Efficient Interactive Multi-Object Segmentation in Medical Images

Leissi Margarita Castañeda Leon and Paulo André Vechiatto de Miranda

Institute of Mathematics and Statistics,
University of São Paulo, Brazil.
{ leissicl@ime.usp.br, pmiranda@vision.ime.usp.br }

Abstract. In medical image segmentation, it is common to have several complex objects that are difficult to detect with simple models without user interaction. Hence, interactive graph-based methods are commonly used in this task, where the image is modeled as a connected graph, since graphs can naturally represent the objects and their relationships. In this work, we propose an efficient method for the multiple object segmentation of medical images. For each object, the method constructs an associated weighted digraph of superpixels, attending its individual high-level priors. Then, all individual digraphs are integrated into a hierarchical graph, considering structural relations of inclusion and exclusion. Finally, a *single* energy optimization is performed in the hierarchical weighted digraph satisfying all the constraints and leading to globally optimal results. The experimental evaluation on 2D medical images indicates promising results comparable to the state-of-the-art methods, with low computational complexity.

Keywords: Medical Image Segmentation · Interactive Segmentation · Graph-based Image Segmentation · Superpixels Segmentation.

1 Introduction

Although automatic segmentation is attractive in real applications, user intervention is inevitable in many practical scenarios [15]. Interactive graph-based methods are commonly used in medical image segmentation tasks, where the image and the object's relationships are modeled as graphs, while the segmentation is obtained by a graph partitioning algorithm subject to hard constraints, such as scribble pixels (*seeds*) selected in the image domain for the foreground objects and background [4].

In the context of multiple object segmentation, each object has its own distinctive features, such as shape constraints [9, 14] and boundary polarity [12, 11], which are advantageous to explore together with the structural relations between the different objects in the image, in order to incorporate prior knowledge to guide the segmentation process. Most such methods are based on graph-cut optimization and are performed by a min-cut/max-flow algorithm [3, 13], using geometric priors based on inclusion or exclusion interactions. However, their globally optimal results are restricted only to some particular cases and even their approximate solutions have a high computational cost.

We propose a hierarchical graph-based approach for the multiple object segmentation in medical images with a low computational cost, overcoming the mentioned limitations from previous works. A similar idea of this method was firstly introduced in [7] and a formal extended version in [6] under the name of *Hierarchical Layered Image Foresting Transform* (HLOIFT). In this paper, a superpixel-based adaptation of the method is presented, leading to a more efficient and adequate solution for large medical images.

2 Main Framework

In this section, we briefly describe our proposed method working with superpixels. Figure 1 shows an overview of our framework using a synthetic phantom image, inspired by [5], where its layout tries to simulate the configuration of thoracic and abdominal organs in a coronal cross-section of a CT scan. The framework receives as input a given image, the seeds for some objects, the tree of relations between objects and their individual priors. Three steps are then performed to produce a labeled image as result.

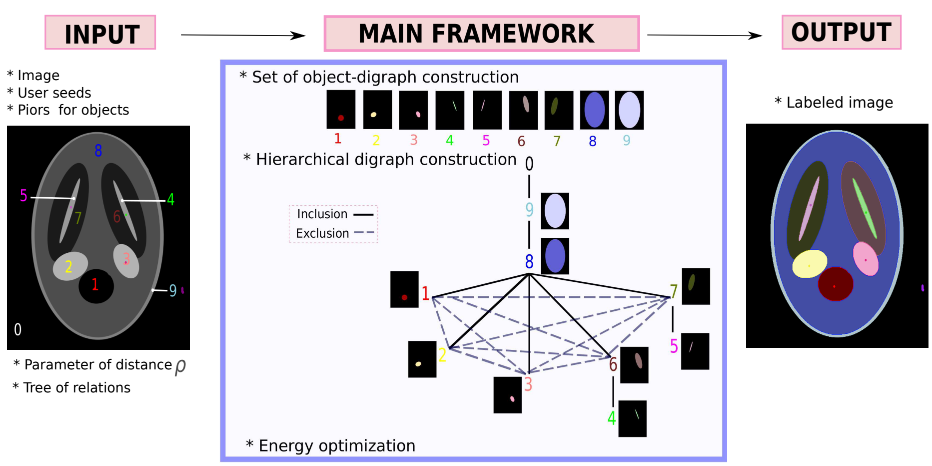


Fig. 1. Overview of our framework. Given the input parameters, a hierarchical weighted digraph of layers (digraphs of superpixels) is constructed and a graph-cut measure is optimized by our algorithm. Finally, we have a labeled image as output.

Set of object-digraph construction We first create a set of m weighted digraphs of superpixels $\mathcal{H}_i$, $i = 1, \ldots, m$, where each digraph corresponds to a single object O_i of an (*n-dimensional*) image $\mathcal{I}$. Each graph $\mathcal{H}_i = (\mathcal{N}_i, \mathcal{A}_i, \omega_i)$

is a triple consisting of a vertex set $\mathcal{N}_i$, a directed edge set $\mathcal{A}_i$ and a weight function ω_i. Each pair ($\mathcal{N}_i$, $\mathcal{A}_i$) is an isomorphic copy of a Region Adjacency Graph (RAG) of the given image $\mathcal{I}$ segmented in superpixels by IFT-SLIC [1], while ω_i is a defined weight function for every $(s,t) \in \mathcal{A}_i$, where s and t are superpixels. For example, we may consider $\omega_i(s,t) = \mid I(s) - I(t) \mid$, where $I(t)$ is the mean intensity inside superpixel t. Of course, ω_i should also highlight the priors for each O_i whenever it is appropriate. For this purpose, we consider the same modification scheme of the weight assignment that was adopted by the regular OIFT method [11] for *boundary polarity* priors, where the polarity of each O_i is defined to highlight boundary transitions from *bright to dark* superpixels or from *dark to bright*. Also, we use the *geodesic star convexity prior*, prioritizing the segmentation of the object with more regular shape. This prior is obtained by setting the weights of some arcs to $-\infty$, according to the scheme proposed in [8]. Moreover, it is still possible to simultaneously handle boundary polarity and shape priors [9].

Hierarchical digraph construction In this step, we generate a *hierarchical* weighted digraph $\mathcal{H} = (\mathcal{N}, \mathcal{A}, \omega)$ as the union of all object-digraphs of superpixels $\mathcal{H}_i$, $i = 1, \ldots, m$, with additional arcs connecting only some of the distinct object-digraphs, based on the priors given by the parent *tree* h and the parameter $\rho \geq 0$ representing the minimal distance between the boundaries of objects. The hierarchy prior (h) between any pair $\langle O_i, O_j \rangle$ of objects is understood as an *exclusion case* when $O_i \cap O_j = \emptyset$, or as an *inclusion case* when one of them is properly contained in the other. For convenience, object 0 is the root of the tree representing the image domain. The notation $h(i) = j$ indicates that $O_i \subset O_j$, being O_j the *parent* of O_i and we say that two objects O_i and O_j are *siblings* if $h(i) = h(j)$, meaning that both have the same parent. For the exclusion case we consider $\|p - q\| > \rho$ for every pixels $p \in O_i$ and $q \in O_j$. Therefore, the weights of the arcs for the *inclusion case* are given by $\omega(s,t) = -\infty$ and $\omega(t,s) = \infty$ for $h(i) = j$, $s \in \mathcal{N}_i$ and $t \in \mathcal{N}_j$, whenever the superpixels s and t have pixels with a distance smaller than ρ. For the *exclusion case*, we have special arcs to avoid overlapping between sibling objects, defining $\omega(s,t) = \omega(t,s) = -\infty$. Under this scheme, it is possible to have many different and sophisticated cases of hierarchical constraints which cannot be easily modeled with graph cuts [3].

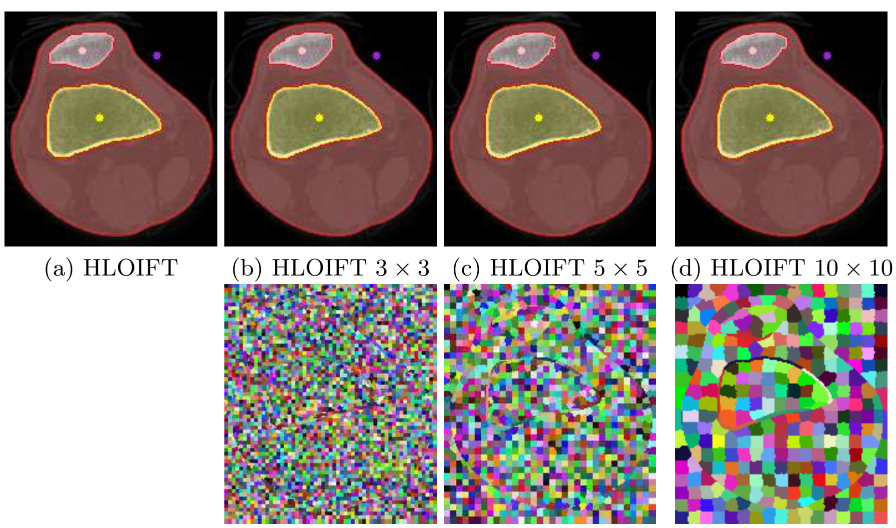
Energy optimization Finally, we execute our proposed method using an algorithm similar to the one presented in [6], but running on the hierarchical weighted digraph of superpixels $\mathcal{H}$ as constructed above. Its output maximizes a single energy defined to ensure that the output satisfies all the constraints, including the constraints imposed by h and ρ, according to the theoretical result presented in [6].

3 Experimental evaluation

This section presents an experimental evaluation of our method to assess its performance. In our first experiment, presented in Table 1, we show the execution time gains of the proposed approach in comparison to Image Foresting Transform (IFT) [10] and the multiple object segmentation by HLOIFT [6] without superpixels, for different image resolutions and superpixel sizes, for the segmentation of three objects in a CT image of the knee with inclusion and exclusion relations. The proposed method significantly reduced the size of the graph, resulting in a great saving of memory and computation time, thus compensating the additional cost of the three object-digraphs (layers) of HLOIFT in relation to IFT that has a single layer. Moreover, the segmentation results for different superpixel sizes were similar to those obtained by HLOIFT at pixel level demonstrating the robustness of the proposed method (Figure 2).

	171×193	342×386	684×772	1368×1544
IFT [10]	8.46	29.26	106.61	333.13
HLOIFT [6]	54.55	200.44	724.73	2,878.91
HLOIFT superpixel size 10×10	0.52	1.88	8.08	33.05
HLOIFT superpixel size 5×5	1.61	8.14	24.78	91.29
HLOIFT superpixel size 3×3	4.37	17.25	62.93	260.24

Table 1. Time in ms for the different methods and image resolutions.



(a) HLOIFT (b) HLOIFT 3×3 (c) HLOIFT 5×5 (d) HLOIFT 10×10

(e) superpixel 3×3 (f) superpixel 5×5 (g) superpixel 10×10

Fig. 2. The segmentation of a CT image of the knee for different superpixel sizes.

We also compared the running time between our approach and the hierarchical min-cut/max-flow algorithm with the inclusion case from [2]. Our approach has the best running time. For an image composed of two objects with the inclusion relation and size of 1520×1280 pixels, our algorithm takes $158.35ms$, $58.06ms$ and $20.38ms$ for superpixels of size 3×3, 5×5 and 10×10, respectively, while HLOIFT takes $1,823.55ms$ and min-cut/max-flow takes $19,021.71ms$, using a laptop Intel Core i3-5005U CPU 2.00GHz $\times 4$.

Finally, we present visual comparisons between our results and the IFT results on different medical images, such as brain, abdominal region and wrist, in Figure 3.

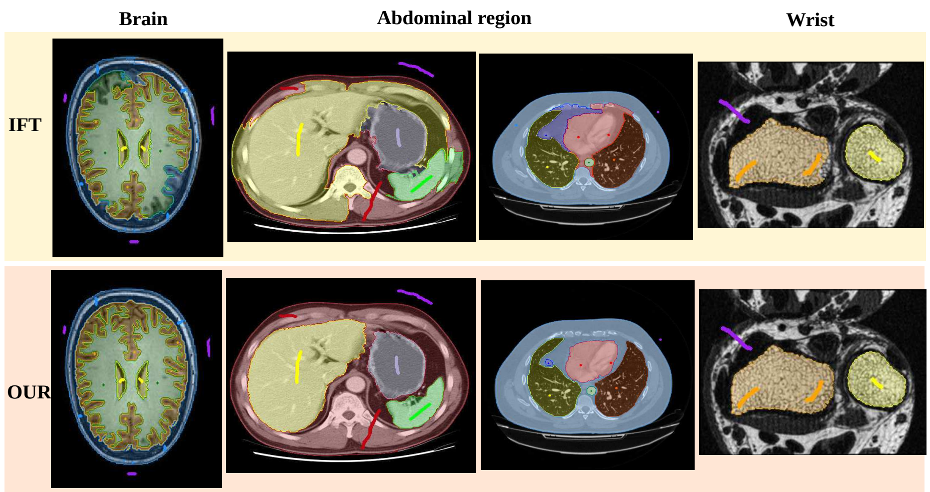


Fig. 3. Segmentation results comparing our method with the IFT method.

4 Conclusions

We proposed a new graph-based method based on superpixels, which computes a globally optimal result for arbitrary hierarchies, optimizing a single energy subject to all individual object priors, as well as their relations, with a low computational cost and being less restrictive. Our experiments show good segmentation results, even when considering a simple measure of dissimilarity for the arc weights. As future work, we are interested in using a machine learning method to estimate the arc weights, exploring other high-level priors, and also to evaluate our method in 3D medical images.

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