COMP 4905 - Honours Project

Liver Segmentation of CT Abdominal Images

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8 - 18 - 2017

Abstract

Robust Liver Segmentation techniques are needed for clinicians to diagnose hepatic diseases and identify tumors. Manual Segmentation can be impractical in certain cases. The goal of this project is to evaluate implementations of Level Set and Graph Cut as feasible techniques to segment CT abdominal axial images. Three slices of ten different livers were segmented using the two techniques. The masks were then compared to ground-truths by using Dice Similarity Coefficient. The Level Set algorithm was found to be more accurate and complete.

Acknowledgements

I would like to thank Dr. Eranga Ukwatta and Dr. David Mould for supervising my project and Fatma Usta and Fatemeh Zabihollahy for their assistance.

1. Motivation

Segmenting the Liver is crucial for radiologists and physicians in order to better identify tumors and diagnose Hepatic diseases. Manual Segmentation is time-consuming, tedious and can sometimes be subjective. Segmentations, normally done with computed tomography (CT) images, remains a challenge because of varying shapes of liver and similar intensities to adjacent organs and tissues. This renders methods such as region-growing to result in leakage in surrounding tissue and therefore become expendable. Statistical Shape Models is a technique which can create segmentations that more accurately models liver shape and prevents segmentation leakage. However this technique needs a training set to create statistical shape models and there is a possibility that a patients liver shape might not be represented in the data especially if it is a post-operative or pathological liver [Gotra *et al*., 2017]. Hence, an accurate technique is needed for segmenting the Liver. The two techniques explored in this study are Level Set and Graph Cut.

2. Background

2.1 Level Set

Level Set is based on active contour model also known as Snake. In the classical Snake method there is an initial contour that moves forward looking for object boundaries or deformations. The object boundaries are determined by minimizing an energy function made of two terms; Internal Energy (E_{int}) and External Energy(E_{ext})[Caselles *et al.*, 1993].

$$E_{Snake} = E_{Int} + E_{Ext}$$

The Internal Energy defines physical properties of the contour such as acceleration, elasticity and rigidity. The external energy is based on features of the image and user defined constraints. There are several methods that are used to minimize the total energy of the contour. A drawback of the Snake model is that it works on the assumption that boundaries are piecewise continuous and it cannot handle topological changes. In 1988, Osher and Set-hian proposed an algorithm named Level Set [Osher and Fedkiw, 2001].

Level set Method is a technique that models hypersurfaces and various topology by solving partial differential equations. The evolution of a two dimensional curve can be regarded as a three dimensional level set function(LSF) by representing the closed curved as a zero level set that is dependent on time $\boldsymbol{t}$.

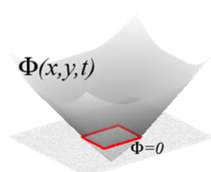

Figure 1: Zero level set of the surface is red square

The LSF takes positive integers inside of the zero level contour and negative values outside. The LSF advances in the normal direction with a speed that is dependent on the curvature and image characteristics. Level Set method is advantageous because numerical computations can be done on a Cartesian plane without having to parametrize all the points on the contour. In addition to this, it can represent topological changes such as merging and splitting naturally [Hoogi *et al.*, 2017].

2.2 Graph Cut

A graph is made up of a set of nodes *V* and a set of directed edges *E* that connect the nodes ($G = (V,E)$). Each directed edge can be assigned weight (cost energy) which can be different from the reverse edge. A node, in the context of image processing, corresponds to a pixel. A graph can contain special nodes called terminals which coincide with the set of labels assigned to pixels. When there are two terminals one is called the source, S and the other the sink, T. A cut will partition the graph G into two disjoint set of nodes that correspond to the sink and source. The optimal cut is the cut with the smallest total weight edges. This is known as the minimum cut (maximum flow)[Freedman and Zhang, 2005].

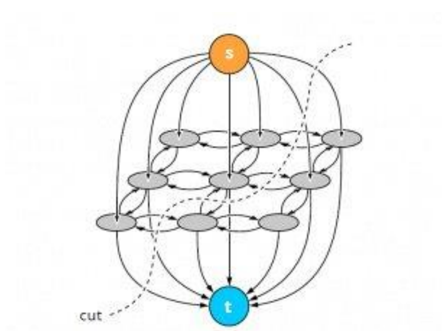

Figure 2: Example segmentation of 3X3 image

3. Objective

The aim of this project was to compare and contrast segmentation algorithms by implementing two algorithms on CT axial abdominal images. The first algorithm is Distance Regularized Level Set Evolution from Chumming Li et al. The second algorithm is a based on a Graph Cut implementation by Boykov and Jolly.

4. <u>Distance Regularized Level Set</u>

4.1 Overview

Many variations Level Set Function contain a re-initialization i.e. the contour periodically stops and reshapes itself. This has been reported to have some erroneous results because sometimes the zero level set is reshaped in such a way that it is further from its expected position. Li et al proposed an implementation that deals with this issue. Distance Regularized Level Set Evolution (DRLSE) is a form of Level Set Evolution that does not require re-initialization. The distance regularized term is used to minimize the energy function of the level set evolution. It is defined with a potential function that forces the gradient magnitude of the level set function to one of its minimum points. The level set evolution has a forward-and-backward diffusion effect which maintains its shape as a signed distance profile near its zero level set while an external energy drives the motion of the zero level set toward desired locations [Li *et al.*, 2010].

4.2 Details

The energy function is defined as:

$$\varepsilon = \mu R + \varepsilon_{ext} \quad (1)$$

The level set regularization term (R) is defined as:

$$R = \int p(\nabla) dx \quad (2)$$

where p is an energy density function.

The external energy is defined as:

$$\varepsilon_{ext} = \lambda L + \alpha A \quad (3)$$

The external energy term is made up of a length term (L) and an area term (A). The length term is used to keep the curve smooth during deformations. The area term (A) calculates the area inside the contour and is used to speed up the contour when it is far away from object boundaries and slow down when it is close. The direction of the level set evolution (shrinking and expanding) is determined by α. The length term and the area term are both defined by edge indicator function g:

$$g = \frac{1}{1 + |\nabla G_\sigma \cdot I|^2} \quad (4)$$

where G_σ is Gaussian kernel with standard deviation σ and I is the input image [Altarawneh *et al.*, 2015].

5. Graph Cut

5.1 Overview

An image can be divided into object and background by defining a cost function to get a globally optimal solution. This is done by providing parameters in the form of boundary term and region terms.

Given a set of pixels P in a neighborhood system N (8 pixels). Let A = $\left(A_1, A_2, A_P \ldots A_{|P|}\right)$ be a matrix whose elements A_P specify assignments of background or object to pixels in P. For example $A_P = 1$ if object and $A_P = 0$ if background. The cost function $E(A)$ can be described as:

$$E(A) = \lambda \cdot R(A) + B_{\{p,q\}} \quad (5)$$

The Region Term $(R(A))$ conveys how an individual pixel fits into an intensity model of the background $(R(bkg))$ and object $(R(obj))$. It is determined by using the seeds marked as background and object to get the intensity distributions. The histograms are then used to set the regional penalties to negative likelihoods.

$$R(obj) = -\ln\Pr\left(I_p \middle| \text{obj}\right) \qquad (6)$$

$$R(bkg) = -\ln\Pr\left(I_p \middle| bkg\right) \qquad (7)$$

The Boundary Term $(B_{\{p,q\}})$ assigns penalties based on the dissimilarity of adjacent voxels. If $A_P = A_q$, then $B_{\{p,q\}} = 0$. To set the boundaries an ad-hoc function was used. If I_p and I_q are similar or if I_p is less than I_q then $B_{\{p,q\}}$ is close to 1, otherwise $B_{\{p,q\}}$ is close to zero. If a pixel is marked as 'background' but is actually in the object it will have a higher Boundary Term [BoyKov and Jolly, 2001].

$$B_{\{p,q\}} = \begin{cases} 1 & if\ I_p < I_q \\ e^{\frac{-(I_p - I_q)^2}{2\sigma^2}} & if\ I_p > I_q \end{cases} \qquad (8)$$

6. Procedure

The dataset consisted of 10 livers. Three slices from the lower half of the liver was used and labelled as top (middle of liver), bottom (bottom of liver) and middle (middle of lower half). The segmentations were confined to the lower half of the liver because the boundary of these slices were more distinguishable bringing about correct manual segmentations.

Level Set was implemented in Matlab based on source code. An RGB version of each image was provided with red contour near the desired boundary as a region of interest. The source code was altered so that this contour could be identified in the dataset. The coefficient for the regularization term mu (μ), coefficient of the weighted length term (λ) and the coefficient of the weighted area term (α) used were 0.02, 5 and 1.5 respectively. These parameters were chosen based on a study done by Altarawneh et al. A Level Set implementation from FIJI was also implemented but it was discarded due its ineffectiveness in distinguishing the liver from adjacent oblique muscle tissue.

Graph Cut was implemented in Matlab. The algorithm first applies a Gaussian Filter to denoise the image. Then a statistics adaptive threshold was used as initialization [Massoptierand Casciaro, 2007]. Lastly the Graph-Cut technique was applied.

Table 1: DSC of Graph Cut and Level Set Segmentations

	Graph Cut	Level Set
10030	0.605	0.954
10050	0.792	0.941
10060	0.928	0.965
10070	0.573	0.879
10080	0.910	0.971
10090	0.843	0.914
10100	0.611	0.937
10110	0.925	0.877
10120	0.621	0.892
10270	0.942	0.955
Average	0.756	0.929
Standard Deviation	0.17	0.04

7. Results & Discussion

Table 1 shows that the average Dice similarity coefficient (DSC) of the Level Set implementation (0.929 ± 0.04) is higher than the DSC of the Graph Cut implementation (0.756±0.17), indicating that the Level Set algorithm is more robust and accurate.

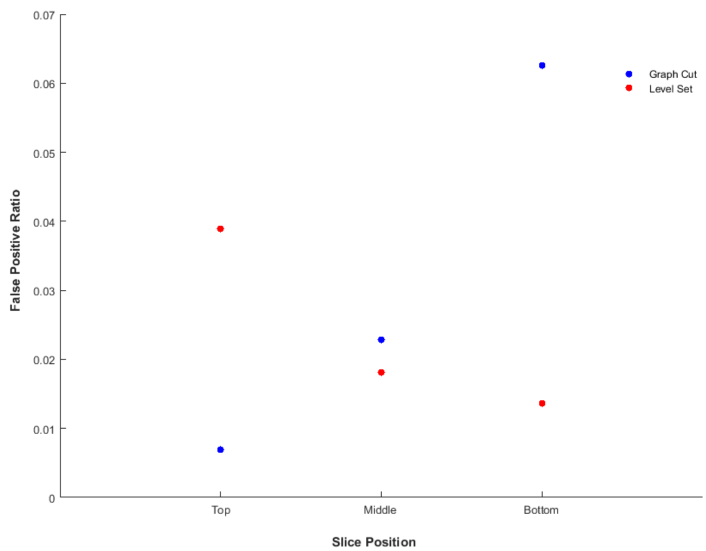

Figure 3 Average FRP for each Slice Position

The Graph Cut algorithm failed to differentiate the liver from large tissues in the body with similar contrast. For example patient 10120 had an abnormally large spleen and the algorithm initialized the spleen as an object. The spleen is on the opposite side of the image so there was no overlap resulting in a DSC of 0. Figure 3 shows that overall Graph Cut had higher false positive ratio (FPR) when evaluating the images on a pixel by pixel basis. The 'Bottom' images had a higher FPR because it is in these regions that other abdominal tissues would be visible in the axial view.

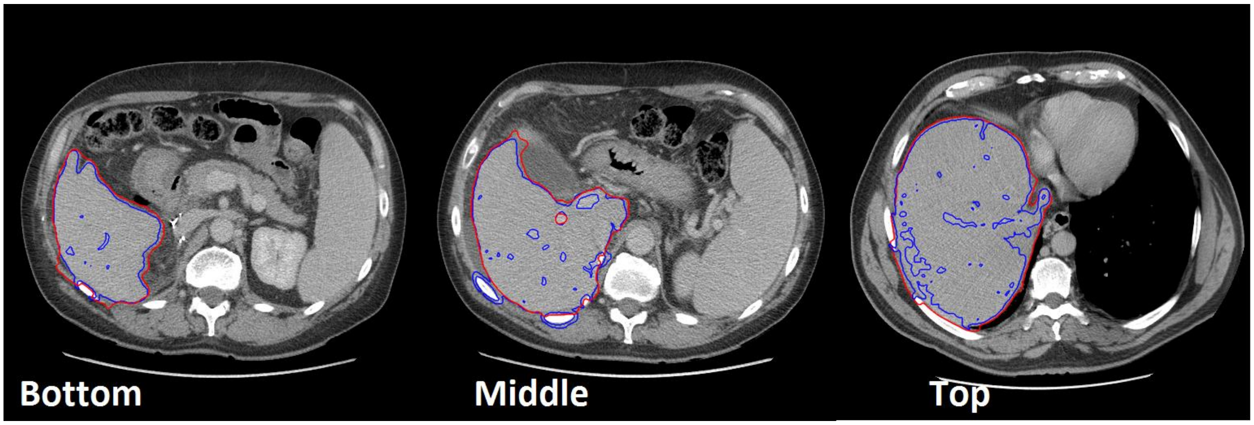

Figure 4 Graph Cut (Blue) and Level Set (Red) segmentations superimposed on to Original Images

When assessing the methods based on accuracy, Level Set is advantages because there is already a predefined contour from which it expands whereas the Graph Cut method is more automatic. In some cases the Level Sets need of a contour for initialization can became problematic when the shape of the Liver is irregular which was most common in the middle slices. There was a slightly higher false negative ratios in the middle slice (0.0054) compared to the top (0.0016) and bottom (0.0014) indicating that the contour would stop prematurely.

Heiman et al also found similar results when they compared interactive approaches to automatic approaches when segmenting CT liver images. After using multiple evaluation measures they found that the automatic segmentations had larger standard deviation of final scores and therefore inferior in terms of reliability [Heiman *et al.,* 2009].

From visually inspecting Figure 4, we can see that the Level Set segmentations had more complete masks whereas the Graph Cut contours had some unfilled regions. This could be a consequence of the heterogeneity of the Liver slice. The livers segmented were cancerous and contained tumors which were visible as areas with lower intensities as shown in Figure 5. Conversely hepatic arteries were also visible as areas with higher intensities and much more prevalent. These extreme intensities would cause these areas to be initialized as background and therefore not be part of the segmentation. In order to better assess Graph Cuts ability to find the boundaries of object and control for these variables the 'imfill' Matlab command can be used to fill the regions and holes. This gave a higher DSC value of 0.783 which is still significantly lower than the Level Set DSC (0.929).

Figure 5 A: Original CT Image B: Manual Segmentation C: Graph Cut Segmentation

8. Conclusion & Future Work

When comparing the Level Set algorithm from Chumming Li et al to the Graph Cut algorithm implemented, from DCS and visual inspection it is evident that the Level Set gives much more accurate segmentations. In order to extend this work it would be more appropriate to compare the Level Set algorithm to more recent versions of the Graph Cut implementations. The Level Set implementation was from 2010 whereas the Graph Cut implementation was based on theory form earlier versions of the algorithm. It might also be beneficial to compare the run times of the algorithms in order to have a more comprehensive assessment. When empirically observing the run times the Graph Cut was significantly faster than Level Set which may be an important factor for clinical applications.

9. References

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