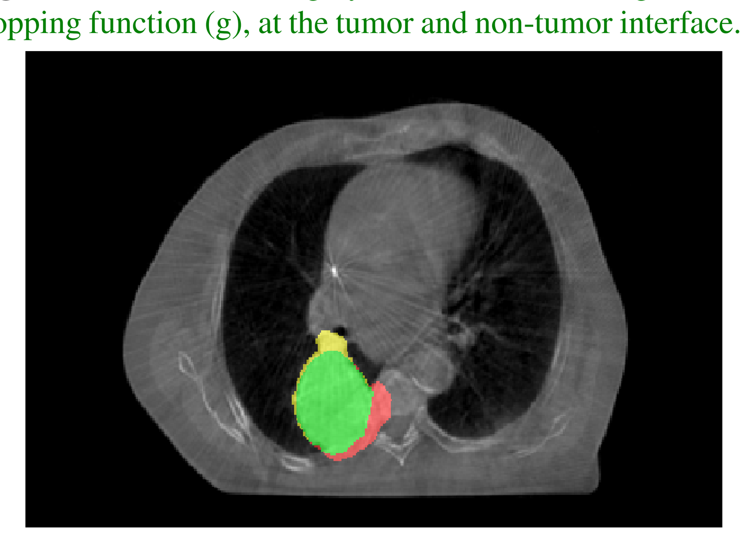

Figure 7: Segmentation result of GB level-sets. Red region is the false positive and the yellow region is false negative. Green region is the true positive.

Figure 8: Segmentation result of GBLA level-sets. Red region is the false positive and the yellow region is false negative. Green region is the true positive.

Conclusions

- There is a 10% significant increase in the mean precision. The mean recall value decreases when compared to the method without using the LRT-attractor.

Forthcoming Research

A comprehensive analysis of segmentation results with varying seed points.

References

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