Comparative study of automatic seed selection methods for medical image segmentation by region growing technique

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Abstract: - Seeded Region Growing technique is very attractive for medical image segmentation by involving the high-level knowledge of image components in the seed selection procedure. However, the Seeded Region Growing technique suffers from the problems of automatic seed generation. A seed point is the starting point for region growing and it's choose is very crucial since the overall success of the segmentation is dependent on the seed input. In this work three automatic seed placement methodologies are reviewed, evaluated and compared on three distinctive medical image databases. The first method is based on region extraction approach, the second one is based on features extraction approach and the last method is based on edge extraction approach. Our results showed that the region extraction approach performs well on the three tested databases. The features extraction approach gives good results with only two databases. Edge extraction approach gives correct results just on one database.

Key-Words: - medical image, seed selection, region growing segmentation, region of interest, feature extraction, edge extraction.

1 Introduction

Segmentation is one of the most difficult and important tasks in medical image processing. This active field of research over the last 20 years helps to make a simple format of medical image and to specify a region of interest (ROI). Segmentation is the process of partitioning an image into several regions according to specific rules. The purpose of segmentation is using these regions for ROI detection to identify any abnormalities or lesions. Quality of segmentation determines the eventual success or failure of the analysis or diagnosis.

Segmentation of medical images using seeded region growing (SRG) technique is increasingly becoming a popular method because of its ability to involve high-level knowledge of anatomical structures in seed selection process [1]. The region growing starts with a seed pixel and then repeatedly adds new pixels to the segment as long as the segmentation criterion is still satisfied on the enlarged segment [2].

Seeded region growing has the advantage of specifying just one interested region by placing a seed inside it. However, the performance of SRG algorithms depends on this position. If a seed point is selected outside the region of interests, the final segmentation result will be definitely incorrect [3].

Many automatic seed selection methods exist but, still now SRG algorithm suffers from the problems of automatic seed generation [4, 5].

In this work, we compare three automatic seed selection methods. The first method proposed by Al-Faris et al. [6] is based on region extraction approach. The second method proposed by Yuvaria et al. [7] is based on features extraction approach. The last method proposed by Pohle et al. [8] and involved by Deboeverie et al. [2] is based on edge extraction approach. For objective comparison they have been tested and evaluated using the same data and criteria.

The organization of the paper is as follows. In Sections II, we discuss previous related literature. We describe the experimental automatic seed selection methods in Sections III. In Section IV, we present results with discussion. Finally in Section V we present our conclusions.

2 Literature review

A seed is a test pixel with ideal characteristic that belongs to the region interested in and should be part of region of interest [9]. Because region growing result is sensitive to the initial seeds, the accurate seed selection is very important for image

segmentation [10]. Numerous works can be found regarding automatic seed selection. These works can be classified on three axes:

- Works based on region extraction approach: the principle of these works is the extraction of the regions by using a segmentation techniques then the selection of seeds inner these regions.

- Works based on features extraction approach: these ones use two steps. In the first step, region features are calculated. Generally, a region is just a window placed on the image. In the second step, a test is performed: if region features values match with some fixed features values a seed is placed in the region.

- Works based on edges extraction approach: these works applied edge detection techniques like gradient calculation, active contour and so on, to prepare seed point choose.

An overview of automatic seed selection methods for medical image segmentation by region growing technique can be obtained from Table 1. The abbreviation "**SR**" is used for seeded selection based on region extraction approach, the abbreviation "**SF**" is used for seeded selection based on features extraction approach and the abbreviation "**SE**" is used for seeded selection based on edges extraction approach. Note that none of the methods have been directly compared to other methods

Table 1. Summary of automatic seed selection methods for medical image segmentation by region growing technique

Authors	Ref.	Year	SR	SF	SE	Used technique
Chang et al.	[11]	1994		✓		Histogram feature
Pohle et al.	[8]	2001			✓	Gradient
Mat Isa et al.	[12]	2006	✓			Moving *k*-means
Poonguzhali et al	[13]	2006		✓		co-occurrence features
Shan et al.	[14]	2008	✓			Binarize technique
Nazahah et al.	[15]	2009	✓			*k*-means
Avazpour et al.	[16]	2009		✓		Pixels intensity
Wu et al.	[17]	2009		✓		2D Co-occurrence texture feature, Gabor texture feature, and both 2D and 3D Semi-variogram texture features are extracted
Li et al.	[18]	2010			✓	Detect edges by using the canny operator
Mustafa et al.	[19]	2010			✓	Active contour model
Al-Faris et al.	[20]	2011	✓			PSO clustering technique
Abdelsamea	[21]	2011	✓			Otsu segmentation method
Maitra et al.	[22]	2011			✓	Edge map
Saad et al.	[23]	2012	✓			Region splitting and merging technique
Meenalosini and Janet	[24]	2012		✓		Histogram feature
Massich et al.	[25]	2012		✓		Pixels intensity, texture and position
Shili et al.	[26]	2013	✓			*Fuzzy* c-means algorithm
Yuvarai et al.	[7]	2013		✓		Statistical features
Al-Faris et al.	[6]	2014	✓			Binarization

3 Experimental automatic seed selection methods

Region growing is one of the most popular techniques for segmentation of medical images due to its simplicity and good performance [23]. Some works use a semi-automatic algorithm and still need some user interaction, while others are fully automatic and the user has only a verification role. In general, region growing methods are sensitive to the initial seed. For the region growing to be

effectively finished, the crucial part is the position of the seed pixel, and it must be selected from which the region growing may start [27]. Therefore, selecting a good set of initial seeds is very important. This section gives a short explication of each experimental automatic seed generation method, detailed can be found in the original paper.

- *Region Extraction Method (REM):* In Al-Faris's study on MRI breast segmentation [6] the SRG was used. The approach started by automatic

selection for the suitable threshold value. The algorithm searches for the maximum value in each row in the image and saves it temporarily. This process is repeated for all the rows until the last. Then a summation of the temporarily stored values is calculated. The mean maximum raw is then calculated by dividing the summation value by the number of rows in the image. The resultants mean value will be considered as the threshold value for the binarization process. Applying morphological open operation (erosion followed by dilation operations) would remove the unwanted small white speckles in the image which do not belong to the ROI and to enhance the boundary of the suspected regions. After, the highest region's density value will be chosen as the main suspected region. Seed is the pixel of the main suspected region with maximum intensity value.

- *Features Extraction Method (FEM):* For Yuvarai et al. [7] a mask is initialized as a part of seed selection. For the regions within the mask the statistical features are extracted. If the extracted features matches with the predefined features of mass then the seed is fixed. Else, if the mask extracted features don't match with the lesion features then the mask position is moved until it satisfies the lesions features. Thus, the mask is scanned for the entire image.

- *Edges Extraction Method (EEM):* Pohle and Toennies [8] take the smallest gradient value as a seed point. Deboeverie et al. [2] added another contrainst: seed must have local gray value extrema. So seed pixels are automatically chosen as local gray value extrema of the image and where the gradient remains small.

4 Experiments and discussion

Image segmentation is a blind task, and there have been lots of researches to guide segmentation in a way that results in better precision ROI selection. Among segmentation algorithms, region growing highly depends on where the growing process starts in order to perform good segmentation result. In this paper we have implemented, tested and compared three automatic seed selection methods: FEM, REM and EEM.

Randomly images are taken from three distinctive medical image databases. Two databases are the same used by the authors of the tested methods. The third one is randomly selected from public medical dataset. So, in this study, the RIDER breast MRI dataset which is downloaded from the National Biomedical Imaging Archive [28], MiniMIAS database provided by the Mammographic Image Analysis Society (MIAS) and Brain IRM collection download from The Cancer Imaging Archive (TCIA) [29]. Tested images are randomly selected from these publicly database. We notify that, in region growing segmentation process, the same similarity measure and the same threshold value is used for the three methods.

Two evaluation criteria are used for the comparison task, namely:
- seed placement,
- statistical results values.

4.1 Seed Placement

With this criterion, we are looking if each method generates correct seed position. A position is correct if and only if it is inner the ROI. In the following, three seed generation examples by the three considered methods are showed.
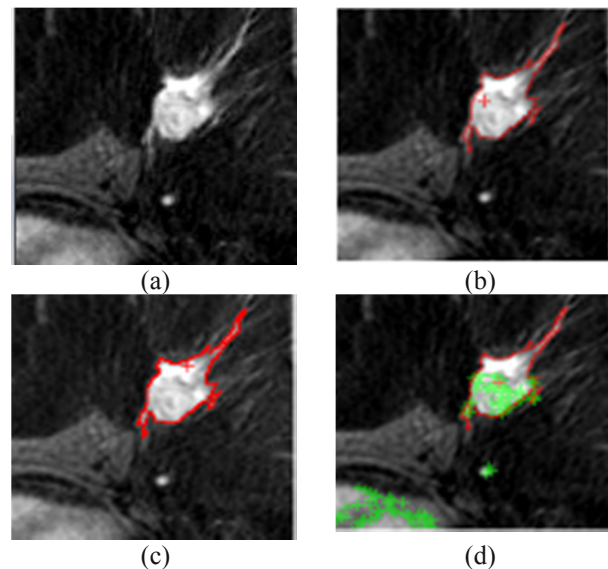

(a)　(b)　(c)　(d)

Fig.1 FEM, REM and EEM application example on a Breast IRM image. (a) original image (b, c, d) seed generation results and segmentation results by using respectively FEM, REM and EEM methods.

Figure 1 illustrates seed selection results and segmentation results using FEM, REM and EEM methods on a breast IRM example extracted from RIDER database. The original image is illustrated in Figure 1(a). Figures 1(b, c, d) shows seed generation results and segmentation results by using respectively FEM, REM and EEM methods. We can see clearly that the three methods had placed correctly the seed inner the ROI, but in different position.

Figure 2 illustrates seed selection results and segmentation results using FEM, REM and EEM methods on a breast MG example extracted from MIAS database. The original image is illustrated in Figure 2(a). Figures 2(b,c,d) shows seed generation results and segmentation results by using respectively FEM, REM and EEM methods.

In this case, EEM method has failed, when, FEM and REM had successes. Seed position generated by both FEM and REM methods is always inner the ROI.

(a)   (b)
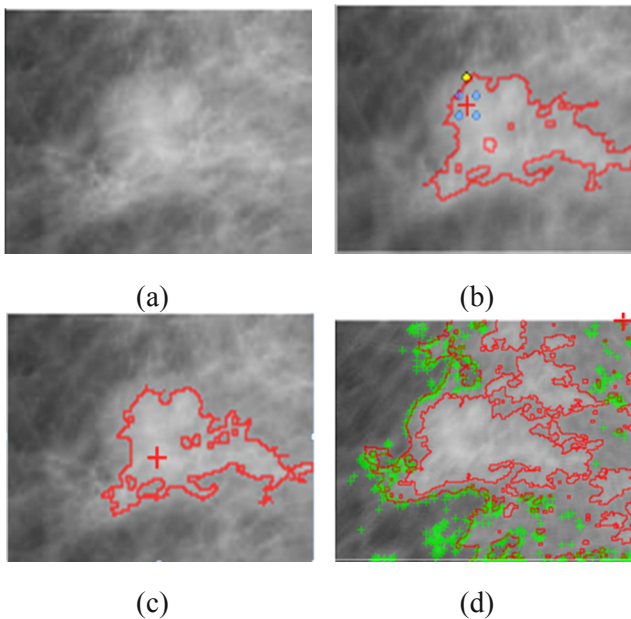
(c)   (d)

Fig.2 FEM, REM and EEM application example on a Breast MG image. (a) original image (b, c, d) seed generation results and segmentation results by using respectively FEM, REM and EEM methods.

Figure 3 illustrates seed selection results and segmentation results using FEM, REM and EEM methods on a Brain IRM example. The original image is illustrated in Figure 3(a). Figures 3(b, c, d) shows seed generation results and segmentation results by using respectively FEM, REM and EEM methods.

FEM and REM placed the seed inner the ROI. Note that the seed position generated by FEM

method is better than the REM's seed position relying on segmentation results. Another time, EEM failed.

Regarding the particular methods results on the three selected database, we make the following observations.

(a)   (b)
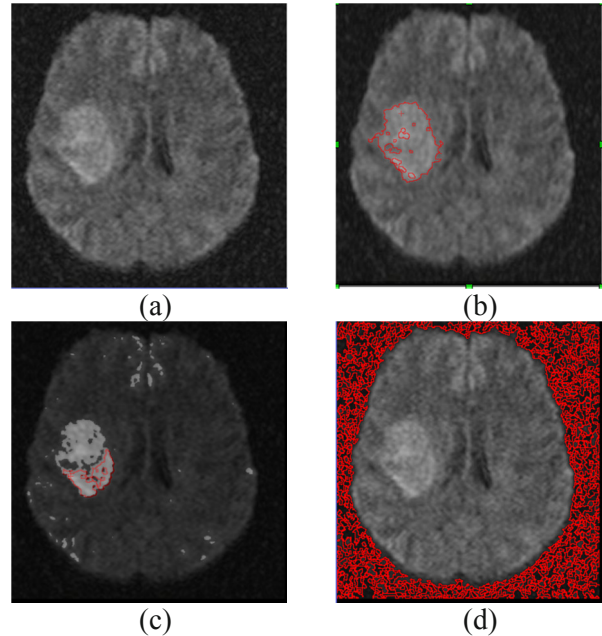
(c)   (d)

Fig.3 FEM, REM and EEM application example on a Brain IRM image. (a) original image (b, c, d) seed generation results and segmentation results by using respectively FEM, REM and EEM methods.

REM method is robust if ROI intensity is higher from its background and, its performance decrease when images noise increase. However, if ROI has low intensity the seed generation failed. In this case a pre-processing step to eliminate region with higher intensity than ROI is necessary.

No matter what the intensity is, FEM can get a better seed selection result as long as the features of ROI match with the predefined features. Otherwise, the seed selection results can be incorrect. Note that it is very hard and expensive in time to fix, in advance, predefined features values. These last must be determinate independently for each kind of medical images which needs a lot of experiments. The big advantage of FEM is its robustness against noise.

Results obtained by EEM are not concluded due to its behavior with the different kind of medical images. EEM gives good results when applying on IRM Breast images, but on IRM Brain images and MG Breast images, EEM failed. According Our interpretation the quality of the images affects well the accuracy of the EEM method. Indeed, IRM Brain images and MG Breast images have a less

quality compared to the IRM Breast ones. However, what shuck, impressed, us was the EEM method success in the cases where the two other seed selection methods failed. In fact, we have observed that for most tested images from the three databases, where FEM and REM generated seed outside the ROI, EEM placed seed inner it. Despite our analysis efforts, we didn't could give an interpretation for this EEM's behavior.

4.2 Statistical Results Values

Concerning this criterion, we are looking for statistical results values given by the tests.

The statistical data given by the plot of the figure 4 shows that the REM seed selection method is the best one. Effectively, it had success in over 50% for all tested images from the three selected database. We can clearly seen, that REM gives 56% of well seed selection for IRM Brain tested images, 80% for IRM Breast tested images and 55% for MG Breast tested images.

FEM seed selection method come in the second position with, 60% correct seed placement for IRM Breast tested images and 60% for MG Breast tested images. Unfortunately, only 28% of correct seed selection is attempts for IRM Brain tested images.

EEM failed in the most IRM Brain tested images and MG Breast tested images, less 15% correct results is obtained for these two kinds of medical images. The contrast is given by IRM Breast images. For those kinds of images, EEM comes very performance: 80% of good seed selection is achieved. No fundament explication can be done for these results. It is possible that more tests can help as to give some interpretation of this behavior.
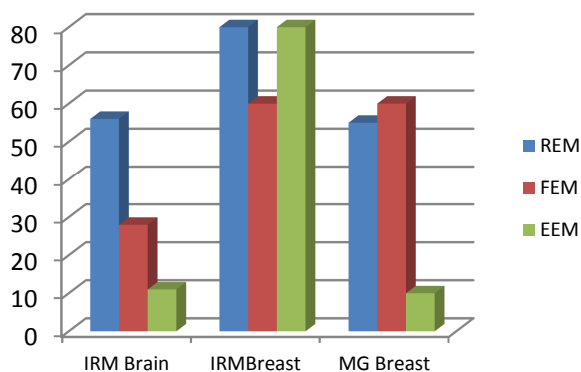

Fig. 4 Statically results of FEM, REM and EEM for MRI and MG tested images

4 Conclusion

Today seeded region growing algorithm is widely used in medical images. Because region growing result is sensitive to the initial seeds, the accurate seed selection is very important for image segmentation.

In this work we have implemented, tested and evaluated three automatic seed selection methods. The first method REM proposed by Al-Faris et al. is based on region extraction approach. The second method FEM proposed by Yuvaria et al. is based on features extraction approach. The last method EEM proposed by Pohle et al. 2001 and involved by Deboeverie et al 2013 is based on edge extraction approach. No absolute winner method in our test.

The tests were elaborated on three different medical images database. REM deals well for all databases. FEM performs for two of them. Unfortunately, EEM failed for two tested databases, in spite its performance increase for the third one.

Finally, we deduced from this study that the three methods gives us good results considering some tests but, according our opinion, no method among them is efficient and general. However, most tests must be added to improve the obtained results.

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