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PERFORMANCE EVALUATION OF REGION-GROWING BASED SEGMENTATION ALGORITHMS FOR SEGMENTING THE AORTA

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Abstract

Region-growing based image segmentation techniques, available for medical images, are reviewed in this paper. In digital image processing, segmentation of humans' organs from medical images is a very challenging task. A number of medical image segmentation techniques have been proposed, but there is no standard automatic algorithm that can generally be used to segment a real 3D image obtained in daily routine by the clinicians. Our criteria for the evaluation of different region-growing based segmentation algorithms are: ease of use, noise vulnerability, effectiveness, need of manual initialization, efficiency, computational complexity, need of training, information used, and noise vulnerability. We test the common region-growing algorithms on a set of abdominal MRI scans for the aorta segmentation. The evaluation results of the segmentation algorithms show that region-growing techniques can be a better choice for segmenting an object of interest from medical images.

Keywords: Seed point, Volume image, Algorithm complexity, CT, MRI, ROI

1.0 INTRODUCTION

The role of image segmentation is inescapable in the identification and classification of regions of interest (ROIs) from digital images [1]. ROIs, depending on the context, can be characterized on the basis of several features, such as shape, contrast, size, texture, gray-scale level [2] etc. The key to successful image segmentation is the selection of good attributes. CT (Computed Tomography), X-rays, Ultrasound and MRI (Magnetic Resonance Imaging) etc. are commonly used modalities for 3D digital image acquisition. One of the most important components of clinical applications, for detection of abnormalities and disease diagnosis, is medical image segmentation [3-6]. Segmentation techniques [7] can be simple such as thresholding or more elaborate such as region growing [7], artificial neural networks [8], edge-detection, morphological methods and many other. The task to segment ROIs from medical images [9, 10] is very challenging, and there are various factors that make medical image segmentation more difficult.

Firstly, in a computer system, representing domain knowledge is difficult. In this case, the domain knowledge acquired by the experts through years of systematic training, is the knowledge of human anatomy and how to determine ROIs in an image. Secondly, the shapes of structures such as arteries within the human body are not only highly variable, but also complex. Thirdly, in medical images large variability between two different people may happen. Fourthly, the intrinsic features associated with medical imaging systems, such as missing information and low contrast, make segmentation of medical images challenging. Even humans have problems in identifying edges with similar pixel intensities in the boundary region. In such a situation, a conventional boundary-finding algorithm based on gradient information would fail. Furthermore, the existence of noise in medical images, like most of the natural images, is inevitable. Noise can be removed with the help of filters. However, by employing filters we can lose details of the image. Similarly, input image type and nature also affect performance [11-13]. The algorithms results may not be same for a specific input image and are affected with different parameters set by the user. There is trade-off in execution time and quality result parameters of the algorithm, for example. This paper demonstrates aorta segmentation over a set of MRI images, provided by our clinical partner, using region-growing based algorithms as the foundation on real world 3D MRI data sets, available in ITK. The work implements region growing based algorithms, evaluates performance, and compares results of these algorithm on images acquired at clinics routinely for the facilitation of the aorta segmentation.

2.0 SEGMENTATION METHODS

There are a number of algorithms available for medical image segmentation in two, three and more dimensions that can be used for the development of a fully functional segmentation application [14, 15]. For these segmentation algorithms, we can tune the parameters according to the characteristics of the image provided as input, anatomical structure or abnormalities to be segmented.

Most of the segmentation algorithms [14, 16] use one of the two approaches for segmentation, disconnectivity and similarity of intensities values. Algorithms based on disconnectivity use abrupt changes in intensity for the partition of an image. This category includes edge detection algorithms, and this type of classification is called edge-based segmentation. Canny edge detection algorithm is an example of this approach. The algorithms that use similarity in intensities for segmentation, extract regions from an image when the similarity criteria is fulfilled. The algorithms that follow this approach are classified as region based segmentation algorithms. Thresholding [17], region-growing [18] and clustering algorithms [19] are based on region-based technique. This paper describes region-growing algorithms.

2.1 Region Growing Algorithms

Region-growing algorithms [18] divide the input image into regions according to predefined criteria. Region based segmentation algorithms start from a seeded region, and evaluate the neighboring pixels based on predefined criteria to determine if they should also be considered part of the object to be segmented. If the criterion is fulfilled, the pixels are added to the region, and the process continues to grow the region. Following are some of the advantages and disadvantages of region based segmentation algorithms.

Advantages of this approach include simplicity, accuracy of segmenting a region based on predefined criteria, freedom of setting the criteria and seed points for segmentation, simultaneous selection of multiple criterions, and good performance while segmenting noisy images. Disadvantages of the approach include more computation, holes or over segmentation due to intensity variation in images, and less effectiveness in case of anatomy variation.

The performance of region based segmentation algorithms can be improved by combining methods of distinct categories, for example, techniques in which edge detection is combined with thresholding. Similarly, segmentation techniques based on morphology combine several of the positive attributes of different other techniques. In order to segment the aorta from MRI scans, we are using region based segmentation algorithms, because we are interested in specific regions of the image. Some of the most commonly used region based segmentation algorithms and their applications on MRI data sets are described in the following sections.

3.0 CONNECTED THRESHOLD

The Connected Threshold algorithm [9] evaluates, for image segmentation, intensity values within a specific range. The algorithm includes those pixels having intensity values inside the upper and lower thresholds set by the user. The implementation of this algorithm can by greatly simplified by flood fill iterator as it visits neighboring pixels and grows region based on criteria determined by the algorithm. Noisy images are pre-processed via an edge preserving smoothing filter due to the sensitivity of connected threshold algorithm to noise. This algorithm has the following parameters:

- Time Step: This parameter is used to compute level-set evolution. Time step value is dependent on image dimension.
- Number of Iterations (NI): The value of this parameter effects algorithm performance as more iterations result in further smoothing and hence increases computation time linearly. On this filter, edge preserving is not absolute and this leads to some degradation on the edges and accentuate with the increase in NI.
- Inside Intensity: Pixels' intensity values within the region to be segmented.
- Seed Index: The user specifies the position of seed index inside a ROI using this parameter.
- Lower Threshold (LT): This parameter sets minimum value of threshold required for a region to be segmented.
- Upper Threshold (UT): Maximum threshold value needed for the segmentation of required object

3.1 Algorithm Implementation For The Aorta Segmentation

Segmenting the aorta, in medical imaging, is a very challenging task. We tested the connected threshold algorithm on a collection of eight different abdominal MRI data sets for evaluating the results of the algorithm. The results, on 3D images, of the algorithm are depicted in Figure 1. The connected threshold algorithm grows region pixels' intensities, according to the seed point, for growing regions. After checking all the pixels in sequence, it adds the pixels, on fulfilling the criteria, in the region. It requires manual initialization. For each image (Figure 1), we have to provide different input values to get desired output. The algorithm produces best results when the intensity distribution is clear.

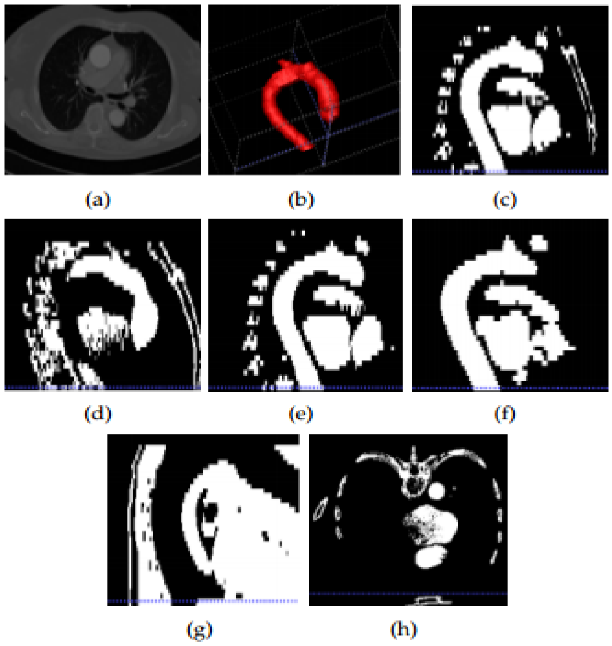

Figure 1 Aorta Segmentation using Connected Threshold Algorithm. (a) One slice of original MRI scan (b) Manual segmentation using ITK-SNAP (c) Segmentation when Number of Iterations (NI) is 0 (d) Slice variability (e-f) Increase in NI with 5 and 25 respectively (g) Increase in the number of iterations as well as threshold value (h) Increase in the number of iterations while decrease the threshold value

The performance of the algorithm degrades on images with low intensity distribution (Figure 1 (h)). It is easy to use the algorithm because there is no need of training. The algorithm is sensitive to noise and gives, by using smoothing factor, different results (Figure 1 (c), (f)). Seed points selection and the order of pixels inclusion in the region are important for connected threshold algorithm. The algorithm, by nature, is sequential and its complexity increases linearly when NI is increased.

4.0 CONFIDENCE CONNECTED

Confidence Connected algorithm [9] performs segmentation using statistical calculations on a given region. For segmenting ROI, it calculates standard deviation, mean of pixels intensity values, and grows region based on user-supplied parameters. The parameters of confidence-connected algorithm are:

- Inside Intensity: Values of pixels intensities inside the region to be segmented.
- Seed Index: It specifies the anatomical region position to be segmented.
- Multiplier (f): Standard deviation is multiplied with this factor. It is also used for defining a range around the mean.
- Radius: This parameter determines neighborhood size.
- NI: NI refers to how many times the mean and standard deviation is recalculated.

4.1 Algorithm Implementation For The Aorta Segmentation

The results obtained, after applying confidence-connected algorithm on a set of abdominal MRI scans, are shown in Figure 2. The confidence-connected algorithm adds pixels to the region based on mean and standard deviation of pixels intensity values. Variation in multiplier factor f affects the algorithm computational complexity as opposed to variation in the NI. Other factors affecting the algorithm performance include, noise (Figure 2 (h)), distribution of intensity (Figure 2 (d)), image radius (Figure 2 (e), (g)) and variation in anatomy (Figure 2 (d)).

The algorithm complexity increases linearly with increasing NI, multiplication factor, radius and image dimensions. The algorithm requires no training and is easy to use; however, for segmentation of images, it uses manual initialization. For 2D images with clean boundaries, the algorithm produces good results, but its performance degrades on 3D images with low resolution and anatomy variation (Figure 2 (g) (h))

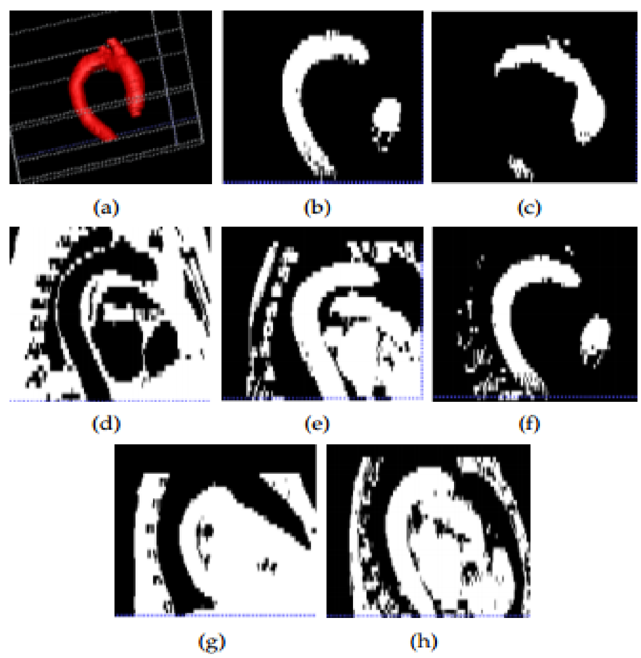

Figure 2 Aorta Segmentation using Confidence Connected Threshold Algorithm. (a) Manual segmentation using ITK-SNAP (b) Segmentation at optimal values (c) Slice variability (d) Segmentation of second image (e) Segmentation with seed value variability (f) Increase radius parameter (g) Increase multiplier (h) Decrease in the number of iterations

5.0 NEIGHBORHOOD CONNECTED

This method [9] partition images into ROIs based on pixels present in the neighborhood of pixels. The neighboring pixels of a pixel, with intensity values inside the range, are included into the region. The algorithm needs seed point, thresholds range within which intensity values must fall for inclusion in the region and radius that determines neighborhood size. The parameters and their details used for the filter are:

- Inside Intensity: Pixels' intensity values of the region to be segmented.
- Seed Index: A value that specifies the position of seed index within the segmented region.
- Lower Threshold: Threshold's lower bound required for segmenting ROI.
- Upper Threshold: Threshold's upper bound for the segmentation of desired object.
- Neighborhood Radius: The parameter specifies the size of the neighborhood.

5.1 Algorithm Implementation For The Aorta Segmentation

Figure 3 shows the results of the aorta segmentation, via neighborhood connected threshold algorithm, from MRI scans. The neighborhood connected threshold image filter grows region, instead of current pixel intensity value, using neighboring pixels' intensities. The various factors that affect the performance of the algorithm consist of radius set by the user (Figure 3 (f)), image with noise (Figure 3 (e)), intensity values distribution (Figure 3 (e), (f)) and human anatomy variation (Figure 3 (f)).

The algorithm needs no training and is easy to use; however, it requires manual initialization. High radius, NI and image dimension increase the algorithm complexity linearly

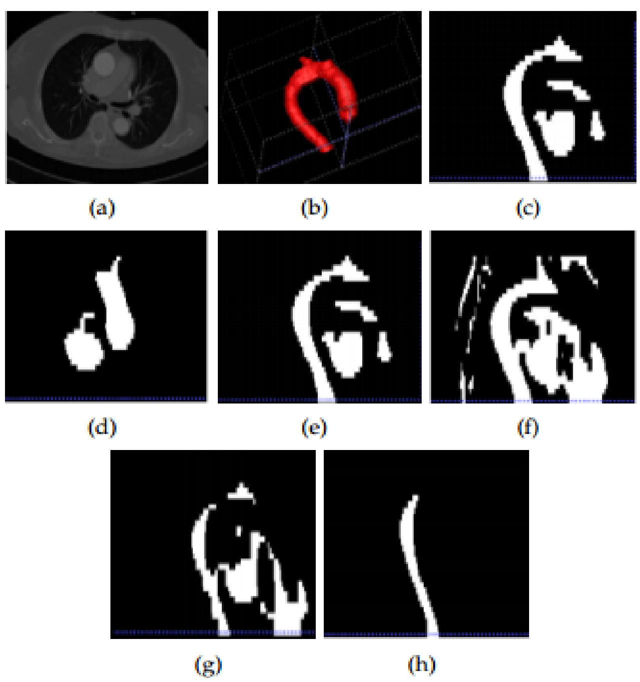

Figure 3 Aorta Segmentation using Neighborhood Connected Threshold Algorithm. (a) One slice of original MRI scan (b) Manual segmentation using ITK-SNAP (c) Segmentation when Number of Iterations (NI) is 0 (d) Slice variability (e-f) Increase in NI with 5 and 25 respectively (g) Increase in the number of iterations as well as radius (h) Increase in the number of iterations while decrease the threshold value.

6.0 OTSU SEGMENTATION

Otsu segmentation algorithm [9] is a histogram based thresholding technique for performing image segmentation. The algorithm classifies the input image pixels into two groups and compute the best threshold value based on variance maximum value between the pixels groups [23-26]. Otsu segmentation technique performs segmentation based on two input parameters. The first one is to set the histogram bin value that is used to define the threshold value and is used for classification. The second parameter is the output in the form of a segmented binary image.

6.1 Algorithm Implementation For The Aorta Segmentation

Figure 4 shows the segmentation results on a slice of three-dimensional MRI scan using Otsu segmentation technique.

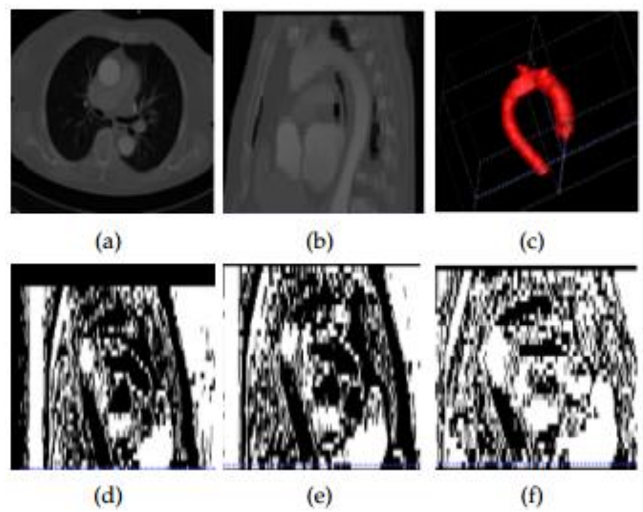

Figure 4 Aorta Segmentation using Otsu Threshold Algorithm. (a) One slice of original MRI scan (b) Slice variability (b) Manual segmentation using ITK-SNAP (d-e-f) Segmentation of aorta at histogram bins 50000, 50 and 4 respectively.

In Otsu segmentation technique, pixels are classified into groups based on histogram. The number of bins value provided by the user affects the performance and complexity of the algorithm. Otsu segmentation gives good segmentation result for medical images as compare to canny segmentation technique. However, for segmentation of an object of interest, it depends on the intensity distribution of the input image [22].

Otsu segmentation technique is automatic, simple to implement, require no training of image but is not effective for separating a region of interest from an image. Similarly, in spite of its usefulness, for separating an object of interest the main drawbacks of this approach are:

- The result of the algorithm is dependent on the image features and selection of an optimal input value is very difficult (Figure. 4 (f)).
- It does not consider the spatial information.

- For images with noise (Figure. 4 (d)) and lacking spatial uniformity (Figure. 4 (e)), the algorithm is not very suitable.

7.0 ISOLATED CONNECTED

Isolated Connected Threshold technique [9] performs segmentation based on a lower threshold value and two seed points. The algorithm grows region based on seed points and threshold value initialized by the user. For the first seed point, the algorithm uses the upper threshold value. To separate the two seed points binary search algorithm is used. The algorithm is very useful in the case where two adjacent structures need to be separated. The algorithm is very sensitive to noise and edge preserving smoothing filters is applied before actual segmentation in order to remove noise and enhance the quality of the image. The algorithm uses the following parameters for segmenting an object from the image.

- Time step: To compute the level set evolution, time step is used.
- Number of Iterations (NI): To remove noise and smooth the input image, the users have to set the number of iterations. Increase in the number of iterations increase the smoothness of the image and computation time for segmentation.
- Seed Index: It indicates the position of the object to be segmented from the image.
- Lower Threshold (LT) value: Minimum threshold value used by the algorithm for desired object segmentation.
- Upper Threshold (UP) value: The maximum threshold value used by the algorithm for segmentation.

7.1 Algorithm Implementation For The Aorta Segmentation

Figure 5 shows the segmented results of one slice of three-dimensional MRI scan using isolated connected segmentation technique. Individual pixel information is used for region growing in isolated connected threshold segmentation algorithm. The algorithm is straightforward but manual initialization makes the algorithm not suitable for practical applications. The algorithm complexity is increased with increase in the number of iterations and dimension of the input image. The algorithm performance is affected by the noise present in the image (Figure. 5 (c) and (g)) and variation of image anatomy (Figure. 5 (d)).

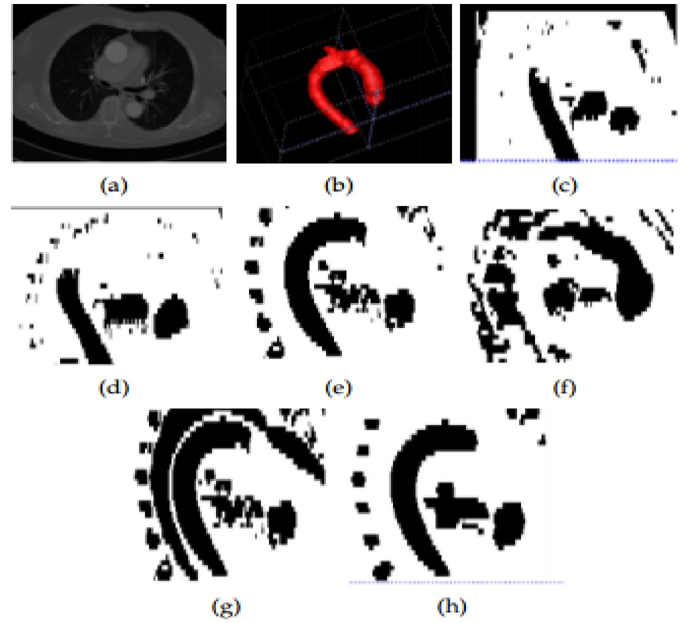

Figure 5 Aorta Segmentation using Isolated Connected Threshold Algorithm. (a) One slice of original MRI scan (b) Manual segmentation using ITK-SNAP (c) One slice segmentation of a three dimensional image (d) Slice variability (e) Decrease the isolated value (f) Increase isolated and seed values (g) Threshold value variability (h) Increase in the number of iterations while decrease threshold values.

8.0 WATERSHED ALGORITHM

The Watershed region based segmentation algorithm [9] uses the concepts of mathematical morphology for segmentation of an image. It was first developed by Boucher [20] and is a vital segmentation algorithm in which the Markov Random Fields are deployed. Najman [20] and Grau [21] have further improved the watershed algorithm by implementing morphological operations for reducing over segmentation and encoding prior information into the algorithm.

There are two main parameters used by the algorithm for segmentation of an image. The first one is the watershed scale level that is also called flood level and is used to control watershed depth. The second parameter is the threshold value that is used during segmentation that acts as lower threshold for the region to be included in the result.

To reduce the effect of noise on the algorithm, and enhance the quality of the image, edge-preserving techniques such as anisotropic diffusion and bilateral filters are used before the actual implementation of the Watershed algorithm.

8.1 Algorithm Implementation For The Aorta Segmentation

Figure 6 shows the segmentation results of one slice of three-dimensional MRI scan using Watershed segmentation technique.

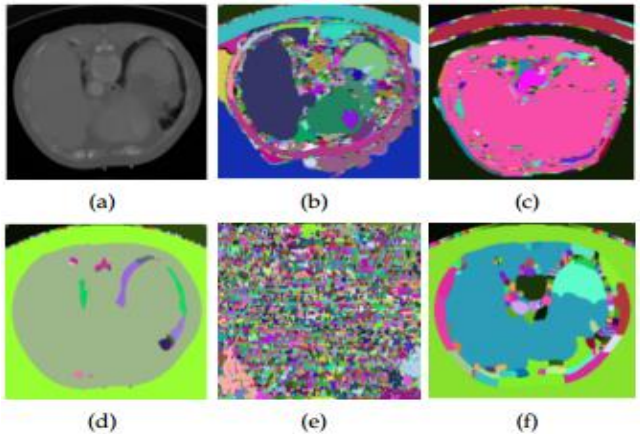

Figure 6 Segmentation of the Aorta using Watershed Algorithm. (a) One slice of original MRI scan (b) Segmentation of the original slice with low threshold value (c-d-e) Variation of threshold value, gradient mode, conductance term and diffusion iterations

Various parameters are needed to be initialized before segmentation. The first parameter is the threshold value that is used to control the under and over segmentation of the algorithm. Low threshold value causes under segmentation while high threshold value reduces computation time and may cause over segmentation of the image. The time required for segmentation depends upon the image information detail contained in the image. An image with more homogeneity and with large number of objects will take more time that the image that contain fewer objects. The main advantages of the Watershed algorithm is its simplicity, easy implementation, parallelism property, intuitiveness and its use for practical applications. However, over segmentation of the image, noise its poor results on segmenting thin structures may affect the algorithm overall performance [21].

9.0 COMPARISON

Based on experiments and analysis we have summarized the results of the above-mentioned region based segmentation algorithms (see Table 1). In order to evaluate the performance, we have used the criterion functions such as information used by the algorithms for growing the region, factors that affect the performance of the algorithms, complexity, sensitivity to noise, need of training, ease of use and manual initialization.

Various factors affect the performance of the algorithms that are image quality, modality, dimension, anatomy variation, texture, image nature and other characteristics of image continuity (see Figure 7). The complexity of region growing algorithm is measured by the time it takes for segmentation and is affected by the homogeneity and type of image to be segmented.

Table 1 Performance evaluation of commonly used two-dimensional region growing based segmentation algorithms.

CRITERIA	CONNECTED THRESHOLD	NEIGHBOR-HOOD CONNECTED	CONFIDENCE CONNECTED	OTSU	WATERSHED	ISOLATED CONNECTED
Information	Individual pixels	Neighbor pixels	Mean and standard deviation of pixels	Variance of pixels	Individual pixels	Individual pixels
Performance	Depends on the number of iterations and intensity distribution	Depends on the radius and intensity distribution	Depends on radius, multiplication factor, intensity distribution and number of iterations	Depends on intensity distribution	Over segmentation may occur	Depends on intensity distribution
Complexity	O(n)	O(n)	O(n)	O(n)	O(n)	O(n)
Manual Initialization	Yes	Yes	Yes	No	Yes	Yes
Sensitive to Noise	Yes	Yes	Yes	Yes	Yes	Yes
Training	No	No	No	No	No	No
Easy to use	Yes	Yes	Yes	Yes	Yes	Yes

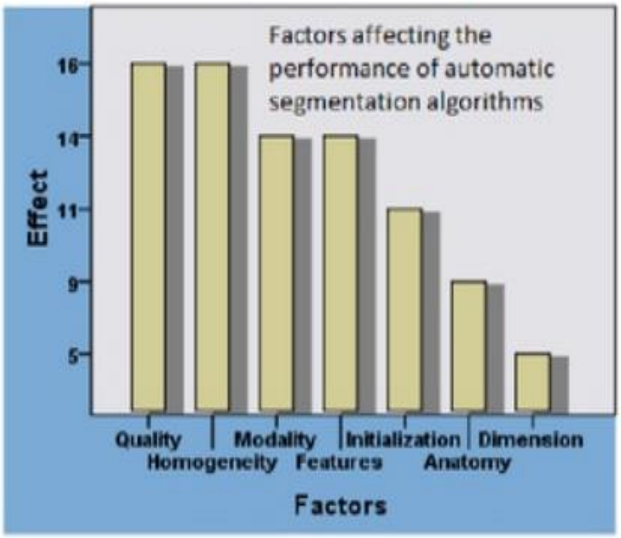

Figure 7 Factors affecting the performance of commonly used region growing based segmentation algorithms

10. 0 CONCLUSION

Medical image segmentation is inevitable within medical image processing based clinical applications for the detection of abnormalities and disease diagnosis. This study evaluates performance, for the facilitation of segmenting the aorta, of leading-edge region-growing based image segmentation algorithms on real world 3D abdominal MR scans obtained at clinics against predefined criteria. Our findings, after evaluating these algorithms, show that the algorithms do not produce a single output for one specific input image or set of images. We conclude that the development of fully automatic segmentation application for the segmentation of medical images, in the presence of different factors, is more difficult and challenging

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