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A Systematic Survey and Evaluation of Blood Vessel Extraction Techniques

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Abstract: The automatic extraction of brain vessels from Magnetic Resonance Angiography (MRA) has found its application in vascular disease diagnosis, endovascular operation and neurosurgical planning. In this paper we first present a concise methodology, pros & cons of well-known vessel extraction techniques. A systematic survey of latest development in the area of vessel extraction by using region growing algorithms is present. Then we detail the main challenges of vessel extraction and segmentation area. Based on review and our experience in the area, we finally present enhancement in region growing algorithm. Our proposed algorithm shows performance improvement as compare to traditional region growing algorithm.

Keywords: Image Processing, Segmentation, Region Growing, Medical Imaging, Vessels, MRA

1. Introduction

Segmentation is a process of partitioning an image into regions on the basis of homogeneity of desired features [1]. Segmentation plays key role in the field of medical imaging and is applied in numerous applications i.e. extraction of blood vessels, detection of tumors, image registration, atlas matching, surgical planning etc. [2]. Images obtained from segmentation are further used in medical applications like diagnosis of different diseases, treatment planning, study of anatomical structure and computer-integrated surgery [3]. Segmentation techniques are depended on the following factors:

a). Imaging modality
b). Application domain
c). Manual, semiautomatic or automatic method
d). Specific features

Medical image segmentation is considered as a difficult task due to variable shapes of objects and different qualities of images causing noise. Although bundle of segmentation techniques have been developed [4-9] still there is no single segmentation technique that is applicable for all imaging applications. The most common region segmentation method is thresholding, which is most often used as an initial step in majority of image processing applications. According to this technique an image is partitioned into two categories of pixels on the basis of selected threshold [10, 11]. One category includes pixels with lesser values than the threshold and other contains pixels with values greater or equal to the threshold. Several techniques have been proposed for threshold selection [12, 13].

2. Comparison of Vessels Extraction Techniques

Segmentation plays a vital role in the diagnosis of vascular diseases. Segmentation techniques are categorized for both general applications and specifically for blood vessels extraction. According to [14] blood vessels segmentation algorithms are categorized as follows:

a). Edge oriented techniques
b). Region based techniques
c). Active contour techniques
d). Hybrid techniques

2.1. Segmentation Using Edge-Oriented Techniques

Intensity values at edges of an image are very high as compared to other regions [15-17]. An abrupt change in intensities is noted at each edge point, which implies rate of change for which derivative is calculated and is called gradient of an image. For a given image I(x, y) the gradient of an image can be presented as:

$$d_x = \partial I/\partial x \quad (1)$$

$$d_y = \partial I/\partial y \quad (2)$$

As continuous differentiation of digital image is not possible due to its discrete nature, so gradient of an image is calculated by differencing, as given below:

$$d_x = I(x+1, y) - I(x, y) \quad (3)$$

$$d_y = I(x, y+1) - I(x, y) \quad (4)$$

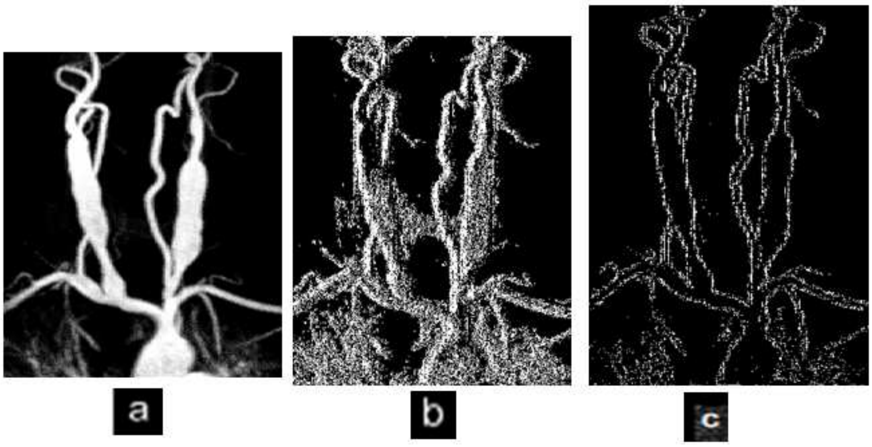


Figure 1. *Example of an edge detection (a) Original image of neck MRA, (b) gradient of an image, (c) edge of an image after applying sobel filter.*

Table 1. *Filtering results of two kernals.*

Kernal 1 = G_x			Kernal 2 = G_y		
-1	0	1	-1	-2	-1
-2	0	2	0	0	0
-1	0	1	1	2	1

An edge detection of neck MRA is illustrated in figure 1. The gradient of an image contains noise and does not result desired edges, shown in figure 1(b). Reason is that all the intensity values with abrupt change are included in the region. In order to get edges only, any filter operator like sobel, canny, laplacian (in case of second order derivative) etc. is apply to the gradient of an image, which removes unwanted region. For example in case of a 3x3 sobel edge operator, there are two 3x3 masks which are given in table 1.

The magnitude of gradiant is calculated using formula:

$$G(i, j) = ((I_1)^2 + (I_2)^2)^{0.5} \quad (5)$$

$$I_1 = G_x * I \quad (6)$$

$$I_2 = G_y * I \quad (7)$$

G_x and G_y both are convoluted with original image matrix I. Several edge detection methods apply gradient operator with the combination of threshold operation on the gradient for decision of existence of edges [18]. As a result binary image indicating edges is obtained, shown in figure 3.1(c). Edge oriented techniques only provide boundaries for segmentation. For detection some further technique is required. Pros and cons of edge detection techniques are illustrated below:

2.1.1. Pros

a). Provides ease for segmentation by defining boundaries of required regions.

b). No previous knowledge is required.

c). No user interaction is needed.It is a time consuming technique.

2.1.2. Cons

a). Detection of edges is dependent on the quality of input images. Edge detection methods do not always provide complete edges as shown in figure 2(b). Original image of brain in figure 2(a) is not clear therefore algorithm was not able to detect edges properly.

b). It can define just boundary of required regions but can't extract whole object like blood vessels.

c). As noises have high intensity values so they also become part of edges.

d). Results are depended on gradient masks.

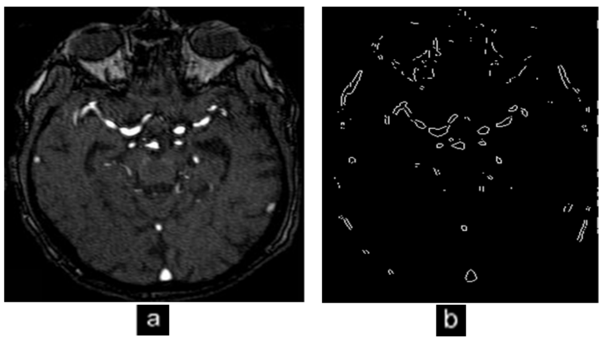


Figure 2. *(a) Original image of brain, (b) incomplete detected edges of an image.*

2.2. Active Contour Techniques

Active contours that are also known as snakes or deformable models are model-based techniques finding object contours using parametric curves that deform under influence of internal and external forces [19-21]. After initialization of any curve close to the boundary of an object by the user a snake that is set of connected points starts deforming and moving towards the desired object boundary. Each snake is basically assigned with energy that either rises or falls depending upon the forces that act on it. Internal forces serve to impose smoothness constraints on the contour while external forces pull the snake towards the desired image features like lines and edges. Figure 3 depicts the resultant image of active contour highlighting the region of tumor in brain.

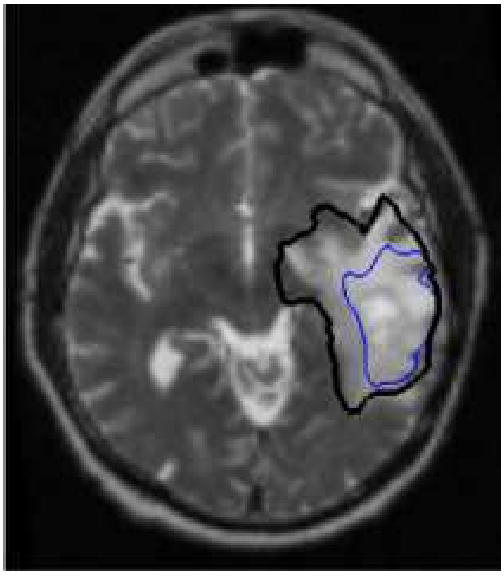


Figure 3. Detection of brain tumor using active contour.

2.2.1. Pros

a). This technique is suitable for detection of large size objects (vessels) like segmentation of coronary arteries or detection of brain tumors.
b). It also works well for occluded, convoluted and twisted blood vessels as described in figure 4.

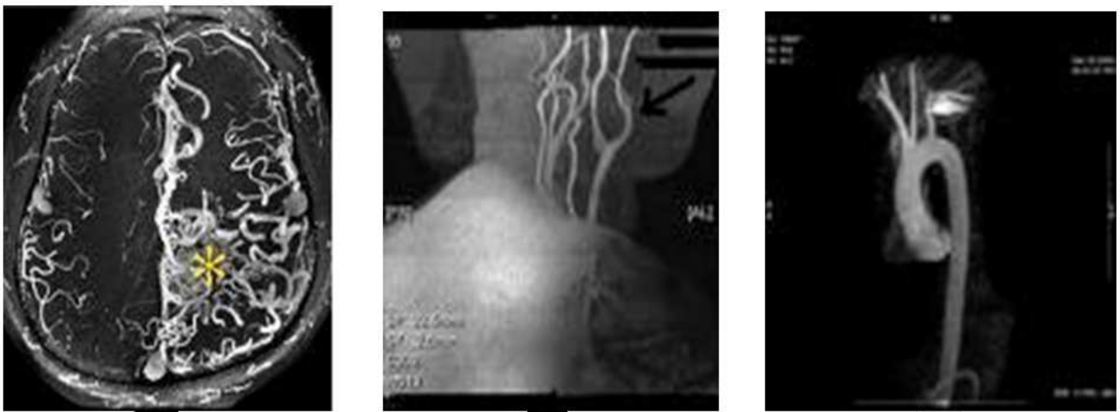
2.2.2. Cons

a). Manual selection of scale factor is required.
b). It does not work for noisy images.
c). In case of thin and complex vessels this technique is unable to extract whole tree of vessels.
d). It is computationally slow because of its complex nature.

2.3. Region Growing Technique

Region growing technique is based upon following two factors:
a). Selection of seed points.
b). Selection of homogeneity criteria.

Both seed points and homogeneity criteria can be selected manually by the user or automatically by the program. Region growing starts from seed points where the neighbors of every seed point are examined to check whether they are sufficient similar to the seed according to a homogeneity criterion [22-24]. All those neighbor pixels of a seed that satisfy the homogeneity criteria condition are added to the region and the process is continue until the neighbors of all the seeds are visited. At the end only required region of interest (vessels) are obtained.



a b c

Figure 4. (a) Image of occluded blood vessels, (b) image of convoluted blood vessels, (c) image of twisted blood vessels.

2.3.1. Pros

a). It is capable of correctly segmenting regions that have the same properties and are spatially separated.
b). As it suppresses the noise so vessels can be detected in noisy images too.
c). The whole tree of vessels can be extracted.
d). In case of automatic region growing technique no user interaction is required.
e). It generates connected regions.

2.3.2. Cons

a). Automatically region growing based techniques are usually computationally slow because of selection of seed points and homogeneity criteria.
b). All the results are dependent on the selection of initial

seeds point and homogeneity criteria.

2.4. Hybrid Approaches

Hybrid approaches are the combination of strengths of all the above three discussed categories [27]. The main drawback of hybrid technique is that they are computationally slow due to integration of multiple techniques. Some of the important features of edge oriented, active contour and region growing techniques are described in table 2.

From above discussion it is concluded that region-growing technique is insensitive to noise and also has the ability to detect whole tree of vessels. Both of these parameters are considered important for segmentation of vessels. Here our focus will be on region growing technique for extraction of vessels using MRA images whose literature review is given below.

Table 2. *An overview of comparison of discussed techniques.*

Techniques	Priori knowledge	Not sensitive to noise	Simplicity	Whole tree detection
Edge oriented	No	No	Yes	No
Active contour	Yes	No	No	No
Region growing	Yes	Yes	Yes	Yes

3. A Systematic Survey of MRA Region Growing Algorithms

Table 3. *A concise updated survey of MRA region growing algorithm.*

Ref.	Description and pros/cons
26	Global thresholding is applied for selection of seed points and local thresholding as stopping criterion for region growing. Average intensity values of image are calculated and applied to the formula of quadratic polynomial, which gives a global threshold value. Seed points are obtained after applying global thresholding. The drawback of this technique is selection of window size because it affects the segmentation process.
27	The fuzzy region growing technique is applied for segmentation of carotid artery ultrasound images. Ultrasound images usually have problem of noises and low contrast. To overcome these problems two preprocessing steps are performed. Histogram equalization is applied in order to increase the dynamic range of the image gray levels. For removal of noise median filter is applied on histogram equalized image. Although the algorithm is insensitive to the seed point location but still it requires a user selected point, which is its drawback.
28	A branch-based region growing technique for segmentation of blood vessels of MRA. According to this technique segmentation is performed individually on each branch. Initially a single seed point is selected manually and then it starts searching for a branch. After finding branch bifurcation it just go for only single branch, remaining are pushed into stack with an assigned label and pope from stack for processing when region of already selected branch is grown till its edge. The advantage of this technique is that whole tree vessels are extracted because of branch detection using local adaptation of growing condition (edge of individual branch). On the other hand its drawback is time consumption due to its branch detection.
29	The proposed algorithm maintains hierarchical priority lists based upon FIFO where the priority to each list is assigned according to value of luminosity. For insertion of new points, lists are accessed randomly. Region growing take starts from any user define seed point. Due to use of simple points this technique guarantees the correct topological segmentation i.e. without any hole. The drawback is its single seed point. The whole part of vascular tree may be lost if that path is disconnected from the path containing seed point. Another drawback is its single threshold value, which covers only the vessels of higher intensity and smaller vessels are ignored.
30	In proposed technique the concept of two threshold values one with higher value and other with lower to cover all the vessels in tree. Multiple seed points are chosen with the help of higher threshold value. The advantage of comparison with segmented neighbor's points is that it disallows the points with too low intensity. The only drawback of this technique is lack of automation for selection of threshold values.
31	This technique a local adaptive thresholding based technique for the segmentation of carotid artery using MRA slices. This technique automatically computes the threshold value by considering a midpoint of maximum and minimum gray levels of only first slice. In addition, the application of the threshold value filters the first slice. Taking into account the anatomical structure of the left and right carotid artery, the filtered slice is divided into two sub regions. Seed points of each sub region are calculated and their eight connecting neighbors are labeled in order to get the region of interest. Connectivity between slices is achieved by drawing the circumscribed quadrangle on the segmented carotid artery with a minimum distance.
32	The homogeneity criteria of only the first slice of an image is calculated by taking the average of all the intensity values of the 8 connected neighbors of seed points and is applied to all other slices in order to preserve connectivity between them. The starting point of each slice is chosen from the intersection of the already segmented region of interest of the previous slice and the current un-segmented region of interest.

4. Challenging Issues of Vessel Segmentation Algorithms

In MRA, the blood vessels show a wide range of intensity values due to the amount of blood flow. This is similar to the region growing technique where the rate of growth is also based upon the range of intensity values. Therefore, the conventional region growing technique fails to extract whole vessels tree. In order to solve the intensity range problem for the segmentation of blood vessels, a range of strategies based upon region growing have been proposed by various authors:

a). In order to validate the accuracy of vessel segmentation, methodologies must be introduced.

b). Automatic selection of threshold must be developed for all approaches, as currently most of the techniques are dependent on the manual selection of threshold.
c). Need of methods that automatically derive parameters locally as well as globally.
d). For improvements in the results of segmentation efficient pre-processing and filtering techniques must be promoted.
e). Introducing methods for connection of broken parts of vessel with the help of partial voluming or filtering during segmentation.

5. Proposed Region Growing Algorithm (PRGA)

PRGA is divided into following phases:

a). Selection of proper threshold value on the basis of maximum intensity values of all slices.
b). Selection of starting slice for appropriate seed point on the basis of threshold.
c). Segmentation of vessels using region growing algorithm.

In the traditional region growing algorithm, results of segmentation are totally dependent on the selection of seed point [32, 34]. An appropriate seed point results in quality segmentation. However, in the majority of MRA datasets, the start of the slices does not contain any required information. As a result of this, we have not applied region growing algorithm directly on the first slice. In order to begin from the required region, we have developed an automatic threshold value. To calculate the threshold, the maximum intensity value of each slice is obtained and stored in an array denoted as max_list. From this max_list, we then find the maximum and minimum intensity values i.e. m_1 and m_2 respectively. Finally the difference between m_1 and m_2 is gained and the threshold formula is given below:

$$T = m_1 - m_2 \tag{8}$$

The maximum intensity of each slice is compared with threshold T given in Eqn. 8. Slices are checked in a sequence in ascending order. Any slice with an intensity value greater or equal to the threshold value is selected as first slice F_1. Region growing algorithm is then applied to F_1 and onwards slices only. In this way, the starting slice F_1 is different for each dataset and is selected automatically according to maximum intensity values. The flow chart of proposed PRGA is shown in figure 5.

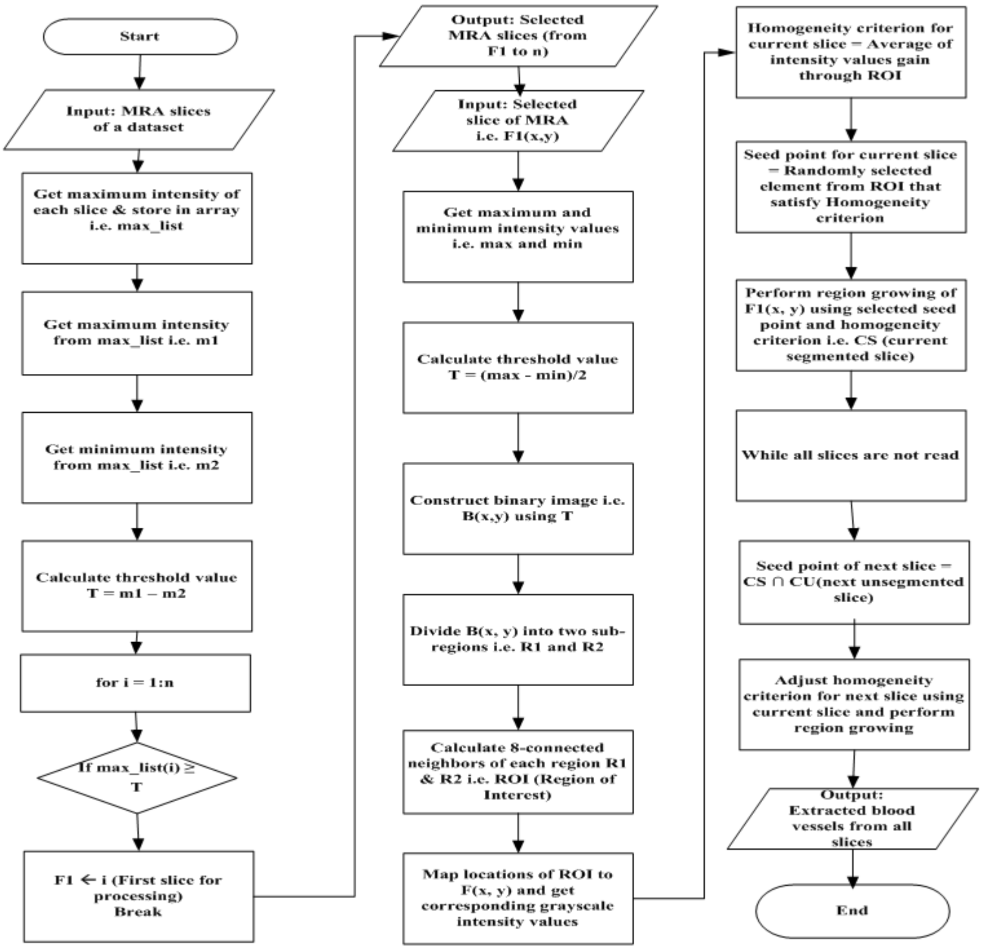


Figure 5. *Flow Diagram for PRGA.*

***Table 4.** Datasets used in the experiment.*

Type	Dimension	Total no of slices	Maximum intensity value of 1st slice	Minimum intensity value of 1st slice	Threshold for 1st slice
Head MRA	576 x 576	118	356	0	178
Renal arteries MRA	576 x 448	72	99	0	50

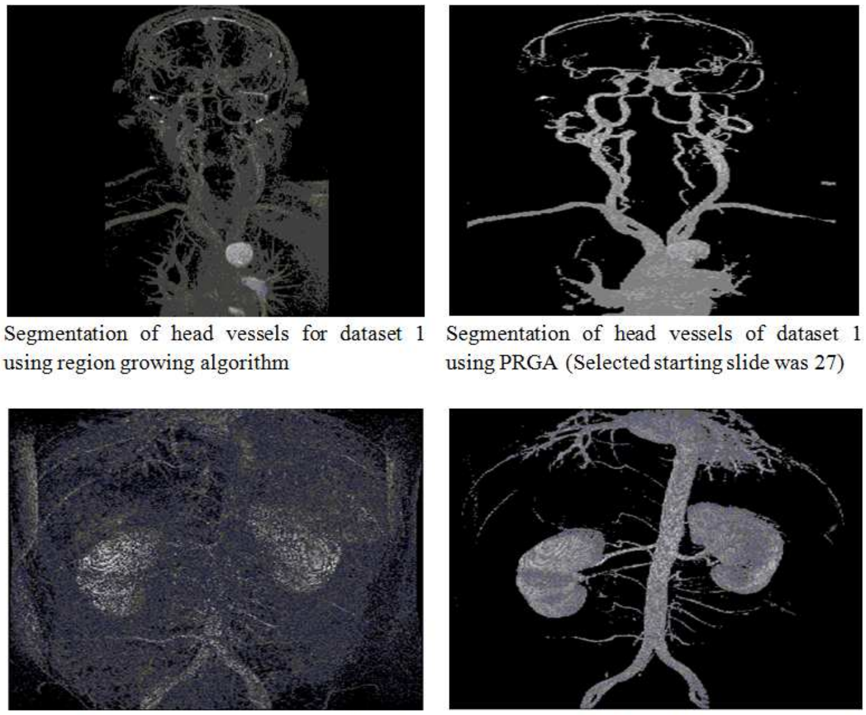
***Table 5.** Datasets used for enhancement.*

Type	Total no. of slices	Starting slice	Maximum intensity value of starting slice	Minimum intensity value of starting slice	Threshold for starting slice(max-min)/2
Head MRA	118	27	644	0	322
Renal arteries MRA	72	9	163	0	82

6. Experiment Setup and Measured Results

Details of datasets used in the experiment are given in Table 4. The vessels segmentation of head MRA for dataset 1, using a region growing algorithm without any enhancement, is shown in Figure 6. Datasets used for enhancements are given in Table 5.

7. Conclusion



Segmentation of head vessels for dataset 1 using region growing algorithm

Segmentation of head vessels of dataset 1 using PRGA (Selected starting slide was 27)

Segmentation of renal arteries for dataset 2 using region growing algorithm.

Segmentation of renal arteries for dataset 2 using PRGA (Selected starting slide was 9)

***Figure 6.** Comparison of PRGA with usual RGA.*

The segmentation of blood vessels is an active research area which plays a significant role in many medical applications including diagnosis, surgery planning and radiation treatment. In this paper we presented various the pros and cons of several of vessels extraction techniques, short survey of MRA region growing algorithms, challenges of vessel segmentations algorithms and a PRGA has been proposed in this paper. PRGA has been tried on two patients of MRA datasets (1 head, 1 renal arteries) of different resolutions and has provided pleasing results.

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Biography

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