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Automated delineation of thyroid nodules in ultrasound images using spatial neutrosophic clustering and level set

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ABSTRACT

An accurate contour estimation plays a significant role in classification and estimation of shape, size, and position of thyroid nodule. This helps to reduce the number of false positives, improves the accurate detection and efficient diagnosis of thyroid nodules. This paper introduces an automated delineation method that integrates spatial information with neutrosophic clustering and level-sets for accurate and effective segmentation of thyroid nodules in ultrasound images. The proposed delineation method named as Spatial Neutrosophic Distance Regularized Level Set (SNDRLS) is based on Neutrosophic L-Means (NLM) clustering which incorporates spatial information for Level Set evolution. The SNDRLS takes rough estimation of region of interest (ROI) as input provided by Spatial NLM (SNLM) clustering for precise delineation of one or more nodules. The performance of the proposed method is compared with level set, NLM clustering, Active Contour Without Edges (ACWE), Fuzzy C-Means (FCM) clustering and Neutrosophic based Watershed segmentation methods using the same image dataset. To validate the SNDRLS method, the manual demarcations from three expert radiologists are employed as ground truth. The SNDRLS yields the closest boundaries to the ground truth compared to other methods as revealed by six assessment measures (true positive rate is 95.45 ± 3.5%, false positive rate is 7.32 ± 5.3% and overlap is 93.15 ± 5.2%, mean absolute distance is 1.8 ± 1.4 pixels, Hausdorff distance is 0.7 ± 0.4 pixels and Dice metric is 94.25 ± 4.6%). The experimental results show that the SNDRLS is able to delineate multiple nodules in thyroid ultrasound images accurately and effectively. The proposed method achieves the automated nodule boundary even for low-contrast, blurred, and noisy thyroid ultrasound images without any human intervention. Additionally, the SNDRLS has the ability to determine the controlling parameters adaptively from SNLM clustering.

1. Introduction

The growth of cells or cysts in the thyroid gland leads to nodules which may be solitary, multiple or fused with each other. Generally, the occurrences of malignant cases among all thyroid nodules are 0.1–0.2% [1]. The frequency of palpable thyroid nodules in adult population is near about 4% to 8%. It generally increases with the age and affects more than 50% of the world's population [2]. A thyroid nodule is usually categorized as hypo-echoic, iso-echoic or hyper-echoic. Previous studies have shown that hypo-echoic nodules with uneven boundaries are more likely to be evolved into malignant nodules [3]. Though the majority of nodules are benign, few of them may be malignant nodule. Therefore, detection of thyroid nodule is aimed to determine a possible malignancy. The malignancy of thyroid nodule's can be assessed by Thyroid Imaging Reporting and Data System (TIRADS) and is categorized as malignant, suspicious for malignancy, borderline, probably benign and benign [2]. Most of the malignant thyroid nodules have distinct histopathological components often merged with surrounding tissues, which make the delineation task difficult [4].

Ultrasound (US) and computerized tomography (CT) are the most commonly used imaging modalities for the detection of thyroid nodules. Primary detection of nodules, such as nodular goiter and thyroid tumors, using US images are well documented in several books and articles [3–5]. Ultrasound image is suitable to detect thyroid nodule due to its vascularity, echogenicity, superficial location, and size. A thyroid ultrasound (TUS) image is blurry and noisy due to artifacts, such as refraction, speckle, acoustic shadowing, and reverberation echo. Segmentation of TUS image in computer-aided detection (CAD) system becomes one of the challenging tasks due to speckle noise and low contrast. One of the major challenges in the

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segmentation of thyroid nodules is to make accurate delineation of nodules within organs due to inherent intensity in-homogeneity of tissue texture and speckle, which appears as bright spots.

In literature, many efforts have been made in nodule delineation using TUS images. Generally, the Active Contour methods using intensity features were used to supervise the contour evolution. One of the models known as Variable Background Active Contour (VBAC) was proposed for nodule detection in TUS images [6–8]. The VBAC model can be employed without pre-processing and is able to detect more than one nodule. It offered more accuracy, topological variations, and edge independency as evaluated to the Active Contour Without Edges (ACWE). A drawback of VBAC is that it is device dependent. In most of the cases, technical skills are required for parameter tuning and time-consuming manual interaction. In spite of this, VBAC is not able to segment isoechoic nodules [8]. ACWE assumed homogeneity for object and background areas. This presumption is violated in TUS images due to the intensity inhomogeneity of the thyroid tissue texture and the presence of calcifications in form of bright spots [9]. Further, Tsantis et al. proposed the hybrid multiscale model (HMM) that integrated the Hough transform and wavelet-based edge detection method for the segmentation of nodules in TUS images [10]. A drawback of the HMM is that it required a priori information about the shape of the nodule boundaries to be detected. Therefore, it was not able to segment benign nodules with elliptical boundaries and malignant nodules which exhibit irregular boundaries. To overcome the drawback of VBAC, Iakovidis et al. integrated the Genetic Algorithm (GA) with VBAC known as GA–VBAC model for nodule segmentation in TUS images with automatic tuning of parameters [11]. Another algorithm named as thyroid boundary detector (TBD) was presented for the detection of thyroid boundaries by providing initial ROI with feature extraction and classification methods in US images [12]. Later, a joint echogenicity–texture (JET) model was presented, which co-evaluated the intensity of image and linear binary pattern (LBP) distributions by Mumford–Shah function [15]. The JET model incorporated the advantages of VBAC to delineate hypo-echoic and hyper-echoic nodules as well as iso-echoic nodules. Furthermore, it overwhelmed the drawbacks of HMM through topological adaptability. A limitation of the JET model is that it is not able to distinguish structures such as bigger blood vessels from actual nodules. Later, thyroid nodule detector (TND) system was presented for nodule detection in TUS images and videos with more than 95% accuracy [16]. One of the thyroid nodule segmentation methods for ultrasound images is given in [17]. The method is consisted of contrast enhancement, smoothing and segmentation based on edge based active contour model. In this method, human intervention is needed for the initialization of active contour model. The performance measures of various thyroid segmentation methods are given in Table 1.

Table 1 reveals the numerous improvements that have been made on CAD of TUS images. The major drawbacks of segmentation methods (such as Support Vector Machine, region growing, etc.) are human interactions such as the pre-labeled ROIs or manually initialized contours. Also, reformulating and training the methods are always time-consuming, especially for complex US images. No work on fully automated thyroid nodule delineation based on unsupervised techniques in ultrasound images is published so far. The echogenicity (such as hypo-, iso- or hyper-echoic), low contrast, non-uniform luminance, speckle noise and other artifacts limit the accuracy of automated delineation of thyroid nodules. Until now the segmentation methods for TUS image are semi-automatic or interactive due to which experts have to initiate, or stopping criteria has to be provided to interrupt the method. To overcome these drawbacks, delineation method has been proposed that performs without any human intervention.

Efforts have been made to automate the segmentation method on ultrasound images using fuzzy clustering to provide rough estimation of contour with the integration of level set method [21–23]. However, the operators are still needed to adjust parameters cautiously for an accurate and effective level set segmentation. The enhanced Fuzzy C-Means (FCM) method with spatial information was given for initialization of level set function [22]. Distance Regularizer Level Set Evolution (DRLSE) method also emerged as a powerful technique in ultrasound segmentation considering its overall performance. But it was not able to track weak edges in US images [24]. DRLSE highly responds on manually initialized contours or pre-labeled ROI, which impedes the automated segmentation of ultrasound image. Hence, an attempt has been made to enhance the DRLSE method in accordance to the application requirements. Neutrosophic based approaches are becoming popular that have been extensively applied to resolve US segmentation problems [25,26,28–30].

As per literature, till date no work is published on level set with neutrosophic clustering for automated nodule delineation in thyroid ultrasound images. In this paper, an integrated scheme named as Spatial Neutrosophic Distance Regularizer Level Set (SNDRLS) is presented for an automatic delineation of nodules in TUS images. Initially, SNLM clustering incorporates spatial information throughout adaptive optimization. Then, parameters of DRLSE are directly obtained from SNLM. Finally, the SNDRLS supervised by SNLM is proposed to delineate the nodules automatically in TUS images. The proposed method is validated on TUS images by comparing its results against delineation from three expert radiologists. Moreover, interpretation of images done by radiologists is subjective. The same dataset of thyroid ultrasound images and comprehensive evaluation metrics are used to compare the performances of different methods.

The rest of the paper is organized as follows. Section 2 presents the materials and methods. Section 3 discusses the experimental results. Discussion and conclusion are given in Sections 4 and 5, respectively.

2. Material and methods

2.1. Image dataset

As no standard dataset is available on thyroid US images, so previous methods reported in literature were performed by authors on their own dataset acquired from different hospitals for testing and validation. In this research, B-mode thyroid US images of 42 subjects were collected from the Department of Radiology, Post Graduate Institute of Medical Education & Research (PGIMER), Chandigarh, India for retrospective study. Out of 42 subjects, 16 were males, 26 were females, whose age ranging from 15 to 70 years. The dataset consists of hyper-echoic and hypo-echoic nodules. The images are of size 628 × 656 pixels, which were acquired with a 256 gray-level depth using IU22 Philips X Matrix with linear probe at a frequency of 17.5 MHz. Each thyroid nodule is outlined by three different experts and the manual delineation is aided as golden standard for comparison. The proposed method was implemented in Matlab 7.9 environment on Toshiba 2.00-GHz Dual-core Laptop.

2.2. Evaluation metrics

The metrics used to investigate the performance of the proposed method on TUS images are area based error metrics and boundary based metrics. Area based error metrics are used to evaluate how much nodule pixels are covered by the automated method correctly and how much are covered wrongly. The boundary based