ELSEVIER

Ultrasound in Med. & Biol., Vol. 22, No. 9, pp. 1177–1181, 1996

0301-5629/96 $15.00 + .00

PII: S0301-5629(96)00144-5

●Original Contribution

APPLICATION OF ARTIFICIAL NEURAL NETWORKS FOR THE CLASSIFICATION OF LIVER LESIONS BY IMAGE TEXTURE PARAMETERS

H. SUJANA,[†] S. SWARNAMANI[†] and S. SURESH[‡]

[†]Department of Applied Mechanics, Biomedical Engineering Division, Indian Institute of Technology, Madras, India; and [‡]Mediscan Systems, Madras, India

(*Received* 11 *March* 1996; *in final form* 8 *July* 1996)

Abstract—Ultrasound imaging is a powerful tool for characterizing the state of soft tissues; however, in some cases, where only subtle differences in images are seen as in certain liver lesions such as hemangioma and malignancy, existing B-scan methods are inadequate. More detailed analyses of image texture parameters along with artificial neural networks can be utilized to enhance differentiation. From B-scan ultrasound images, 11 texture parameters comprising of first, second and run length statistics have been obtained for normal, hemangioma and malignant livers. Tissue characterization was then performed using a multilayered backpropagation neural network. The results for 113 cases have been compared with a classification based on discriminant analysis. For linear discriminant analysis, classification accuracy is 79.6% and with neural networks the accuracy is 100%. The present results show that neural networks classify better than discriminant analysis, demonstrating a much potential for clinical application. Copyright © 1996 World Federation for Ultrasound in Medicine & Biology.

Key Words: **Ultrasonic scan, Texture parameters, Neural network classification, Hemangioma, Malignancy.**

INTRODUCTION

Ultrasound imaging is a powerful tool for characterizing the state of soft tissues for medical diagnostic purposes. Ultrasound imaging instruments present two-dimensional images based mainly upon the amplitude of the returned radio-frequency (RF) signal. The sonographer can determine whether or not the tissue is normal by observing the brightness and texture compared to surrounding areas. However, in some cases, it may be difficult to diagnose from the image alone, and a biopsy examination must be conducted, even though there are risks involved, such as in the case of hemangioma (Jeffrey and Ralls 1995). Moreover, the image may not provide reliable information about the type of abnormality (i.e., benign or malignant). The goal of the present study is to enhance the capability of diagnosing disorders of tissues and organs. Based on previous works (Garra *et al.* 1993; Gebbinck *et al.* 1993; Goldberg *et al.* 1992; Layer *et al.* 1990), it is believed that this can be achieved by obtaining the texture parameters and applying a powerful pattern recognition technique based on artificial neural networks. In the present study, the technique is applied to differentiate liver lesions, such as malignancy and hemangioma, where only subtle differences could be seen in B-scans, offering limited scope of accurate differentiation.

Liver hemangioma is a benign lesion, the size of which varies from a few millimetres up to several centimetres in diameter and consists of fine blood capillaries (Robbins and Cotran 1982). They appear as a mass sharply delineated from adjacent liver parenchyma (Bolondi *et al.* 1984). The sonographic appearance of the capillary hemangioma overlaps enough with the appearance of significant lesions to make definitive distinction difficult or impossible, especially in patients with malignancy and specifically in some cases of hepatocellular carcinoma, cholangiocarcinoma and some metastases (Jeffrey and Ralls 1995). Biopsy is a reasonable way to evaluate hemangiomas, but there is risk of postbiopsy hemorrhage (Jeffrey and Ralls 1995). Therefore, there is a need for improving the accuracy of existing ultrasonic imaging techniques for differentiation, and this is possible using additional image texture information not hitherto fully exploited.

Address correspondence to: Dr. S. Swarnamani, Department of Applied Mechanics, Biomedical Engineerining Division, Indian Institute of Technology, Madras 600 036, India.

The texture of the ultrasonic scan images is concerned with the spatial (statistical) distribution of grey tones and thus carries information on tissues involved in scans (Haralick *et al.* 1973). Statistical pattern recognition procedures allow a quantitative description of the ultrasonic B-scan image texture. The texture parameters, such as first and second order statistical parameters and run length statistical parameters, can be used to describe quantitatively the microstructure and macrostructure of the tissue (Haberkorn *et al.* 1990). The first order texture sufficiently characterizes the grey-level histogram, which displays the occurrence frequency of all grey levels in the image cluster. The second order statistics describe, in addition, the spatial correlation between the image elements and thus characterize the distribution pattern of scatterers forming the images. Due to the lack of spatial information, the parameters derived from the first order statistics have limitations in quantifying the number, size and orientation of localised textures in the image. Hence, parameters such as first order gradient distribution, the grey-level co-occurence matrix and the grey-level run-length matrix are used. Several characteristic features of image structure can be extracted from the grey-level co-occurrence matrix (Layer *et al.* 1990). In addition, the two-dimensional grey-level run-length histogram counts the number in the grey-level range (Chu *et al.* 1990). These parameters are used to get additional information about the macrotexture of the image (Haberkorn *et al.* 1990). Zatari *et al.* (1993) made an attempt to differentiate normal and abnormal livers by neural networks based on ultrasound speed and attenuation coefficient, but here livers with fatty infiltration, cirrhosis and fibrosis were placed under one classification and differentiation of abnormalities was not reported. Ostrem *et al.* (1991) classified benign and malignant lesions of breast tissue using neural networks and ultrasound speed based on attenuation coefficients. Goldberg *et al.* (1992) and Garra *et al.* (1993) classified benign and malignant breast lesions using texture features and artificial neural networks. Recently, ultrasonic diagnosis of fatty liver was performed using echo-intensity histograms (Hiroyuki and Yasuaki 1996). Since histograms give only the occurrence frequency of grey levels, in this study, first, second and run-length statistics, which give characteristic features called texture parameters of the image structure, are used to classify liver abnormality. The texture parameters are classified by artificial neural networks to improve diagnostic accuracy.

The neural network approach has been employed by several investigators to characterize soft tissues and has reported that it outperforms the traditional statistical classifiers, such as nearest neighbour and the linear discriminant analysis (Garra *et al.* 1993; Gebbinck *et al.* 1993; Goldberg *et al.* 1992; Rinast *et al.* 1993; Zatari *et al.* 1993). Artificial neural networks are information processing structures that solve problems not by means of pre-specified algorithms, but rather by learning from examples that are presented. Neural networks consist of a number of nodes, called neurons, which are arranged in layers and connected by weights. An input pattern is transformed into an output pattern by means of the nonlinear response curves of the neurons and the excitatory or inhibitory effect of interconnecting weights. During successive iterations through this training set, the weights are updated with the help of a learning algorithm, and finally, the system is able to associate a specific output with a particular class of inputs. Backpropagation (Lippmann 1987) is a supervised method to train feedforward neural networks and has been used for medical diagnosis (Ostrem *et al.* 1991; Prentza and Wesseling 1995; Zatari *et al.* 1993). Application of the neural network seems to have improved classification accuracy (Gebbinck *et al.* 1993; Rinast *et al.* 1993).

In this study, differentiation of hemangioma and malignant lesions of liver is attempted utilising texture parameters and neural networks, the application of which has not been reported so far in literature. The method presented appears to have improved the accuracy of detection by ultrasonic scans.

MATERIALS AND METHODS

Texture parameters

A commercial ultrasound scanner (ATL-Ultramark 9HDI) with a 3.5-MHz curvi-linear array transducer was used to obtain the liver scans. The B-scan images with an amplitude resolution of 8 bits (256 grey levels) were recorded on a VHS videocassette. Biopsies were performed to determine the type of tumor. Ultrasonic scans were analysed using the videotaped image in a Matrox MVP-AT image-processing system. The various regions of interest were divided into blocks, each containing 100 pixels corresponding to an area of 12.3 mm^2. Because the texture parameters were considered sensitive to the size of the sampling matrix (Weszka *et al.* 1976), and the size of the tumor in this study varied in the chosen patient group (4 mm to 5 cm), a 100-pixel block was chosen for sampling so that even the minimum size tumor could be analysed. The pixel values were read from the region of interest. A set of grey tone spatial dependence probability distribution matrices and grey length matrices were computed and, from these, texture parameters were estimated based on a technique reported earlier (Chu *et al.* 1990; Haberkorn *et al.* 1990). The texture parameters obtained from the blocks were averaged to obtain the parameters for the whole tumor and the number of pixels per patient ranged from 6254 to 6868. Similarly, texture parameters were obtained from the normal regions of liver for comparison. Because the malignant tumors generally evoke changes in reflectivity in the surrounding tissue (i.e., margin due to oedema infiltration etc. which form rims [Jeffrey and Ralls 1995] which are are apparently seen in the scan), the margin area was not considered for analysis and the region beyond the margin was considered as the normal unchanged tissue.

Texture parameters used. First and second order grey-level statistics include: mean grey-level (MGL); variance of grey-levels (VAR), skewness (SKEW); contrast (CONT); angular second moment (ASM); correlation (CORR); entropy (ENT), as defined by Haberkorn *et al.* (1990). Run- length statistics include: run-length distribution (RLD); long-run emphasis (LRE); low grey-level run emphasis (LGRE); and high grey-level run emphasis (HGRE), as defined by Chu *et al.* (1990).

These parameters are utilised as inputs to the two classifiers, namely neural networks and linear discriminant analysis.

Artificial neural networks

The backpropagation neural network technique was used. The neurons of the input layer represent the texture parameters; the output layer represents diagnosis, i.e. normal, hemangioma or malignancy. An adaptive learning rate backpropagation algorithm, in which the learning rate varies from one iteration to the next, was used for faster convergence (Haykin 1994). The sigmoid nonlinear function was used to transform the weighted sum of the inputs of a node. From the available sets of data, 75% were randomly selected as the training (learning) set, and the remaining 25% were used to test the network. The training set consisted of 40 normals (N), 15 hemangiomas (H) and 30 malignancies (M). The test set consisted of 13 N, 5 H and 10 M.

The input layer has 11 neurons, and output layer has 2 neurons with target values (0–0 for normal, 0–1 for benign and 1–1 for malignancy). The training set with the target values is presented to the network and the network is trained by adapting the weights until the minimum error is reached. The patterns were presented randomly. The network is trained to a learning tolerance of 1%. The neural network tool-box of the 386-Matlab package was used. The challenge is to construct a network that is sufficiently simple such that the connective weights are meaningful and good performance is observed for both the training set and the test set. The optimal network is determined by many test runs to ensure its rapid convergence and correct classification by varying the following parameters:

1. Number of hidden layers.
2. Number of neurons in the hidden layers.
3. Momentum rate.

The performance of the network is measured by the sum-squared error. The network with architecture 11–4–2 (11 input layer neurons, 4 hidden layer neurons and 2 output layer neurons) and a momentum rate of 0.9 was chosen as the optimal network.

Linear discriminant analysis

To crossvalidate the artificial neural network result, the texture parameter data set was classified by the well-established transparent technique, linear disciminant analysis, using the STATGRAPHICS package.

RESULTS

Texture parameters

Table 1 shows the texture parameters for 40 M, 20 H and 53 N. It may be seen, in general, that the mean grey level is maximum for hemangioma, indicating higher scattering compared to normal and malignant tissues. Hemangiomas are made up of closely packed aggregates of thin-walled capillaries (Robbins and Cotran 1982) and contribute to more scattering. Malignant tumors show higher contrast and lower ASM because they are usually inhomogeneous (Jeffrey and Ralls 1995). Hemangiomas show more emphasis on lower grey levels, indicating smaller sized cells. To obtain more accurate classifications from these parameters, artificial neural networks (i.e., backpropagation) are used.

Table 2 shows the results of classification by neural networks; the numbers in parentheses indicate the results for the test set. After neural network training, all the data in the training set and test set were classified correctly. The accuracy of classification is 100%.

The results of classification by linear discriminant analysis are given in Table 3. Dicriminant analysis correctly classified 90 of 113 cases for an accuracy level of 79.6%.

DISCUSSION

The information contained in the ultrasound image is a result of the complex delineation of interaction between ultrasound waves and tissue components. Accuracy of conventional classification based on clinical B-scan methods is limited by recognition of important features and the experience of the sonographers. Other quantitative methods utilising full features of the images have invoked the potential of linear discriminant analysis, neural networks, etc., requiring computa-

Table 1. Texture parameters for 40 malignancy, 20 hemangioma and 53 normal liver (mean ± standard deviation).

Texture parameter	Malignancy	Hemangioma	Normal
MGL	30.76 ± 3.6	43.93 ± 6.93	26.12 ± 2.01
VAR	63.75 ± 6.8	37.55 ± 3.9	34.86 ± 2.9
SKEW	0.000137 ± 0.000009	0.000134 ± 0.000004	0.000165 ± 0.000012
CONT	20.31 ± 1.3	17.77 ± 0.9	14.77 ± 1.5
ASM	0.010 ± 0.001	0.0118 ± 0.0009	0.014 ± 0.0008
CORR	0.0991 ± 0.007	0.1612 ± 0.015	0.1822 ± 0.0095
ENT	4.796 ± 0.08	4.737 ± 0.06	4.479 ± 0.12
RLD	72.21 ± 2.85	81.17 ± 3.56	68.52 ± 1.95
LRE	1.426 ± 0.12	1.223 ± 0.08	1.5755 ± 0.09
LGRE	0.00072 ± 0.00007	0.00128 ± 0.00015	0.00153 ± 0.00011
HGRE	2358.41 ± 52.5	990.52 ± 35.1	1068.66 ± 31.78

tional support. Advances in fast-processing computers have enabled application of these computational methods leading to better differentiation of diseases.

The concept of neural networks allows an entirely new approach to the computerized perception of image data. Learning from a knowledge base is a most attractive feature of neural networks, which also results in optimum classification. This ability is achieved by interaction between several layers in the net with the input features and output classification. Comparing the results obtained using the neural network with those obtained using linear discriminant analysis show that the neural networks outperform this traditional statistical classifier. This finding has also been observed by others (Gebbinck *et al.* 1993; Ostrem *et al.* 1991).

To work with neural networks it is necessary to develop a database of training patterns and experiments with network architectures and training methods to obtain an optimum network. The limitation of greater computational burden and more experimentation from the design aspect may be offset by the advantages of better classification. For this, extraction of image feature data is essential, which requires appropriate data reduction to produce a vector of characteristic parameters. The performance of the classification algorithm depends on this vector of parameters and their interdependence. Thus, designing a system for automatic interpretation of images predominantly consists of a meticulous definition of the vector of parameters, which are distinctly dependent on the extracts of the images.

Although hemangiomas can be detected by a blood-pool scintigram and NMR, these techniques are expensive, and the blood-pool scintigram method is an invasive technique in which a radioactive dye is injected and causes inconvenience to the patient. The small hemangiomas are barely detectable by scintigram (Wiener and Parulekar, 1979). Ultrasound is a simple, noninvasive and inexpensive imaging system, for which an attempt has been made to increase diagnostic accuracy. The present technique, which uses texture parameters and neural networks, identifies the type of liver lesions with 100% accuracy, whereas linear discriminant analysis showed an accuracy of 79.6% in cases of malignancy and hemangioma. Extension of the present technique to ocular melanoma is in progress and will be reported in the future.

SUMMARY

In this article, ultrasonic differentiation of liver lesions (i.e., hemangioma and malignancy) is presented. A set of texture parameters was obtained from the clinical B-scan image and utilized as input to two classifiers, namely, backpropagation neural networks and linear discriminant analysis. The results show that the neural network technique classifies the lesions better than discriminant analysis.

Table 2. Neural net classification results: Table entries are the numbers of cases in the training set (in test set).

	True class		
Predicted class	H	M	N
H	15 (5)	0 (0)	0 (0)
M	0 (0)	30 (10)	0 (0)
N	0 (0)	0 (0)	40 (13)

H—hemangioma; M—malignant tumor; N—normal.

Table 3. Linear discriminant analysis results.

	True class		
Predicted class	H	M	N
H	13	7	0
M	6	24	0
N	0	0	53

H—hemangioma; M-malignant tumor; N—normal.

REFERENCES

Bolondi L, Labo G, Gandolfi L. Diagnostic ultrasound in gastroenterology. Rome: Piccin/Butterworths; 1984.

Chu A, Sehgal CM, Greenleaf JF. Use of gray level value distribution of run lengths for texture analysis. Patt Recog Lett 1990;12:415–420.

Garra BS, Krasner BH, Horii SC, Ascher S, Mun SK, Zeman RK. Improving the distinction between benign and malignant breast lesions: the value of sonographic texture analysis. Ultrason Imag 1993;15:267–285.

Gebbinck MS, Verhoven JTM, Thijssen JM, Schouten TE. Application of neural networks for the classification of diffuse liver disease by quantitative echography. Ultrason Imag 1993;15:168–169.

Goldberg V, Manduca A, Ewert DL, Gisvold JJ, Greenleaf JF. Improvement in specificity of ultrasonography for diagnosis of breast tumors by means of artificial intelligence. Med Phys 1992;19:1475–1481.

Haberkorn U, Zuna I, Lorenz A, Zerban H, Layer G. Echographic tissue characterization in diffuse parenchymal liver disease: correlation of image structure with histology. Ultrasonic Imaging 1990;12:155–170.

Haralick RM, Shanmugam K, Dinstein I. Textural features for image classification. IEEE Trans Syst Man Cybernet 1973;SMC-3:610–621.

Haykin S. Neural networks. New York: Macmillan; 1994.

Hiroyuki O, Yasuaki M. Sonographic diagnosis of fatty liver using a histogram technique that compares liver and renal cortical echo amplitude. J Clin Ultrasound 1996;24:25–29.

Jeffrey RB, Ralls PW. Sonography of the abdomen. New York: Raven Press, 1995.

Layer G, Zuna I, Lorenz A, Zerban H, Haberkorn U. Computerized ultrasound B-scan texture analysis of experimental fatty liver disease: influence of total lipid content and fat deposit distribution. Ultrason Imag 1990;12:171–188.

Lippmann R. An introduction to computing with neural nets. IEEE ASSP Mag 1987;4:4–22.

Ostrem JS, Valdes AD, Edmonds PD. Application of neural nets to ultrasound tissue characterization. Ultrason Imag 1991;13:298–299.

Prentza A, Wesseling KH. Catheter-manometer system damped blood pressures detected by neural nets. Med Biol Eng Comput 1995;33:589–595.

Rinast E, Linder R, Weiss HD. Neural network approach for computer-assisted interpretation of ultrasound images of the gallbladder. Eur J Radiol 1993;17: 175–178.

Robbins SL, Cotran RS. Pathologic basis of disease. Philadelphia: WB Saunders; 1982.

Weszka JS, Dyer CR, Rosenfeld A. A comparative study of texture measures for terrain classification. IEEE Trans Syst Man Cybernet 1976;SMC-6:269–285.

Wiener SN, Parulekar SG. Scintigraphy and ultrasonography of hepatic hemangioma. Radiology 1979;132:149–153.

Zatari D, Botros N, Dunn F. In vivo liver differentiation by ultrasound using an artificial neural network. J Acoust Soc Am 1993;96:376–381.