Thyroid Nodule Segmentation Using Active Contour Bilateral Filtering on Ultrasound Images

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Abstract— **Utilization of ultrasound imaging with various resolutions as modalities for thyroid nodules examination is growing rapidly. This is consistent with an increase in incidence of thyroid malignancy. Thyroid ultrasound examination is considered superior to other medical imaging modalities for its non-invasive, practical, inexpensive and painless. In the examination process, a radiologist expects areas of thyroid nodules that can be localized precisely from the surrounding normal tissue. Thus boundary of the nodules can be seen as to be regular or irregular. Boundary is one of the important features of malignancy that doctors use to make a diagnosis. Most malignant nodules have unclear and irregular boundaries. Imprecise segmentation result will lead to misdiagnosis based on boundary characteristics. Active contour segmentation technique is applied for detecting boundary of thyroid nodules and separating them with normal tissue iteratively. However, the characteristics of the ultrasound image that brings speckle noises make the segmentation process more complicated. It also resulted in interpretation errors and inaccuracies diagnosis made by a doctor. The intricacy of irregular nodule area can not easily be solved by changing the value of iteration on active contour. Therefore, speckle noise reduction method is needed to overcome this problem so that nodule area segmented properly. In this paper speckle noise reduction is done with bilateral filter. Comparison of image segmentation results of thyroid nodules with and without bilateral filter is attached at the end of this article. The combination of bilateral filter and active contour showed better results with the edge of the nodules firmly and clear.**

Keywords—nodul; active contour; speckle; bilateral filter.

I. INTRODUCTION

Clinically [1], thyroid nodules are lumps that are not normal in the thyroid gland. Nodules can be solids, liquids (cystic) and a combination of both (complex cystic) with irregular shapes like circles or irregular. In the ultrasound image, nodules indicated by the appearance of different shades of gray texture from the surrounding tissue. Through the character of these nodules doctor can diagnose whether he has the potential to become cancerous thyroid malignant or benign. Based on recent data [2] it is known that the incidence of thyroid cancer findings is increasing from year to year in many countries from different continents, even the top five most common cancers, especially in women.

In a previous study [3] showed that 13-76% of thyroid nodules discovered by ultrasound and today has become a tool of the most effective screening of thyroid nodules among other imaging modalities [4]. This is quite reasonable because the ultrasound is very economical and is not an invasive imaging techniques that require special preparation before use, so it is a safe modality and without contraindications both for patients and clinicians [5]. However, the ultrasound image contains a lot of speckle noise which makes objects appear blurred with an intensity that is not uniform, this has resulted in decreasing of Signal to Noise Ratio (SNR) value [5]. It is known [4] that ultrasound imaging is much more operator-dependent, interpreting ultrasound images required a lot of experience. Error in interpretation of by doctors is due to the noisy ultrasound images. Therefore, examining the clarity of boundaries is very important in diagnosis. Nodule segmentation is an important step because many crucial features for discriminating benign and malignant lesion are related to lesion shape and boundary as mentioned in [1][6]. Most malignant lesions have unclear and irregular boundaries. Imprecise segmentation result will lead to misdiagnosis based on boundary characteristics.

Some of researchers [7][8][9][10] localised the object area with active contour segmentation, but less concerned with the influence of speckle noise in ultrasound images. Involution of irregular nodule area cannot easily be solved by changing value of iteration on active contour, although it has been pursued by region of interest (ROI). There should be an effort to reduce speckle noise to confirm the edges of objects so easily segmented with little iterations and retains its original texture. Refers to the comparison of various filters which exist [5][11], its proved bilateral filter is the best algorithm to reduce speckle noise.

In this paper, active contour segmentation and bilateral filtering are combined to separate the thyroid nodule areas. Ultrasound images undergo speckle noise reduction, followed by segmentation of the nodule areas with active contour.

II. Theoretical Basis

A. Bilateral Filtering

Bilateral Filtering first introduced by [12] is one type of low pass filter which is intended to smooth the image while maintaining the quality of the edges of objects. Performance and reliability of these filters in reducing speckle described in detail by [5], while the general equation is as follows:

$$h(p) = \Gamma^{-1}(p) \int_{\Omega(p)} f(\xi) c(\xi, p) s\big(f(\xi), f(p)\big) d\xi \quad (1)$$

where

$$\Gamma(p) = \int_{\Omega(p)} c(\xi, p) s\big(f(\xi), f(p)\big) d\xi \quad (2)$$

$f(p)$ is an original image, $h(p)$ is the filtered image, $\Omega(p)$ is a measure of neighborhood window, while ξ is a representation of the pixel location.

$c(\xi, p)$ and $s\big(f(\xi), f(p)\big)$ respectively defined as :

$$c(\xi, p) = exp^{\left(\frac{-\|p-\xi\|^2}{2\sigma_c^2}\right)} \quad (3)$$

$$s\big(f(\xi), f(p)\big) = exp^{\left(-\frac{(f(p)-f(\xi))^2}{2\sigma_s^2}\right)} \quad (4)$$

where σ_s is the standard deviation of the Gaussian random value on spatial area and σ_c is the standard deviation for the Ω window area.

B. Active Contour

The fundamental idea in active contour models is to evolve a curve, subject to constrains from a given image u_0, in order to detect object in that image [13]. For instance, starting with a curve around the object to be detected, the curve moves toward its interior normal and has to stop on the boundary of the object [13]. Active contour as one of the area-based segmentation algorithm is capable of detecting an object image by minimising the energy difference. This method is an improvement over the edge-based segmentation using image gradient.

Based on the exposure of [9], an evolving curve C in the image space Ω can be defined as the frontier of a subset ω of Ω $((\omega \subseteq \Omega$ and $C = \partial\omega)$. Symbol ω represents the region occupied by foreground pixels. $inside(C)$ denotes the region ω and $outside(C)$ denotes the region $\Omega\backslash\varpi$. Here, the image u_0 is assumed to be composed of two regions of approximately constant intensities c_1 and c_2 that is intensity of the object and intensity of the background respectively. If the object's boundary is C, then inside of C the intensity value should be equal to c_1. Outside of C, the intensity value should be equal to c_2 . Chan and Vese [13] explain the following energy :

$$F(c_1, c_2, C) = \mu.Length(C) + v.Area(inside(C)) + \eta_1 \int_{inside(C)} |u_0(x,y) - c_1|^2 dxdy + \eta_2 \int_{outside(C)} |u_0(x,y) - c_2|^2 dxdy \quad (5)$$

where $\mu \geq 0$, $v \geq 0$, $\eta_1, \eta_2 \geq 0$ are fixed constant. The length of the curve, $Length(C)$ and the area of the region inside C, $Area(inside(C))$, are two regularizing terms. Chan and Vese [13] set value of $v = 0, \eta_1 = 1, \eta_2 = 1$ and Moar [9] add value $\mu = 0$. The segmentation of lesion from the background is accomplished by solving the minimization problem $\inf_{c_1, c_2, C} F(c_1, c_2, C)$.

Let $C \subset \Omega$ be defined as the zero level set of a Lipschitz function $\varphi : \Omega \to R$, so :

$$\begin{cases} C = \partial\omega = \{(x,y) \in \Omega : \phi(x,y) = 0\} \\ inside(C) = \omega = \{(x,y) \in \Omega : \phi(x,y) > 0\} \\ outside(C) = \Omega\backslash\varpi = \{(x,y) \in \Omega : \phi(x,y) < 0\} \end{cases}$$

Using the step function H and impulse function δ_0 defined by Chan dan Vese [13], the energy $F(c_1, c_2, C) = F(c_1, c_2, \phi)$ can be expressed as follows :

$$F(c_1, c_2, C) = \int_\Omega |u_0(x,y) - c_1|^2 H\big(\phi(x,y)\big)\, dx\, dy + \int_\Omega |u_0(x,y) - c_2|^2 \Big(1 - H\big(\phi(x,y)\big)\Big)\, dx\, dy \quad (6)$$

The constants c_1 and c_2 can be expressed relative to :

$$c_1(\phi) = \frac{\int_\Omega u_0 H(\phi(x,y))\, dx\, dy}{\int_\Omega H(\phi(x,y))\, dx\, dy} \quad (7)$$

$$c_2(\phi) = \frac{\int_\Omega u_0 (1 - H(\phi(x,y)))\, dx\, dy}{\int_\Omega (1 - H(\phi(x,y)))\, dx\, dy} \quad (8)$$

The evolution of ϕ can be parametrized as follows :

$$\frac{\partial\phi}{\partial t} = \delta_0(\phi)[(u_0 - c_1)^2 + (u_0 - c_2)^2] = 0 \quad (9)$$

The segmentation algorithm follows an iterative method that apply $\phi(x,y,s)$ at time $t = s.\Delta t$. The value of $c_1(\phi, s)$ and $c_2(\phi, s)$ can be calculated by applying equations(12) and (13). Then $\phi(x,y,s+1)$ can be computed by the following discretization and linearization of (14) in :

$$\phi(x,y,s+1) = \phi(x,y,s) + \Delta t.\delta_0\big(\phi(x,y,s)\big).[-(u_0(x,y) - c_1(s))^2 + (u_0(x,y) - c_2(s))^2] \quad (10)$$

where Δt denotes the time step size and $u_0(x,y)$ representation of initial image.

III. Material and Methods

The images used in this experiment were obtained with the permission from Department of Radiology Sardjito Hospital Yogyakarta. Fig.1 shows the left lobus thyroid of female patients aged 53 years. Nodule areas were marked with a light green color box. They were acquired from General Electric Ultrasound machine probe P3 Series 7Mhz in November 2012 ago.

Flowchart showing the proposed algorithms shown in Fig.2. Resolution of the input image is 640 x 480. The computation time takes longer if the segmentation process is performed on the entire image field. Therefore segmentation area is focused on the Region of Interest (ROI) of a rectangle measuring range of 150 x 100 pixels. The challenge here is to separate the nodule is in the ROI area right on the edge of the boundary. ROI indicated by a blue box and nodule boundary indicated by the green line on Fig.3.

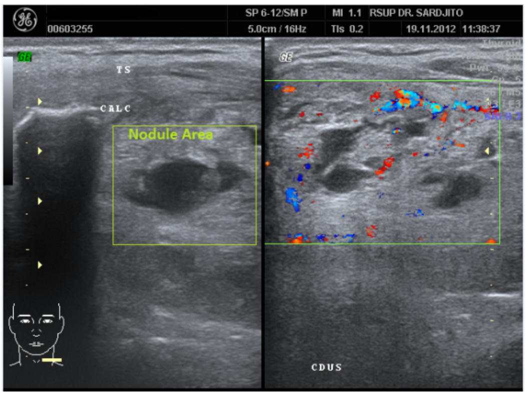

Fig 1. Ultrasound Images of Thyroid Nodule

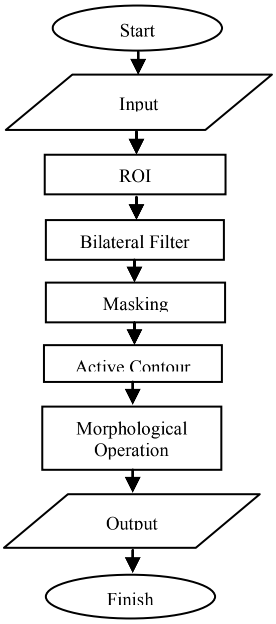

Fig2. Flowcart of Active Contour Bilateral Filtering

Speckle reduction efforts with bilateral filter can be said as well as the smoothing process. As the smaller ROI area then the filtering process will run faster. Bilateral filtering results can be seen at the title SRBF-Specke Reduction Bilateral Filtering on Fig.3. There, it can be seen that SRBF image softer than the ROI image. The active contour segmentation results without bilateral filtering is shown on Fig.4.

In addition to narrowing the screening area, the ROI is also used to determine the initial masking. As mentioned in Eq.(5) on a theoretical basis, that the active contour is the process of minimising the energy difference between the inside and outside contour area. Therefore, it is necessary to determine initial shape before starting the iterations. The process of determining the initial contour of this is called a masking.

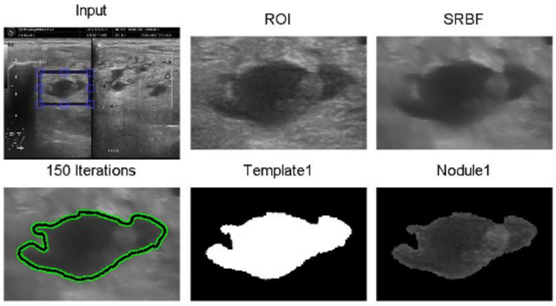

Fig 3. Active Contour Bilateral Filtering

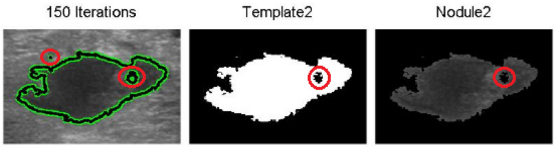

Fig 4. Active Contour Without Bilateral Filtering

Different from masking in [5], here a rectangular shape is used following the ROI size. Determining the appropriate masking area will produce segmentation results properly and also with minimal iteration consumptions. Initials masking shape will be narrowed to the concomitant of increasing iterations and stop when it is right on the edge of the nodule boundary. Nodule size of each input is different; therefore, the size of the ROI is designed to be flexible and adaptive to the image dimensions of the nodule. If m X n is the size of the ROI then the masking size is half of the ROI dimensions that is $0.5mX0,5n$. Both ROI and initial masking in the same center point.

The output of an active contour segmentation is a binary image of black and white. This binary image is used as a template to get the nodule area by applying a simple morphological operations such as AND, OR and NOT. Referring to Fig.3, the initial masking snugly against the edge of the nodule boundary when the 150th iteration. *Template1* is the result of the active contour segmentation. *Nodule1* obtained from the morphological operation between *Template1* and *ROI* image.

IV. RESULTS AND DISCUSSION

Bilateral filtering is done to soften the edges of the nodule. The information contained in the original image optimally maintained. It is important for image recognition and classification purposes if desired in subsequent studies. We use computed performance metrics as in the study of Wu *et al* [5] that are MSE (Mean Square Error), SNR (Signal to Noise Ratio), PSNR (Peak Signal to Noise Ratio), AD (Average Different) and SI (Speckle Index). These fifth indexes are benchmarked because these values exceed the performance of other filters in reducing speckle in ultrasound medical images [5].

Smaller value of MSE and AD showed more similarity between filter image and the original ones. Amount of information that can be maintained in the image shown by the SNR and PSNR values. The greater value of both SNR and PSNR indicates that the information from original image can be maintained properly. The SI index shows the amount of speckle noise inside the images. Low values are expected in this study so that the content of the speckled noises can be significantly reduced.

TABEL I BILATERAL FILTER PERFORMANCE (NOTE : THE SI VALUE OF ORIGINAL IMAGE ON THIS RESEARCH EQUALS 1.43e-5 AND *WU'S* RESEACH EQUALS 3.65e-6)

	MSE	SNR	PSNR	AD	SI
Proposed method	53.19	19.92	30.87	0.0221	1.32e-5
Wu *et al* [5]	26.88	16.45	33.84	0.0229	3.42e-6

From Table I, there are only two values that surpass the results of Wu *et al* [5], namely SNR and AD neither the others. Other index values are comparable. Among the five values of the index are quite able to demonstrate the quality of speckle noise reduction is the value of SI. Table I shows the content of speckle produced by Wu *et al* [5] experiment is smaller than the results of this study, however it can be seen that the content of speckle noise in the original image in Wu *et al* [5] is far less than that of the proposed method. It is important to note on how many speckle reductions that have been successfully carried out. Wu *et al* [5] is able to reduce speckle content of the value SI 3.65e-6 into 3.42e-6, while in this study, the value of SI is reduced from 1.43e-5 to 1.32e-5. Showing that the proposed method and Wu *et al* [5] have the same capability and indicates the filter are comparable to previous work.

In addition to refine the edges of nodules, bilateral filters are also able to minimise iterations on active contour. In the image demarcated, adding value iteration does not affect the results of segmentation. However, it is very difficult to get a firm's image on the ultrasound machine due to presence of many speckle contents in it. Comparison of the segmentation process between bilateral filter and without bilateral filter can be seen in Fig.3 and Fig.4. Can be seen in Fig.4 the active contour segmentation without bilateral filter is very rough and produces many errors. Unwanted segmentation results or error are marked in the red circles.

V. CONCLUSION

Results segmentation of thyroid nodules on ultrasound image of the active contour is less than optimal because of the influence of speckle noise. Bilateral filtering support active contour segmentation effectively. This is demonstrated by the localization of the nodule area is clear and unequivocal. SNR and PSNR that shows information of the image can be maintained well. Impairment SI indicates the success of the speckle noise reduction in ultrasound images. However, more research is still needed to make more adaptive iteration number on active contour. Thus the segmentation process can be run without estimate the value iteration manually.

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