Current Methods in Medical Image Segmentation: A Review

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***Abstract*—In this paper, different approaches are discussed for medical image segmentation. These are based on thresholding, learning, modeling and automatic fuzzy method. Segmentation techniques, discussed under these approaches are used in different applications. In identification of brain lesions, vessel lumen segmentation and histopathology cancer image segmentation. Further used in tissue segmentation based upon image processing chain optimization, combining graph cut and oriented Active Appearance Model (AAM) and in brain image segmentation by using fuzzy symmetry. These techniques overcome various limitations of conventional medical image segmentation techniques.**

Keywords: CTA, MRA, MRI, Segmentation, Thresholding

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments or sets of pixels, which are also known as super pixels. Basically segmentation is used to simplify and/or analyze images [1] [2]. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. In image segmentation process a label is assigned to every pixel in an image and pixels with the same label share certain characteristics. Set of segments obtained as a result of image segmentation and these segments collectively cover the entire image. Image segmentation using thresholding was not satisfactory in medical imaging. Due to the high dimensionality of the image relative to smaller sample sizes direct estimation of the statistical variation of the entire volumetric image was challenged, vascular segmentation was not easily possible and automated reconstruction of cortical surface was also the most challenging problem in the analysis of human brain Magnetic Resonance Imaging (MRI). Labeling a histopathology image as having cancerous regions or not was a critical task in cancer diagnosis. Only 2D models were used, 3D models were not compatible in medical imaging.

II. THRESHOLDING BASED SEGMENTATION

Thresholding based segmentation, in which one threshold value is used to select the area of interest and this threshold value can be selected by using prior knowledge or from image information. Further threshold approach can be edge based, region based or hybrid. In edge based approach, edge information is required. Canny edge detector and Laplacian edge detectors work on this approach. Canny edge detector uses the threshold of gradient magnitude to find the potential edge pixels and suppresses them through the procedures of the non - maximal suppression and hysteresis thresholding. In this, the detected edges are consisted of discrete pixels, may be incomplete or discontinuous. So, it is necessary to apply post-processing like morphological operation to connect the breaks or eliminate the holes. Pixels inside a structure tend to have similar intensities and from this observation idea of region-based algorithms developed. Region growing algorithm is a typical algorithm of this type. In this algorithm firstly initial seeds are selected then it search for the neighbored pixels whose intensities are inside the intervals defined by the thresholds and then merge them to expand the regions. Statistical information and a priori knowledge can be incorporated to the algorithms to eliminate the dependence on initial seeds and make the algorithm automatic. For example, a homogeneity criterion was introduced in [3], which made the region growing algorithms adaptive for the different locations of initial seeds.

These algorithms mainly rely on the image intensity information, so they are hard to handle the partial volume effects and control the leakage. Watershed algorithms are typical example of this algorithm [4], which combines the image intensity with the gradient information. In this algorithm, gray scale images are considered as reliefs and the gradient magnitude of each pixel is treated as elevation. Watershed lines are defined to as the pixels with local maximum of gradient magnitude. Segmentation procedure is used to construct watersheds during the successive flooding of the gray value relief. Watershed algorithms can achieve better results due to the combination of image information, but when the images are noisy or the objects themselves have low signal-to-noise ratio these algorithms tend to over-segmentation. Hybrid threshold-based algorithms can further combine with other techniques to perform the segmentation [5]. Due to the noise influence and partial volume effect algorithms based on threshold are seldom used alone because the edges of organs or structures in medical images are usually not clearly defined.

III. LEARNING BASED SEGMENTATION

In learning based approach, there may be use of statistical learning, supervised, unsupervised, can be weakly supervised also. Techniques based upon this approach are following

A. *Individualized Statistical Learning from Medical Image Databases*

This method works on comparison of normative set of images with other images and statistical variation is estimated; as a result abnormalities are identified as deviations from normality. Direct estimation of the statistical variation of the entire image is not possible because of high-dimensionality of images relative to smaller sample sizes [6]. Similarly, large numbers of lower dimensional subspaces are iteratively sampled that capture image characteristics ranging from fine and localized to coarser and more global. Within each subspace, a "target-specific" feature selection strategy is applied to further reduce the dimensionality. Marginal probability Density Functions of selected features (by considering only imaging characteristics present in a test subject's images) are estimated through Principal Component Analysis (PCA) models, in conjunction with an "estimability" criterion that limits the dimensionality of estimated probability densities according to available sample size and underlying anatomy variation.

A test sample is iteratively projected to the subspaces of these marginal's as determined by PCA models, and its trajectory tells about potential abnormalities. The method is used for segmentation of various brain lesion types, and for simulated data on which superiority of the iterative method over straight PCA is demonstrated.

With this method problem of high dimensionality of the image domain relative to the typically available sample sizes get solved by introducing an iterative method for sampling subspace, by incorporating many more images from healthy subjects into the model, the performance of this method could be improved.

B. *3D Vessel Lumen Segmentation Techniques: Features and Extraction Schemes*

The segmentation of vascular structures is particularly valuable for diagnosis assistance, treatment and surgery planning. Segmentation is fundamental step for the accurate visualization of vessels from complex datasets and for the quantification of pathologies. Unfortunately, most angiographic clinical routines still rely heavily on manual operations. Modern 3D imaging modalities are Computed Tomography Angiography (CTA) and Magnetic Resonance Angiography (MRA), manual segmentation can quickly add up to hours of processing. In this context, automatic and semi-automatic image processing tools aim at easing and speeding up reviewing tasks, reducing the amount of manual interaction and lowering inter-operator variability. Vascular segmentation is an especially specific and challenging problem [7].

Besides general, acquisition-dependent considerations about contrast, resolution, noise and artifacts, vascular networks can be particularly complex structures. Blood vessels potentially exhibit high variability of size and curvature. Their appearance and geometry can be perturbed by stents, calcifications, aneurysms, and stenos. Finally, they are often embedded in complex anatomical scenes, surrounded by other organs. Basic components of this method are appearance and geometric models, image features, extraction schemes.

Models correspond to the prior assumptions made on the target vessels, e.g., elongation and hyper-intensity. Features are the vessel dedicated image measures used to estimate the models on the image, e.g. local intensity curvatures. Finally, the extraction scheme represents the algorithmic core of a vascular segmentation method. A way to improve existing algorithms in terms of both performance and automation can thus be the design of new sequential combinations.

C. *Layered Optimal Graph Image Segmentation of Multiple Objects and Surfaces for the Brain*

LOGISMOS-B, based on probabilistic tissue classification, gradient vector flows and the LOGISMOS graph segmentation framework. Quantitative results on Magnetic Resonance Imaging (MRI) datasets from both healthy subjects and multiple sclerosis patients using a total of 16, 800 manually placed landmarks illustrate the excellent performance of the algorithm with respect to spatial accuracy. Even in the presence of multiple sclerosis lesions, average signed errors were only 0.084 mm and 0.008 mm for white and gray matter respectively. Observation from statistical comparison gives that LOGISMOS-B produces a significantly more accurate cortical reconstruction than Free Surfer [8], the current state-of-the-art approach.

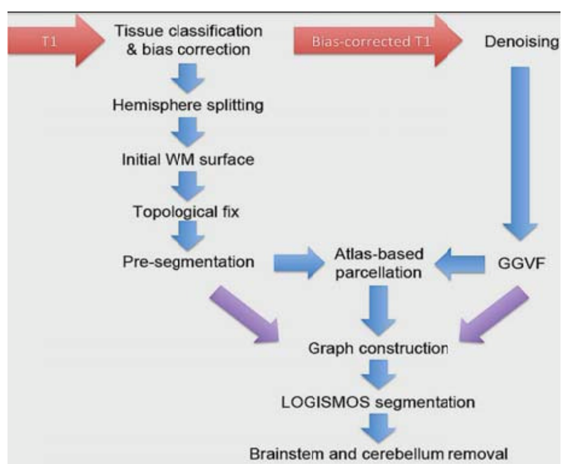

Fig. 1 Pipeline Overview

Furthermore, LOGISMOS-B enjoys a run time that is less than a third of that of Free Surfer, which is both substantial, considering the latter takes ten hours per subject, and this method provides statistically significant speedup. Cortical segmentation method LOGISMOS-B1 consists of four main steps that are Pre processing of raw image to create a rough preliminary segmentation; graph construction; LOGISMOS segmentation; and post-processing for removal of brain stem and cerebellum. An overview of the pipeline is given in Fig. 1. This method offers improved anatomic accuracy and dramatically reduced computational requirement.

D. *Weakly Supervised Histopathology Cancer Image Segmentation and Classification*

Labeling a histopathology image as having cancerous regions or not is a critical task in cancer diagnosis. It is also clinically important to segment the cancer tissues and cluster them into various classes. Existing supervised approaches for image classification and segmentation require detailed manual annotations for the cancer pixels, which are time-consuming to obtain.

A new learning method, Multiple Clustered Instance Learning (MCIL) for histopathology image segmentation. MCIL method simultaneously performs image-level classification (cancer vs. non-cancer image) as shown in Fig. 2. medical image segmentation (cancer vs. non-cancer tissue), and patch-level clustering (different classes [9].

Under this concept, Multiple Instance Learning (MIL) performs the above three tasks in an integrated framework. In addition, under this contextual constraints are introduced as a prior in MCIL, which further reduces the ambiguity in MIL. Experimental results on histopathology colon cancer images and cytology images demonstrate the great advantage of MCIL over the competing methods.

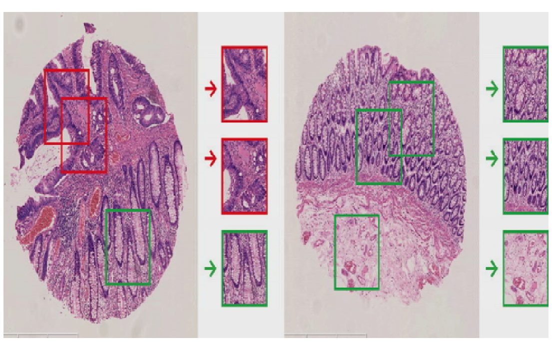

Fig. 2 Cancer and Non Cancer Images

The advantages of MCIL are evident over the state-of the- art methods that perform the individual tasks, which include easing the burden of manual annotation in which only image-level label is required and perform image-level classification, pixel-level segmentation and patch-level clustering simultaneously. In addition, we introduce contextual constraints as a prior for MCIL which reduces the ambiguity in MIL. MCIL and contextual MCIL are able to achieve comparable results in segmentation with an approach of full pixel-level supervision in experiment. This will inspire future research in applying different families of joint instance models to the framework of MIL/MCIL, as the independence assumption might be loose.

IV. Model Based Segmentation

A. *Statistical Shape Models for 3D Medical Image Segmentation*

Nowadays, model-based segmentation approaches have been established as one of the most successful methods for image analysis by matching a model. Model contains information about the expected shape and appearance of the structure of interest to images, in this segmentation is conducted in a top-down fashion. This method is more stable against local image artifacts and perturbations than conventional low-level algorithms. While a single template shape is an adequate model for industrial applications where mass produced, rigid objects need to be detected, this method is prone to fail in case of biological objects due to their considerable natural variability [10]. Information about common variations thus has to be included in the model.

A straight-forward approach to gather this information is to examine a number of training shapes by statistical means, leading to Statistical Shape Models (SSMs). Training data for SSMs in the medical field will most likely consist of segmented volumetric images. Depending on the segmentation method used, the initial representation can be in form of binary, voxel data, fuzzy voxel data (e.g. from probabilistic methods), or surface meshes. Data originating from other sources of acquisition, e.g. surface scanning might be represented differently. In any case, all shape representations can be converted into each other, and the choice of shape representation is the first fundamental decision when designing statistical shape models. Most of the subsequent steps depend on this initial decision, and many methods are technically limited to certain representations, include constructing shape models which is basically extracting of the mean shape and a number of modes of variation from a collection of training samples. Obviously, the methods employed strongly depend on the chosen shape representation. After this Shape correspondence that is basically modeling the statistics of a class of shapes requires a set of appropriate training shapes with well-defined correspondences.

Depending on the chosen representation, the methods of how to best define these correspondences vary. In any case, establishing dense point correspondences between all shapes of the training set is generally the most challenging part of 3D model construction, and at the same time one of the major factors influencing model quality (the other one being the local gray-value appearances).After construction the model is fitted to new, previously unseen data. For this purpose, a model of the appearance of the structure of interest is required to be trained from sample data, due to the large size of the search space in 3D, most methods applied to locate an SSM in new image data use local search algorithms that require an initial estimate of the model pose.

B. Medical Image Segmentation by Combining Graph Cuts and Oriented Active Appearance Models

This method is combination of active appearance model (AAM), Live Wire (LW) and Graph Cuts (GCs) for abdominal 3D segmentation of organs. This method consists of two phases training and segmentation. In training phase AAM algorithm is constructed and LW boundary cost functions and GC parameters are estimated, and segmentation phase consists two main parts recognition or initialization and delineation [11].

In the recognition step, a pseudo-3-D initialization strategy is employed in which the pose of the organs is estimated slice by slice via a multi object OAAM (MOAAM) method. In the delineation part object shape information generated from the initialization step is integrated into GC cost computation.

C. Fuzzy C-Mean (FCM) Method for Segmentation of Brain MRI Image

In this method, with the help of Self Organizing Map(SOM) clustering algorithm initial cluster centers are selected, after many iterations of this algorithm final cluster centre is obtained. The winning neural units and their corresponding weight vectors from each layer result in an abstraction tree. A particular region of the image at a certain level of abstraction is represented with one node of this abstraction tree [12]. Under this segmentation is performed on demand by transverseing the abstraction tree in Breadth-First Search(BFS) manner starting from root node until certain criteria is satisfied. If the sum of variances of weight vector divided by size of weight vectors is less than element of weight vector if the size of abstraction tree is expanded else the node is labeled as closed node and regions corresponds to closed nodes constitute a segmented image.

D. LVQ Method for Segmentation of Brain MRI Image

Linear Vector Quantization (LVQ) technique is supervised learning technique obtain decision boundaries based upon training data .In this method three layers are there input, competitive and output layer [12]. Input data is classified in the competitive layer and then those classes or patterns are mapped to the target class in the output layer, under this winner neuron is selected based upon the Euclidean distance then weights of this winner neurons can be adjusted by using different algorithms.

E. SOM and Hybrid SOM Method for Segmentation of Brain MRI Image

In SOM method, firstly find the winning neuron and secondly updating weight of the neuron and its neighboring pixels based upon input [12]. Hybrid SOM combines self organization and topographic mapping technique.

F. Markov Random Field (MRF) Model and Fast Fourier Transform (FFT) Based Segmentation for Segmentation of Brain MRI Image

In Markov Random Field model neighborhood information is used, because most neighborhood pixels are in same class as a result influence of noise decreased [12]. FFT based segmentation used in brain segmentation because in all tumors boundaries between active and necrotic part are not clear, for this radix 4 FFT partitions Discrete Fourier Transform (DFT) into four quarter length DFT's of groups of every fourth time sample, total computational cost reduced by these FFT outputs which are reused for computing the output.

G. Tissue Segmentation in Medical Images Based on Image Processing Chain Optimization

Differential evolution method is purposed to optimize an image processing chain .In this method training is based upon three sample images provided by an expert [13]. Mainly Differential Evolution(DE) method is population based optimization method, idea behind DE is generating trial parameter vectors, for every vector in the population, DE selects randomly two other vectors, subtract them and add the weighted difference to randomly chosen third vector(base vector) to produce mutant vector, cross over rate (user defined value) is used for every vector in mutant population to control the fraction of parameter values that are copied from the mutant and target vector to trial vector, if trial vector have equal or lower fitness value than that of its target vector, then it replaces the target vector in next generation, otherwise target retain its place for at least one more generation, steps are repeated for every vector in population to generate new population.

This method trying to overlap gold images by well known images generated by experts and images processed with this technique.

V. AUTOMATIC FUZZY APPROACH FOR SEGMENTATION

A. MRI Brain Image Segmentation by Fuzzy Symmetry Based Genetic Clustering Technique

Automatic segmentation technique of MRI of brain using new fuzzy point symmetry based genetic clustering technique is proposed, which is able to evolve the number of clusters present in the data set automatically [14]. In this assignment of points to clusters are based on point symmetry based distance rather than the Euclidean distance and because of this, proposed algorithm Fuzzy Variable string length Genetic Point Symmetry(Fuzzy VGAPS) enable to identify any type of cluster irrespective of its shape size convexity and this method automatically evolve the clusters.

VI. Conclusion

In this paper, various segmentation techniques applied for medical images are briefly explained. All the discussed techniques overcome various limitations occurred in medical image segmentation like direct estimation of the statistical variation of the entire volumetric image, vascular segmentation and in the analysis of human brain magnetic resonance imaging(MRI) automated reconstruction of cortical surface was the most challenging problem. Labeling a histopathology image as having cancerous regions or not was a critical task in cancer diagnosis. 3D models were not compatible in medical imaging. Performance of these medical image segmentation techniques can be improved in future by incorporating many more images from healthy subjects into the models, by the design of new sequential combinations of different methods, for more optimization many algorithm can be added in pre and post processing phases, combination of graph cut and OAAM can be improved by introducing parallelization and by incorporating the spatial information.

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