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Multiregion Object Segmentation Methods - A Survey

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Abstract: ***Image segmentation is the elementary step to investigate metaphors and haul out data from them. It is the field widely researched and still offers various challenges for the researchers. This paper tries to put glow on the critical ideology on the methods used to fragment an image. Image segmentation can be roughly be categorized as semi-interactive approach and fully habitual approach and the algorithms industrial lies in either of this approaches. Image segmentation is a critical step as it frankly influences the overall success to understand the image. This paper concentrates on the various approaches used to segment multiregion objects like Graph method, Lagrangian duality, Hausdorff distance, level set etc. A comparison was made between Lagrangian duality and level set approach in segmenting multi region objects. In these techniques it is found that level set approach outperforms the others in mltiregion object segmentation.***

Keywords: Segmentation Methods, Image, Cluster, Graph-cut, Hybrid Methods

1. Introduction

An image is essentially a two dimensional function of spatial coordinates, f(x, y), and amplitude of this function at a given coordinate gives the intensity value of the image. The image can be expressed as the product of functions of illumination and reflection.

$$F(x,y) = i(x,y)*r(x,y) \quad (1)$$

where i(x,y) is the task of intensity and r(x,y) is the function of reflectivity. Digital image processing is appliance of different algorithms on the image to get better the eminence of the image by removing noise & other redundant pixels and also to get more in turn on the image. Among the various image processing techniques image segmentation is very crucial step to analyze the given image. This paper mainly focuses on the various methods that are widely used. The images are segmented using MatLab software.

2. Biomedical Image Segmentation

Image segmentation is a mid-level dealing out procedure used to investigate the image and can be defined as a dealing out method used to order or cluster an image into several disjoint parts by alignment the pixels to form a section of homogeneity based on the pixel individuality like gray level, color, texture, intensity and other features. The main function of the segmentation procedure is to get more information in the region of interest in an image which helps in annotation of the object scene. Image segmentation aims at domain-independent partition of the image into a set of visually distinct and identical regions with respect to certain properties. The main goal of segmentation is to clearly make a distinction the object and the background in an image

If R represents an image, then the image segmentation is simply division of R into subregions R1,R2…..Rn , such that and is governed by following set of rules:

a) Ri is a connected set, i=1,2,…..n.
b) Ri ∩ Rj = Ø for all i and j, i ≠ j
c) Q(Ri) = True for i= 1,2,…n.
d) Q(Ri U Rj) = False for adjoint regions, Ri and Rj Where Q(Rk) is a logical predicate.

The set of laws described above mentions about connection, one-to-one relationship, homogeneity and non-repeatability of the pixels after segmentation respectively

Biomedical image segmentation is at the nub of a mixture of biomedical imaging applications, such as computer aided diagnosis, therapy planning and delivery, computer aided interventions, and in the image scrutiny and quantification of histological facts. Even though great advances in image segmentation, the accurate schedule (or even semiautomatic) partitioning of biomedical images with composite scenes and substance remains a difficult problem. Many attempts have been made to include prior knowledge into the task of segmentation, since insertion of shape, appearance and topological priors have proven useful for obtaining more accurate and conceivable segmentation results. Many objects in biomedical images consist of numerous regions, where each region has a important numerical connection, or relations, with other regions of the object. For example, in histology and microscopy images, each cell consists of a cell membrane, nucleus and nucleolus, where the cell membrane contains the nucleus, and the nucleus contains nucleolus. These interactions between an object's regions have often been ignored in microscopic histology image segmentation or enforced via some adhoc post processing (e.g. via parameter sensitive morphological operations or thresholding).

3. Multi Region Object Segmentation

Segmentation is a partitioning of an image into several segments. This can be the partitioning of an image into one segment belonging to a object in the image and one segment belonging to the surroundings in the image. Each pixel is given a label corresponding to which segment it is part of. In multi-label segmentation more than one object is searched for in the image and in multi-region segmentation each pixel can be part of more than one label. In applications information about an image can be known a priori. When segmenting an image of the heart you know before you start that there are two chambers (in a healthy patient) and that the chambers are surrounded by the heart muscle. This in- formation can be used to improve the segmentation by im-posing restriction in between the different regions. There are many approaches used in multi-region object segmentation.

1. Graph method
2. Hausdorff distance
3. Active contour without edges
4. Lagrangian duality
5. Level set

3.1 Graph Method

This method shows how to encode numerical connections between distinct region and boundary models, such as regions being interior / outer to each other along with preferred distances between their restrictions. With a single graph cut [4], this method extracts only those multi-region objects that satisfy such a combined model. This method sidesteps the unwrapping issue entirely. We do not need center-lines, have no topological constraints, and do not suffer from numerical deformation introduced by unwrapping. This method involves containment, exclusion, attractive force and minimum distance that can be between objects.

3.2 Hausdorff Distance

The Hausdorff distance [3] prior is fundamentally different from the tubular distance prior. It constitutes a potentially NP-hard optimization problem be-cause the involved energy is a combination of submodular and supermodular terms. We will show that this problem can be approximated efficiently using the submodular, supermodular procedure. This technique was inspired by the concave-convex procedure for continuous functions. Our algorithm changes the underlying graph in a way different from earlier submodular, supermodular techniques. For example, besides changing the edge capacities, we also replace certain edges modifying the graph's connectivity. This operation maintains the value of the previous solution, but the corresponding cut is no longer the global minimum and it can be recomputed. Our connectivity modifications are based on the signed distance maps of the current segmentation, which can be efficiently computed in linear time. Typically, our method converges within 5-10 iterations. This approach supports containment, maximum and minimum distance between objects, but it does not handle exclusion between objects. In this we enhance the popular Mumford-Shah model to incorporate two important geometrical constraints, termed containment and detachment, between different regions with a specified minimum distance between their boundaries. Our method is able to handle multiple instances of multi-part objects defined by these geometrical constraints using a single labeling function while maintaining global optimality. We show the efficacy and advantages of these two constraints and show that this convex continuous method is superior to other state of the art methods, including its discrete counterpart, in terms of memory usage, and metrication errors. In this we focus on segmentation tasks where two regions must be separated by a third. Specifically, we focus primarily on the geometric constraint containment where one region separates a second region from the background. Other geometric constraints can also be enforced using the same framework, such as detachment, where the background separates two regions. This addresses the problem of multi-region segmentation with these two important geometrical constraints, containment and detachment with a minimum distance (or thickness) between regions boundaries, in a continuous framework while maintaining global optimality. We choose these two geometrical constraints due to their intuitive definitions, descriptive power, and ability to help properly segment regions with weak intensity appearance models. Using a continuous framework provides several advantages over discrete methods: 1) no metrication error 2) less memory usage 3) efficient parallelizability, and 4) allowance for sub pixel resolution

3.3 Active Contour without edges

We use active contour model [1] to section images with more than two regions, by proposing a new multiphase level set framework for the problem. With a reduced number of level set functions, triple junctions and complex topologies can be represented. The phases used in the partition do not produce "vacuum" and "overlap." Finally, in the piecewise smooth case, based on The Four Color Theorem; we confirm that merely two level set functions properly should be sufficient to signify any partition. A new multiphase level set framework for image segmentation using the Mumford and Shah model, for piecewise constant and piecewise smooth optimal approximations. This method is also a generalization of an active contour model without edges based 2-phase segmentation. These models can identify individual segments in images with multiple segments and junctions, as compared with the initial model, where the detected objects were belonging to the same segment. We also propose a new representation for multiphase motion by level sets allowing for triple junctions. Finally, these models inherit all the advantages of our active contour model without edges: detection of edges with or without gradient, detection of interior contours, automatic change of topology, robustness with respect to noise. The models can perform in parallel active contours, segmentation, denoising, object and edge detection.

3.4 Lagrangian Duality

The main involvement of our work is a multi-region segmentation framework with good optimizability. Our agenda builds on the multi-region scheme presented in where it is shown that geometric relationships, for example, when one object is included in another, can be modeled and globally optimized via graph cuts. The key property that makes this achievable is that the resulting energy minimization problem is submodular. We also identify submodular relationships; how-ever, we go beyond submodularity to enable other geometric relationships and priors to be incorporated into the model. In the focus is on characterizing when the problem becomes submodular. The typical procedure for solving non submodular energies of this type is so-called Roof Duality (RD). However, the method is quite memory severe and can be slow. We develop a Lagrangian dual approach [2] to solve these non submodular energies. The method is valuable over roof duality; it uses almost partially as much memory and we empirically show that it is quicker. This method considers the restraint, segregation, magnetism force and minimum distance between objects.

3.5 Level Set

Here we focus on encoding two useful geometric constraints, containment and exclusion between the regions of multi-region objects, into the level set formulation. Using level sets embedding functions [6] that are based on distance transforms (as is usually done) enables us to naturally enforce optional distance constraints between different regions. Our framework can enforce attraction forces as well as minimum and maximum distances between regions' boundaries. This work is a continuous local optimization framework. we introduce an R*R constraints matrix, C, that encodes the containment and exclusion constraints, where R is the number of regions of an object in the image to be segmented. Our motivation to introduce C is to provide a framework where one can encode geometrical constraints (containment/exclusion) easily and intuitively.

Table 1: Encoding containment and exclusion into matrix C

Constraint	Matrix C
i contains j	Cij > 0
i and j are disjoint	Cij < 0 AND Cji < 0
i and j have no constraint	Cij = Cji = 0

In addition to encoding the containment and exclusion constraints, we also encode the distance constraint into C such that Sij = sign(Cij) defines the containment or exclusion of objects i and j (Sij > 0 means i ontains j and Sij = Sji < 0means i and j are excluded from one another), and │ Cij │ indicates the distance between these two regions. Note that sign(C) is symmetric with respect to exclusion, i.e., if i excludes j, j also excludes i.

To ensure that our level set-based framework is numerically stable, we place an upper bound for the time-step δt, using the Courant-Friedrichs-Lewy (CFL) condition [17]. The stability condition is

$$F_{max}\delta t \leq \min(h_x, h_y, h_z)$$

where hx, hy and hz are the grid spacing in the x, y and z direction, respectively, and Fmax is the maximum absolute force (also known as speed function) applied to the level set at each iteration. For hx =hy = hz = 1, at each iteration we make sure that δt ≤1/Fmax. Violating the CFL condition results in instabilities.

4. Experimental Discussion

Experiment was performed for brain image, histology and microscopy images and in these images level set approach outperforms the other four methods. Segmentation was verified for regions that are not contained by other regions, contained by other regions, memory usage for segmentations in Lagrangian duality with 4 graph connectivity and 8 graph connectivity and in level set approach ,and it is found that level set approach is best in performance.

Table2: Comparison of Lagrangian duality with Level set

	Lagrangian duality	*Level set*
Regions that have not been contained by other regions	4-C: 0.89 ±0.04 8-C: 0.90 ± 0.05	0.91 ±0.02
Regions that contained by (or excluded from) others	4-C: 0.89 ±0.05 8-C: 0.90 ±0.04	0.90 ±0.04
Overall	4-C: 0.89 ± 0.04 8-C: 0.90 ±0.05	0.91 ±0.03
Memory usage (MB)	4-C: 120 ± 99.30 8-C: 167 ±101.60	1.86 ±1.37

The Table 2 provides the comparison between Lagrangian duality and Level set approach. The Level set approach provided a overall efficiency of 0.91±0.03 and a memory usage of 1.86±1.37.

5. Conclusion

This work shows that level set approach outperforms all the other methods. As future work we plan to add priors like shape to improve the descriptiveness of objective function and improve optimizability.

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