Image Segmentation by the Image Foresting Transform

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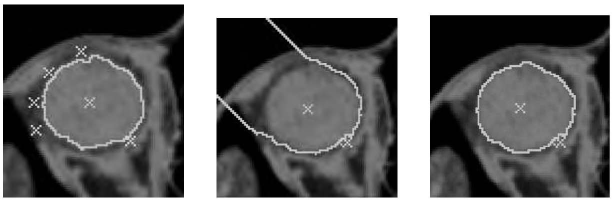
Abstract. *The "Image Foresting Transform" (IFT) reduces image processing problems into a minimum-cost path forest problem in a graph derived from the image. We present three new image operators based on the IFT for image segmentation. The first method extends and combines approaches based on fuzzy connectedness, reducing user involvement. The second combines the IFT with graph-cut measures to circumvent problems of the traditional graph-cut approaches. The third handles the leaking problem of watershed-based approaches by pruning trees of the forest. The proposed methods run in linear-time, are extensive to multidimensional images, and the last two are also free of "ad-hoc" parameters, and require only internal seeds.*

1. Introduction

We consider the problem of defining the precise spatial extent of a desired object in a given image, namely *image segmentation*. Segmentation has been a hard challenge and the methods can be divided into boundary-based or region-based approaches. We address region-based approaches which are directly extended to multidimensional images.

We present solutions that run in linear time and aim to minimize user involvement, such that automatic segmentation becomes feasible in some situations. The proposed methods use the *Image Foresting Transform* (IFT)— a tool for the design of image processing operators based on connectivity [Falcão et al. 2004b]. In the IFT, an image is interpreted as a graph whose nodes are image pixels and whose arcs are defined by an *adjacency relation* between pixels. For a given set of *seed pixels* and suitable *path-cost function*, the IFT computes a minimum-cost path forest in the graph whose roots are drawn from the seed set. Each tree in the forest consists of pixels more strongly connected to its root than to any other seed, in some appropriate sense. The methods solve segmentation by exploiting different properties of the forest.

The Master's dissertation is available at [Miranda 2006] and its related publications are [Falcão et al. 2004a, Falcão et al. 2005, Miranda et al. 2006, Falcão et al. 2006, Bergo et al. 2006]. This paper briefly overviews the methods as follows. Section 2 reduces user involvement as compared to [Udupa and Samarasekera 1996, Saha and Udupa 2001] by exploiting the optimum costs. The ordered propagation of the nodes is used in Section 3 to optimize graph-cut segmentation as compared to [Shi and Malik 2000, Wang and Siskind 2001, Boykov and Jolly 2001]. Section 4 handles the leaking problem of watershed-based approaches [Vincent and Soille 1991, Saha and Udupa 2001] by exploiting a combinatorial property of the forest and by pruning its trees.



(a) (b) (c)

Figure 1. Segmentation by seed competition of the eye ball in a CT image of the eye orbit. (a) One internal seed and many external seeds are required for segmentation. (b) Segmentation fails when some external seeds are removed. (c) A value of κ limits the influence zone of the internal seed where the seed competition fails.

2. Seed competition with κ-connectivity

The *strength of connectedness* of a pixel with respect to a seed is inversely related to the cost of the optimum path connecting the seed to that pixel in the graph. A set of pixels is said a *κ-connected component* with respect to a seed, when they are reached by optimum paths whose costs are less than or equal to κ. Previous approaches define the object as the union of all κ-connected components created from each seed separately using a single value of κ (which requires one IFT for each seed) [Udupa and Samarasekera 1996], or eliminate the use of κ thresholds by seed competition between internal and external seeds [Saha and Udupa 2001] (as in Figure 1a).

We show that seeds with different values of κ can considerably improve segmentation in both paradigms. When the seed competition fails (Figure 1b), these thresholds should limit the influence zones of the seeds avoiding connection between object and background (Figure 1c). Of course, this comes with the problem of finding the values of κ for each seed, but we provide an automatic way to determine them.

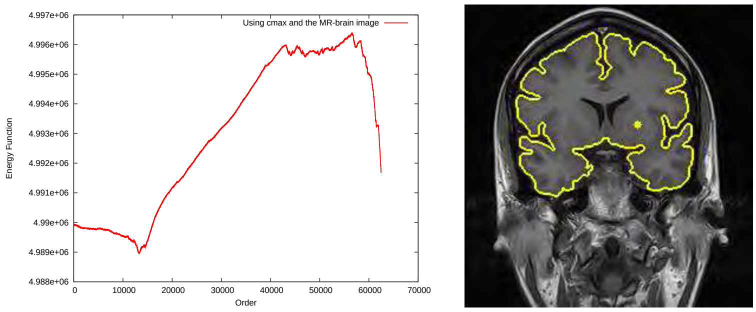
The *cost of a path* used is given by the maximum arc-weight along it and higher values are assigned to arcs across the object boundaries. As consequence, when the paths cross the boundary, several pixels in the background will be reached by optimum paths with the same cost, considerably increasing the size of the propagation wavefront (set of pixels with the same cost). The automatic κ detection is based on this phenomenon.

The method was evaluated using 100 selected images from Magnetic Resonance (MR) and Computerized Tomography (CT) from data sets of 7 objects. The new method has considerably reduced the number of user interactions in medical image segmentation with respect to the previous classical approaches.

3. Region growing by ordered propagation with graph cut

Image segmentation using graph cuts have become very popular in the last years. These methods are computationally expensive. Approaches for graph-cut segmentation usually assume that the desired cut (segmentation) is a global minimum of an objective function. Unfortunately, this can be only verified within a reduced search space under certain hard constraints since false-cut boundaries due to similarities between object and background are very common in practice.

We propose a linear-time solution based on the IFT to circumvent these problems.



(a) (b)

Figure 2. (a) The cut measure versus the pixel propagation order for energy function using the MR-brain image. (b) The respective segmentation using the same seed.

Our method computes an ordered region growing from a set of seeds inside the object, where the *propagation order* of each pixel is proportional to the cost of an *optimum path* in the image graph from the seed set to that pixel. Each pixel defines a region which includes it and all pixels with lower propagation order. The boundary of each region is a possible cut boundary, whose cut measure is also computed and assigned to the corresponding pixel on-the-fly (Figure 2a). The object is obtained by selecting the pixel with minimum-cut measure and all pixels within its respective cut boundary (Figure 2b).

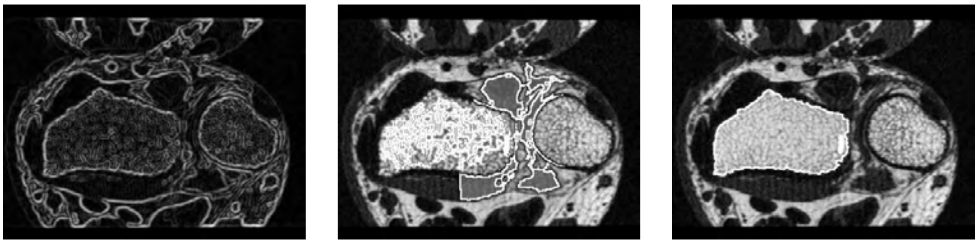
Our method essentially reduces the search space by ordering possible cuts from inside to outside the object. It requires lower arc weights across the object's boundary than inside it in order to include the desired cut in the reduced space. When this weight assignment is not achieved, the method can still work by adding more seeds.

We presented and evaluated our method for three cut measures: normalized cut [Shi and Malik 2000], mean cut [Wang and Siskind 2001] and an energy function [Boykov and Jolly 2001]. We have selected the detection of archaeological fragments for our experiments. In this application, the boundary of each fragment has to be perfectly detected to reassemble the original object. The results show accuracy greater than 90% for some cut measures. Therefore, we may conclude that our approach is a significant contribution in graph-cut segmentation.

4. Tree-pruning segmentation

In approaches based on optimal seed competition, such as watershed-based approaches [Vincent and Soille 1991, Saha and Udupa 2001], each object is defined by the union of the influence zones of its internal seeds. The absence of boundary information and/or heterogeneity of the background usually cause invasion (leaking) of object seeds in influence zones of background seeds and vice-versa (Figure 1b). Tree pruning uses only internal seeds and exploits the leaking problem to solve the segmentation. In comparison to advanced region-growing approaches from internal seeds [Udupa and Samarasekera 1996], the criterion to disconnect object and background is not based on the costs of the optimum paths but on a combinatorial property of the forest (Figure 3).

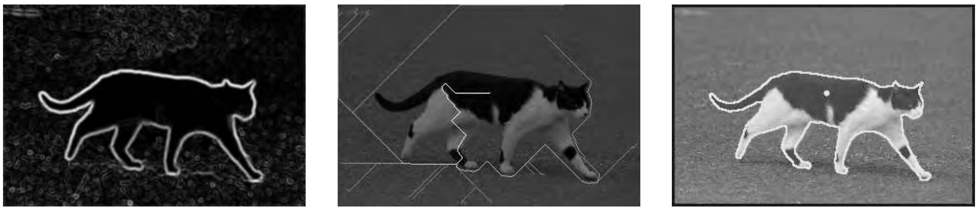
In tree pruning (TP), the seeds are chosen inside the object and the path-cost function (the maximum arc-weight along the path) usually connects object and background



(a) (b) (c)

Figure 3. (a) A gradient-like image where the object is a bone of the wrist. (b) The region growing of the IFT from internal seeds. The leaking occurs before filling the entire object, and therefore a cost threshold will not work. (c) The object may still be obtained by tree pruning.

by optimum paths (*leaking paths*), which cross the object's boundary through its "most weakly connected" parts (*leaking pixels*) (Figure 4a-b). These internal seeds compete among themselves and only a few seeds become roots of leaking paths. A *combinatorial property* of the forest is exploited to automatically identify the leaking pixels and eliminate their subtrees, such that the remaining forest defines the object (Figure 4c).



(a) (b) (c)

Figure 4. (a) A gradient-like image. (b) The original image overlaid by some leaking paths which ramify into several branches on the object's boundary. (c) The resulting segmentation with TP.

The experiments to evaluate TP used 990 images (352×240 pixels) from a database of license plates. We wish to find the precise location and spatial extent of the plates. In this application seed selection is a difficult task, because any attempt to estimate seeds inside a plate is likely to find seeds in other parts of the image. Therefore, a natural strategy is to run the methods for candidate seed sets, score the candidate objects, and choose the one with the best score. The score of an object can be obtained based on shape features, since the plates are deformed rectangles and we used a simple seed selection method based on thresholding and morphological operations [Miranda et al. 2006]. TP correctly segmented 931 (94.04%) license plates out of 990. Among the 59 missed plates, 28 (2.8% of the database) were due to the scoring process and 31 (3.13% of the database) were due to errors of the TP method. We have also showed in [Bergo et al. 2006] that TP outperforms the Watershed Transform and a recent approach for license plate detection.

The extension of TP to 3D was also evaluated for 3D MR-image segmentation of the human brain and compared with a template-based approach, widely used for medical research, called *SPM2* [Frackowiak et al. 2003]. TP not only provided better segmentation results than SPM2 on real images, but also was much faster (about 9 times faster) on the same workstation.

5. Conclusion

Three new segmentation methods were presented and compared with classical approaches, resulting significant contributions to the state of the art in segmentation.

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