Thyroid Nodule Segmentation and Classification in Ultrasound Images

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Abstract—**This paper proposes, a novel computer based approach for benign or malignant assessment of thyroid nodules in ultrasound images. Ultrasound imaging is one of the frequently used diagnosis tool to detect and classify abnormalities of the thyroid gland. The proposed approach comprises of four important stages: pre-processing, segmentation, feature extraction and classification. Rayleigh trimmed anisotropic diffusion filter is used for pre-processing. A watershed algorithm is used to segment the nodule region. An artificial neural network (ANN) and support vector machine (SVM) classifiers are employed for the classification task, utilizing feature vectors derived from gray level co-occurrence (GLCM) features. The classification results are evaluated with the use of accuracy, sensitivity and specificity. It is derived that SVM classifier provides better result than ANN for discriminating benign and malignant nodules, obtaining accuracy 92.5%, sensitivity 96.66% and specificity 80%.**

Keywords— Thyroid Ultrasound; Anisotropic Diffusion; Computer Aided Diagnosis(CAD); Watershed Segmentation; GLCM; SVM; ANN;

I. INTRODUCTION

Thyroid gland belongs to the endocrine system. They are located in the neck just in front of the larynx. Thyroid nodules are common in adults and are indicative of potential thyroid cancer [1]. The thyroid nodule rate is approximate 2-7% of the population in India. Thyroid nodule formation is due to abnormal growth of thyroid cells into a lump within the thyroid. Their prevalence is estimated up to 50% of the asymptomatic population when determined by ultra-sonography (US), though only a small portion of them (<7%) are malignant [2].

The major challenge for the medical community is the identification of benign and malignant risk factors of thyroid nodules, thus avoidance of unnecessary and costly invasive procedures for patients with benign nodules. Thyroid gland is covered by a thin layer of muscle. Due to superficial location of the thyroid gland, ultrasound technology has become the most widely used imaging modality for the diagnosis and fallow up of thyroid disorders [3].

In the present study, a new computer based approach has been developed towards the automatic classification of thyroid nodules, in terms of benign or malignant. The proposed method comprises at first de-speckling of ultrasound image based on Rayleigh trimmed anisotropic diffusion filter. Secondly extract the nodule from the ultrasound image by watershed segmentation method. Thirdly, extracting second order statistical textural GLCM features from the segmented thyroid nodule. Finally classify the thyroid nodule as benign or malignant by using ANN and SVM classifiers. The performance of the proposed method is evaluated with the help of matrices, such as accuracy, sensitivity and specificity.

The rest of this paper is organized as follows. Section II presents the image database. Section III elaborates the proposed method. And section IV refers to the results obtained. A discussion along with a summary of conclusions is provided in the last section.

II. MAGE DATABASE

The images used in this work are a set of B- mode thyroid ultrasound images provided by JSS Hospital, Mysore. All ultrasound examinations were performed with a digital ultrasound system Philips HD11XE. A linear array transducer with a frequency range of 3-12 MHz used. All the ultrasound images were stored in digital imaging and communications in medicine (DICOM) format. The work comprised 40 images; the radiologist reviewed all the images and divided the 40 images in two major categories: benign nodule images (30) and malignant nodule images (10).

III. PROPOSED METHOD

A. Pre Processing

Figure 1 shows the block diagram of the proposed method for thyroid nodule classification. An inherent characteristic of ultrasound imaging is the presence of speckle noise. Speckle is a random, deterministic presence in an image formed by coherent radiation of the medium containing many sub resolution scatters [4].

Speckle has a negative impact on ultrasound imaging, since it tends to reduce the image effective resolution, contrast and SNR of ultrasound images. Effective de-speckling is critical prior to other image processing approaches performed on ultrasound images such as segmentation, feature extraction and classification [5].

In this work we used a novel de-speckling method. Based on the assumption of Rayleigh distribution of speckle [6], the proposed method first estimates the relative standard deviations of the signal. Then the results are used to determine the parameter which controls an alpha trimmed mean filter to suppress the primary noise. Finally anisotropic diffusion is performed to make the filter result robust and provides high SNR value [7].

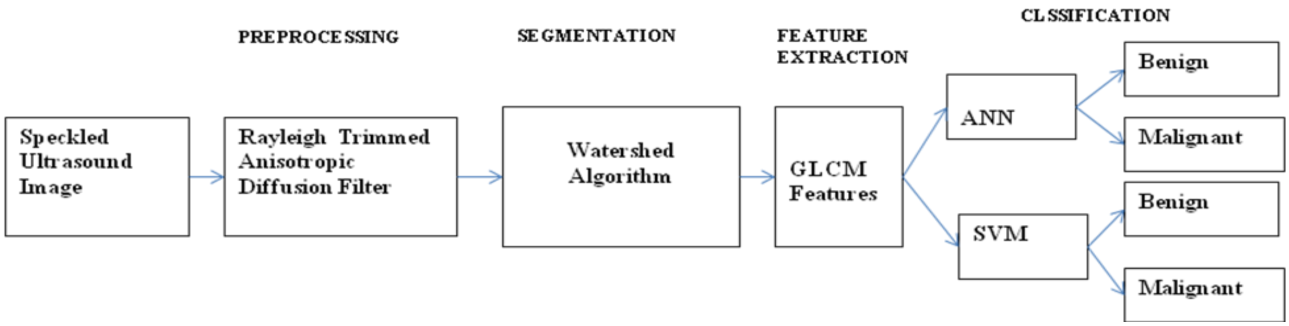

Fig.1 Block diagram of the proposed method for thyroid nodule classification.

The alpha-trimmed mean filter is

$$f = 1/(n-2[\alpha n])\sum_{j=1+[\alpha n]}^{n-[\alpha n]} g(j) \qquad (1)$$

Where g(j) denotes the pixel value arranged in ascending order and α in the range 0 to 0.5. The parameter α denotes the trimmed extent of the filter.

The nonlinear partial differential equation (PDE) to enhance the edges in an image.

$$\begin{cases} \partial I / \partial t = div[c(|\nabla I|).\nabla I] \\ I(t=0) = I_0 \end{cases} \qquad (2)$$

Where div is the divergence operator, ∇ is the gradient operator, c(x) the diffusion coefficient and Io the original image.

This filter effectively utilizes the statistical characteristics of speckle and reduces speckle significantly while retaining important features. The filter is robust, relatively not dependent on the setting of parameters and provides high SNR value. The objective of pre-processing is to enhance the contrast of the object and background, and suppress noise present in the ultrasound images [8].

B. Watershed segmentation

Morphological watershed algorithm is an algorithm which is based on region segmentation. The basic idea is to simulate the process that water flow submerges landform, to split the different areas through forming the dams between different regions. Watershed transform regards gray scale image as a geomorphic surface, and assumes to make a hole in the surface of each minimum area, water will slowly immerse in the surface from these holes, and starting from the minimum of lowest point, water will gradually submerge the catchment basin of the image. In addition, at a certain point, when the water from two different minimums increasingly rises to come together, it will build a dam at this point, at the end of the soaking process; each region minimum is surrounded by the dam of corresponding catchment basin, all the dam collection constitutes the watershed, which divide the image we input into different regions [9].

The whole watershed process can be described by mathematics: Let M1, M2…MR represent a minimal area of the image f(x,y),C(M_i) represents the catchment basin related to the minimal area Mi, min and max represent Gray-scale maximum and minimum of the image f(x, y) respectively. Suppose that T[n] represents a set in which all points (s,t) suffice g(s,t)<n, that is to say: T[n] = {(s, t)|g(s, t) < n}. From a geometric perspective, T[n] is the set of points located below plane g(s,t)=n in image f(x,y) , that is to say, n represents the immersion depth of step n. For a given catchment basin, in the step n, it will appear a certain degree of immersion (may not appear). Suppose that in step n, the minimal area miss immersed, let $C_n(M_i)$ represent a part of the catchment related to minimal area Mi, which is the horizontal surface area formed in the catchment basin C_n(Mi), when the immersion depth is n.

In order to facilitate the discussion, we may regard C_n (M_i) as a two value image, which can be represented by the following equation: C_n(Mi) = C(M_i) ∩ T[n]. In other words, if it is at the position (x,y), suffice (x, y) ЄC(M_i) and (x, y)ЄT[n], than C_n(Mi) = 1, otherwise $C_n(M_i)$ = 0. If the Gray value of the minimal area Mi is n, than in the step n+1, the immersed part of the catchment and the minimal area are exactly the same, that is C_n + 1(M_i) = M_i. As a result of the watershed segmentation, we can see that the phenomenon of over-segmentation is quite serious [10].

Therefore, the segmentation function must be filtered by minima imposition technique in order to avoid over segmentation. This technique requires the determination of a marker function to point the relevant structures within the image to control the flooding only to the catchment basins associated to each marker [11]. This technique is known as marker-controlled watershed transformation and it is a robust and flexible method for segmenting objects with closed contours [12]. Marker functions are selected to remove spurious minima. The marker function is chosen from the internal marker and external markers. The external markers are the background Markers calculated by imposing the irrelevant regional minima. Internal markers are object marker calculated from watershed function on the gradient image. The internal and external markers are logical OR to get the desired marker function [13].

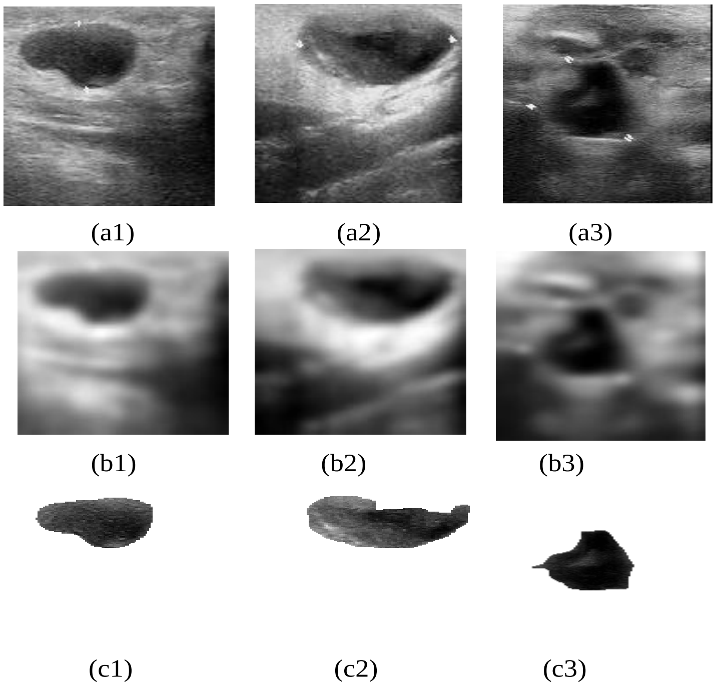

Fig. 2 Results of the proposed method: (a1-a3) original image; (b1-b3) pre-processed image; (c1-c3) final segmented image.

TABLE 1 Equation of GLCM Features

FEATURES	EQUATIONS
Energy	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)^2$
Correlation	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{(i-\mu i)(j-\mu j)\,p(i,j)}{\sigma_i \sigma_j}$
Entropy	$-\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} p(i,j)\log(p(i,j))$
Homogeneity	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \frac{p(i,j)}{1+\lvert i-j\rvert}$
Cluster Shade	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (i+j-\mu_x-\mu_y)^3\,p(i,j)$
Contrast	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} \lvert i-j\rvert^2\,p(i,j)$
Inverse Difference Moment	$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} (1/(1+(i-j)))\,p(i,j)$

C. Feature extraction

The goal of feature extraction is to maximize the discriminating performance of the feature group. Feature vectors highly affect the performance of the classification Thus, how to extract useful features and make a good selection of the features is a crucial task for CAD systems [14]. The GLCM texture method is a way of extracting second order statistical texture features from gray level images, such as ultrasound B-mode images.

A GLCM is a matrix where the number of rows and columns is equal to the number of quantized gray levels N, in the image. The matrix element p(i, j) is the set of second order statistical probability values for changes between gray level i and j at a particular displacement distance(d) and angle(θ).

In this work, we extracted seven textural features with four angles (θ) for d=2: 0^o, 45^o, 90^o, 135^o. Hence totally we extracted 28 features; they show discrimination between malignant and benign nodule [15]. The seven textural features are defined in table 1.

D. Classification

Artificial neural networks are the collection of mathematical models that imitate the properties of biological nervous system and the functions of adaptive biological learning. It is a self learning system that changes its parameters based on external or internal information that flows through the network during the learning phase. In this work we used Back- propagation neural network [16]. Back-propagation neural network is a feed-forward ANN with supervised learning process. It has a hidden layer with 10 neurons. The performance of back-propagation neural network is better than that of linear classifiers such as k-means classification etc with classification accuracy=87.50%, sensitivity=93.33%, and specificity=70%. However, the training process is stochastic and unrepeatable even with the same data and same initial conditions.

Support vector machine, is a supervised learning technique that seeks an optimal hyper plane to separate two classes of samples. Kernel functions are used to map the input data into a higher dimension space where the data are supposed to have a better distribution, and then an optimal separating hyper plane in the high-dimensional feature space is chosen [17].

The SVM was applied to classify benign and malignant nodules. Both performance and time cost of SVM were compared with ANN on the same data set. The performance of the SVM outperformed the ANN with classification accuracy=92.50%, sensitivity=96.66%, and specificity=80%. The drawbacks of the ANN are, consumes more time for classification, also, the mapping to higher dimension is complex and training time increases exponentially with the input data dimension.

Quantitative measurement of classification accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) for both ANN and SVM classifiers are calculated in terms of true positive (TP), true negative (TN), false positive (FP), false negative (FN). Table 2, shows the performance parameters equation.

TABLE 2 Equations of Parameters

PARAMETERS	EQUATION
Accuracy	(TP+TN)/N
Specificity	TN/(TN+FP)
Sensitivity	TP/(TP+FN)
Positive Predictive Value(PPV)	TP/(TP+FP)
Negative Predictive Value(NPV)	TN/(TN+FN)

IV. RESULTS

The ultrasound image database used in the proposed method includes 40 images (30 benign thyroid nodules and 10 malignant thyroid nodules). Figure 2 shows the speckled thyroid US images, pre-processed images and segmented nodules. Table 3 shows the classification results obtained with ANN and SVM. It can be noticed that the maximum accuracy, sensitivity, specificity and maximum area under the curve (AUC) obtained with ANN approach is 87.5%, 70%, 93.33% and 0.88 respectively. And the maximum accuracy, sensitivity, specificity and AUC obtained with SVM approach is 92.5%, 80%, 96.66% and 0.91 respectively.

V. DISCUSSION

This proposed method utilizes 28 textural features to efficiently distinguish between benign and malignant thyroid nodules. The 28 textural features from the extracted nodule within the ultrasound images were applied as classification criteria. The ANN and SVM models utilized all the features to classify the thyroid nodule. The training and diagnostic procedure of SVM is faster and more stable than that of feed-forward neural network.

The proposed CAD system with the entire feature set for classifying benign or malignant with good accuracy (92.5%) and a relatively high sensitivity (96.66%). Our experimental results suggest that using textural features based on nodule for classifying benign and malignant nodules is effective and reliable. In terms of decision making, the high sensitivity and NPV demonstrated that the proposed CAD system recognize malignant nodule and reduce the need for unnecessary biopsies for benign nodules.

Thus, this CAD system is useful for differential diagnosis of thyroid nodules based on ultrasound images, and could lead to a decreased need for thyroid biopsies. Medical costs and adverse reaction will be reduced as well.

TABLE 3 Results of Classifiers

PARAMETERS	ANN CLASSIFIER	SVM CLASSIFIER
True Positive(TP)	28	29
True Negative(TN)	7	8
False Positive(FP)	3	2
False Negative(FN)	2	1
Positive Predictive Value(PPV)	90.32 %	93.54 %
Negative Predictive Value(NPV)	77.77 %	88.88 %
Sensitivity	93.33 %	96.66 %
Specificity	70.00%	80.00%
Accuracy	87.50 %	92.50 %

In the future, we hope to improve the performance of the proposed CAD system by adding other features of thyroid nodules. Additionally, three dimensional sonography is being used increasingly in the clinical setting. Feature work should also apply the proposed CAD system to three dimensional sonograms.

VI. CONCLUSION

Ultrasound imaging is widely used to inspect the nodules in thyroid gland. However, similar gray levels between thyroid benign nodule and malignant nodule can confuse the radiologists and the physicians. In addition, artifacts also degrade the quality of US images making the real shape and components of the nodules difficult to determine easily.

To solve these difficulties, this paper presents a computer based method for segmenting nodules and classifying the nodules as benign or malignant. We use an advance anisotropic filter for de-speckling, sophisticated watershed algorithm to segment the nodule region. Finally an ANN and SVM classifiers are applied to classify the thyroid nodules. Experimental results show that the proposed method achieves high accuracy than other classifiers such as k-NN, Bayesian.

In future, we can use more features to classify different types of nodules rather than two. The extended idea is to use more images, which will be essential to valid the process.

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REFERENCES

[1] Cancer facts and figures 2013. Atlanta: American cancer society; 1-8, 2013

[2] S. Tsantis, N. Dimitropoulos, D. Cavouras, G. Nikiforidis. “A hybrid multi-scale model for thyroid nodule boundary detection on ultrasound images”. Elsevier journal on computer methods and programs in biomedicine 8 4 (2 0 0 6) 86–98

[3] Michalis Savelonas, Dimitris Maroulis, Manolis Sangriotis. “A computer-aided system for malignancy risk assessment of nodules in thyroid US images based on boundary features”. Elsevier journal on computer methods and programs in biomedicine 9 6 (2 0 0 9) 25–32

[4] Burckhardt, C.B., 1978. “Speckle in ultrasound B-mode scans”. IEEE Trans. Sonics Ultrason. 25 (1), 1–6.

[5] Sonia H, Contreras Ortiz, Tsuicheng Chiu, Martin D.Fox. “Ultrsound image enhancement: A review”. Biomedical Signal Processing and Control 7, 419-428, 2012.

[6] Yinhui Deng, Yuanyuan Wang and Yuzhong Shen. “Speckle reduction of ultrasound images based on Rayleigh-trimmed anisotropic diffusion filter”. Elsevier journal on Pattern Recognition Letters 32 (2011) 1516–1525

[7] Yu, Y. & Acton, S. T. “Speckle reducing anisotropic diffusion”. IEEE Transactions on Medical Imaging, 11(11), 1260-1270, 2002.

[8] Sonia H, Contreras Ortiz, Tsuicheng Chiu, Martin D.Fox. “Ultrsound image enhancement: A review”. Biomedical Signal Processing and Control 7, 419-428, 2012.

[9] Noble, J.A. and Boukerroui, D. “Ultrasound image segmentation: A survey”. IEEE Trans. on Medical Imaging 25, 8 , 987-1010, 2006.

[10] Jie Zhao, Wei Zheng, Li Zhang and Hue Tian. “Segmentation of ultrasound images of thyroid nodule for assisting fine needle aspiration cytology”. Zhao et al. health information science and systems 2012, 1:5

[11] W.Gomez,L.Leija,W.C.A.Pereira and A.F.C.Infantosi. “Segmentation of Breast Nodules on Ultrasonographic images Based on Marker Controlled Watershed Transform”. ISSN 1405-5546, 2009.

[12] Vincent, L. & Soille, P. “Watersheds in digital spaces: an efficient algorithm based on immersion simulations”. IEEE Transactions on Pattern Analysis and Machine Intelligence, 13(6), 583-598, 1991.

[13] Vincent, L. & Soille, P. “Watersheds in digital spaces: an efficient algorithm based on immersion simulations”. IEEE Transactions on Pattern Analysis and Machine Intelligence, 13(6), 583-598, 1991.

[14] R. M. Haralick, K. Shanmugam, and I. Dinstein, “Textural features for image classification,” IEEE Trans. Syst.Man Cybern. Smc3, 610–621, 1973.

[15] Xiaofeng Yang, Srini Tridandapani, Jonathan J. Beitler and David S. Yu, Emi J. Yoshida, Walter J. Curran and Tian Liu. “Ultrasound GLCM texture analysis of radiation-induced parotid-gland injury in head-and-neck cancer radiotherapy: An in vivo study of late toxicity”, Med. Phys. 39 (9), 5732-5739, 2012.

[16] Chuan-Yu Chang, “ classification of the thyroid nodules using SVM”, IEEE2008

[17] Yu-Min Chiang, Jo-Mien Weng. “A Texture Classification Method based on Gray-Level Co-Occurrence Matrix and Support Vector Machines”. Journal on European International Journal of Science and Technology Vol. 2 No. 10 December, 2013

[18] Gonzalez, R.C., Woods, R.E., 2002. Digital image processing, second ed. Prentice Hall Inc., New Jersey.