GRAPH CUTS IN 3D MAGNETIC RESONANCE DATA SEGMENTATION

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ABSTRACT

Segmentation methods suitable for 3D image analysis are especially important in robotics and medical imaging, where 3D data acquisition is available. This paper focuses on graph-cuts application in segmentation of the magnetic resonance images. The background of the implemented method is presented in the paper, followed by the evaluation of the method on real images for which the ground truth was determined by a technician and a radiologist.

1. INTRODUCTION

Segmentation is an important step in image analysis: in order to analyze an object present in the image, the object has to be separated from the background. Current research in the laboratory of Imorphics and the University of Manchester, ISBE is focusing mainly on object analysis and model creation, while such model can be created, analyzed and evaluated only after performing a successful segmentation. The results of the segmentation are therefore influencing all further processes.

We are focusing on segmentation of 3D magnetic resonance images (further MRI) using graph-cuts method. The main aspect of graph theory is that it models relations between objects of certain characteristics by creating a structure containing vertices and edges. The real structure is quantitatively described in graph model through edge weight values and nod's intensity values. The data structures in graph theory can be adjacency matrixes (in case of 2D structures) or 3D arrays, which are suitable for representing an image structure. In further chapters, we will introduce the graph-cuts theory together with max-flow min-cut algorithm, followed by description of the version which was implemented in this project. The evaluation of the implemented method will be presented, focusing on its the performance on artificial and especially real magnetic resonance images. The introduction of regional properties in graphs will be discussed in the evaluation section, showing the results and proposing the future modifications.

2. GRAPH CUTS AND MAXIMUM FLOW ALGORITHMS

A graph $G = \langle V, E \rangle$ is a structure consisting of vertices V and edges E which interconnect them. The edges are quantitatively described by the weight assigned to them. When using graphs in imaging, each pixel is represented by a vertex, while neighbouring pixels are interconnected by edges – these are called n-links. There are also special vertices in graphs, which we call terminals and which can be connected to any nods in the graph by a t-link. When using graph cuts for segmentation purposes, terminals represent possible labels of the pixels. In binary segmentation, the terminals are usually called the Sink (abbreviated as T) and the Source (abbreviated as S).

A simple graph can be seen in figure 1, where a graph with undirected edges and two terminal nods was constructed for a greyscale 2D image. When performing a segmentation task, the weights of n-links are often evaluated as a function of the difference between the pixel intensities, although for other purposes we can evaluate them differently. Regarding the strength of the t-links, these correspond to the user or otherwise set correspondence of certain pixels with the particular label (sink or source). A segmentation using the graph cuts can be performed only when we find a cut $C = \{S, T\}$ which separates the two terminals S and T. Such cut is quantitatively described by its cost, which is the sum of all weights of the edges included in the cut. A minimum cut on the graph is such cut which separates the sink from the source and whose cost is globally minimal. [3]

The minimization tasks are often performed by the means of minimizing an energy function. In fact, when using graph cuts for segmentation purposes, this can be shown as a minimization of a special energy function, as expressed by Boykov and Jolly [2]:

$$E = \lambda \cdot R(A) + B(A) = \lambda \sum_{p \in P} R_p(A_p) + \sum_{\{p,q\} \in N} B_{\{p,q\}} \cdot \delta(A_p, A_q) \tag{1}$$

$$B(p,q) = e^{\frac{-(I(p)-I(q))^2}{2\sigma^2}} \tag{2}$$

Where A is a vector of binary assignments of points p to background or foreground, P is the set of pixels, N is the set of neighbouring pairs, *R(A)* is a regional part and *B(A)* is the boundary part of the function, assigning penalties to the particular realization of A; the coefficient λ is affecting the importance of regional vs. boundary properties. The boundary term is implemented in the graph as the weights of n-links, the regional term includes the t-link weights.

The max-flow algorithms are often used when trying to find the minimal cut in a graph. The principle of the max-flow algorithm lies in the equivalence of the min-cut and the max-flow problem. When we perceive the edges as capable of carrying flow, while their capacity is represented by the weight of the edge, we can try to push a maximum flow through the graph directed from one terminal to the other terminal. When we push the maximum flow through the graph, the set of bottlenecks (the edges with zero residual capacity) corresponds to the minimum cut in the graph.

There are different ways how to compute the maximum flow. In this project, we will focus on the augmenting paths algorithms, focusing on one particular application: the algorithm proposed by Boykof et al for segmentation of N-dimensional images [1]. In general, the augmenting path algorithms are based on searching for a shortest path from terminal S to terminal T, which is then augmented by the value of the lowest residual weight (bottleneck) in the path - this lowest weight value in the path chain is subtracted from all edge residual weights in this path. Then we perform the search again, now that we cannot find the path through the blocked edge(s), other residual capacities are blocked and this iteratively repeats until a path cannot be found (S and T areas are separated by edges with zero residual capacity). The Dinic's method was building a new search tree each time to find the shortest path. This way the path found is ensured to be the shortest one, though for the cost of rebuilding the tree which is computationally very demanding. Thus Boykov and Kolmogorov proposed reusing the trees and show that even that their version of the algorithm has generally worse time complexity, the performance in most applications is better than the one of the Dinic's algorithm. [2]

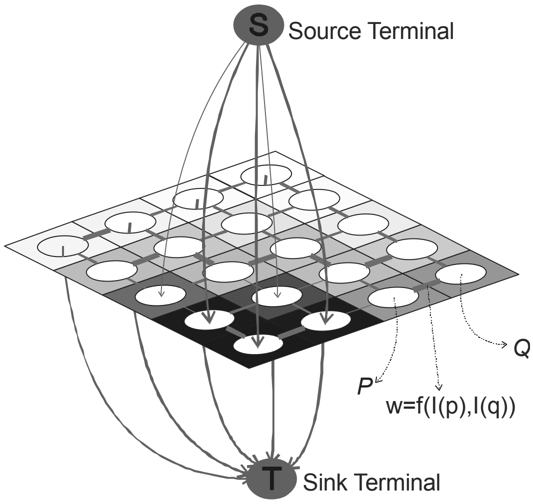


Figure 1: Graph example: 2D greyscale image with the terminals introduced

3. EVALUATION OF THE METHOD

Initially, the implemented method was tested on an artificial spherical 3D image with specified gradient characteristics. The image was successfully segmented, using the boundary properties in equation 2 the highest gradient area was detected and the boundary was placed in the correct position. After proving the initial functioning of the method, we advanced to more complicated real 3D images. There are two aspects which should be discussed before we proceed to the evaluation of the results: first problematic aspect is that we are evaluating an interactive method, implying that any user interaction is being evaluated as well. Therefore all following segmentations were processed only allowing one human interaction with the method, giving the initial seeds for the segmentation (only about 2 – 5 seeds for each image). Second aspect is that with real images, there are ambiguities in the solution; therefore ground truth of the segmentation was obtained which was the result of a cooperative effort of a technician and a radiologist.

First real images to be processed were of brain ventricles. The following criteria were selected for quantitative evaluation:

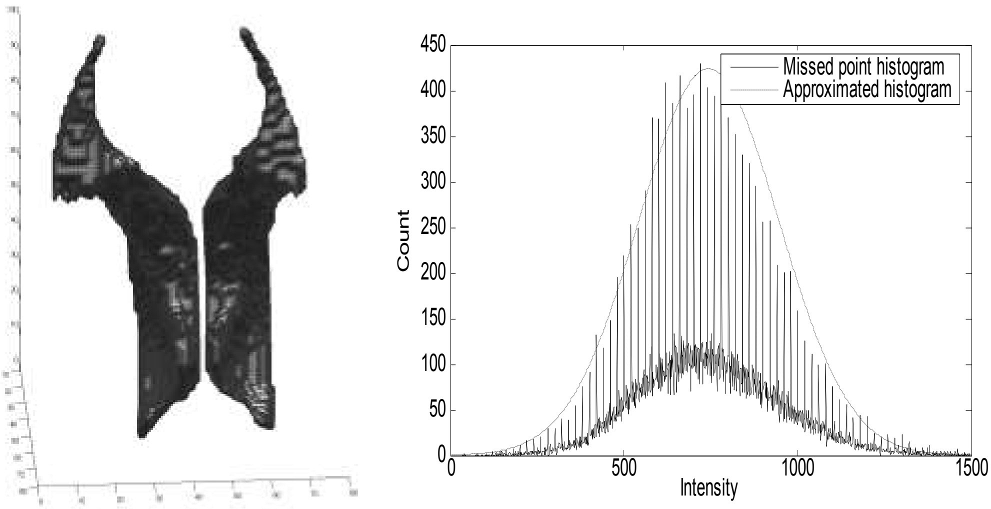
- Tanimoto score, evaluated as $T = \dfrac{N_{common}}{N_{obtained} + N_{target} - N_{common}}$, where N is a count of pixels common for ground truth and our segmentation, obtained in the segmentation or present in the ground truth
- Average distance of the segmented objects' surfaces

About 12 ventricles were processed in the analysis. The average distance between the targeted (ground truth) and the obtained surfaces is 1.95 pixels, the average scored Tanimoto coefficient is 60.9%. While the average distance result is quite good, the Tanimoto score is relatively low due to the structured character of the ventricles – in general it is valid that the larger the area of the surface is, the more difficult it is to get high scores using Tanimoto score. The reason this was found to be in a consistent under-segmentation. Using the histogram of the distance from the surface, it was found that most points in our segmentation surface were one pixel distant from the ground truth; this was confirmed by the thin layer of missed pixels. There are two possible explanations for this problem: one could be in the ambiguous definition of the ground truth, which could have tried to completely include the ventricles in the object instead of focusing on the most probable boundary. Second reason can be observed from the energy criteria and it is the fact that in some cases where over a wide border between object and background a relatively constant gradient occurs, graph-cuts naturally tend to under-segment convex objects.

We have investigated possibilities of correcting the under-segmentation and one possible solution to this would be an introduction of regional properties into the graph. We have implemented regional properties reflecting the intensity models of the object and the background, inserting the regional properties using t-links to the points surrounding the segmentation from the first iteration, than performing the segmentation again with the altered edge system. The results for 9 images are shown in table 1 and although the improvement in scores is quite obvious, it has to be noted that some disturbance in the shape has been noticed.

Table 1: Segmentation results: effect of the regional properties

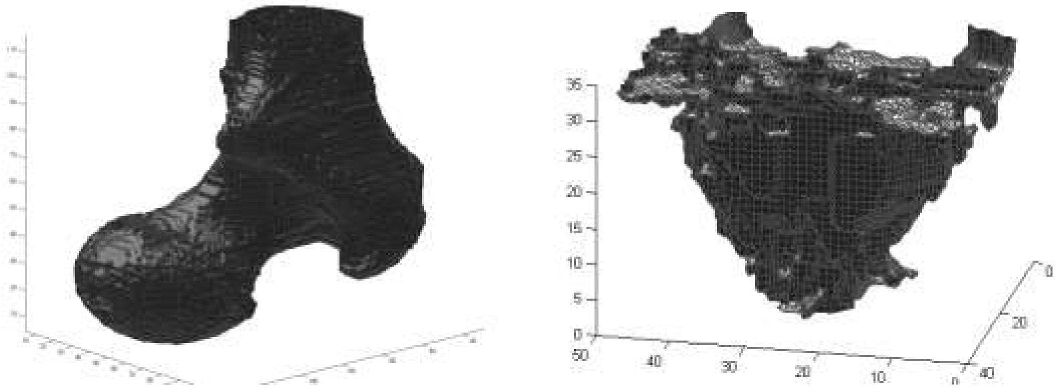
	Image Number	1	2	3	4	5	6	7	8	9
Boundary properties only	Tanimoto	68.1%	64.2%	33.4%	67.7%	49.2%	79.5%	56.4%	78.3%	51.5%
	Avg. distance [pixels]	4.25	1.50	1.01	1.36	1.19	2.54	1.18	3.17	1.38
Histogram based regional properties	Tanimoto	74.1%	72.2%	42.6%	73.0%	54.9%	84.7%	65.6%	79.0%	59.0%
	Avg distance [pixels]	2.32	1.35	1.01	1.23	1.11	1.62	1.12	3.08	1.27



a) b)

Figure 2: Brain ventricles segmentation; a) 3D segmented image; b) missed points histogram/model

The method was also tested on other image sets. First, very complicated low-resolution prostate images were processed. Due to the presence of other organ parts in proximity of the prostate, results after first pass though were not sufficiently segmented and other iterations were necessary while user interaction was involved. Since user interaction would have been evaluated in case the scores had been quantified, we are only showing the graphical results in figure 3. Hip bones were also segmented, though ground truth information was not available for the evaluation; the results are also shown in figure 3.



a) b)

Figure 3: Other segmented objects: a) hip bone; b) prostate image

4. CONCLUSION AND FUTURE OUTLOOKS

The implemented graph-cuts method was successfully tested and evaluated on artificial and real images and the introduction of selective regional properties based on intensity models proved to be enhancing the solution to a certain degree. In future, a very promising way of extending the graph-cuts segmentation method is a more complex introduction of regional properties using shape priors and ideally the active shape models. Such segmentation would ideally allow less interactivity, which is in fact the measure of success in graph-cuts segmentation: the more effectively the prior knowledge is implemented in the algorithm, the less interaction would be required from the user. On the other hand, the interactivity is a key feature for the future applications in medical practice, since it allows the user to correct and alter the solution of the segmentation.

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