Overview of Automatic Seed Selection Methods for Biomedical Images Segmentation

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Abstract: *In biomedical image processing, image segmentation is a relevant research area due to its wide spread usage and application. Seeded region growing is very attractive for semantic image segmentation by involving the high-level knowledge of image components in the seed point selection procedure. However, the seeded region growing algorithm suffers from the problems of automatic seed point generation. A seed point is the starting point for region growing and its selection is very important for the success of segmentation process. This paper presents an extensive survey on works carried out in the area of automatic seed point selection for biomedical images segmentation by seeded region growing algorithm. The main objective of this study is to provide an overview of the most recent trends for seed point selection in biomedical image segmentation.*

Keywords: *Automatic seed selection, biomedical image, region growing segmentation, region of interest, region extraction, edge extraction, feature extraction.*

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1. Introduction

The number of biomedical images has grown significantly in the recent years. It has been generally agreed that visual interpretation of such images is very important for clinical diagnosis, localization of pathology, study of anatomical structure, treatment planning, evolution of therapy, computer integrated surgery, surgical planning, post surgical assessment, abnormality detection and so on. But, biomedical images are noisy and more complex to be understood so it would be important to represent them in a simple format or in an easier and more meaningful manner for analysis. Consequently, for faster and better interpretation, experts have to be assisted by image processing techniques applied on biomedical images.

Segmentation is one of the most difficult and important tasks in biomedical images processing. It consists of dividing an image into multiple homogenous fragments making a simple format of biomedical image so that the Regions Of Interests (ROIs) are specified. There are many existing algorithms for image segmentation. The widely used one is seeded region growing algorithm.

Region growing algorithm introduced by Adams and Bischof [2] and improved by Mehnert and Jackway [14] is robust, rapid and free of tuning parameters. Segmentation of biomedical images using seeded region growing technique is increasingly becoming a popular method because of its ability to involve high-level knowledge of anatomical structures in seed selection process [7]. However, the seeded region growing algorithm suffers from the problems of automatic seed generation [6, 14]. A seed point is the starting point for region growing and its selection is very important for the segmentation result. If a seed point is selected outside the region of interest, the final segmentation result will be definitely incorrect. Due to the low quality of biomedical images, most of the seeded region growing methods require the seed point to be selected manually in advance. But, the obvious way to improve the seeded region growing technique is to automate the process of seed point selection.

In this work, some state-of-the-art methodologies for seed point placement are reviewed. The motivation of this research is to provide an overview of the most recent trends for seed point selection in biomedical image segmentation. This survey focuses on the various techniques used for seed point selection with their strengths and weaknesses.

2. Seeded Region Growing Principal

Seeded region growing principal is based on selecting initial seed points located inside the ROI then adding neighboring pixels according a suitable membership criterion. 4 or 8 connected neighbors are frequently examined to determine the most similar ones in order to use them to grow progressively to fill a coherent region. This process runs iteratively until a stopping criterion is met. The growing process will produce a single region containing pixels with similar properties as the seed pixel.

In practice, two problems are related to seeded region growing method: the first one is the choice of the similarity criteria and the second problem is the seed selection. Seed selection problem is the most difficult one because it affects directly the quality of segmentation [16].

3. Seed Selection Criteria

To answer the question how to choose a seed point relevant to the interesting objects, some authors put special criteria for automatic seed point selection, the most used are:

1. Seed's position: for Li and Wan [8] the seed point has to be inside the region and mustn't fall on noise points or edge points. Unfortunately, this condition seems to be very general and doesn't give any information about the exact seed point location in the region. Wu *et al*. [24] put two conditions for seed point position.
1. The seed point must be located inner homogenous objects;
2. The seed point must be near the center of the region. Wu *et al*. [24] give more information about seed point location which must be the region center point but, they don't specify how to determine this center. Li and wan [8] define the region center as being the region composed by points which have a distance from nearest edge greater than a given threshold value. For Abdelsamea [1], we just have to make sure that the seed point candidate is not on the boundary of two regions and/or is not outlier.
2. Seed's neighbors: The distance between the seed pixel and its neighbors has to be small enough to allow continuous growing [24]. So, the seed pixel must have a higher similarity with its neighbor [8, 18].
3. Seed by region: For an expected region, at least one seed point must be generated in order to produce this region; Seeds points for different regions must be disconnected [18].

4. Automatic Seed Placement Background

Several papers have discussed automatic seed point selection for region growing segmentation in biomedical images. The seed point selection can be based on regions homogeneity, features, or edges. Hence, automatic seed point selection methods can be classified into three categories: Region extraction based methods, edge extraction based methods and feature extraction based methods. Other different seed point selection methods have been proposed by some researchers.

An overview of automatic seed selection methods for biomedical 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 feature extraction approach and the abbreviation "SE" is used for seeded selection based on edge extraction approach.

Table 1. Overview of seed selection methods in biomedical images segmentation region growing technique.

Reference	SR	SF	SE	Other	Technique	Applied on
Pohle and Toennies 2001[20]			✓		Gradient	Biomedical
Madabhushi and Metaxas 2003[9]				✓	Quantitative mathematical formula	Ultrasound
Poonguzhali and Ravindran 2006[21]		✓			co-occurrence features	Ultrasound
Shan *et al.* 2008[23]	✓				Binarization	Breast Ultrasound
Wu *et al.* 2009[24]		✓			2D Co-occurrence texture feature, Gabor texture feature, and both 2D and 3D Semi-variogram texture features are extracted	Abdominal MR
Mustafa et al. 2009[17]	✓				*k*-means	Multicells of *ThinPrep*®
Alattar *et al.* 2010[3]			✓		Active contour	Mycocardial MR
Senthilkumar *et al.* 2010[22]				✓	Harris	Medical image
Al-Faris *et al.* 2011[4]	✓				PSO clustering technique	Breast MRI
Abdelsamea 2011[1]	✓				Otsu segmentation method	Biomedical
Maitra *et al.* 2011a[10]			✓		Edge map	Mammogram
Maitra *et al.* 2011[11]			✓		Edge map	Mammogram
Mohd *et al.* 2012[15]	✓				Region splitting and merging technique	Brain
Noorul Mubarak *et al.* 2012[18]				✓	Harris	Medical image
Meenalosini *et al* 2012a[12]		✓			Histogram feature	Mammogram
Meenalosini *et al* 2012b[13]		✓			Histogram feature	Mammogram
Yuvaraj and Ragupathy 2013[25]		✓			Statistical features	Mammogram
Al-Faris *et al.* 2014[5]	✓				Thresholding	Breast MRI

4.1. Automatic Seed Selection Methods Based on Region Extraction Techniques

Based on region extraction, the automatic seed point selection approaches extract the region then select the seed inside this region.

Shan *et al*. [23] proposed a novel automatic seed point selection algorithm for breast ultrasound images. The proposed algorithm is composed of the following five steps:

1. *Speckle reducing*: speckle noise is reduced by using Speckle Reducing Anisotropic Diffusion technique.
2. *Threshold selection*: background and foreground are separated by an iterative select thresholds method based on the histogram and breast lesion's spatial characteristics.
3. *Boundary-connected regions deleting*: After image binarization, all regions connected with any of the

4 image boundaries and did not have intersection with the center-window are deleted

4. *Regions ranking*: Score formula rank is calculated for each left region. The lesion region is the winning region which had the highest score value.
5. *Seed point selection*: seed point is the center of the winning region.

To extract ROI from multicells of *ThinPrep*® images *k*-means clustering is used by Mustafa *et al*. [17]. From the extracted ROI zero order moment (m_{00}) and first order moment (m_{10} and m_{01}) are calculated. The seed point position (x_r ,y_r) is determined by application of the Equation (1).

$$x_r = \frac{m_{10}}{m_{00}} \quad y_r = \frac{m_{01}}{m_{00}} \tag{1}$$

For breast tumor segmentation on Magnetic Resonance Image (MRI), Al-Faris *et al*. [4] start their approach by skin detection and deletion. The Level Set Active Contour (Chunming's algorithm) is used to detect the breast skin border and the Morphological Thinning Algorithm is used to remove the breast skin border. The Particle Swarm Optimization (PSO) clustering technique is adopted for the process of partitioning the breast into several clusters. To extract the ROI, all the clusters are ranked in an ascending order according to their intensity values then; the region with the highest cluster is selected. The centre of the selected region is chosen as the seed point.

Recently, Al-Faris *et al*. [5] have replaced the PSO technique by the thresholding one. In their novel method of ROI extraction, they use a new algorithm for an automatic evaluation of the suitable threshold value. This algorithm searches for the maximum value in each row within the image and saves it temporarily. This process is repeated for all the rows until the last one. After that, the 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.

In order to segment biomedical images by an automatic seeded region growing process, Abdelsamea [1] applied the Otsu segmentation method for the ROI extraction after noise reduction by a median filter. To remove the outlier points and all points located on the boundary of the ROI, he used a *RXR* neighborhood mask. Only the points with neighbors located within the mask and not determined as a background are kept as seeds points.

For brain lesion detection by a fully region growing technique, Mohd *et al*. [15] performed a seed point selection based on three steps. Firstly, a pre-processing operation composed of intensity normalization; a background removing and a gamma-low transformation are applied. Secondly, the region splitting and merging technique is used for the ROI detection. Finally, the seed point is selected by the execution of the following algorithm:

Algorithm 1. Mohd Saad et al. Seed point selection

1. *P(i)= histogram(ROI)*
2. *Calculate divergence measure*

$$div(i) = \frac{dx}{dy} p(i)$$

3. *Optimal-threshold = the first nearest to zero value after divergence's maximum peak.*
4. *Seed = pixels that are higher than the Optimal-threshold.*

4.2. Automatic Seed Selection Methods Based on Edge Extraction Techniques

To prepare a seed point choice, automatic seed point selection researches based on edge extraction techniques applied edge detection techniques like the gradient calculation, the active contour and so on.

In their approach of medical image segmentation using region growing technique, Pohle and Toennies [20] performed a very simple method for seed point selection. They considered the smallest gradient value as a seed point. For them, it is the way to be sure that the seed point is always located within a region.

Alattar *et al*. [3] proposed a new seed point selection method for myocardial cine Magnetic Resonance (MR) images segmentation. In their work, the seed point is the pixel at a equi-angles on the estimated interior contour. The active contour model is used for an interior contour estimation.

To help radiologists in diagnosing breast cancer, Maitra *et al*. [10, 11] developed a masses detection approach in digital mammograms using region growing principal. [10, 11] approach's includes two innovations. The first one is the formulation of a homogeneity enhancement algorithm namely a Divide and Conquer Homogeneity Enhancement Algorithm (DCHEA). The second one is the implementation of a new Edge Detection Algorithm (EDA). The EDA result consists of an edge map. The edge map is used in breast boundary detection and pectoral muscle elimination. After breast (without pectoral muscle) delimitation, a coloring strategy based on region growing principal is applied to extract the masses. The coloring strategy is composed of 11 steps. Step 2 explains the process of seed point selection: If a pixel is not colored and is not a boundary pixel; therefore, it is considered as a seed point.

4.3. Automatic Seed Selection Methods Based on Feature Extraction Techniques

Automatic seed point selection approaches by feature extraction techniques apply two steps: the first one for the features extraction and the second one for the seed identification. In their approach, automatic technique for masses segmentation on ultrasound images by using region growing technique, Poonguzhali and Ravindran [21] selected the seed point automatically from the abnormal region based on co-occurrence features and run length features. This approach begins by computing the Haralick co-occurrence features. For Poonguzhali and Ravindran [21], energy and entropy co-occurrence features can easily distinguish between homogeneous and non-homogeneous regions. So, points with high energy and entropy values are selected. The run length features are calculated around the selected points. The seed point is defined as the selected point whose run length feature value is equal to all its neighborhood run length features values.

A new texture feature-based seeded region growing algorithm is proposed by Wu *et al*. [24] for automatic segmentation of organs in abdominal MR images. Wu et al. generate features vector for each pixel. The Vector includes the 2D Co-occurrence texture feature, the Gabor texture feature, and the 2D Semi-variogram texture feature.

Using features vectors, Wu et al. built a cost function Equation (2) by adding three sub-functions corresponding to three criteria:

1. The spatial distance from the pixel to the centre point of the ROI.
2. The Euclidean distance on feature space from the pixel to the centroid of the ROI and.
3. the sum of the Euclidean distance on feature space from the pixel to its neighbours.

The seed point is the pixel of the ROI with a minimum cost function value.

$$f(x,y) = \omega_1 * g_1(x,y) + \omega_2 * g_2(x,y) + \omega_3 * g_3(x,y) \tag{2}$$

$$\textit{with} \quad \omega_1, \ \omega_2 \quad \textit{and} \quad \omega_3: \ \textit{weights}$$

To detect cancer in mammograms, Meenalosini *et al*. [12, 13] used a region growing technique with a seed point generation based on histogram analysis. In their approach, a pre-processing stage composed of four operations is necessary. Firstly, the median filter is applied to remove noise and high frequency components. Secondly, the morphological operations with thresholding are performed to eliminate labels and x-ray marks. Thirdly, the normalization is introduced to reduce the variation in brightness. Finally, the adaptive histogram equalization is performed for contrast enhancement. The seed point generation starts by computing the histogram and the accumulated histogram. After, peaks locations in the histogram are found. An alarm pixel is generated using a specific condition based on peaks location. This alarm pixel is used as the seed point for region growing process.

As a part of the mammographic mass segmentation process, Yuvaraj and Ragupathy [25] propose a new seed point selection method based on statistical features. Mean, dissimilarity, sum average, sum variance and auto correlation are significant statistical features able to identify a mass. These features are computed and fixed for masses which have been previously identified by the expert. To detect a mass in mammograms, a mask is placed on the image. If the statistical features extracted from the regions within the mask do not match with the predefined features of masses, the mask is then shift. If not, the initial pixel of the mask is taken as the seed point.

4.4. Automatic Seed Selection Methods Based on Other Techniques

An automatic tumor detection method using the region growing technique in ultrasound images is proposed by Madabhushi and Metaxas [9]. To determine the true seed point from a set of random selected points $\{C_x\}$ a quantitative mathematical formula τ_{C_x} Equation (3) is developed.

$$\tau_{C_x} = \frac{\tau_{C_x}(i,t) \quad \zeta_{C_x} \quad Y_{C_x}}{d_{C_x}} \tag{3}$$

Where $\tau_{C_x}(i,t)$ refers to the joint probability value that C_x belongs to a tumor. ζ_{C_x} corresponds to the mean of the $\tau(i,t)$ value of pixels in a circular region around pixel C_x . Y_{C_x} is the row position of C_x and d_{C_x} is the Euclidean distance between the candidate seed point and the centroid of the image. The point which maximizes τ_{C_x} is the true seed point from the random selected points.

In order to segment medical images, a hybrid region growing algorithm was defined by Noorul *et al*. [18]. In this algorithm, the Harris corner detect theory is used to auto find the growing seeds points. The same principal is adopted by Senthilkumar *et al*. [22].

5. Discussion

The success of automatic seed selection methods based on region extraction is closely linked to the success of the ROI identification. If the ROI is well identified, it will be easy to place the seed point inside. In order to increase the rate of correct ROI identification, most automatic seed selection methods based on region extraction apply a heavy pre-processing step. Noise reduction, contrast enhancement, artifacts elimination and other techniques are used to remove undesirable regions and improve the ROI extraction. The application of all these pre-processing techniques doesn't offer a guaranty of a well ROI extraction. In some cases, automatic seed selection methods based on region extraction may fail. On the other hand, a correct identification of the ROI allows a correct choice of the seed point. This last can be placed in center area of the lesion. In this situation, the seed's position criterion is verified. Moreover, seed's neighbors criterion is verified, too since the ROIs are homogeneous. The criterion three, seed by region, is also valid because it is possible to place a seed in each detected ROI.

Due to the important number of features present in literature, features selection is the hardest step in automatic seed selection methods based on features extraction. Obviously, it is impossible to use all the proposed features. Consequently, a selection is necessary. Up to now, the only way to select the significant features is through testing some of them and choosing those which give the best recognition. As a result, the performance of automatic seed selection methods based on features extraction is deeply influenced by the selected features. So, a good features selection allows a correct ROI recognition and, a correct ROI recognition leads to a good seed placement. Consequently, the three criteria seed's position, seed's neighbors and seed by region are guaranteed only and only if the ROI recognition succeeds. Unfortunately, there is a possibility of bad recognition in some cases.

Seed selection methods based on edge extraction techniques need a pre-processing step to eliminate bad edges and close the remaining ones. Nevertheless, edges may be over-detected due to the biomedical images texture nature. So, a post- processing step to reduce the over-segmentation problem is necessary. Otherwise, this over-segmentation can have an undesirable effect: several seeds are generated for the same region; this means the loss of the three criteria, seed's position, seed's neighbors and seed by region.

6. Conclusions

There are several potential approaches to improve seed point selection for biomedical image segmentation using region growing algorithm. These approaches can be subdivided into three categories. The first category, based on region extraction uses a segmentation technique to extract ROIs then, selects seeds inside these regions. The second category, based on edges extraction applies edge detection techniques like gradient calculation, active contour and so on, to prepare seed point choice. The last category, based on features extraction consists of features calculation followed by seeds identification. Some other works are also proposed.

It is very hard to state which is the most competitive method in matter of automatic seed selection. Each method has its strength and its weakness. Works should be therefore carried on towards a comparison using the same medical image database in order to measure the efficiency of each method.

Most researches affirm that if the seed position is near the ROI centre, the segmentation becomes therefore more effective and efficient. However, it is still difficult to obtain accurate seeds automatically from the image [7, 19].

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