Iterative Quad Tree Decomposition Based Selection, & Detection & Segmentation of Breast Tumor Images using Region Growing Snake Contours

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Abstract— Mammography is currently the best method for detecting a breast cancer early, before the malignant tissue is substantial enough to feel or cause symptoms. However, the interpretation of a mammogram is often difficult and depends on the expertise and experience of the radiologist. Most of the problems or limitations in mammography can be overcome by using digital image processing techniques. Computer-aided-diagnosis (CAD) system can be used to assist the radiologists and the physicians analyses the overall images, and find tumors that a radiologist might not spot. Combining computer-aided-diagnosis with mammography will improve the ability to find cancer. There are number methods researched by scholars for medical image segmentation in which region growing and contour gradient based methods work efficiently at the tumor boundaries. But major requirement for such methods need a starting point or called as seed point in between the tumor. Their fore accuracy of actual tumor detection depends highly on the truly detected seed point.. Also the second drawback is their location such that they found near the boundary areas of tumor which results in the leakage of segmentation algorithms through weak boundary points. All these limitations has been covered in this work. Iterative quad tree has been improved with the help of morphological operations which gives seed point at the centroid of the tumor. Experimental results shows that proposed method gives high accuracy in truly segmentation of breast tumors in collected dataset.

Key words: Snake Contour Segmentation, QTD Algorithm, Ultrasound Images, Tumor Localization

I. Introduction

Ultrasonography has been one of the most powerful techniques for imaging organs and soft tissue structures in human body. It has been used for breast cancer detection in recent years because of the advantages of ultrasound (US) imaging such as no-radiation, sensitive to dense breast, low false positive rate, portable and cheap cost. Therefore, US imaging becomes one of the most important diagnostic tools for breast cancer detection. However, due to the nature of US imaging, the images always suffer from the poor image quality caused by speckle noise, low contrast, blurred edge and shadow effect. These make the segmentation of the interested lesions quite difficult. One of the frequently used segmentation methods is region growing. 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 interests (ROIs), the final segmentation result would be definitely incorrect.

Due to the low quality of US images, most of these region growing methods require the seed point be selected manually in advance. In order to make the region growing segmentation fully automatic, it is necessary to develop an automatic and accurate seed point selection method for US images. However, seldom works have been done in this area and the relevant works are rare and immature. All the existing methods take into account only the statistics texture features for a mass region (i.e, the mass is darker than the surrounding tissues and more homogeneous than other regions), seldom considers spatial features of a US mass (such as a mass frequently appears at the upper part of image and is barely connected with the image boundary). Therefore, the probability of a selected seed point outside the lesion is high, especially in the noisy and low-contrast images. In this paper, we develop a new automatic seed point selection method for US images QTD and active contours. The method not only considers the texture features of a lesion, but also incorporates the spatial characteristics of a lesion by considering quad tree decomposition and active contours to correct the seed point near the center of the lesion.

II. Background

Rashid Al Mukaddim et. al. (2016) proposed a novel approach to detect seed points inside breast lesions. Beginning with image pre-processing to enhance tumor-like hypoechoic and anechoic regions, we rank the candidate seed points using a novel approach and choose a seed point. Both qualitative and quantitative analysis are performed to evaluate the proposed method. It is also compared with two other automatic seed point selection methods on the same dataset and found to outperform both. We also assessed the factors that make seed point selection challenging. The radiologists are yet to be comfortable using a fully automated diagnosis system. However, even if these systems are used only to assist radiologists, the higher the accuracy, the simpler their jobs, because less intervention is required.

Samual H. Lewis et. al. (2012) investigated marker-controlled watershed segmentation for breast tumor candidate's detection. Instead of applying watershed segmentation directly on mammograms, we studied a morphological approach to clean up images and then determined foreground and background markers, which addressed the issue of over-segmentation and made the watershed segmentation result more reliable. The experiment with MIAS showed a 90% detection rate for mass tumors.

Yingguang LI et. al. (2012) introduces a PAORGB method for segmenting breast tumors in ultrasonic images. The proposed method is based on the particle swarm optimization algorithm to suitably set the values of the parameters (i.e. k and □), so as to overcome the problem of under-segmentation or over-segmentation in the RGB segmentation algorithm. Having carefully selected the evaluation function of PSO based on the between-class variance maximum theory (OTSU), the proposed approach makes it possible to find the optimal or suboptimal combination of k and □. The quantitatively experimental results have demonstrated that the proposed method significantly improves the performance of the RGB and outperform the conventionally used region based methods (i.e. the K-means and the FCM).

Mohammad I. Daoud et. al. (2012) introduced a semi-automated algorithm for segmenting tumors in ultrasound B-mode images. The algorithm uses a custom-made active contour model that is specifically designed for tumor segmentation. Two ultrasound-based features are employed to identify the tumor boundary, where both features are computed from ultrasound decompressed images. The first feature is the signal-to-noise ratio of ultrasound envelope data that is sensitive to the scatterer number density of the tissue. The second feature is based on the pixel gray-level values of the tumor that appear darker than the surrounding healthy tissue.

Ye-Hoon Kim et. al. (2013) employed an evolutionary multiobjective optimization (EMO) technique to find set of optimized parameters for ultrasound image segmentation, which were satisfying two objectives at the same time. As a novel EMO, the reinforcing proximity evolutionary algorithm (RPEA) was proposed to find out efficient parameter sets of active contour model. The proposed RPEA was based on strengthened proximity to the Pareto-optimal front and calculation of distance between the entire solutions. For the performance evaluation, RPEA was applied to the tumor segmentation problem of ultrasound breast images. As a results, RPEA generated more practical solutions with better proximity to Pareto-optimal front than the conventional algorithm. Moreover, various parameter settings optimized were compared in terms of describing ability of tumor lesion and processing time.

Guan-Lin Chen et. al. (2014) [50] proposed a method for accuracy evaluation to outline tumor contour, calculate tumor areas and centers of the maps plotted by physicians and outlined by this method. Find accuracies by overlapping centers and calculating overlapping areas and non-overlapping areas. The accuracy of this method reaches 90%.

Peng Jiang et. al. (2012) [51] investigated using machine learning based methods for breast tumor detection. Specifically, the AdaBoost classifier was employed to localize the tumor candidates, quantized intensity features with SVM were utilized to refine the result set and the random walks algorithm was used for tumor boundary segmentation. The effectiveness of the proposed methods was well demonstrated by the experimental results.

HUANG Zhanpeng et. al. (2016) [52] presented a novel liver segmentation method based on watershed segmentation and regions merging to extract liver area from CT images. For the CT images are noise and complex, the Gaussian filter is used to smooth the image. Then the multi-scale morphological gradient is calculated before the watershed segmentation. And the similarity criteria is calculated by analyzing the character of the neighboring sub-blocks of seed points chosen by the user. Finally the watershed image is merged based on similarity criteria.

P M Shivamurthy et. al. (2016) [53] proposed a novel idea of initializing the contour and edge gradient computation. This involves detection of seed points for initializing the contours using foreground markers extracted through morphological operations. The centroids of the markers serve as the contour initialization point and are effective in segmenting the overlapped objects. To assist in segmenting object boundary effectively, the edge gradient information has been computed using the morphologically reconstructed image resulting in better edge information. The efficiency of the proposed work has been studied with respect to the object detection accuracy and overlap resolution measures as compared to the manual delineation obtained by the expert pathologist. The proposed approach has been compared with the geodesic active contours without foreground markers.

Abdelali Elmoufidi et. al. (2015) [54] presented an approach for the segmented and detected boundary of different breast tissue regions in mammograms, by using dynamic K-means clustering algorithm and Seed Based Region Growing (SBRG) techniques. The strong point of our study is that we dynamically generated the number of breast tissue regions in mammograms, and automatically selected the seeds points of region growing technique, therefore, automatically segmented different breast tissue regions in mammograms.

III. PROPOSED TECHNIQUE

The proposed algorithm named a Quad tree based seed point detection algorithm. Quad tree is trees data structure in which every node either ends up on a leaf having interesting spatial information, or subdivided itself into further four level Quad trees. Quad trees are mostly used to divide a 2-D space by partitioning it into four quadrants. QTD is a data structuring technique used for storing 2D data with efficiency. There are two ways of QTD: one is bottom-up and another is top-down. We are employing top-down in this work. The core idea of top-down Quad tree is to decompose internal node into further 4 children according to the decided threshold.

In the proposed procedure, we will build up a system as programmed seed point choice strategy for the ultrasonic pictures which will used to recognize the tumors by utilizing the technique say wind shape based division. The ultrasonic picture is taken at that point commotion from that picture is lessened as dot say there is some clamor in the picture is available which at times make some decrease in the picture so in the dot decrease the picture commotion is done as such subsequent to getting the picture after spot decrease then the difference of the picture is appropriately improved and all the element are plainly preoccupied.

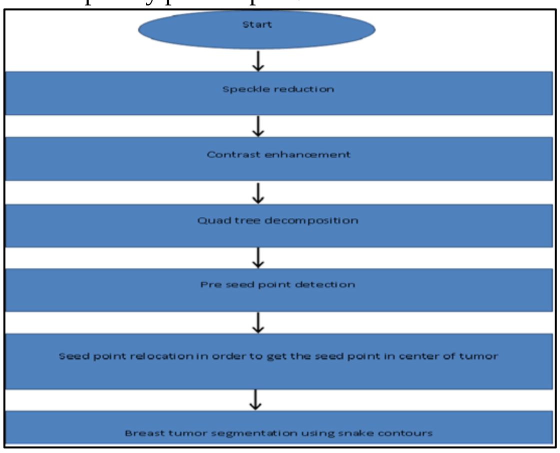

Fig. 1: The Flowchart of System Design

1) The first step is Brest segmentation is the process of segmentation allows separating the breast from other object in the mammogram images.
2) A seed point is the starting point for region growing and its selection is very important for the segmentation result.
3) Appropriate seed position selection in mammogram images can be difficult to achieve and requires a radiologist experienced with the algorithm, knowledge of the application.
4) First image has been divided into four similar size of blocks. Then its minimum and maximum values have been calculated.
5) This seed point is used by region growing snake contour method in order to segment out the tumor in the image.
6) Performance evaluation of the detected tumor has been carried out using sensitivity, specificity and accuracy metrics.

IV. RESULTS & ANALYSIS

In order to access the accuracy and performance of segmented results, we have used the following terms:

A. Sensitivity

Sensitivity is a statistical measure that defines the proportion of true positive subjects with the disease in a total group of subjects with the disease

$$\text{Sensitivity} \coloneqq \frac{TP}{TP + FN}$$

In other words, it yields the probability of getting a positive test result in subjects with the disease. Hence it relates to the potential of a test to recognize subjects with the disease [49].

B. Specificity

This measure of accuracy of a diagnostic test is complementary to sensitivity. It is defined as the proportion of subjects without the disease with negative test result to the total number of subjects without disease

$$\text{Specificity} \coloneqq \frac{TN}{TN + FP}$$

C. Accuracy

The overall accuracy is the analysis of the proposed model in the terms of overall accuracy, which is computed by dividing the total number of true cases (including true negative and true positive), by all of the cases.

$$\text{Accuracy} \coloneqq \frac{TP + TN}{TP + TN + FP + FN}$$

TP	252371
TN	7464
FP	1823
FN	486
Sensitivity	0.9980
Specificity	0.8037
Accuracy	0.9911

Table 4.1: Table showing different Accuracy Parameters

In order to implement a completely automatic segmentation method for breast cancer US images, we propose a new, robust, fast and automatic seed point selection algorithm. The algorithm needs no prior information or training process. By taking into account both the homogeneous texture features and spatial features of the breast lesions; we successfully find the seed points for maximum number of images found in World Wide Web. The quantitative results demonstrate the robustness of our seed

V. CONCLUSION

Breast segmentation is the first step in many Computer Aided Diagnosis methods, the process of segmentation allows to separate the breast from other objects in the mammogram Images. A seed point is the starting point for region growing and its selection is very important for the segmentation result. Appropriate seed position selection in mammogram images can be difficult to achieve and requires a radiologist experienced with the algorithm and knowledge of the application field. To overcome this limitation, we introduce a new method to select a seed point automatically based on iterative quad tree decomposition of the image. First image has been divided into four similar size of blocks. Then its minimum and maximum values have been calculated. If the selected block has difference of min and max values greater than a threshold, then the chosen block is subdivided into further four blocks. Similar procedure has been adopted until it satisfies the required conditions. Then mean value has been compared form the developed blocks such the maximum sized block but having least mean intensity value has been chosen as a seed point. This seed point is used by region growing snake contour method in order to segment out the tumor in the image. Experimental results have been carried out on number of images collected from internet and method works on almost all types of images. Performance evaluation of the detected tumor has been carried out using sensitivity, specificity and accuracy metrics In order to implement a completely automatic segmentation method for breast cancer US images, we propose a new, robust, fast and automatic seed point selection algorithm. The algorithm needs no prior information or training process. By taking into account both the homogeneous texture features and spatial features of the breast lesions; we successfully find the seed points for maximum number of images found in World Wide Web. The quantitative results demonstrate the robustness of our seed selection method. After seed point selection, snake contour segmentation has been applied which segments out the tumor region very efficiently. Experimental results show that snake contour based segmentation gives approx. 95% accuracy on the collected dataset in efficient detection of the tumor region in the breast image

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