An Interactive Segmentation Algorithm for Thyroid Nodules in Ultrasound Images

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Abstract. Thyroid disease is extremely common and of concern because of the risk of malignancies and hyper-function and they may become malignant if not diagnosed at the right time. Ultrasound is one of the most often used methods for thyroid nodule detection. However, node detection is very difficult in ultrasound images due to their flaming nature and low quality. In this paper, an algorithm for the formalization of the contour of the nodule using the variance reduction statistic is proposed where cut points are determined, then a method of selecting the nearest neighbor points which form the shape of the nodule is generated, later B-spline method is applied to improve the accuracy of the curve shape. The extracted results are been compared with graph_cut and watershed methods for efficiency. Experiments show that the algorithm can improve the accuracy of the appearance of modality and maximum significance of data in the images is also protected.

Keywords: Thyroid nodules · Nodule detection · B_spline curves · VR-Statistics

1 Introduction

The thyroid is a small gland located near the bottom of the neck. It produces hormones that affect heart rate, cholesterol level, body weight, energy level, mental state and a host of other conditions. Epidemiologic studies have shown that palpable thyroid nodules occur in approximately seven percent of the population, but nodules found incidentally on ultrasonography suggest prevalence up to 67 percent [1]. Thyroid nodules are abnormal lumps growing within the thyroid gland which may represent various different conditions including cancer. The risk of developing a palpable thyroid nodule in a lifetime ranges between 5 and 10 % while 50 % of people with solitary nodules detected by experienced physicians have additional nodules detected when further examined by ultrasonography [2]. Ultrasound imaging (US) can be used to detect thyroid nodules that are clinically occult due to their size or shape. However, the interpretation of US images, as performed by the experts, is still subjective. An image analysis scheme for computer aided detection of thyroid nodules would contribute to the objectification of the US interpretation and the reduction of the misdiagnosis rates.

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Ultrasound (US) images contain echo perturbations and speckle noise, which could make the diagnostic task harder. Additionally, image interpretation, as performed by the experts, is subjective. Therefore, a method for computer aided thyroid nodule detection should take into consideration the inherent noise characteristics of the US images and be capable of interpreting these images, based on explicit image features [3]. In order to accomplish computer-aided diagnosis of thyroid nodules on ultrasound images, the nodule's location and its margin must be clearly defined. Some methods based on fully automatic algorithms have been used in Ultrasound images but the lack of efficiency and loss of data might occur. These methods also can produce unacceptable segmentation results for complex scene images. However, manual locating of nodule boundary highly relies on physician's subjective decision. Other methods based on Graph_cut algorithms are also been popular in the last few years [4–7]. Though these sorts of methods might work well to some extent in the form of dividing the "object" and "background" of the image but still when noise diffused edges or occluded objects occur, traditional graph cut algorithm cannot get satisfied segmented object [5].

Poor US image quality and drawbacks caused by the nature of ultrasound limit the performance of various segmentation methods. The final result of the tumor location often depends on region selection. In this study, we proposed a method for thyroid nodule boundary detection based on the combination of radial gradient and Variance-Reduction statistics. We then implement an algorithm to automatically detect the nodule boundary mainly by connecting the most neighbour cut points located in the area of the boundary. Results of the proposed method are then improved with B-Spline method to elaborate the appearance of the curve.

2 Proposed Method

2.1 Analysis

The method implemented here is used to find the maximum and minimum manifest variation of the colors in the original pictures, the region of interest (ROI) is automatically generated based on the selected major and minor axis of the nodule manually inputted by the medical staff. Its radial lines are start growing from the center of the selected ROI to the maximum points that can be generated as shown in Fig. 1 (a–d).

Three colored of cut points on each radial line are searched by the Variance-Reduction statistics so that each cut point resulting in a minimum sum of two group's total sum of square, as in (1).

$$\min_{a}\left\{\sum_{i=1}^{a-1}(x_i-\mu_1)^2+\sum_{i-a+1}^{N}(x_i-\mu_2)^2\right\} \tag{1}$$

In (1), if a radial line has N number of pixels and their grayscale values are represented in the formula as $\{x_1, x_2, .., x_a, .., x_{N-1}, x_N\}$, where x_i is the grayscale value of the pixel point in order from the center to the boundary of ROI, and x_a is the grayscale value of the cut point that results in the minimum sum of two total sums of squares in which μ1 and μ2 are respectively, the average of the grayscale values of the inner pixels and outer pixels separated by the cut point. Moreover, two additional cut points are found using (1) from the two segments of the radial line separated by the first cut point as shown in Fig. 2.

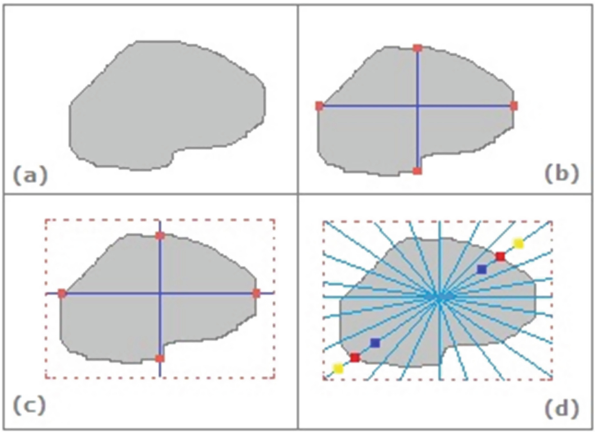

Fig. 1. Diagram of the working of the analysis (a) the main image. (b) input selected by the physician. (c) ROI new matrix based on the selection of major and minor axis. (d) process of cut points starting with the four nodes of the selected axis-es.

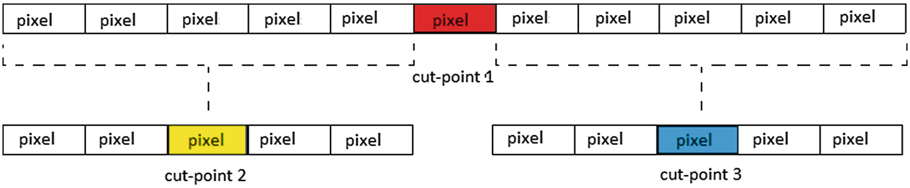

Fig. 2. Three colored cut-points generated by the variance reduction statistic (Color figure online)

2.2 Filtering

The proposed algorithm is applied to the previously generated method taking into account that we need to obtain the most desired cut points located in the area of the boundary. The inferred cut points later shaped the contour. An Input has been generated in the form of lines Matrix where the cut points are represented by three different colors considering Red points as primary.

Firstly, we created a constant value that represented the maximum number of cut points located into different groups called sections. The longest section will start the iteration here and during this process, a thresholding value is maintained in a sense of connecting last point of the last selected section to the next one. After selecting the next connected point we removed the other unwanted points and again start the next phase simultaneously as shown in Fig. 3(c).

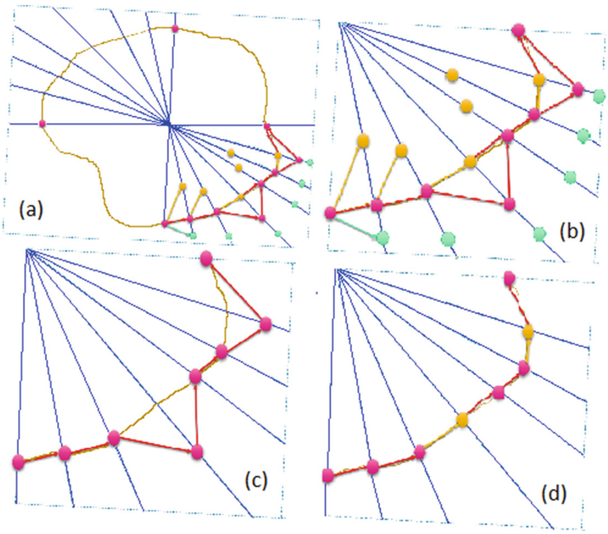

Fig. 3. (a) Creation of section (b) deciding the expected boundary (c) boundary without filter (d) boundary after filtered points.

To avoid some abnormal points that appeared due to the expected noise, the abnormal coordinates been evaluated too to determine the weight of availability and select the most desired closely points. The output matrix will later include the best suitable points coordinators and been extracted as shown in Fig. 3(d).

2.3 B-Spline Method

In filtering method, the result points are stored in a global variable which in term formed the (n * 2) matrix. The exterior of the boundary is appeared to be tortuous and hence the spline stage is generated. Input points are selected by a certain ratio generated and controlled by a changeable constant said to be K.

Depending on how many control points we decide the value of K. Different parameters are occurred using the B-Spline interpolation formula as in (2).

$$x(u) = \sum_{i=0}^{i=n} N_{i,k}(u)x_i \qquad (2)$$

For closing the curve, a certain number of control points were added in which spline range started from that number to $(e + 1)$ point. Then all points of that range are appended and the result spline points are drawn as shown in Fig. 4(b).

2.4 Performance Analysis and Evaluation

The performance of the proposed method is evaluated for the delineation of thyroid nodules of 26 ultrasound images. The process for segmenting organs and structures

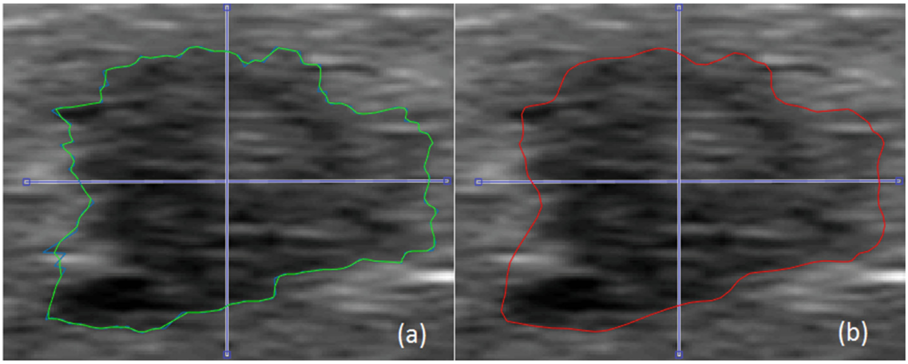

Fig. 4. (a) The output result of filtered method. (b) B-spline resulted in method applied on the extracted result

from medical images is gaining increased importance in the diagnosis of diseases specifically in Thyroid Nodules. And in guiding minimally invasive surgical and therapeutic procedures, the evaluation protocol for the further studies should take into consideration the boundary shape of the contour.

To evaluate the capability of the proposed method, the corresponding performances of our method, graph_cut method [7] and automatic tumor detection based on watershed method [8] were measurable compared. A measure of the accuracy of the thyroid tumor location is measured and the TPF, TNF, FPF, FNF, and Accuracy were also calculated. Each equation is defined as (3–7):

If VS and VT represent the regions enclosed by the segmented boundary and the "true" boundary respectively, we define the true positive volume (TP) as the volume enclosed by both the "true" and algorithm segmented boundaries i.e., $VTP = VS \cap VT$, the false positive (FP) volume is $VFP = VS - VT$, the false negative (FN) volume is $VFN = VT - VS$, and the true negative (TN) volume is $VTN = SCENE - VS - VT$ briefly explained as in Fig. 5.

(TPF) is the volume fraction in the "true" segmented boundary that is also enclosed by the algorithm segmented boundary; the (FNF) is volume fraction enclosed by the "true" boundary that was missed by the segmentation algorithm, the (FPF) is the volume fraction enclosed by the algorithm segmented boundary that was not enclosed

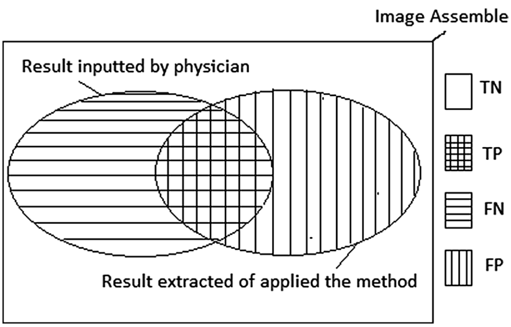

Fig. 5. Evaluation process structure

by the "true" boundary, and the (TNF) is the volume fraction in the background scene that was not enclosed by the "true" boundary and was not enclosed by the algorithm boundaries. After all the accuracy factor is generated. Accordingly the result of this comparison is been studied and shown in Table 1.

Table 1. Comparison of the proposed method and other published methods

Method	TPF (%)	FNF (%)	FPF (%)	TNF (%)	Accuracy (%)
Graph_cut	83.08	16.92	0.19	99.81	99.45
Watershed method	82.96	17.04	0.15	99.85	99.52
Proposed method	82.49	17.51	0.10	99.90	99.63

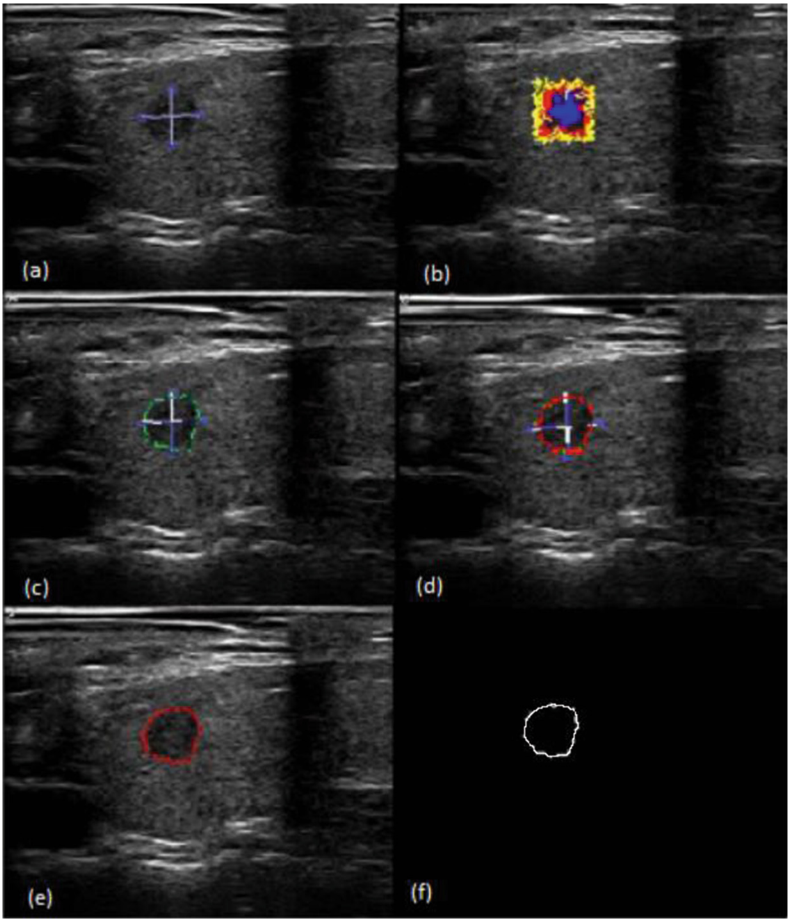

Fig. 6. Result of applying our proposed method (a) selecting the axis on the expected nodule (b) variance reduction method (c) applying the proposed filtering and shape the result (d) applying the b-spline method (e) redraw the final result (f) segment the result for further study.

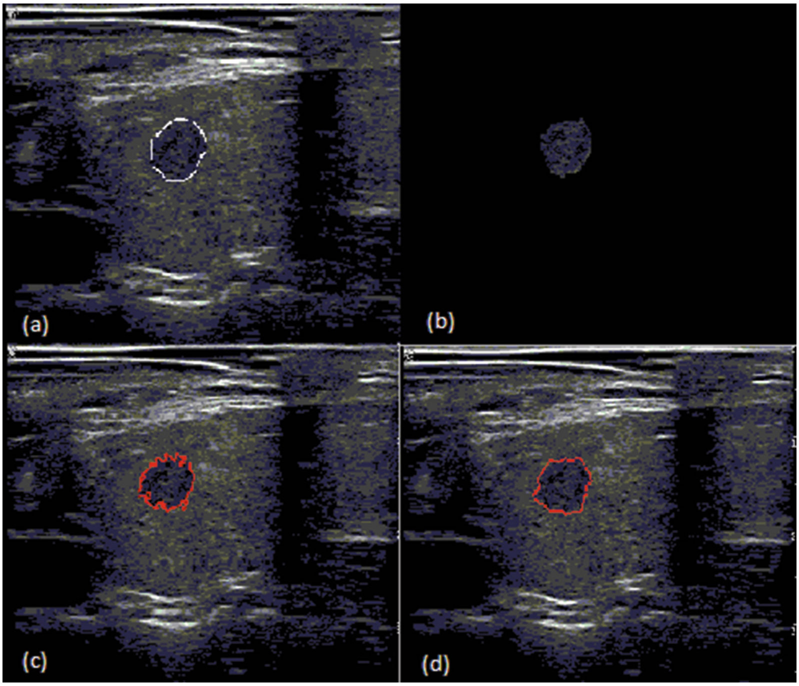

Fig. 7. (a) Result inputted by the doctor. (b) the result of graph_cut method. (c) the result of the automatic watershed method (d) result of our proposed method.

$$TPF = \frac{|A_A \cap A_G|}{|A_G|} \tag{3}$$

$$FNF = \frac{|A_G - A_A|}{|A_G|} \tag{4}$$

$$FPF = \frac{|A_A - A_G|}{|A_G|} \tag{5}$$

$$TNF = \frac{|\overline{A_A \cup A_G}|}{|\overline{A_G}|} \tag{6}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{7}$$

Where A_G represent the area of the ground truth of foreground and its complement is A_G, A_A represent the area of segmented foreground by the tested segmentation method. Table 1 lists the results of the corresponding formulas of the three measured methods applied on 26 images. We can see that our method achieved the best of the accuracy results (Figs. 6 and 7).

3 Conclusion

In this paper, an algorithm for detecting the contour of thyroid nodule is applied based on parameters that been extracted from the combination of radial gradient and variance-reduction statistic. The proposed method is applied depending on the most closely connected cut points which are located in the area of the boundary. Later the b-spline method is applied so that the final result would be more apparent and to avoid the tortuous resulted from the filtered method. The information of current US image is needed where the image can be changed to a binary image. This takes over the disadvantage of the graph_cut method as some of the data would be lost when applied. Detection accuracy of our method appeared clearer than the watershed automatic method.

The results of the experimental study presented in this paper also led to the following conclusions for the proposed scheme:

- The proposed scheme can improve nodule detection accuracy.
- The proposed scheme can considerably decrease processing time needed for nodule detection.
- Its application clinical practice is feasible and could contribute to the reduction of false medical decisions.

Future work and perspectives include:

- A scheme for application in an integrated real-time system for the assessment of the thyroid gland.
- Experimentation to determine the optimal feature extraction and classification methods for Thyroid Nodule detection.
- Performance of the proposed scheme will be investigated on images acquired from different US imaging system.
- An open problem is still precision, the efficiency of the results of our proposed algorithm compared to the real results inputted by the medical staff is a bit less where the process of finding compatible smoothing methods and reducing the noise of the images would be targeted.

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