Thyroid Volume Estimation Analysis with Neural and Fuzzy-Neuro Techniques - A Comparative Study

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ABSTRACT

This paper presents a comparative study of various methods that used to identifies the thyroid volume from the ultrasound images. The Radial basis function neural network method, and by the hybrid structure of neural network and the fuzzy logic method. The performance of the algorithms Active Contour without edges, Localized region Based active contour and Distance Regularized Level Set will improve the results by 80%, the hybrid structure of the neuro – fuzzy method was improved from 81% to 92.9% by using Fuzzy-RBF, Fuzzy-MLP, and Fuzzy-CSFNN methods.The result shows that the Fuzzy Neuro method gives the highest accuracy level the by using the neural network method for detecting the thyroid volume from the segmentation process.

Key words: Neural Network, Neuro-Fuzzy, Thyroid Volume.

1. INTRODUCTION

The thyroid gland or simply thyroid is found in the neck. The thyroid gland controls how quickly the body uses energy, makes proteins and controls how sensitive the body is to other hormones. The thyroid gland is a butterfly shaped organ and is composed of two cone like lobes or wings. Too much or too little thyroid hormone causes pathological changes or as cancers. The thyroid cancer is a painless mass in the neck. It is very unusual for the thyroid cancers to present with symptoms. Therefore, physicians often diagnose abnormal symptoms of the thyroid gland by its volume. Various medical images such as x-rays, ultrasound, Computer tomography (CT), Magnetic resonance images (MRI) etc., plays an important role to identifying the diseases. Among these several diagnostic modalities, ultrasound image is the most popular one. It has several favorable properties: it is inexpensive and easy to use; it is not inferior to MRI or CT images in terms of diagnostic value; it can follow anatomical deformations in real time during biopsy and treatment; and it is non-invasive and does not require ionizing radiation. However, US images contains echo perturbations and speckle noises which can make diagnosis difficult. Although MRI and CT have clear visualization than US images, US images are often adopted due to their cost effectiveness and portability. US images provide a timely approach to acquire thyroid gland image, and it is useful for dispensary in remote districts or in mobile medical services. An inherent characteristic of US imaging is the presence of multiplicative speckle noise. Speckle noise generally tends to reduce the image resolution and contrast, inducing a degree of uncertainty. The processing techniques of US images are continuously developed in last years. Several segmentation methods for anatomical objects from US images have been developing in the prostate, tumors in the breast and the thyroid nodule [1-4].

2. BACKGROUND

For reducing the speckle noises that produced in the US images are reduced by the various segmentation processes and by the different algorithms were used. There are number of persons were working in this segmentation on thyroid gland. In the paper thyroid segmentation and volume estimation in ultrasound images, Chuan-Yu Chang, Yue-Fong Lei, Chin-Hsiao Tseng, and Shyang-Rong Shih, the authors used five steps to find the thyroid volume estimation [1]. First to locating the probable thyroid region and the image was enhancement and made some feature extraction with the help of image processing techniques then training the neural networks to find the proper thyroid image and with the help of that image the thyroid volume was estimated. In the another paper Canan SENOL , Tülay YILDIRIM titled thyroid and breast cancer disease diagnosis using fuzzy-neural networks used an hybrid method of using the neural network and the fuzzy method for the thyroid gland segmentation. In this a new hybrid structure in which Neural Network and Fuzzy Logic are combined is proposed and its algorithm is developed. Fuzzy-CSFNN, Fuzzy-MLP and Fuzzy-RBF structures are constituted, and their performances are compared. Conic Section Function Neural Network (CSFNN) unifies the propagation rules of the Multilayer Perceptron (MLP) and the Radial Basis Function (RBF) networks at a unique network by its distinctive propagation rules. That means CSFNNs accommodate MLPs and RBFs in its own self-network structure. This approach is implemented in a well-known benchmark medical problem with real clinical data for thyroid and breast cancer disease diagnosis [3]. The paper titled A Segmentation Method and Comparison of Classification Methods for Thyroid Ultrasound Images, Nikita Singh, Alka Jindal, the authors provide information about segmentation and classification methods that are very important for medical image processing. They uses the groups of Benign and Malignant thyroid nodules images. These images used to analysis the classification accurately. GLCM extracts the total 13 features and these features are used to analysis in classifiers such as SVM, and KNN using neural netwoeks. [4].

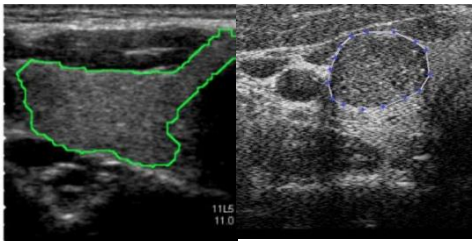

Figure 1.Ultrasound images of Thyroid gland

3. METHODOLOGIES

3.1 By The Neural Method

3.1.1 Thyroid segmentation and volume estimation methods

In order to directly estimate the thyroid volume from the US images the thyroid segmentation must be accurate. The segmentation results of the thyroid gland were obtained by the trained radial basis function neural network. A specific region growing method in then applied to retrieve the complete thyroid region. Based on the segmentation region of thyroid the thickness and the depth of the thyroid gland, and the depth of the thyroid gland the volume is estimated using the particle swarm optimization algorithm [5].

The thyroid volume estimation and segmentation was done by the following five steps as 1) locating the probable thyroid region and image enhancement, 2) feature extraction, 3) training RBF neural network, 4) thyroid recovery, and 5) volume estimation.

The thyroid image was located by the US scan, then for the image enhancement the adaptive weighted median filter was used to remove the speckle noises and to reduce the influence of feature extraction.

$$W_{i,j} = \{ W_0 - \frac{gD\sigma^2_{x,y}}{\mu_{x,y}} \} \quad (1)$$

The adaptive weighted median is an MxM region {Ii,j} is defined as the pure median of the extended sequence formed by taking each term Ii,j, Wi,j, times and a morphological operation was done by 3x3 closing and opening operators to reduce the redundancy.

The gray level compensation was used to adjust the intensity of the probable thyroid region. This was done by using

$$T(x,y) = \begin{cases} 255 & \text{if } T(x,y) - \Delta GL > 255 \\ 0 & \text{if } T(x,y) - \Delta GL < 0 \\ T(x,y) - \Delta GL & \text{otherwise} \end{cases} \quad (2)$$

Then by various feature extraction methods such as haar wavelet, coefficient of local variation feature, histogram feature, block difference of intensity probabilities and normalized multiscale intensity difference.

3.1.2 Haar Wavelet Feature

The mean and the variance of the low low frequency subband were computed as follows:

$$\text{Mean of LL band } \mu_{x,y} = \frac{1}{m^2}\sum_{(x,y)\in B} I(x,y) \quad (3)$$

$$\text{Variance of LL band } \sigma 2_{x,y} = \frac{1}{m^2}\sum_{(x,y)\in B-\mu_{x,y}} I(x,y) \quad (4)$$

3.1.3 Coefficient of local variation

The coefficient of local variation is a normalized measure of dispersion of a probability distribution. The coefficient of local variation of a pixel located at (x,y) is defined as follows:

$$LCV_{x,y} = \sigma_{x,y} / \mu_{x,y} \quad (5)$$

3.1.4 Histogram Feature

The histogram feature measures the texture characteristics of an MxM block. The value of the histogram feature is defined as:

$$HF = \sum_{i=H-10, i\neq H}^{H+10} \text{histo}(i) \quad (6)$$

$$H = \text{argmax}(\text{histo}(i))$$

3.1.5 NMSID Feature

The NMSID is defined as the difference between the pixel pairs with horizontal, vertical, diagonal and asymmetric diagonal directions.

$$\left[\begin{array}{l} \sum_{x=0}^{M-1} \cdot \sum_{y=0}^{M-K-1} \cdot I(x,y) - I(x,y+K) / M(M-K) + \\ \sum_{k==1}^{n} \cdot \sum_{x=0}^{M-K-1} \cdot \sum_{y=0}^{M-1} \cdot I(x,y) - I(x+y,K) / M(M-K) + \\ \sum_{x=0}^{M-K-1} \cdot \sum_{y=0}^{M-K-1} \cdot I(x,y) - I(x+K,y+K) / (M-K)2 + \\ \sum_{x=0}^{M-K-1} \cdot \sum_{y=0}^{M-K-1} \cdot I(x,M-y) - I(x,M-(y+K)) / (M-K)2 \end{array} \right] . 4$$

(7)

3.1.6 RBF Neural Network and Recovering

Here the Radial basis function neural network classifies the block into thyroid gland and non-thyroid gland by using the stochastic gradient based supervised learning algorithm. The trained RBF neural network classifies the block into the thyroid gland and the non-thyroid gland. For each thyroid block, the number of thyroid blocks was calculated in its 8 nearest neighbors. Finally, the largest connected component is extracted from the classified US image. The region of the largest connected is considered as part of the thyroid gland region. Using the aforementioned procedures, a pure region of the thyroid gland can be extracted. However, the shape of the segmented thyroid region is serrated, and thus, a refinement procedure is required to recover the complete shape of the thyroid gland.

3.1.7 Volume Estimation

In this the particle swarm optimization algorithm is used to estimate the parameters of the thyroid volume equation which is

$$\text{Volume} = a * (\text{AreaL} \times \text{DL} + \text{AreaR} \times \text{DR} + b) \quad (8)$$

The area of all slices and the inter-slice distance were then integrated to calculate the actual volume of thyroid gland.

3.2 By Fuzzy-Neuro Method

In this a hybrid structure of the fuzzy logic and the neural network were formed by the canansenol and tulayyildirim in the paper titled thyroid and breast cancer disease diagnosis using fuzzy neural network. They formed fuzzy-CSFNN, Fuzzy-MLP, and Fuzzy-RBF structure and compared [17].In Fuzzy-MLP hybrid structure, they consider an MLP with an input layer, output layer and a hidden layer. Hybrid layer was trained by levenberg-Marquardt back propagation algorithm. They choose the number of MFs as 2 for each input data vector and choose bell- shaped typed MFs. Membership function of output was selected as linear and transfer function was selected as pure linear.

In Fuzzy-RBF structure, same FIS setup parameters for a fair comparison they chosen the number of MFs as 2 for each input data vector, and they selected bell shaped type MFs. Membership function of output was chosen as linear.

And Fuzzy-CSFNN structure, the NN part was constituted by CSFNN. They chose the number of MFs as 2 for each input data vector and preferred bell shaped type MFs. Membership function of output was selected as linear and transfer function was selected as pure linear.

4. EXPERIMENTAL RESULTS

In this chapter the result that taken by using the NN, Fuzzy-Neuro and by using different classifiers methods were discussed.

4.1Neural Method

In this there are five steps were followed to estimate the thyroid volume. By training the RBF Neural Network the thyroid volume was estimated by using the PSO algorithm. In this the maximum number if iterations was 200, the population size was 12, the dimension of the search space was set to 2, w=1/(2xln(2)), and c1 and c2 were both set to 0.5+ln(2). This was done for ten times and the result was shown below.

Table 1. Volume Estimation of Thyroid Gland Results by Neural Network Method

Training numbers	case 1	case 2	case 3	case 4	case 5	MSE
1 (a=0.8967,b=0.6962)	22.578	17.577	21.502	20.268	12.609	0.582
2 (a=0.9729,b=-0.9499)	22.792	17.366	21.624	20.285	11.976	0.873
3 (a=0.9162,b=-0.0205)	22.338	17.228	21.238	19.976	12.152	0.743
4 (a=0.8165,b=1.69562)	21.621	17.067	20.641	19.517	12.543	0.889
5 (a=0.901,b=0.3217)	22.309	17.284	21.287	19.992	12.279	0.6
6 (a=0.9231,b=-0.1284)	22.398	17.25	21.29	20.019	12.135	0.745
7 (a=0.8874,b=1.0853)	22.741	17.791	21.676	20.454	12.875	0.598
8 (a=0.9083,b=0.4464)	22.612	17.546	21.522	20.271	12.514	0.613
9 (a=0.862,b=2)	23.035	18.228	22.001	20.814	13.452	0.868
10 (a=0.8143,b=1.7823)	21.654	17.112	20.677	19.555	12.601	0.838

4.2By Fuzzy-Neuro Method

With the help of the Matlab simulation the results of the Fuzzy-MLP, Fuzzy-RBF and Fuzzy-CSFNN were compared. In MLP structure, training process was repeated 10 times since it gives different results depending on random initialization of weights. Then the average of the results was taken. Table 2 shows the results of the hybrid schemes.

Table 2. Results for Thyroid Volume By Fuzzy Neuro Mehtod

	Normal	Hyper	Hypo	Average
Fuzzy-MLP	108	20	22	88.53%
Fuzzy-RBF	88	20	21	81.54%
Fuzzy-CSFNN	115	24	20	92.93%

5. CONCLUSION

The Ultrasound images are widely used for clinical diagnosis, although it is time consuming for physicians to manually segment the thyroid nodule. To reduce the time consumption for identifying the thyroid, the image processing methods were implemented. There are several methods were used to identified the thyroid nodule. In this Neural Network and Fuzzy-Neuro methods were used to classify the nodule. Results obtained from these methods have been investigated to getting the higher accuracy level of the thyroid nodule. The performance of the algorithms by using the neural network method the Active Contour without edges, Localized region Based active contour and Distance Regularized Level Set will improve the results by 80%, and the hybrid structure of the neuro – fuzzy method was improved from 81% to 92.95%. The results show that in the hybrid structure having Fuzzy-CSFNN methodology had the capability to produce the highest accuracy of 92.95% for detecting the thyroid volume estimation from the ultrasound image.

6. REFERENCES

[1] Chuan-Yu Chang, Yue-Fong Lei, Chin-Hsiao Tseng, and Shyang-Rong Shih. THYROID SEGMENTATION AND VOLUME ESTIMATION IN ULTRASOUND IMAGES. IEEE Transaxtions on Biomedical Engineering, June 2010, vol 57,No 6.

[2] I.S.Isa, Z.Saad, S.Omar, M.K.Osman, K.A.Ahmad, H.A.MatSakim, 2010, SUITABLE MLP NETWORK ACTIVATION FUNCTIONS FOR BREAST CANCER AND THYROID DISEASE DETECTION, Second International Conference on Computational Intelligence.

[3] Canan SENOL, Tulay YILDIRIM, THYROID AND BREAST CANCER DISEASE DIAGNOSIS USING FUZZY-NEURAL NETWORKS. Nov 2009, IEEE International Conference on Electrical & Electronics Engineering.

[4] Nikita Singh, Alka Jindal, A SEGMENTATION METHOD AND COMPARISON OF CLASSIFICATION METHODS FOR THYROID ULTRASOUND IMAGES, july 2012, International Journal of Computer Applications, Vol 50 – No.11.

[5] JaspreetKaur, Alka Jindal, COMPARISON OF THYROID SEGMENTATION ALGORITHMS IN ULTRASOUND AND SCINTIGARPHY IMAGES, july 2012, International Journal of Computer Applications, Vol 50 – No 23.

[6] EystrationsG.Keramidas, DimitrisK.Iakovidis, DimitrisMaroulis, THYROID TEXTURE REPRESENTATION VIA NOISE RESISTANT IMAGE FEATURES, 2008, 21st IEEE International Symposium on Computer Based Medical Systems.

[7] Chuan-Yu Chang, Yue-Fong Lei, Chin-Hsiao Tseng, and Shyang-Rong Shih. THYROID SEGMENTATION AND VOLUME ESTIMATION IN ULTRASOUND IMAGES, 2008, IEEE International Conference on Systems, Man and Cybernetics.

[8] Eva N.K.Kollorz, Dieter A.Hahn, Rainer Linke, TmmeW.Goecke, Joachim Hornegger, and torstenKumert, QUANTIFICATION OF THYROID VOLUME USING 3-D ULTRASOUND IMAGING, APRIL 2008, IEEE TRANSACTIONS ON MEDICAL IMAGING, Vol 27 – No 4.

[9] MichalisA.Savelonas, DimitrisK.Lakovidis, IoannisLegakis, ACTIVE CONTOURS GUIDED BY ECHOGENICITY AND TEXTURE FOR DELINEATION OF THYROID NODULES IN ULTRASOUND IMAGES, July 2009, IEEE Transations on Information Technology in Bioscience, Vol 13 – No 4.

[10] FatemehSaiti, AfsanehAlaviNaini, Mahdi AliyariShoorehedeli, Mohammad Teshnehlab, THYROID DISEASE DIAGNOSIS BASED ON GENETIC ALGORITHMS USING PNN AND SVM, 2009, 3rd International Conference on Bioinformatics and Biomedical Engineering.

[11] Jieming Ma, Si Luo, ManjiriDighe, Dong – Jun Lim, and Yongmin Kim, DIFFERENTIAL DIAGNOSIS OF THYROID NODULES WITH ULTRASOUND ELASTOGRAPHY BASED ON SUPPORT VECTOR MACHINES, 2010, IEEE, International Ultrasonics Symposium Proceedings.

[12] Roberta Carraro, Filippo Molinari, and MaurilioDeandrea, CHARACTERIZATION OF THYROID NODULES BY 3-D CONTRAST-ENHANCED ULTRASOUND IMAGING, 2008, 30th Annual International IEEE EMBS Conference.

[13] Chhuan-Yu Chang, Hsiang-Yi Liu, Chin-Hsiao Tseng, and Shyang-Rong Shih, AUTOMATIC DIAGNOSIS OF THYROID GRAVES' DISEASE IN ULTRASOUND IMAGES, 2009, 9th International Conference on hybrid Intelligent Systems.

[14] Si Luo, Eung-Hun Kim, ManjiriDighe and Yongmin Kim, SCREENING OF THYROID NODULES BY ULTRASOUND ELASTOGRAPHY USING DIASTOLIC STRAIN VARIATION, 2009, 31st Annual International Conference of the IEEE EMBS Conference.

[15] N.Hu, D.B.Downey, A.Penster and H.M.Ladak,PROSTATE BOUNDARY SEGMENTATION FROM 3D ULTRASOUND IMAGES, Medical Physics, Vol 30.No.7, pp. 1648-1659, july 2003.

[16] T.Loupas, W.N.McDicken and P.L.Allan, AN ADAPTIVE WEIGHTED MEDIAN FILTER FOR SPECKLE SUPPRESSION IN MEDICAL ULTRASOUNIC IMAGES, IEEE Transactions on Circuits Synthesis, Vol. 36, pp.129-135, Jan 1989.

[17] C.H.Lee, Y.C.Lin, HYBRID LEARNING ALGORITHM FOR FUZZY NEURO SYSTEMS, IEEE International Conference on Fuzzy Systems, Budapest, Hungary, July 2004.