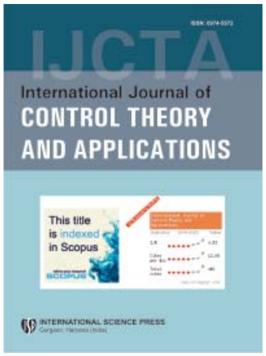

International Journal of Control Theory and Applications

ISSN : 0974–5572

Volume 9 • Number 40 • 2016

Segmenting Abdominal CT Images using Localized Active Contour Model

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Abstract: Medical Image Segmentation is an important image processing technique that divides an image into contiguous regions or segments and used to locate objects and boundaries such as lines, curves, etc. in images. Applications of Medical Image Segmentation include the study of anatomical structure, localization of pathology, quantification of tissue volumes, treatment planning, and computer-integrated surgery. But problems such as noise, variation of contrast, in-homogeneities in Region of Interest arise during the segmentation process results inaccuracy. The paper addresses a methodology which is using Localized Region Based Active Contour model for efficient segmentation. However, its performance is highly dependent on appropriate contour initialization. This approach consists of two stages. First, the abdominal CT image slices are pre-processed using log filter. Then, localized region based Active Contour technique is used to segment the kidney regions from the pre-processed image. For this, the input image is masked and considerable segmentation accuracy is achieved through number of iterations. This methodology can be done on medical images from different modalities.

Keywords: *- Medical, Image Segmentation, Active Contour, Computed Tomography.*

1. INTRODUCTION

Image Segmentation [4] is one of the most important issues in computer aided medical imaging. Image Segmentation techniques enable the design of semi-automated and automated segmentation techniques. Segmentation methods are dependent on two important features of intensity similarity and discontinuity. First, the method is to divide an image based on abrupt variation in edge intensity. Second, the method is to partition an image into regions that are similar according to predefined criteria. Regions are disjoint with some property for each region such as pixel intensity, gray level texture, or color, etc.

Image segmentation techniques are used in the analysis and diagnosis of numerous applications such as the study of anatomical structure, localization of pathology, and quantification of tissue volumes, treatment planning, and computer-integrated surgery. Segmentation plays a major role in medical image processing, particularly for abnormalities detection in Computed Tomography (CT), Magnetic Resonance Image (MRI), Computed Radiography (CR), and Ultrasonography (US). These technologies have increased our knowledge of healthy and diseased anatomy and are critical components in diagnosis. In medical image processing, an image is captured, digitized and filtered for segmentation and extracting required information. Image segmentation is still a challenging task for researchers and developers to develop a universal technique for image segmentation. Manual segmentation methods generate errors. These methods are time-consuming. Segmentation by the expert is variable. So, there is a high need to have an efficient computer-based system that accurately examines the boundaries of organs with a minimum interaction of user interface.

Segmentation of medical images identifies the human anatomy structures. Image segmentation is a fundamental process in medical image analysis to interpret medical images. Learning how to segment anatomic structures is a significant part of Medical Image Segmentation [1,2,3,4,10]. The Medical Image Segmentation is not trivial because of the variability and complexity of the Region of Interest, poor contrast, complex nature of medical images, different imaging modalities, image features and dimensions, incomplete boundaries, artifacts, noise, and intensity inhomogeneity [11]. In medical imaging applications, to get better segmentation performance, efficient and practical algorithms need radiologists to adjust segmentation parameters. Most computerized systems work semi-automatically or interactively because of the complexity of parameter adjustment in the Medical Image Segmentation. So, many works have been made to make the segmentation efficient and automatic. Machine learning provides sufficient means for this purpose.

The technique behind Active Contour is to deform contour and to minimize a given energy function for better segmentation [5-9]. Two classifications of active contours are edge-based and region-based.

Edge-based active contour methods are used to identify object boundaries [12,13]. But these methods are highly sensitive to noise and also dependent on initial contour selection. The second category of the region-based method is identifying the image region assuming the regions with similar intensities [14-17].

This paper is organized into four sections. The next section discusses Related Work. Section 3 presents the methodology for medical image segmentation and Section 4 discusses experiments and results. Finally Section 5 concludes the paper.

2. RELATED WORK

S.N. Kumar et. al. [23] presented a neural network based automatic detection of liver in computer tomography images. In their work, they used neural network for the classification of pixels and interested region is extracted using localized region based Active Contour model.

Lankton and Tannenbaum[24] proposed a framework using energy localized with region-based segmentation.

Boying Wu and Yunyun Yang [25] suggested a methodology for image segmentation based on local-and-global-statistics Active Contour model.

P.V. Kishore [26] et. al. [26] presented a technique for tumor identification in CT medical images using Semi Automatic Active Contour Models

2.1. Model Based Techniques

Deformable models are used in the segmentation of image domain or the segmentation of higher dimensional image data (stacks of images) by considering curves or surfaces. The images deform under the influence of internal and external forces to delineate object boundary. The internal forces preserve the shape smoothness of the model, while the external forces preserve the image features to drive the model toward the desired position that is to the desired region boundaries. It is difficult for parametric deformable models to adapt the model topology during deformation. However geometric deformable models are designed to handle topological changes.

Two general classes of deformable models are the parametric deformable models and the geometric deformable models. Parametric deformable models referred as snakes or active contour models are represented explicitly as parameterized curves in a Lagrangian formulation. Geometric deformable models are represented implicitly as level sets of two-dimensional distance functions that evolve according to an Eulerian formulation. The deformable model that has attracted the most attention to date is popularly known as 'snakes' (Kass *et al.*, 1988). Deformable curve, surface and solid models gained popularity after they were proposed for use in computer vision (Terzopoulos *et al.*, 1988) and computer graphics (Terzopoulos and Fleischer, 1988).

The classical active contour models have several limitations. One limitation is that the initial contour must be close to the true boundary or it will likely converge to a wrong result. To address this problem, increase the capture range of the external force fields and guide the contour toward the desired boundary. Another limitation is the poor convergence of classical snakes to boundary concavities. The GVF snake is an effective model that can be employed to solve this problem**.**

The second class of deformable models, namely the geometric models, use a distance transformation to define the shape. The geometric deformable models were introduced independently by Malladi et al. and Caselles et al.. The main advantage of parametric models is that they are robust and usually very fast in their convergence, depending on the predetermined number of control points. However, an obvious weakness of these models is that they are topology dependent: a model can only capture a single ROI, and therefore, in images with multiple ROIs, multiple models have to be initialized, one for each ROI.

3. METHODOLOGY

Segmentation process is initiated by the appropriate selection of initial contour on region of interest. tracking boundary. As medical images which are corrupted by heavy noise, and other imaging artefacts. The localization based Active Contour model is used for automated medical image segmentation. This method automates the initialization with number of iterations for efficient segmentation.

3.1. Pre-processing

In the pre-processing stage, the log filter is used for noise removal. Noise detection and noise removal operations results enhanced image after applying Log filter.

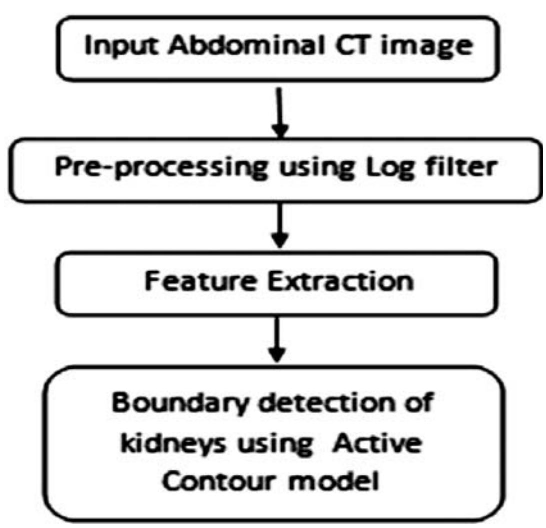

Figure 1: Methodology

3.2. Binarization

After pre-processing, pixel intensities greater than 100 were turned to white and pixel intensities lesser than 100 were converted to black. The resultant image with foreground region of interest and unimportant regions were turned to black.

3.3. Feature Extraction

Features such as local features and texture features are extracted for the segmentation of kidneys from abdominal CT images. Some of the local features are mean, variance, local minimum, local maximum, spatial feature of pixels and texture features are contrast, intensity, energy and homogeneity.

3.4. Localized Active Contour Model

For effective detection of kidney regions, the local features are extracted and then contour is placed on the region of interest. The contour is growing with the regions-based on intensity and this process is the iterated number of times for efficient segmentation. The localized region based active contour model is tracing the boundary of the kidney regions. This technique is comparing the intensity inside the contour region with the outer neighborhood pixels and increasing the contour if they are identical.

4. EXPERIMENTS AND RESULTS

4.1. DataSets

The abdominal CT images for five patients have acquired for this study with 0.6mm slice thickness. Each CT image consists of 300 to 500 slices and enhanced image slices from each data set are used for this analysis.

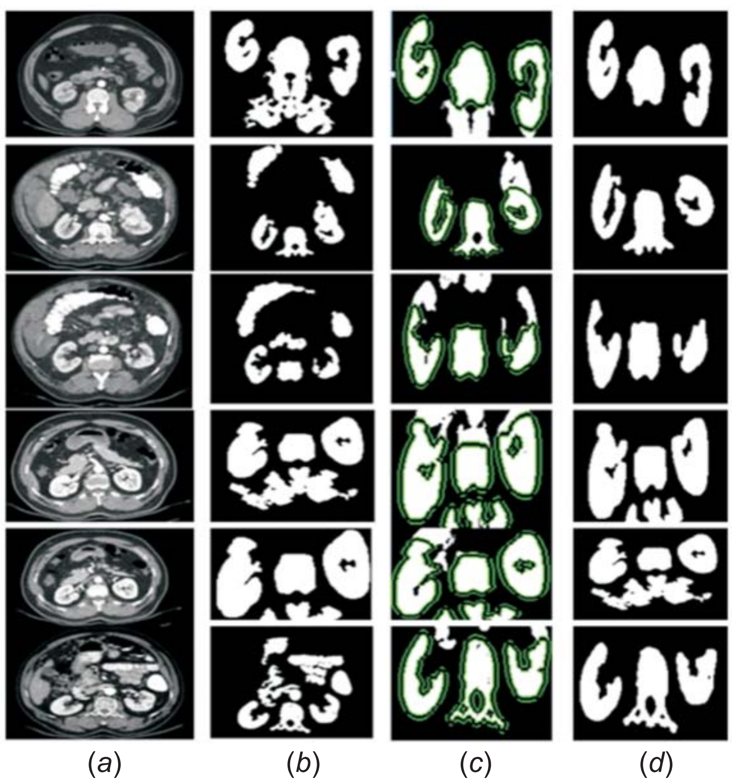

Figure 2: Localized Region Based Active Contour Segmentation

1. Input CT image
2. Binary image
3. Boundary image using contour
4. Segmented image

5. CONCLUSION

The proposed Segmentation algorithm is a better approach for automated segmentation of medical applications. The proposed algorithm eliminates the problems in manual segmentation. In this paper, we focused on a construction of automated image segmentation method that deals with multi-modal medical images. The proposed algorithm is more robust to noise and retains computational simplicity. The potential areas for further research would be Developing a hybrid segmentation scheme that performs segmentation of medical images to yield superior performance by evaluating parameters and optimization of algorithms by parallel segmentation to reduce its segmentation time.

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