ARGDYP: AN ADAPTIVE REGION GROWING AND DYNAMIC PROGRAMMING ALGORITHM FOR STENOSIS DETECTION IN MRI

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ABSTRACT

In this paper, a novel image analysis algorithm *Adaptive Region Growing and DYnamic Programming* (ARGDYP) is proposed for stenosis detection in Magnetic Resonance (MR) images. ARGDYP combines an adaptive region growing method for 3-D vessel tracking and a dynamic programming approach for 2-D vessel boundary detection. Our experiments based on both real and simulated MR data show that the proposed algorithm is able to accurately measure the cross sectional area of a blood vessel and thus determine whether or not there is a stenosis.

1. INTRODUCTION

Magnetic Resonance Imaging (MRI) is a powerful tool to non-invasively image the blood vessels in the human body. Recently the study of the carotid artery that supplies the major portion of blood to the brain has attracted a lot of attention in MRI research [1]. To determine whether or not there is a stenosis, a narrowing or constriction of the cross sectional area of a carotid artery, it is crucial to determine the cross sectional area of the vessel as a function of position in MR images. If the stenosis is more severe than 70%, an operation is needed [2].

In this paper, we propose a novel image analysis algorithm: ARGDYP for stenosis detection in MR images. ARGDYP consists of adaptive region growing based vessel tracking in 3-D images and dynamic programming based boundary detection in 2-D slices. Specifically ARGDYP first traces the whole vessel in the 3-D image and highlights it in each 2-D slice, then tracks the boundary on each slice to measure the cross section area. Finally the ratio of cross section area in different slices is compared to see whether a stenosis happens.

The rest of the paper is organized as follows. In Section 2, we briefly review related works and provide our motivation through an illustrative example. Section 3 describes the complete ARGDYP algorithm in details. We present our experimental results on both real and simulated MR data in Section 4. Section 5 concludes the paper.

2. RELATED WORKS

Vessel tracking is the key components of automated radiological diagnostic systems. A variety of methods have been proposed in the literature for vessel tracking and boundary detection in MR images [3, 4, 5]. The simplest class is the intensity-based thresholding (IBT) method that classifies points as either greater or less than a given intensity [6]. IBT methods are often achieved by applying statistical classification methods to the signal intensities, or in conjunction with morphological image processing operations. Thresholding on MR images for vessel tracking is proven problematic, however, even when advanced techniques such as non-parametric, multi-channel methods are used. It suffers errors due to image intra-scan intensity inhomogeneities.

Region growing technique segments image pixels of an object into regions. Two pixels can be grouped together only if they have the same intensity characteristics and they are close to each other. Recently Yim et al [7] proposed a gray-scale skeletonizing method for the detection of vessel paths and the determination of branching patterns of vascular trees from magnetic resonance angiography images. Their approach are based on the ordered region growing algorithm that presents an image as an acyclic graph, which can be reduced to a skeleton by specifying vessel endpoints or by a pruning process.

In general, the region growing methods are more mature and their results are more reliable when compared with thresholding approaches because of user interaction. However the conventional region growing method only consider the grouping criterion in “global” sense and thus can not achieve ideal result in vessel tracking, which is illustrated in the following example.

We apply conventional region growing on one MR image set. To present the image better, we perform Maximum Intensity Projection (MIP) on this image set. MIP is a method that records the maximum intensity among all slices for each coordinates. The effect looks like penetrating the images. The MIP image of this image set in sagittal plane (y,z) is shown in Figure 1 and the MIP on transverse plane (x,y) is shown in Figure 2.

Assume that we are interested in the vessel at the right hand. The conventional region growing results are highlighted in both MIP images. We can see clearly that the interested vessel is differentiated from other vessels. However the growing stops too early and some pixels that belong to the vessel area are not included. The underlying reason is that the signal strength drops as the time passes during MR image acquisition process. This is reflected in the images that the average intensity in the cross section changes in adjacent slices. The characteristic of MR images must be considered in the algorithm to achieve satisfactory results.

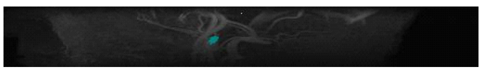

Fig. 1. Maximum Intensity Projection (MIP) in sagittal plane (y, z) after region growing, and the vessel is highlighted in green.

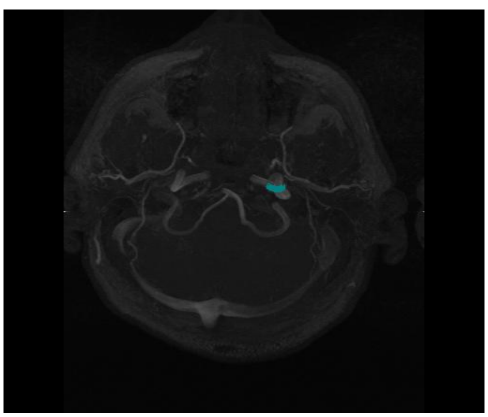

Fig. 2. Maximum Intensity Projection (MIP) in transverse plane (x, y) after region growing, and the vessel is highlighted in green.

3. ARGDYP

3.1. ARGDYP overview

In this paper, we propose an Adaptive Region Growing and DYnamic Programming (ARGDYP) algorithm for vessel tracking and boundary detection. Our algorithm design is based on the nature of human body and MRI mechanism, which are summarized as follows:

- The intensity inside the vessel usually has higher value than in the boundary.
- The average intensity in the cross section changes from one slice to the next slice.
- The vessel has tubular shape in 3-D and the smooth boundary in the 2-D images.
- Sometimes the edge of vessel in MR images has a large degree of blurring.

The flow chart in Figure 3 shows how ARGDYP algorithm works. After 3-D data set is reconstructed, it traces the whole vessel in the 3-D image and highlight it, then tracks the boundary on each 2-D slice to measure the cross section area. Finally the algorithm compares the ratio of area in different slice to see whether a stenosis happens.

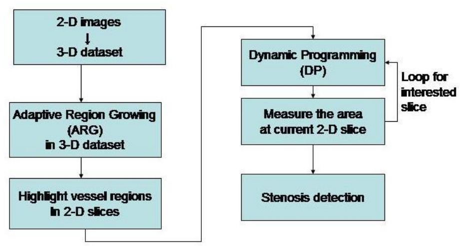

Fig. 3. Flow chart of Adaptive Region Growing and DYnamic Programming (ARGDYP) algorithm

In the following, we discuss the two major steps, adaptive region growing and dynamic programming in greater detail.

3.2. Adaptive region growing algorithm

The adaptive region growing utilizes the fact that the points inside the vessel have higher intensity than in the boundary and the signal strength drops as the time passes by. We compensate the signal strength dropping by calculating the standard deviation from intensity distribution of the local vessel area.

Adaptive Region Growing (AGR) algorithm is implemented by the following steps:

1. Prompt user to choose one area inside the vessel, calculate the standard deviation of intensity value in the area and store it into variable $regionsd$;
2. Prompt user to chose one point as seed point, and store its intensity in $seedintens$.
3. Check each neighbor of the seed point, if its intensity is inside the range $(seedintens - k \times checksd, \infty)$,

count it as a vessel point, where $checksd$ stores the current local standard deviation and is initialized by $checksd = regionsd$. k is a constant and $k = 2$ gives the best results in our experiment after trying $k = 1, 2$, and 3.

4. After all the neighbors have been checked, calculate the standard deviation of the neighbors, and update $checksd$.

5. After the current seed point is done, find the nearest vessel point in Euclidian distance to the seed point and make it the new seed point. Go back to step 3 until all vessel points have been used as seed points.

3.3. Dynamic programming algorithm

A Dynamic Programming algorithm is applied for boundary detection after ARG algorithm provides us with the initial vessel region. We draw N rays from the center point of the vessel region. The furthest vessel point on each ray is defined as an anchor point and we search $(P-1)/2$ points inward and outward along the ray. In other words, we search totally P points on each ray. The final boundary consists of N points (one point on each ray) and is obtained by maximizing the energy function defined in Equation 1.

An energy function is used to calculate energy $C(r, m)$ for each point r on the m ray. We know the vessel has tubular shape in 3-D and the smooth boundary in 2-D. Also the edge of vessel may have a large degree of blurring in MR images. Thus the energy function has two terms: a derivative term $G(r, m)$ to calculate the gradient and a radius limiting term $R(r, m)$ to avoid leakage and to cut through any potential vessel bifurcations. Specifically we propose to identify the points on the boundary by maximizing the following energy function $C(r, m)$,

$$C(r,m) = \frac{G(r,m)}{G_{max}} - \alpha \frac{R(r,m)}{P} \quad (1)$$

where G_{max} is for normalization and it represents the maximum derivative, and P is the total search points on the ray, also the biggest difference in the radius. α is a constant and represents the relative weighting of gradient term and radius limiting term. In practice, we have found that $\alpha = 0.04$ creates an appropriate balance that leaves enough flexibility for the derivative term to dominate but allows the radius term to keep the arcs varying slowly and prevent leakage.

To maximize the overall energy of the boundary, we need to search all possible combinations for the P points per ray on total N rays. The complexity of the exhaustive search is given by $\Theta(P^N)$, which is intractable for any real MR data. We use Dynamic Programming to decompose the optimal result into discrete stages. For the first s rays, we use the exhaustive search to select s points and put them in $resultSet$. For the next t rays, we check them one by one and add points into $resultSet$ gradually. In our experiment, we set $s = 3$, $t = 1$.

4. EXPERIMENTAL RESULTS

We apply ARGDYP to stenosis detection with real MR data. The experimental results of ARG are highlighted in sagittal plane (y, z) (Figure 4) and transverse plane (x, y) (Figure 5). Compared with Figures 1 and 2, it is clear that the results from ARG is much better than conventional region growing method.

Fig. 4. Maximum Intensity Projection (MIP) of the result images in in sagittal plane (y, z) after ARG by choosing k = 2, and the vessel is highlighted in green.

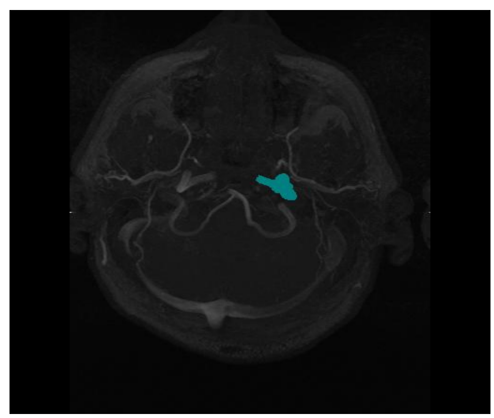

Fig. 5. Maximum Intensity Projection (MIP) of the result images in transverse plane (x, y) after ARG by choosing k = 2, and the vessel is highlighted in green.

Because the vessel begins and ends vaguely during MR scan, we notice that the result from ARG is still not very good at the beginning and ending slices of the vessel. For example, at a beginning slice of the vessel, only a few points near the center position are included (see Figure 6). After deploying dynamic programming algorithm, the vessel detection results are improved significantly (see Figure 7).

Using ARGDYP, we perform extensive stenosis detection experiments based on various simulated MR data with different imaging parameters such as sampling resolution, scan time, and Signal to Noise Ratio (SNR). The detection bias (error in percent) for different sampling matrix sizes

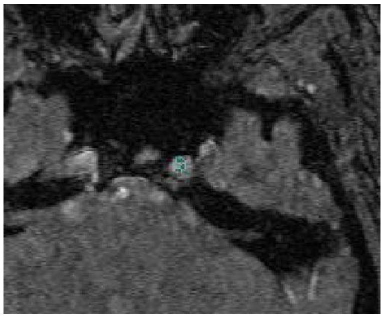

Fig. 6. The 2D image slice (x, y) in the start part of the vessel. The vessel is highlighted in green

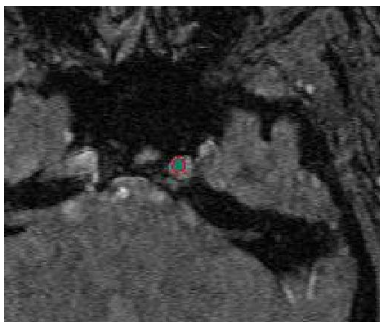

Fig. 7. The result of dynamic programming based boundary detection on the image slice in 6. The vessel is in green with the boundary highlighted in red.

and SNRs is reported in Figure 8. The results suggest that the proposed algorithm is able to make the stenosis detection with an error that is less than 5% (required by the physician in practice) given proper image acquisition parameters. Based on our study, it is also possible to describe how best to collect the data in MRI to be able to determine the vessel's cross sectional area within a certain accuracy.

5. CONCLUSION

In this paper we propose a new algorithm *Adaptive Region Growing and Dynamic Programming* (ARGDYP) to detect stenosis in MR image. ARGDYP consists of vessel tracking in 3-D image and boundary detection in 2-D slice. Our experiment results based on both real and simulated MRI data show that ARGDYP is able to provide stenosis detection with high accuracy.

6. REFERENCES

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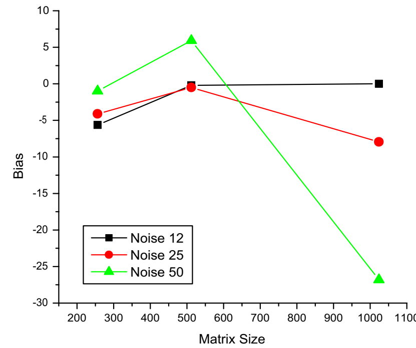

Fig. 8. Bias in percent vs. sampling matrix for a vessel of diameter 64 in 3 different starting SNR levels.

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