Texture Analysis of Thyroid Ultrasound Images for Diagnosis of Benign and Malignant Nodule using Scaled Conjugate Gradient Backpropagation Training Neural Network

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Abstract

A thyroid is largest endocrine gland, a butterfly shape with two lobes which produces hormones that control body metabolism. The nodules are found in thyroid may be benign or malignant. The ultrasound (US) preferred over the other medical imaging modalities which is used to observe the subcutaneous body structures & internal organs for possible pathology or lesions. The physicians are deducing useful information concerning the tissue characterization and structure which is still subjective matter, Thus quantitative analysis of US images give the objective method for thyroid nodule diagnosis. In this paper, gray level co-occurrence matrix (GLCM) texture characterization techniques are used for feature extraction & extracted features are classified using scaled conjugate gradient backpropagation training neural network (SCGBNN) for diagnosis of thyroid nodule are described. The experimental results show the performance measure of SCG backpropagation training neural network in terms classification accuracy.

Keywords: *Thyroid Nodule, Ultrasound (US), GLCM, SCGB Neural Networks.*

1. Introduction

A thyroid is largest endocrine gland in the body, a butterfly shaped organ compose of the cone like lobes. It is located in the lower part of the neck below the Adam apple. The thyroid gland produces the T3 & T4 hormones that affects the heart rate, cholesterol level, body weight, energy level, mental state and controls a host of other body functions. Thus the function of thyroid is to regulate the body metabolism [1]. The thyroid diseases are common worldwide. In India too, there is significant burden of thyroid diseases. According to a projection from various studies on thyroid disease, it has been estimated that about 42 million people in India suffer from thyroid diseases. It covers the main five thyroid gland disease included the Hypothyroidism, Hyperthyroidism, Goiter, Autoimmune Thyroiditis, Thyroid cancer [2].

A National Cancer Registry program (NCRP) maintains the reliable data of cancer patient on the magnitude & pattern of cancer in India. The projection of thyroid cancer cases in year of 2010 is around 16,215 & by the year of 2020 goes up to 19,113. The cases of malignant thyroid nodule are found to be more in female to that of male. The projection of thyroid cancer in female for year of 2010, 2015 & 2020 is 11,751; 12,808 & 13,955 significant over male i.e. 4,464; 4,798 & 5,158 for the respective years. The other figures of thyroid disease are turn out to be significant in the Indian context. The preferred diagnosis method used for possible lesions are ultrasonography. [3]

All radiological modalities like ultrasound, CT, Scintigraphy, SPECT, MR, PET, X-rays etc. play an important role in process of disease diagnosing and have become major evidence to ensure disease. But ultrasound (US) possesses a rare combination of advantages including portability, invasive, real-time data acquisition and affordability [4]. US are a diagnostic imaging tool used to visualize subcutaneous body structures and internal organs for possible pathology or lesions. The physicians are deducing useful information concerning the tissue characterization and structure. Thus, US have become an invaluable tool for the accurate diagnosis and follows up of different pathologies in a variety of tissues and organs [5].

The detection of the pathological diseases such as thyroid nodule by physicians is still subjective matter & while making manual diagnosis from images, some relevant information need not to be recognized by human visual system. In the suspicious cases FNA, Cytological test are done to find the malignancy risk. Thus to provide the objectification for disease diagnosis the various texture characterization techniques are utilized which draws statistical information from US image. Thus quantitative information is used to classify into benign & malignant thyroid nodule.

2. Related work

There have been various attempts towards the subjective techniques for diagnosis of thyroid gland nodule. Some of the earlier research for thyroid nodule diagnosis is described. In [4]. the 13 GLCM texture & geometric features extracted from thyroid images by region based active contour segmentation method & classified using SVM, KNN and Bayesian [4].

In [5], the Contour let Transform (CT) using LP and DFB filters to the 3rd level decomposition are used for detection hypoechoic and isoechoic nodules from normal thyroid nodule. A Gaussian kernel SVM classifier is applied along the SFFS algorithm with or without coefficient thresholding. In [6], the texture features based on the CT using different types of filters banks with a selection scheme SFFS algorithm were classified by k-NN algorithm.
In [7], a novel computational approach using Radon Transform for the thyroid tissue characterization of US image were utilized. Supervised classification experimentation using KNN (k=5), SVM with polynomial kernel was done to differentiate normal and nodular thyroid US images for detection malignancy risk.
In [8], the normal and hypoechoic nodule were classified using 2 First-order and 168 co-occurrence features drawn from manual rectangular ROI & PCA for optimal subset using Binary Logistic Regression.
In [9], a novel approach that correlates thyroid malignancy, LBP, FLBP, and FLGH Ultrasound texture features which discriminated by SVM with linear, polynomial and Gaussian kernel with or without fusion of texture using 10 fold cross validation or 1 way ANOVA. In [10], a novel fuzzy feature extraction method (FLBP). The FLBP approach was experimentally evaluated using supervised SVM with linear, polynomial, radial basis, sigmoid kernel for classification of nodular and normal thyroid US images. In [11], the joint texture analysis on US and Cytological images were processed to optimally highlight the cancerous region in same image. The 20 textural features were generated which contain 4 GH, 10 GLCM and 6 RLM from US image. 20 morphological and textural features were extracted from segmented nuclei of Cytological image. An SVM classifier with 2nd degree polynomial kernel & Bayesian with quadratic kernel were used in distinguishing correctly low from high-risk thyroid nodules.

3. Material & Method

Medical ultrasound images of thyroid gland are selected for texture analysis in experimental work. These ultrasound images contained some of abnormal images having benign thyroid nodule (non cancerous) and malignant thyroid nodule (cancerous). The total 85 thyroids US images were used which contains total 48 cancerous and 37 non-cancerous was selected in database. These thyroid images are available in image gallery of Wilmington Endocrinology PA on website. The image size of 546 × 410, with 24 bit depth size, true color image, format of images are JPEG.
The Matlab R2010a software is used for experimental work. The preprocessing steps required for the analysis is gray scale conversion & image resizing into 256×256 of true color images selected in database. Then GLCM texture feature extraction & classification of texture feature are carried out & described in fallowing section.

3.1 Texture Analysis Method:

The texture features analysis is a useful way of increasing the quantitative information obtains from medical images. It is an ongoing field of research, with applications ranging from the segmentation of specific anatomical structures and the detection of lesions, to differentiation between pathological and healthy tissue in different organs. Texture analysis uses radiological images obtained in routine diagnostic practice, but involves an ensemble of mathematical computations performed with the data contained within the images [12]. According to the methods employed to evaluate the inter-relationships of the pixels, the forms of texture analyses are categorized as structural, model-based, statistical and transform methods [13].

3.1.1 Structural Methods

This represents texture by the use of well-defined primitives. A square object is represented in terms of the straight lines or primitives that form its border. The advantage of these methods is that they provide a good symbolic description of the image. On the other hand, it is better for the synthesis of an image than for its analysis. [12].

3.1.2 Model-Based Methods

An attempt is made to represent texture in an image using sophisticated mathematical models (such as fractal or stochastic). The model parameters are estimated and used for the image analysis. The disadvantage is the computational complexity involved in the estimation of these parameters [12].

3.1.3 Statistical Approaches

These are based on representations of texture using properties governing the distribution and relationships of grey-level values in the image & normally achieve higher discrimination indexes than the structural or transform methods [12].

3.1.4 Transform Methods

The texture properties of the image may be analyzed in a different space, such as the frequency or the scale space. These methods are based on the Radon, Gabor or Wavelet transform. The Wavelet transform is the most widely used because of the ease with which it may be adjusted to the problem in question [12].

3.2 Texture Feature Extraction Methods

Medical images possess a vast amount of texture information relevant to clinical practice. For example, US images of tissues are not capable of providing microscopic information that can be assessed visually.

However, histological alterations present in some illnesses may bring about texture changes in the US image that are amenable to quantification through texture analysis. This has been successfully applied to the classification of pathological tissues from the liver, thyroid, breasts, kidneys, prostate, heart, brain and lungs [12].

The most commonly used texture features are Gray Level Histogram, Run-length matrix, Gray Level Co-occurrence matrix, contour let transform, Wavelets transform, Radon Transform, Local Binary Pattern, Fuzzy Local Binary Pattern, Fuzzy local Gray Histogram.

These texture feature found in literature of texture analysis on ultrasound medical images of thyroid gland for detection of thyroid nodule as a benign or malignant tissue from normal one. In this paper, gray level co-occurrence matrix (GLCM) based texture feature extraction approach is fallowed which explain next in detail. The ten texture features extracted from GLCM are described mathematically next section 3.2.1.

3.2.1 Gray Level Co-Occurrence Matrix

Using histograms in calculation will result in measures of texture that carry only information about distribution of intensities, but not about the relative position of pixels with respect to each other in that texture. Using a statistical approach such as co-occurrence matrix will help to provide valuable information about the relative position of the neighboring pixels in an image.

Given an gray scale image I, of size N×N, the co-occurrence matrix P can be defined as

$$P(i,j)=\sum_{x=1}^{N}\sum_{y=1}^{N}\begin{cases}1 & ; I(x,y)=i \text{ and } I(x+\Delta x, y+\Delta y)=j\\ 0 & ; \text{otherwise}\end{cases} \quad (1)$$

Here, the offset (Δx, Δy), is specifying the distance between the pixel-of-interest and its neighbor. Note that the offset (Δx, Δy) parameterization makes the co-occurrence matrix sensitive to rotation. Choosing an offset vector, such that the rotation of the image is not equal to 180 degrees, will result in a different co-occurrence matrix for the same (rotated) image. This can be avoided by forming the co-occurrence matrix using a set of offsets sweeping through 180 degrees at the same distance parameter Δ to achieve a degree of rotational invariance (i.e., [0 Δ] for 0 degree: P horizontal, [-Δ, Δ] for 45 degree: P right diagonal, [-Δ 0] for 90 degree: P vertical, and [-Δ −Δ] for 135degree: P left diagonal).

The GLCM matrix computed from the thyroid gland ultrasound images are of the size 256×256. Then texture features were extracted from GLCM matrix from each of the thyroid gland ultrasound image database & the mathematical equations for the texture features are given as follows:

Autocorrelation	$\sum_i \sum_j (i\,.\,j)P(i,j)$	(2)
Contrast	$\sum_i \sum_j \lvert i-j \rvert^2 P(i,j)$	(3)
Correlation	$\sum_i \sum_j \frac{(i-\mu x)\,.(j-\mu y)P(i,j)}{\sigma x\,.\sigma y}$	(4)
Cluster Prominence	$\sum_i \sum_j (i+j-\mu x-\mu y)^4\, P(i,j)$	(5)
Cluster Shade	$\sum_i \sum_j (i+j-\mu x-\mu y)^3\, P(i,j)$	(6)
Dissimilarity	$\sum_i \sum_j \lvert i-j \rvert\, P(i,j)$	(7)
Energy	$\sum_i \sum_j \lvert P(i,j)\rvert^2$	(8)
Entropy	$-\sum_i \sum_j P(i,j)\log(P(i,j))$	(9)
Homogeneity	$\sum_i \sum_j \frac{P(i,j)}{1+\lvert i-j \rvert}$	(10)
Maximum Probability	$\max_{i,j} P(i\,,j)$	(11)

Notation & expression used for calculating the GLCM statistics are as shown below.

Notation	Meaning	
μx	$\sum_i \sum_j i\,.\,P(i,j)$	(12)
μy	$\sum_i \sum_j j\,.\,P(i,j)$	(13)
σ_x^2	$\sum_i \sum_j (i-\mu_x)^2\,.\,P(i,j)$	(14)
σ_y^2	$\sum_i \sum_j (j-\mu_y)^2\,.\,P(i,j)$	(15)

The above motioned ten features extracted 85 image database are utilized for feature classification. The feature classification is done to identify the malignant thyroid nodule from that of benign thyroid nodule. The classification method used in evaluation is described in next section.

3.3 Classification Method

For the experimental evaluation of GLCM texture features extracted from ultrasound thyroid gland images was classified by scaled conjugate gradient backpropagation training feed forward neutral network. It is a two-layer feed-forward network, with differential sigmoid transfer function in hidden neuron layer and linear transfer function in output neurons layer & Gradient descent weight and bias learning function is utilized for updating the weights. It can classify vectors arbitrarily well for a given enough neurons in its hidden layer.

The network will be trained with scaled conjugate gradient Backpropagation has fast convergence as compared to that of generalized backpropagation learning.

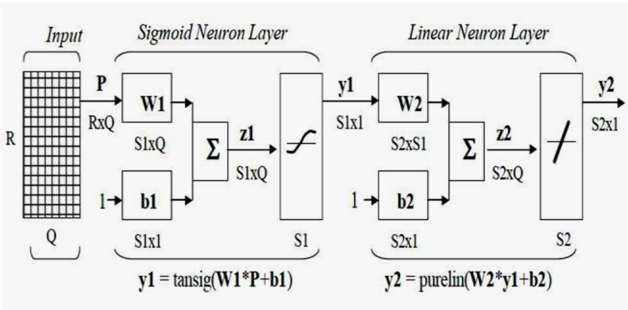

Fig. 1 A two layer feed forward neural network.

The fig 1 shows the two layer feed forward network, the input layer with Q neurons are supplied with texture feature vectors having Q representative R elements. The numbers of neuron in hidden layer are adjusted as desired to get accurate results. In the hidden layer Si neurons are connected to the input layer Q neurons by weight W1. Therefore the weight vector W1 connecting input & hidden layer neurons of size Si×Q.

The net input at hidden layer is calculated as

$$net1 = \sum W1 * P + b1 \qquad (16)$$

Where, P is the input to the input layer neurons

W1 is the weight between input & hidden layer

b1 is the bias to the hidden layer neurons

The output of the hidden layer Y1 is calculated as

$$Y1 = tansig(net1) \qquad (17)$$

The tan sigmoid transfer function is utilized in hidden layer to calculate a hidden layer's output from its net input & mathematical equation of tan sigmoid transfer function is

$$tansig(X) = \frac{2}{1+e^{-2X}} - 1 \qquad (18)$$

The output layer has N neurons depending on classes of the problem as in our case; there are two classes such as benign nodule & malignant nodule. Y1 is the input to the output layer neurons. The hidden layer Si neurons is connected to the output layer neurons Sj by weight W2 & bias b2, where size of weight matrix is Sj×Si. The net input at output layer is calculated as

$$net2 = \sum W2 * Y1 + b2 \qquad (19)$$

Where, Y1 is the input to the input layer neurons

W2 is the weight between hidden & output layer

B2 is the bias to the output layer neurons

The output of the output layer Y2 is calculated as

$$Y2 = purelin(net1) \qquad (20)$$

The pure linear transfer function is utilized in output layer to calculate a layer's output from its net input.

The basic backpropagation algorithm adjusts the weights in the steepest descent direction. In the conjugate gradient algorithms a search is performed along conjugate directions, which produces generally faster convergence than steepest descent directions. In most of the training algorithms, a learning rate is used to determine the length of the weight update (step size). In most of the conjugate gradient algorithms, the step size is adjusted at each iteration. A search is made along the conjugate gradient direction to determine the step size that minimizes the performance function along that line. This line search is computationally expensive, because it requires that the network response to all training inputs be computed several times for each search.

The scaled conjugate gradient algorithm (SCG), developed by Moller, and was designed to avoid the time-consuming line search. This algorithm combines the model-trust region approach, with the conjugate gradient approach [14].

The parameter σ determines the change in the weight for the second derivative approximation. The parameter λ regulates the indefiniteness of the Hessian.

The training with SCG algorithm can require more iteration to converge than the other conjugate gradient algorithms, but the number of computations in iteration is significantly reduced because no line search is performed.

4. Results

The two layer feed forward neural network is trained with 90% of features vector from the database & 10% of features vector is used in testing the network performance using SCG backpropagation training algorithm. The following figure shows the training performance of SCG backpropagation neural network for the features extracted from GLCM matrix with offset [01], means along horizontal direction with single pixel distance.

The fig. 2 shows the best performance of in terms of mean square error of 0.33301 at epoch 311. Then fig. 3 shows the overall confusion matrix for the same GLCM offset.

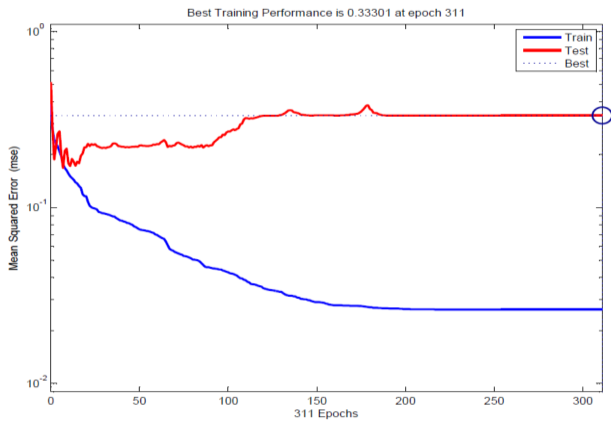

Fig. 2 performance of SCG learning backpropagation neural network for features extracted from offset [0 1]

The neural networks were classified malignant nodule with 95.33% accuracy & benign nodule with 91.89% accuracy. The overall accuracy of classifier was 94.11%. There are such a five instances, where the neural network has been incorrectly classified the nodule. The fig 4 shows the ROC curve for same GLCM offset, the shape of ROC curve shows the SCG backpropagation neural network has good performance.

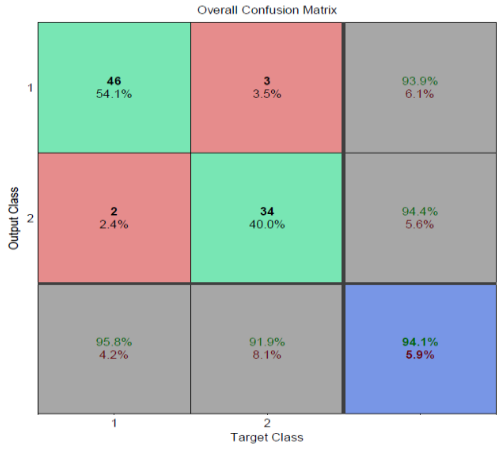

Fig. 3 Confusion matrix of classifier for features with offset [0 1]

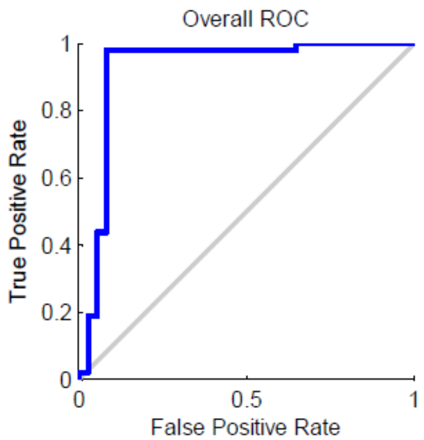

Fig.4 ROC curve for features with offset [0 1]

All the texture features extracted for four orientations (0°, 45°, 90°, & 135°) & 15 distances (1, 2… 15 pixels) are trained & tested using SCG backpropagation neural network. The table 1 shows the accuracy (Acc), positive predictive rate (PPV), negative predictive rate (NPV), Sensitivity (Se), & specificity (Sp) as mean ± standard deviation along one GLCM orientation.

Table 1: Performance measure of classifier for one GLCM orientation

Offset	*Acc (%)*	*PPV (%)*	*NPV (%)*	*Se (%)*	*Sp (%)*
[0 Δ]	96.94 ± 1.98	97.22 ± 2.57	96.57 ± 4.15	97.46 ± 3.02	96.52 ± 3.09
[-Δ 0]	97.09 ± 1.53	97.50 ± 1.79	96.58± 2.79	97.41 ± 2.08	96.79± 2.22
[-Δ Δ]	97.49± 1.53	97.78 ± 2.55	96.12 ± 3.31	97.86 ± 2.42	97.25± 3.05
[-Δ -Δ]	97.72 ± 1.69	97.92± 2.23	97.48 ± 2.34	98.08 ± 1.77	97.37± 2.76

4. Conclusions

Texture analysis of ultrasound medical images using quantitative information of the tissue characterization and structure are used for the detection of thyroid nodule. 10 gray level co-occurrence based texture features being extracted from 37 benign and 48 malignant thyroid images are use to classify into risk of malignancy using two layer feed forward neural network with scaled conjugate gradient backpropagation training with nine neurons in hidden layer. The tan sigmoid & purelin transfer functions are utilized in hidden & output layer respectively with sigma of $5.0e^{-5}$ & lambda of $5.0e^{-7}$. The performance of classifier shows the classification accuracy of 97.37 ± 1.68%. This classifier accuracy is calculated as mean of accuracies mentioned in table 1 of performance measure of classifier. It's providing the objective method to physician for diagnosis of thyroid gland ultrasound images for detection of nodules malignancy risk. The classification of benign & malignant nodule will provide the second opinion to the physician about treatment of patient's and thus, the proposed work will help the physician to minimize the misdiagnosis rate of pathological diseases.

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