Interactive Segmentation of Medical Images: A Survey

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Abstract

Image segmentation is a fundamental process in most systems that support medical diagnosis, surgical planning and treatments. Generally this process is done manually by clinicians, which may be time-consuming and tedious. To alleviate the problem, a number of interactive segmentation methods have been proposed in the literature. These techniques take advantage of automatic segmentation and allow users to intervene the segmentation process by incorporating prior-knowledge, validating results and correcting errors, thus potentially lead to accurate segmentation results. In this paper, we present a survey of interactive segmentation techniques popular for medical image analysis.

1 Introduction

Due to the restrictions imposed by image acquisition, pathology, and biological variation, the medical images captured by various imaging modalities such as X-ray computed tomography (CT) and magnetic resonance imaging (MRI) are generally of high complexity and ambiguity. Image segmentation is typically used to locate objects of interest and their boundaries to make the representation of a volumetric image stack more meaningful and easier for analysis. Traditionally, this process is manually done slice by slice, which requires expert knowledge to obtain accurate boundary information for the regions of interest. This editing process may take a lot of time as well. A number of computer-aided segmentation techniques have been developed for medical images, which can usually be distinguished as automatic methods and interactive methods.

Automatic segmentation techniques such as thresholding [64], watershed [23], edge detection [48], morphological operation [32], shape analysis [19], and supervised learning [57] are usually applicable for the segmentation of well-circumscribed objects. When applied to a stack of medical images, they are able to generate rough segmentation results. These results can be further refined by the intervention of human experts. In computer-aided diagnosis, therapy planning and treatment, interactive segmentation [6, 29, 76] has become more and more popular in recent years, as the combination of human experts and machine intelligence can provide improved segmentation accuracy and efficiency with minimal user intervention [35]. The improved segmentation results can be used to reconstruct the 3D structures of tissues and enhance the real-time visualization on the screen for clinicians to navigate within the tissues freely. This can provide great benefits to many applications including locating tumors, measuring tissue volumes, surgery, and diagnosing diseases.

In this survey, we will focus on the interactive segmentation methods for medical images. Our goal is to better understand the implications of user interaction for the design of interactive segmentation methods and how they affect the segmentation results.

2 Interactive Segmentation Methodologies

Interactive segmentation [50, 63] plays an important role in the segmentation of medical images, where user intervention is suggested as an additional source of information. They leverage the expert knowledge of users to produce accurate segmentation of anatomical structures, which facilitates measurement and diagnosis of various diseases. Many approaches have been taken in interactive segmentation, which can be broadly classified into the following categories.

2.1 Fundamental approaches

In this section, we will review some common techniques (e.g., level set, region growing) that are used in interactive segmentation of medical data.

Edge-based and region-based level set segmentation methods provide a direct way to estimate the geometric properties of anatomical structures. They are popular as a general framework for many applications of medical image analysis [3, 17], such as brain MR images and 3D CT of carotid arteries. Region growing [1] is a simple region-based interactive segmentation method. Several variants of this technique have been proposed for medical image segmentation, e.g., the adaptive region growing algorithm introduced in [69]. They perform well with respect to noise and usually produce good segmentation results. However, these techniques may result in holes or over-segmentation due to noise or variation of intensity.

Statistical approach [25] is also applied to identify different tissue structures from medical images, which involves manual interaction to segment images in order to obtain a sufficiently large set of training samples. This technique is mainly applicable for problems with sufficient prior knowledge about the shape or appearance variations of the relevant structures [15, 30]. Mortensen and Barrett [49] developed an effective graphical tool (Intelligent Scissors) for performing 2D segmentation by providing immediate feedback for boundary selection as the mouse moves, which gives the user constant awareness of what belongs to the current selection. Other graph-based segmentation tools include region-based Intelligent Paint [55] and 3D Live Surface [2].

2.2 Learning-based approaches

This interactive strategy can react dynamically to the user based on the input priors (e.g., shape and appearance), and then predict the segmentation results for the user. In this framework, the user only needs to label the foreground and background on a single volumetric data, the algorithm learns the correlation between them adaptively, and completes the segmentation on other volumetric data automatically. The goal is to improve the performance of the computational part and possibly reduce the need for future user intervention, leading to interaction efficiency.

In the method described by Elliot et al. [20], the segmentation result obtained with user interaction is compared to the result obtained when the default parameter settings are used. The difference between the two is used to calibrate the parameters for the computational part, which are used as default values in future segmentation sessions. In slice-by-slice segmentation of 3D images, the information obtained with interaction in one slice can be propagated to the next in different ways. In [61], all the pixels inside the resulting object are propagated as seeds for region growing in the next slice. In the active paintbrush [44], selected points inside and outside the resulting object are propagated as 'hint' that indicate regions in the next slice where the object should (or should not) be located. The interactive method described in [11] uses a set of reference contours drawn by the user to find the optimal parameters for an elastic-contour model using a genetic algorithm. The optimized parameters are used in all the other slices in the same or another dataset. In Yu's method [77], the resulting boundary itself is propagated as the initial contour for deformation in the next slice. In the method by Wink et al. [68], the contour in the next slice is estimated on the basis of local similarity measures of the image intensity pattern at the resulting boundary.

To overcome the application dependency, Bhanu and Fonder [5] proposed a learning-based interactive segmentation approach, in which the user can select sets of examples and counter-examples to interactively train the segmentation. The image segmentation is guided by a genetic algorithm that learns the appropriate subset and spatial combination of a collection of discriminating functions, associated with image features. The genetic algorithm encodes the discriminating functions into a functional template representation, which can be applied to the input image to produce a segmentation result. In [66], Veeraraghavan and Miller combined SVM-based active learning with GrowCut interactive segmentation to achieve a robust segmentation despite user variability with a comparable accuracy to a fully user guided segmentation with half number of user interactions on average.

The lack of labeled multimodal medical image data is a major obstacle for devising learning-based interactive segmentation tools. Transductive learning (TL) or semi-supervised learning offers a workaround by leveraging unlabeled and labeled data to infer labels for the test set given a small portion of label information. Lee et al. [36] proposed a novel algorithm for interactive segmentation using TL and inference in conditional mixture naïve Bayes models (T-CMNB) with spatial regularization constraints.

2.3 Energy minimization-based approaches

This class of segmentation methods partitions an image into different regions based on energy minimization. Among many other approaches, graph cut-based methods and deformable model-based methods are particularly popular in medical image segmentation. These techniques aim to find a global optimal solution for the boundary and region segmentation of objects in images and their performance can be efficiently improved by involving users in the process, putting users in the loop, but minimizing user input.

2.3.1 Graph cut-based approaches

Based on combinatorial optimization, graph cut [6, 59] solves the segmentation by minimizing an energy function defined on a combination of both region and boundary terms. In this approach, a graph is composed of vertices representing image pixels or voxels, and edges connecting the vertices. The graph edges are assigned some nonnegative weights or costs, and a cut is a subset of edges that partition the vertices into disjoint sets. The cost function consists of both regional and boundary information, which needs to be well defined to provide a globally optimal solution. Many current techniques use graph cut for image segmentation. It has been shown to be effective in the segmentation of images [40, 56] and volumes [2]. The use of graph cut for segmentation of 3D surfaces has been extensively validated for medical image volumes [39]. However, the execution time can be tens of minutes to cut volumes of 2-8M voxels. To accelerate the process, a single layer of oversegmentation regions has been used in the place of voxels for medical volumes which reduces the computation time to tens of seconds [78]. Lombaert et al. [43] used a resolution pyramid to perform coarse-to-fine refinement, enabling computation on the order of tens of seconds as well. In these techniques, the users are involved in the process by roughly marking out the objects of interest and the background before applying the graph cut-based segmentation. By instant feedback, additional user interaction is specified to refine the results.

2.3.2 Deformable model-based approaches

Based on variational framework, deformable modeling [13, 21, 29, 45] segments images by minimizing an energy function defined on a continuous contour or surface. It can adapt to complex shape variations and incorporate priors to regularize segmentation. Deformable modeling has been widely applied in applications such as shape extraction and object tracking, in which curves or surfaces evolve under the influence of both internal and external forces to extract the object boundaries.

Explicit models such as active contour model (Snakes) [21, 29] represent contours or surfaces in their parametric form during deformation, which have the ability to track the points on the curves or surfaces across time, and are suitable for real-time applications. However, they generally have difficulties in handling topological changes due to the parameterization of the curves or surfaces. To address these limitations, McInerney and Terzopoulos [47] developed topology adaptive deformable models by formulating deformable surfaces in terms of an affine cell image decomposition to deal with topological changes usually existing in medical image volumes. This explicit model requires a periodic reparameterization mechanism to manage complex shapes and changes in topology. This technique can effectively segment complex anatomic structures from medical volume images. However, it only performs well when the model is required to inflate or deflate everywhere, which limits its applications. New approaches [7, 18, 33] have been proposed to handle topological changes. These techniques generally involve a set of heuristic algorithms to detect self-intersections and handle splitting and merging of the deforming grid, which can be computationally expensive. In addition, they may not work well on structures consisting of complex topologies.

To address the limitations of explicit deformable models, implicit deformable models [13, 45] are introduced, based on the theory of curve evolution and the level set method [51, 58]. In the implicit models, the evolution of curves or surfaces is implicitly represented as a level set of a higher dimensional scalar function and the deformation of the models is based on geometric measures such as the unit normal and curvature. Thus, the evolution is independent of the parameterization and topological changes such as splitting and merging can be handled automatically. Implicit deformable models have been widely used in the segmentation of anatomical structures from 3D medical images [3, 28, 34].

Deformable models often vary in the object boundary representation and external force field used. Previous approaches can be distinguished as gradient-based methods [37, 45, 54, 72, 74], region-based methods [14, 17, 30, 53, 67], and hybrid methods [31, 70]. Gradient-based techniques have been found useful when there is limited prior knowledge and image gradients are reasonable indications of object boundaries. However, they require careful initialization and it may be difficult for them to achieve initialization invariance and robust convergence. This is especially true when segmenting objects with complex geometries and shapes in 3D images. Region-based techniques have been widely applied to image segmentation as well. In the popular approach [14], Chan and Vese assumed the image consists of regions of approximately piecewise-constant intensities, and then extracted the objects based on the average intensities inside and outside the contour. This method is useful for the extraction of objects with smoothly varying boundaries. However, it has difficulties dealing with image regions with intensity inhomogeneity. Other region-based approaches also assumed that the image objects are composed of distinct regional features. This is usually not true for real images due to intensity inhomogeneity and multimodal nature. In the hybrid approach [31], Kimmel used image gradient vector directions as an alignment measure, combined with the geodesic active contour and minimal variance criterion [14].

The alignment measure is used to optimize the orientation of the curve with respect to the image gradients. This measure, together with the gradient-based geodesic measure and the region-based minimal variance criterion is then used to push or pull the contour towards the image boundary. However, this hybrid technique requires careful tuning of the different parameters associated with various measures in order to efficiently bridge the image gradient and regional information. In addition, only local edge information is used in the alignment measure, while edge information of pixels located away from the contour is not considered.

The geometric active contour models [13, 45] and subsequent geodesic active contour models [12, 60] have difficulties in handling the boundary concavities, weak edges and image noise. The generalized gradient vector flow [73, 74] achieves some improvements but has convergence issues caused by saddle or stationary points in its force field. In [71, 72], Xie and Mirmehdi presented a novel edge-based model where the introduced external force field is based on the hypothesized magnetic force between the active contour and object boundaries. This method shows significant improvements in handling weak edges, broken boundaries, and complex geometries. However, its analogy based on magnetostatics cannot be directly applied to 3D or higher-dimensional images. Recently, Yeo et al. proposed a novel 3D deformable model [75, 76] based on a geometrically induced external force field, which is called the geometric potential force (GPF) field as it is based on the hypothesized interactions between the relative geometries of the deformable model and the object boundary characterized by image gradients. The evolution of the deformable model is solved using the level set method so as to facilitate topological changes automatically. The bi-directionality of the proposed GPF field allows the new deformable model to deal with arbitrary cross-boundary initializations, which is very useful in the segmentation of complex geometries, and facilitates the handling of weak image edges and broken boundaries. Moreover, the GPF deformable model can effectively overcome image noise by enhancing the geometrical interaction field with a nonlocal edge-preserving algorithm. The vector force field introduced in this work is a generalized version of the magnetic force field described in the MAC model [72], but it can be extended to higher dimensions.

3 Interactions in Medical Image Segmentation

In an interactive segmentation framework, user intervention is tightly coupled with an automatic segmentation algorithm leveraging the user's high-level anatomical knowledge and the automated method's computational capability. Real-time visualization on the screen enables the user to quickly validate and correct the automatic segmentation results in a sub-domain where the variational model's statistical assumptions do not agree with the user's expert knowledge. The user intervention mainly includes initialization of the methods, checking the accuracy of the results produced by automatic segmentation, and corrections to the segmentation results using specialized interactive segmentation tools. As shown in Table 1, interactions in the segmentation of medical images can be broadly classified into three types: pictorial input on an image grid, parameter tuning, and menu option selection. The segmentation results obtained with new configurations (e.g., mouse clicking/drawing, new parameter values, another menu option) are visualized on the screen in real time for further user evaluation.

Interactive segmentation techniques are very important for fast and reliable extraction of the regions of interest. The level of user interaction in different methods varies in terms of the amount and type of information provided by the users. Their underlying mathematical framework is a significant factor determining the form of interaction. In region growing-based methods [1, 69], the interaction is the selection of initial seed points. In the united

Interactions in Medical Image Segmentation	Examples
Pictorial input (points, lines, or regions) on an image grid	Points of background and objects [24, 26, 44] Seeds for region growing [1, 69] Point of object for initiating an inflating 3D balloon [22] Center point and radius [9] Rectangles indicating regions of interest [42] Features of different types of objects [65] Points attracting/repelling the contour [13, 21, 29] Initial curve/surface of objects of interest [46]
Parameter tuning using slider, dial, or similar interface	Scale for computing image derivatives [10, 42] Balance of weights in the cost function [8] Maximum number of iterations [10] Maximum size of segmented regions [62]
Menu option selection by mouse clicking	Accept/reject the segmentation results [65] Type of geometry model [8, 27] Properties of objects of interest [26]

Table 1: Type of interactions in the segmentation of medical images.

Snakes framework [41], the user controls the snake evolution by 'planting' seed points. The GrabCut technique [56] is based on the discrete graph-cut approach, where image pixels represent graph vertices. The partitioning of the image into object and background regions is obtained by solving the min-cut problem in graphs. The user controls the segmentation by labeling regions, which are correspondingly assigned to either the source or the sink of the graph. The selected regions provide color statistics that characterize the object and the background and are utilized for segmentation. In [52], Paragios presented a semi-automatic segmentation of the left ventricle. The method uses linear or quadratic interpolation to convert the user input into closed structures. Therefore, the feedback is not part of the level set formulation. In [38], a method applying dual-front active contours and active regions for 3D cortical segmentation is proposed. The user can modify the initialization of the active region by adding or deleting labels. A probabilistic level-set method which supports user interaction is demonstrated in [16]. The user-labeled input points are viewed as independent measurements of the scene. In [4], Ben-Zadok et al. developed a novel active-contour segmentation framework, which supports an intuitive and friendly user interaction subject to the 'bottom up' constraints introduced by the image features. Applying the level-set method [51], a fully automatic segmentation is first obtained by minimizing a cost functional that is uniquely based on the image data. The user does not 'edit' the initial segmentation, but influences its evolution with a few mouse clicks located in regions of 'disagreement'. The user input is represented as a continuous energy term that is incorporated into the primary level-set cost functional. This additional term affects the gradient descent process by attracting it toward a new local minimum, which results in a modified segmentation consistent with both the low-level image data and the top-down user feedback points.

4 Conclusion

In this paper, we briefly introduce the interactive image segmentation techniques in many medical applications. Interactive segmentation aims to achieve interaction efficiency by incorporating intelligence with automatic segmentation, leading to the ability of learning user intention and dealing with new volumetric images. To be viable for practical applications, an interactive segmentation approach should (i) minimize user interaction, (ii) minimize segmentation variability among users and (iii) be computationally fast to allow quick user editing. These concerns can be addressed by combining the machine learning techniques with interactive segmentation algorithms. Therefore, such a combined approach could provide a promising direction for accurate segmentation of medical images. A possible direction for future work could be how to efficiently learn the intention of the user so as to reduce the number of user interactions.

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