IMAGE SEGMENTATION IN MEDICAL IMAGING VIA GRAPH-CUTS[1]

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An organ segmentation is usually first step of liver treatment. We introduce a semi-automatic method for liver segmentation based on Graph-Cuts. Our experiments compare expert segmentation with our algorithm. We compare two different sets of parameters. Our software implementation is freely available

Introduction

Living donor transplantation and other modern methods of liver treatment are usually based on computed tomography (CT). Our work is motivated by two following clinical application. First is living-related liver transplantation (LRLT). It is the case when healthy voluntary donor gives a part of his liver to treated person. Second are oncologic resections. It is treatment for patient with liver cancer.

Manual extraction of individual anatomical information of liver and its vascular system is complex mental and very time consuming work. It is difficult to mentally construct 3D vessels anatomy from planar data of CT. Machine learning techniques provide wide range of methods which can facilitate human operator work. Computer assisted planning enables individual anatomy visualization and gives a support for operability decisions.

Our application is written in Python and software can be downloaded from http://github.com/mjirik/pyseg_base

Methods

There are some steps in our application which need to be done, so we can get satisfactory result. First step is data acquisition. Medical data are stored in DICOM format. Each slice is usually stored in single file. We used pydicom library with some improvements to read data. There are some limitations of this library. We have added ability to read DICOM overlay. It was important because this is way how we obtain an expert annotation of our data.

There are two groups of liver segmentation methods, semi-automatic and automatic. Automatic methods works without any sort of operator interactivity (for example [9]). Semi-automatic algorithms require some user intervention and the result is operator dependent (for example [12]). For clinical applications user control over the result is great advantage of these methods as long as lower error rate as shows [6]. Survey on liver segementation methods is presented in [8].

Segmentation used in this paper is based on Graph-Cut (GC). First use of of max-flow/mim-cut algorithms to minimize certain energy functions in computer vision problems is described in [11]. Segmentation problem is converted into graph issue. Boykov et al. showed in [3, 4, 1] max-flow/min-cut algorithm with some important improvements.

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For our application we have used implementation which is described in [7, 5].

By using Graph-Cuts, we minimize cost function E(A):

$$E(A) = \lambda R(A) + B(A) \qquad (1)$$

Here A is labeling. Each pixel A_p can represent 'object' or 'background'. Term $R(A)$ is related to region properties and $B(A)$ is related to boundary properties of image. The λ coefficient weights region term versus boundary term.

$$R(A) = \sum_{p \in P} R_p(A_p) \qquad (2)$$

Region term is used for setting penalty to each pixel p which describes how similar is its intensity to the model of background or object.

As show image 1 the graph is constructed based on input data and selected cost function. By its partition into two disjoint subsets image

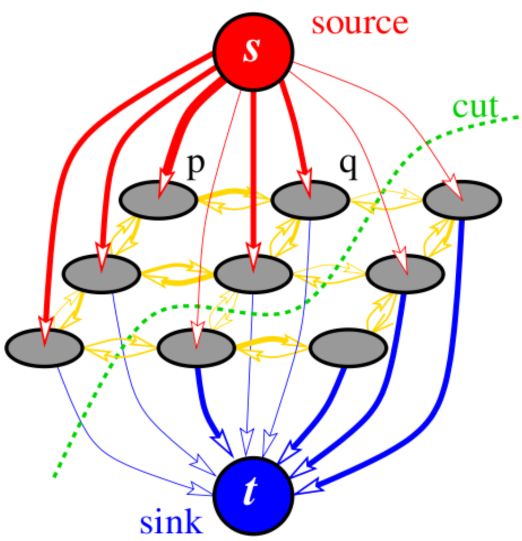


Image 1: Graph-Cut [4]

segmentation is performed.

Main problem is edge weights setting. There are two types of edges in the graph. N-links (neighboor-links) are associatad with edeg properties and it connects (usualy) two neighboring nodes. T-links (terminal-links) are linked to region image properties and are connected to two terminals in graph.

Weights of T-links R_p to object and background vertex are given by model of object and background.

$$R_p(obj) = -\ln\left(Pr\langle I_p|O\rangle\right) \qquad (1)$$
$$R_p(bkg) = -\ln\left(Pr\langle I_p|B\rangle\right)$$

In our case likelihood $Pr\langle I_p|O\rangle$ and $Pr\langle I_p|B\rangle$ for object and background are given by gaussian mixture model with three components. It is based on image density (intensity) of data from user interaction. Image Model parameters are estimated by expectation maximization (EM) algorithm [10].

$$B(A) = \sum_{p \in P} B_{\{p,q\}} \cdot \delta(A_p, A_q) \qquad (3)$$

$$\delta(A_p, A_q) = \begin{cases} 1 & if A_p \neq A_q \\ 0 & otherwise \end{cases} \qquad (4)$$

Term $B(A)$ reflects boundary penalties of segmentation. Boykov et al. [2] suggests using function that penalizes discontinuities between pixels. We used constant penalty a for segmentation boundary. It means that objects with large surface area are more penalized then objects with same volume and smaller surface area.

Well known weakness of graph-cut algorithm is memory usage. It quickly increases with image size because of large number of edges in the constructed graph. For three dimensional data has every pixel 8 connections (6 N-links and 2 T-links) which makes this problem even more acute. We face it with two processes. First approach is setting of region of interest (ROI). Memory usage is much lower if when we work with the certain data subset.
Second preprocessing step is data resampling. Data are resized to defined voxel size. It decreases computational complexity, and in addition to that, we get voxel with equal three dimensions. It allows easier setup of

$B(A)$ energy term. N-links in all directions are

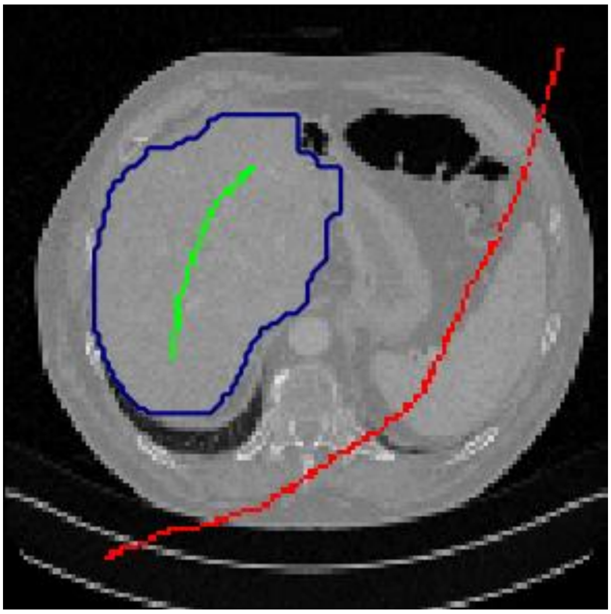


Image 2: Segmentation of liver with input seeds

set on same constant value.

In our experiments we used two data sets. As first dataset we used data from Segmentation of the Liver Competition 2007 [14]. We used five liver images from this dataset for experiments with Grah-Cut parameters. We have reference segmentation data for this dataset.

Second dataset is set of 8 patients. For each case we have contrast enhanced computer tomography scans. Venous and arterial phase CT images were obtained. We have used venous data because of better contrast between liver and other tissues. Data are anotated by experts. They manually segmented the liver and evaluated its volume. Sadly we have only volume in ml given by expert volumetry without 3D volumetric segmentation.

Evaluation of volumetric segmentation can be performed in many different ways. Some of them are described in SLIVER07 documentation [13] we will use volumetric overlap error (VOE) and relative absolute volume difference (VD). Volumetric overlap error is number of voxels in the intersection of our segmentation and reference segmentation divided by number of voxels in the union of both segmentations. Relative absolute volume difference is total volume difference between reference segmentation and evaluated segmentation divided by number of voxels of the reference. This number evaluates only two scalar numbers. Highest score can be given by totally non-perfect segmentation with same volume as reference.

Results

First experiment was performed to set optimal size of voxel. We have used subset of SLIVER data – five images from training set. Our operator segmented these five images with various sizes of voxel. Average volume difference and volumetric overlap error for each voxelsize is in Table1. A processing time of each segmentation was measured and average value is in table too.

Table 1. Evaluation of voxel size parameter

voxel size [mm]	VD [%]	VOE [%]	Time [s]
1,5	-7,25	5,54	367,91
2	-7,84	6,71	130,88
3	-6,12	5,90	168,20
4	-6,77	6,62	168,05
6	-9,48	8,19	186,16
9	13,28	17,50	130,60

Second experiment is based on comparison of expert manual segmentation and semiautomatic methods based on Graph-Cut segmentation. Fist step in our experiment is setting of region of interest. It is done with manual sekection. Based on first experiment results we used resampling to voxels with all dimensions equal to 2 mm.

The method is tested with two different setups. In first experiment is parameter a set to 30 while in second experiment is this value equal to 15.
All resulst are shown in table 2. First column is expert segmentation. Second column is Graph-Cut segmentation with $a = 30$. Third column is GC with $a = 15$. In last two columns is shown difference between manual segmentation and semi-automatic method.

Last row of the table shows average values. For differences is constructed with absolute value.

Table 2. Volume Difference

Data	Expert [ml]	GC a=30 [ml]	GC a=15 [m]	Diff a=30 [%]	Diff a=15 [%]
D1	597	723	694	-21,1	-16,2
D2	1151	1175	1073	-2,1	6,8
D3	1006	1122	1043	-11,5	-3,7
D4	1757	1641	1680	6,6	4,4
D5	1425	1314	1346	7,8	5,5
D6	1391	1331	1340	4,3	3,7
D7	3013	2758	2887	8,5	4,2
D8	1653	1730	1743	-4,7	-5,4
avg	1499	1474	1475	8.33	6.24

Discussion

In first experiment we wanted set optimal size of voxel. Image 3 show data from table 1 in graphic form. It can be seen that with increasing size of voxel increases both measured volumetric errors VD and VOE. Measured time is more complicated. With bigger voxels is segmentation not as precise and operator compensate it with more iterations of segmentation process. Small voxelsize is computationally demanding. For voxelsizes smaller than one is algorithm time consuming.

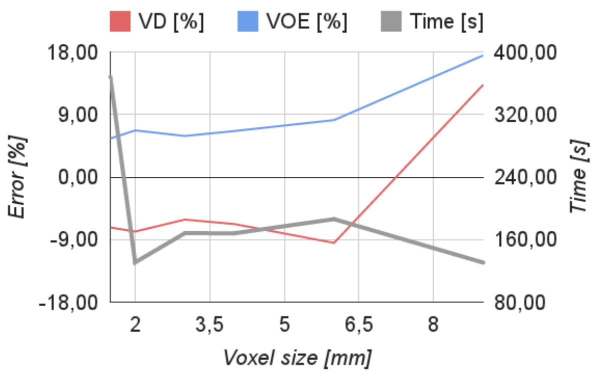


Image 3: Error and time dependency on voxel size

As you can see from our experiments semi-automatic segmentation brings alternative to manual segmentation of liver. Manual segmentation take about 30 minutes from expert time. As you can see from table 1 semiautomatic method can be performed in less than 3 minutes. Difference between both setting is almost one percent. Lower constant a bring better results but it is more time consuming.

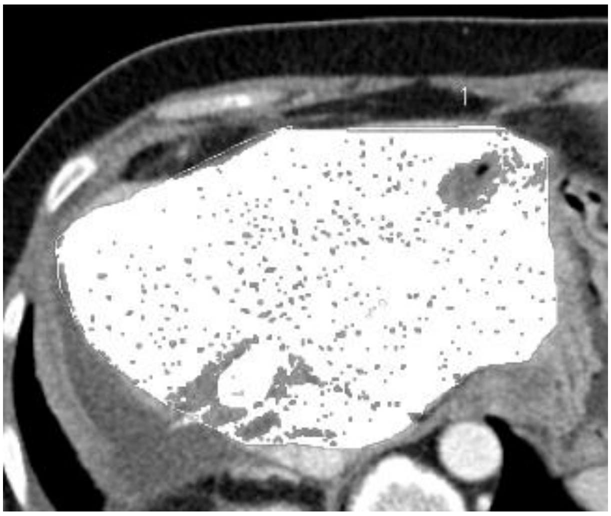


Image 4: Expert liver segmentation of D1 data

In the experiment we compare expert with semiautomatic method. Results of expert are operator dependent. Image 4 show problematic liver segmentation of data D1. Machine based semi-automatic segmentation gives more consistent outputs.

Conclusion

Our work introduces possibilities of computer assisted diagnostic for liver treatment. Semi-automatic methods can save time of operator and brings consistent performance. Our algorithm can measure volume with error 6.24%. Based on our experiments the optimal resampling resolution for liver segmentation is 2 mm. The experiments shows that careful parameter setup of methods can give us some improvement. Our algorithm is freely available.

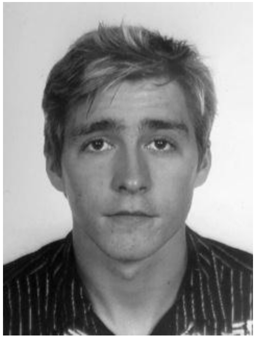
References

1. Boykov, Y.; Jolly, M.-P.: Interactive Organ Segmentation Using Graph Cuts . 2000: s. 276-286.
2. Boykov, Y.; Kolmogorov, V.: An Experimental Comparison of Min-cut/Max-flow Algorithms for Energy Minimization in Vision. 2001: s. 359-374.
3. Boykov, Y.; Veksler, O.; Zabih, R.: Markov random felds with efcient appro-ximations. Computer Vision

and Pattern Recognition (CVPR), 1998, 1998: s. 648-655

4. Boykov, Y. Y.; Jolly, M. P.: Interactive graph cuts for optimal boundary & region segmentation of objects in N-D images. Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on, ro£ník 1, 2001: s. 105-112 vol.1
5. Andrew Delong, Anton Osokin, Hossam N. Isack, and Yuri Boykov. Fast Approximate Energy Minimization with Label Costs. International Journal of Computer Vision, 96(1):1-27, July 2011
6. Heimann et al. Comparison and evaluation of methods for liver segmentation from CT datasets. IEEE transactions on medical imaging, 28(8):1251-65, August 2009.
7. Vladimir Kolmogorov and Ramin Zabih. What Energy Functions Can Be Minimized via Graph Cuts? IEEE Trans. Pattern Anal. Mach. Intell., 26(2):147-159, 2004.
8. Ahmed M. Mharib, Abdul Rahman Ramli, Syamsiah Mashohor, and Rozi Binti Mahmood. Survey on liver CT image segmentation methods. Artificial Intelligence Review, 37(2):83-95, April 2011.
9. L Rusko and G Bekes. Fully automatic liver segmentation for contrast-enhanced CT images. MICCAI07: Segmentation in the Clinic, pages 143-150, 2007.
10. A. P. Dempster, N. M. Laird and D. B. Rubin. Maximum likelihood from incomplete data via the EM algorithm. Journal of the Royal Statistical Society, B, vol. 39, no. 1, pp 1-38, 1977
11. D. Greig, B. Porteous and A. Seheult. Exact Maximum a posteriory estimation for binary images. Journal of the Royal Statistical Society, series B, , pp 271-279, 1989
12. D. Selle, B. Preim, A. Schenk and H. O. Peitgen. Analysis of vasculature for liver surrgical planning. Journal of Medical Imaging. Vol. 21, pp 1344-1357, 2002
13. Bram van Ginneken, T. Heimann, and M. Styner 3D Segmentation in the Clinic: A Grand Challenge, http://sliver07.org/p7.pdf
14. Heimann, Tobias, et al. "Comparison and evaluation of methods for liver segmentation from CT datasets." Medical Imaging, IEEE Transactions on 28.8 (2009): 1251-1265.

Biography of the authors



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