Overview of Medical Image Segmentation Process of Selected Magnetic Resonance Images; Manual Segmentation and Active Contour/Snake Model

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Abstract— Image segmentation is the procedure which differentiating a digital image into segments and enables meaningful images. Image segmentation also locates objects and boundaries by labeling each pixel. Image segmentation is part of image processing and it is a fundamental step to analyze images. This is mid-level technique in image processing event. It is a fundamental step and overall quality of the image directly depends on image segmentation. There is a different type of methods available for image segmentation such as manual segmentation, intensity-based methods, discontinuity based methods, similarity-based methods, clustering methods, graph-based methods, Pixon based methods and hybrid methods. Different types of segmentation techniques are used for segmentation. Based on the application, a single or a combination of segmentation techniques can be applied to solve the problem effectively. This report evaluates the manual and active counter/snake methods in a medical imaging context by use of commercially available MATALB.
Key words: Image segmentation, MRI, Image processing, Active contour, Manual Segmentation, Snake model

I. Introduction

Medical image data play a central role in diagnosing of diseases; there are various medical imaging modalities available such as X-ray, Computed Tomography (CT), Magnetic Resonance Imaging (MRI) and Ultrasound. Among those modalities MRI play an important role in medical imaging sciences because it provides soft tissue detailed image at a high resolution of living tissues, MRI raw data helps to detect tissue deformities such as cancers and other different pathological conditions [1].

In order to perform good quantitative studies, within the region of interest it must be well defined. There are many problems associated with quality of the image because almost all the initial data of images are noisy, and some of the data is not that much adequate to visualize, therefore image processing is crucial for the medical purpose. The big challenge of medical image process is in image segmentation, because image segmentation defines boundaries of the region of interest where abnormal tissues also there, so the accuracy of segmentation techniques provide exact size of abnormal tissue, such techniques make precise of treatment plan especially in cancer therapy [2].

Since there are many proposed techniques available for image segmentation, however, the selection of technique depends on modalities, applications and anatomical area. Artifacts are also big challenges on the quality of the image; because it may lead to misinterpretation of disease, common artifacts also significantly influence the process of image segmentation [3]. The segmentation has two objectives, first one is to decompose an image into regions for further analysis and the second one is to perform a change of representation of an image for faster analysis [4].

Completely manual segmentation method would be to draw the desired borders directly onto the raw image. The user can pick intensity by pointing to a pixel it will be a border of segmentation. The major challenges are, it will take too much time and be prone to errors, especially due to fatigue. Manual segmentation has both advantages and disadvantages; however, it is entirely based on human factors [5].

Automatic segmentation techniques categorized as either supervised or unsupervised [6]. The supervised method needs operator interaction in the whole process but unsupervised methods required only after finished the process even though operator interaction needed for error correction if there is any inadequate outcome [7].

There is no standard algorithm for segmentation. Each imaging system has advantages and disadvantages, few methods are more general as compared to specialized algorithms and can be applied to a wider range of data [8]. In this paper general MATLAB code used to analyses segmentation techniques.

II. Methodology

The mathematical functions have been used to test the manual, active counter and snake methods. For each test, two different transversal images of human artery taken from MRI has been used see

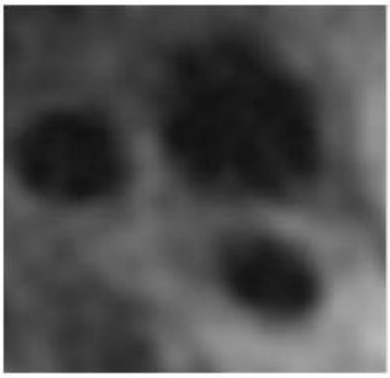

Fig. 1: Axial image of human artery-T1W

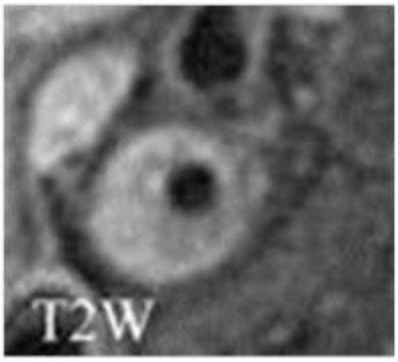

Fig. 2: Axial image of human artery-T2W

figure 1 & 2. Those images are analyzed by MATLAB.

Following steps carried out to analyses manual segmentation of figure 2

Following MATLAB code used to detect edges

```
clear;
close;
I = imread('Figure.2.jpg');
min_thr = 0.0;
max_thr = 50;
I_th = threshold_seg(I, min_thr, max_thr);
%edge detection
I_edge = sobel_bru(I_th);
figure;
imshow(I_edge,[]);
```

Once edge detected following MATLAB code used to get point coordinates

```
hold on;
xy = [];%xy store the coordinates
  n = n+1;
  xy(1,n) = xi;
  xy(2,n) = yi;
end
```

Following MATLAB bode used to perform active contour/snake model of figure 1 and figure 2

```
clear;
I = imread('Figure.1 or 2');
xy = snake_bru(I,0.05,0,10);
xy = snake_bru(I,0.05,0,10);
```

xy: the coordinates for the points in the boundary

Snake_bru: function for snake

There are many edge detection techniques available

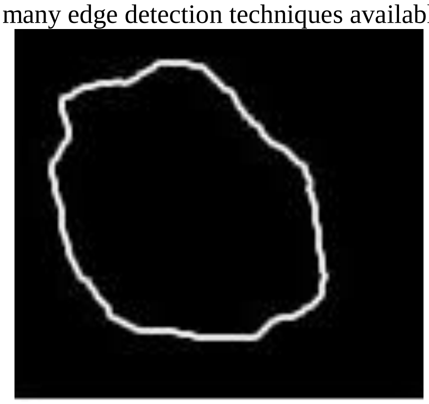

Fig. 3: Edge detected after Sobal

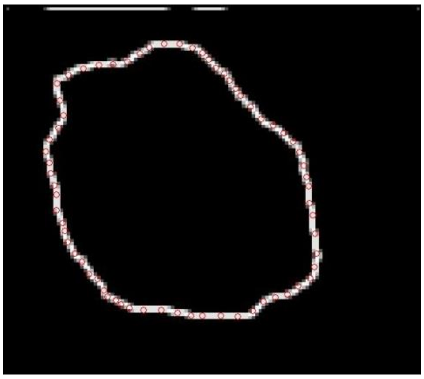

Fig. 4: Located the region of interest after Sobal

I: the image you want to use snake deform model

0.5: α coefficient, 0.5: β coefficient

10: iteration number, it decides how many times you will run. In the program, left click to pick the point, and right click to finish the initial boundary definition

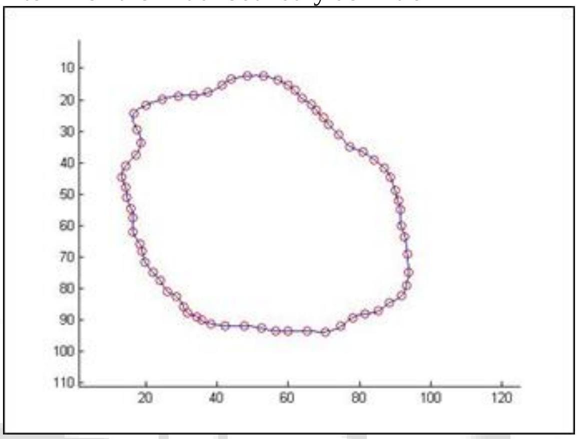

Fig. 6: Initial countour before activated

III. RESULTS AND DISCUSSIONS

A. Manual Segmentation

such as Sobel, Prewitt, Roberts, and Laplacian, here Sobel method used to detect the edge of arterial lumen boundary as seen in figure 3.

Once edge detected another MATLAB code used to get coordinate for the image matrix, the pointer is located in the region of interest and tracked along the edges while point coordinates stored as seen in figure 4. Subsequently, the segmented area was displayed on XY axis as seen in figure 5.

Manual segmentation has many disadvantages than advantages because the segmentation methods may suffer from observer bias.

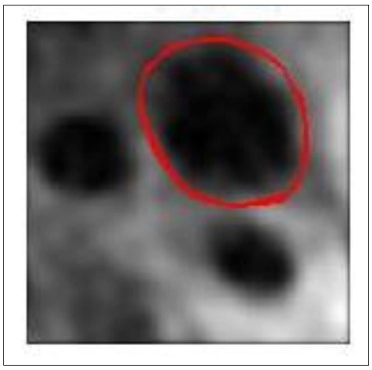

Fig. 7: Initial contour after activated

Manual segmentation needs proper training and knowledge to end user about the region of interest, the user needs to pay attention about volume estimation and expected the size and any other significant outcome such as noises.

Manual Segmentation consumes time and it is not suitable for a large number of cohort image segmentation, long duration of work is great challenging on accuracy. Manual labeling may lead to inconsistent labeling across the area [9]. Detecting boundaries mainly depend on anatomical landmarks and few other features of the region, there are limitations and challenges with almost all the techniques. These challenges can be reduced by high technology such as high field (7T) MRI system [10].

B. Active contour and Snake

An active contour is based on energy minimizing procedure which will detect specified features within an image. It is like elastic circles on the surface of an image which can be dynamically moved depend on the number of iterations given by the user.

It is initially set by control points connected by lines between each point it is known as initial counter. (Figure- 6) The contour will then be attracted to features in the image extracted by internal energy creating an attractor image (Figure.7) [11]. It is observed there is three major challenges concern with traditional active contour methods. First of all, due to the external energy limitation of the traditional model, during the initial outline is not close to the actual target edge, it's easy to converge at a wrong edge. Second, of all, the application on the highly concaved area the outline is hard to fix with the exact outline. Finally, the changes of topology of the medical image are complex due to various tissues; therefore, it is difficult to divide accurately [12].

In the medical image manual segmentation solve the issues mainly based on those three challenges, there are several numerical applications to overcome the problem, the applications are specific to each region, one of the common approaches is the standard deviation (σ) has to be a small number, which results in a Gaussian power capacity can only be attracted the model to the border of object close to initial border. However, the active contour/snake model is a well-known image segmentation model which is largely used in various images processing especially in the medical image processing.

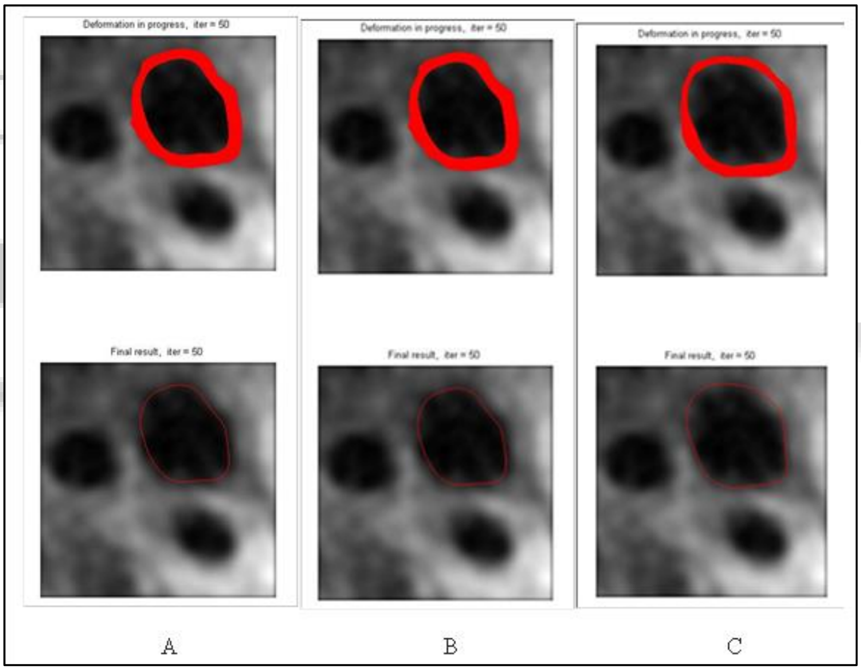

Fig. 8: Initial contour after activated and randomly selected near (A), middle (B) and far (C) filed control points for axial image of human artery-T1W (Fig.1)

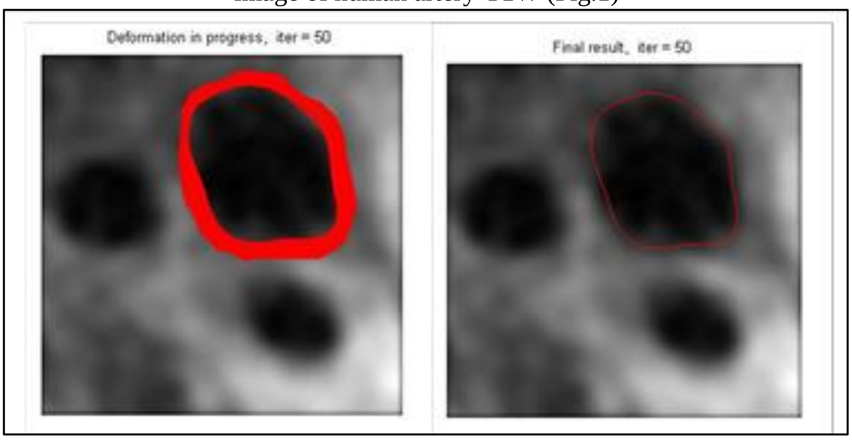

Fig. 9: Initial contour after activated

constant functional values xy = snake_bru (I, 0.5, 0.5, 50); used for all figure 8 A, B and C to check the sensitivities of initial contour. Initial contour at figure 8C, is far from the detecting contour line, the initial contour at figure 8 A is very closer and at middle on figure 8 B. It is observed the snake will follow boundary within the image, and it is very sensitive to initial contour, therefore the curve must be as near as possible to the detecting contour. And also active contour struggled in continuing into boundary where the place is concavities as seen in figure 8 C and figure 9. Number of iterations also doesn't influence significantly in this changes as seen in figure 9.

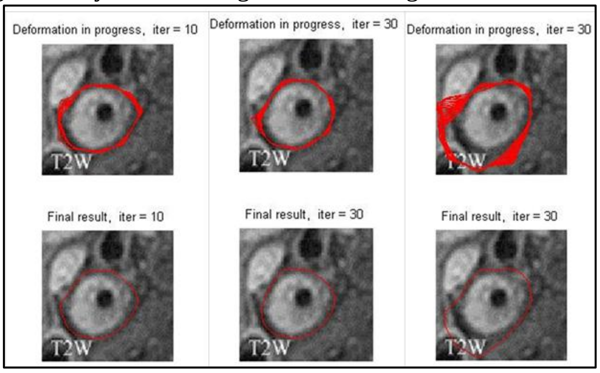

Fig. 10: Initial contour after activated and randomly selected near (A), middle (B) and far (C) filed control points for axial image of human artery-T2W (Fig.2)

Same result has been noticed with the second transvers MRI image of human artery (Figure 2) as seen in the series of figures given below; Figure 10

In the snake model, the boundary should be darker than other areas, if not snake fail to deform to the required boundary. The identified boundary is very sensitive to the initial boundary, so it is recommendable to try with very close initial boundary to the real boundary. Further it is advisable to choose the points for the initial boundary in a reasonable space for α and β, usually, the first derivative is larger than the second derivative, thus a can be smaller than β, while still can specify a different value.

And can obtain the optimal value for α and β for selected processed images, so can try different values. Such as: $0 <= \alpha <= 1$, $0 <= \beta <= 1$, different combinations can give different final results as seen on Figures 8, 9 and 10.

IV. Conclusion

There are many segmentation methods available however no any gold standard technique available for medical image segmentation, typically comparison of different techniques provides an observational based conclusion. Therefore much work still remains to meet broader needs of standardized protocols and algorithms. Because there is a different type of imaging modalities needs to address such microscopic images, microarrays, and other radiology modalities. This study found that manual tracing is more dependent on human factors and provide practical information for making decisions in the choice of snake model.

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