RESEARCH ARTICLE

Segmentation of Medical Images using Image Registration

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Abstract— Medical image segmentation is one of the most essential task in many medical image applications, as well as one of the most complex tasks. Medical image segmentation aims at partitioning a medical image into its constituent regions or objects, and isolating multiple anatomical parts of interest in the image. The precision of segmentation often determines the final success or failure of the whole application. For example, when doctors want to reconstruct a 3D volumetric model of the heart, they need to segment the regions of heart in a series of 2D images. If segmentation is done wrongly, the reconstruction will be erroneous. Therefore, considerable care should be taken to improve the reliability and accuracy of segmentation in medical image analyzing and processing. If the region of interest in image have homogeneous visual feature then the segmentation is very easy. However, in more general medical applications, images are much more complex, and difficulties exist inevitably in segmenting these images. The difficulties of medical image segmentation are mainly based on the nature of imaging technology, dealing with low contrast image with noise, image properties, overlapping parts of an image. Due to these difficulties, intelligent algorithms are needed to segment multiple anatomical parts of medical images. One promising approach is registration-based segmentation. A model of the anatomical parts of interest is constructed. The model is registered to the image of a patient. When registration is correctly performed, segmentation of the various anatomical parts is done. By representing prior knowledge in the model, registration-based segmentation can handle complex segmentation problems and produce accurate and complete results automatically.

Keywords: Image segmentation, Image registration, correspondence

I. INTRODUCTION

Registration based segmentation uses registration method to achieve segmentation. However, registration is dissimilar from segmentation. To simplify the differences, we define the problems segmentation, registration, and correspondence. The most general forms of these definitions are given.

Segmentation

Given an image, partition it into several disjoint regions or objects of interest. In the simple case, the regions or objects have homogeneous visual characteristics. In the complex case, the

regions or objects correspond to anatomical parts that may not have homogeneous visual characteristics.

Registration

Given two images, or a model and an image, of the same anatomical parts, find a possibly non-rigid transformation to spatially align their corresponding parts.

Correspondence

Given two sets of points or other entities, such as edge segments and surface patches, and a measure of the similarity between two points or entities, find a mapping function from one set to the other that maximizes the similarity of each pair of points or entities.

These three problems are different but related. Segmentation aims at isolating the anatomical parts of interest from one given medical image, whereas registration seeks to spatially align anatomical parts in two images, or one model and one image. The objective of correspondence problem is to find the mapping function between two sets of entities subject to some constraints such as maximizing the similarity between the corresponding pairs of entities.

In many cases, registration can be used as a powerful method for solving segmentation problem, i.e., registration-based segmentation. Registration is also related to correspondence. If correspondence is known, registration can be easily performed by computing the best transformation given the known corresponding points. If correspondence is not known a priori, the registration algorithm needs to determine the best transformation and correspondence at the same time. Automatic registration-based segmentation typically means solving the problem of registration without known correspondence.

II. REGISTRATION-BASED SEGMENTATION

In registration-based segmentation algorithms, a model is built to represent the prior knowledge, such as the shape, features or relative positions of anatomical parts. After correctly registering the model to the target image, the segmentation is also done. The model used here can be a general deformable model or an atlas. In this section, general deformable model based segmentation approaches are discussed first, followed by atlas-based approaches.

2.1 General Model-Based Approach

The model-based segmentation methods discussed in this section refer to the registration-based segmentation methods that use general deformable models. There are three popularly used deformable models, namely active contour (snake), active shape (eigenshape) and level set.

2.1.1 Active Contour (Snake)

Active contour or snake model represents a contour by a series of points. A snake can be deformed to match any kind of shape under the constraints of three kinds of forces: internal forces, image forces and external forces. Internal forces are constraints on the stretching and bending of the snake. Image forces are given by image features such as edges that attract the snake. External forces contain external constraints on the snake such as spring force and repulsion. The aim of a snake algorithm is to iteratively deform the snake by moving the snake points to minimize the total energy so that the snake can fit the image features well. The total energy is the weighted sum of the energy of internal forces, image forces and external forces. Traditional snake has two main drawbacks. Firstly, it is too sensitive to initialization, and secondly, it cannot be attracted by concave parts of image contour. Xu et al.

has proposed a new image force, Gradient Vector Flow (GVF), to solve these two problems. Gradient vector flow is derived from the diffusion of gradient vectors of edge map. Compared with traditional snake, GVF snake can snap onto concave parts of image contour and is less sensitive to initialization.

The snake algorithm has proved to be very useful for many applications. , Atkins et al. used snake algorithm for brain segmentation in MR images. Snake has also been applied to the segmentation of liver and heart in CT images, and carpal bone in x-ray images

(a)   (b)   (c)
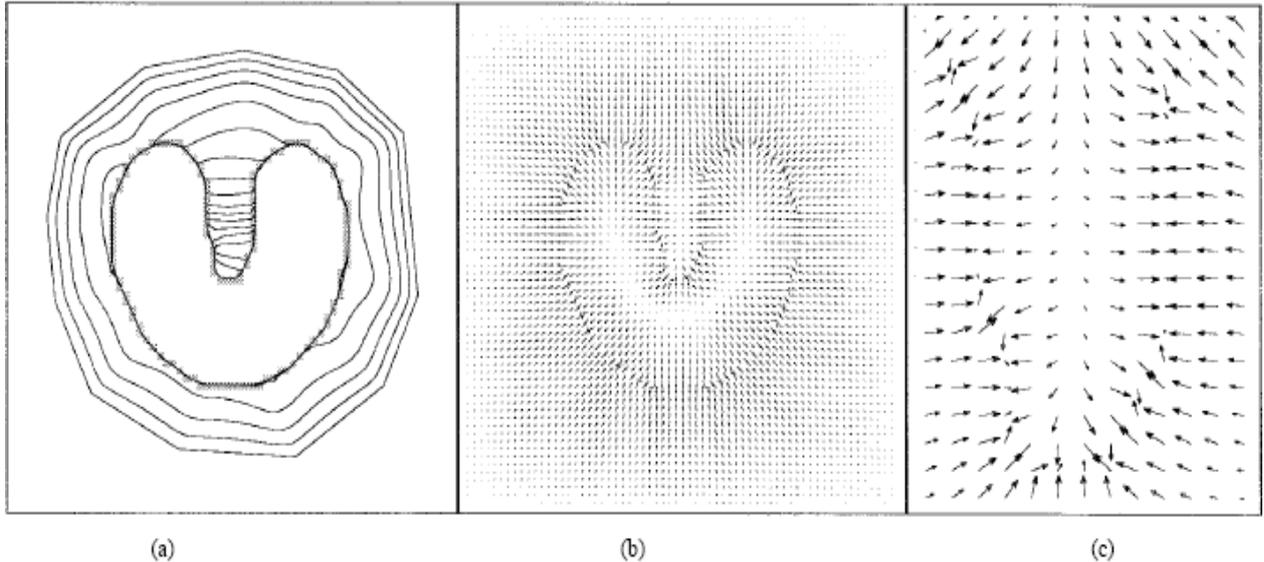
Figure: Gradient Vector Flow [69]. (a) Deformation of the snake. (b)GVF image force. (c) Close-up of the concave part of the boundary.
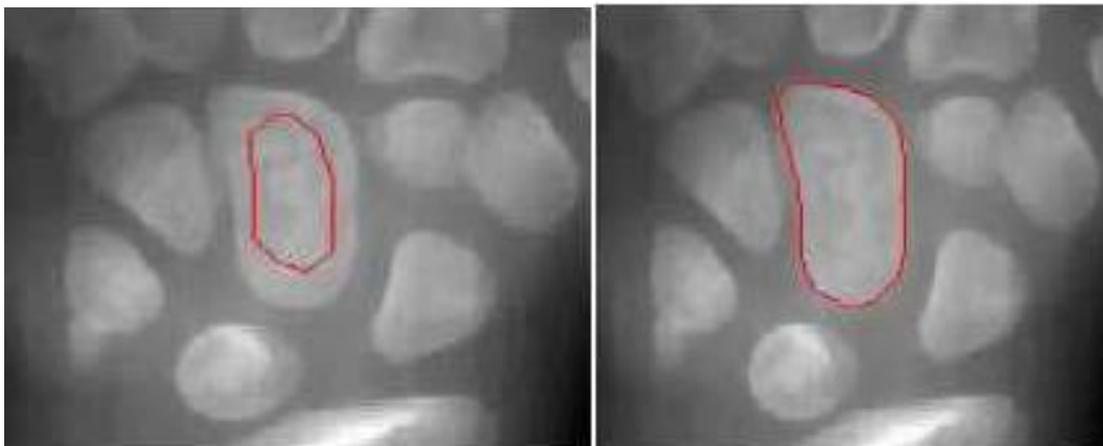

Figure Carpal bone segmentation using snake algorithm. (a) Initial contour. (b) Final result.

If the snake is well designed and the three forces are well balanced, the snake can perfectly fit the boundaries of anatomical parts. However, if the parameters are not set appropriately, snake can produce poor result. Even with GVF, the snake algorithm is still sensitive to noise and requires good initialization in general. Moreover, snake cannot handle topological changes when it evolves over time.

2.2.2 Atlas-Based Approach

Atlas-based approach has become a standard paradigm for exploiting prior knowledge in medical image segmentation. In atlas-based segmentation, manual or semi-automatic segmentation is performed once on a sample image to construct a spatial map called the atlas. Given a target image, the atlas is deformed non-rigidly and registered to the target image. Various non-rigid registration methods can be used in the registration process. The registered atlas gives the segmentation result.

In general, the atlas-based approach first aligns the atlas to the target image by some global transformation. Then, local refinement of each part of the atlas is performed to accurately extract the contours of the anatomical parts of interest. Ding et al. applied a robust and automated method of registering 2D atlas to 2D CT abdominal images. They used ICP algorithm first to perform a global alignment. Then, the distribution of gradient is used to guide the refinement of the contours of each anatomical part. Finally, a snake with gradient vector flow is applied to obtain the final object boundaries. Atlas-based approach has also been applied for segmentation of brain CT images, brain MR images and abdominal CT images.

Constructing atlas based on a single sample may have some problems. Firstly, the selected single sample may not be a typical one. Secondly, the atlas based on a single sample cannot contain any information of variability. So, it cannot determine whether a deformed shape is an acceptable shape. Probabilistic atlas was proposed to solve these problems. The probabilistic atlas is constructed by a set of training samples. It represents the spatial distribution of probability that a pixel belongs to a particular organ. The active shape model can be used in a probabilistic atlas. By exploiting prior knowledge properly, atlas-based approach can solve the initialization problem of most deformable model approaches. It can also handle medical images with low contrast and inhomogeneous visual features since it knows the desired shapes of the anatomical parts. Therefore, atlas based approach has the potential of solving very complex medical image segmentation problem. The difficulty of using atlas-based approach lies on the construction of an appropriate atlas.

Figure : An example of atlas-based approach. (a) Atlas contours (white curves). (b) Atlas registered onto the target image after global transformation. (c) The result of local refinement. (d) Final result after applying snake algorithm.

III. CONCLUSIONS

Snake do not handle topological changes as the model contour evolves over time, while level set is designed to handle topological changes. Training samples are needed for atlas-based methods. Most of the general deformable model-based approaches are sensitive to initialization because they do not have the prior knowledge of the anatomical structures. Atlas-based approach can solve the initialization problem by constructing an atlas from proper prior knowledge. Registration methods, including deformable model approaches, can be used as part of atlas-based approach to accurately locate the contours of the objects of interest in the target image. The difficulty of using atlas-based approach lies on the construction of the proper atlas. A simple atlas is easy to build but may have limitations in segmenting complex medical image. On the other hand, building a complex atlas that contains a rich amount of prior knowledge is tedious. Registration-based segmentation methods include general deformable model based methods (snake, active shape and level set) and atlas-based methods. These methods can segment complex medical images with inhomogeneous visual features and low contrast. They are less sensitive to noise compared to general segmentation algorithms. Therefore, registration-based segmentation methods are widely used in complex medical image segmentation applications.

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