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Performance Evaluation of Feature Extraction methods for Classifying Abnormalities in Ultrasound Liver Images using Neural Network

S.Poonguzhali[1] , Dr.G.Ravindran[2]

Abstract - **Image analysis techniques have played an important role in several medical applications. In general, the applications involve the automatic extraction of features from the image which is further used for a variety of classification tasks, such as distinguishing normal tissue from abnormal tissue. In this paper, the classification of ultrasonic liver images is studied by using texture features extracted from Laws' method, Autocorrelation method, Gabor Wavelet and Edge frequency method. The Features from these methods are used to classify three sets of ultrasonic liver images-Normal, Cyst and Benign and how well they suit in classifying the abnormalities is reported. A Neural Network classifier is employed to evaluate the performance of these features based on their recognition ability.**

Keywords: Feature Extraction, Classification, Image analysis, Neural Network, Performance analysis.

I. INTRODUCTION

Diagnostic ultrasound is a useful clinical tool for imaging organs and soft tissues in the human body. The gray-scale type of display is useful in the detection of tumors. One of its important applications is liver imaging. Liver focal diseases concentrated in a small area of the liver tissue, while the rest being normal. In some cases, it may be difficult to diagnose from the image alone, hence a Biopsy examination must be conducted.

Benign lesion contains very fine blood capillaries. The capillary appearance of benign lesion in ultrasound image overlaps enough with the portion of distinctive lesions. This makes the tissue differentiation very difficult or impossible.

[1]S.Poonguzhali is with the Centre for Medical Electronics, College of Engineering , Guindy, Anna University,Chennai, TamilNadu, India(poongsma@yahoo.com).

[2]Dr.G.Ravindran is with the Centre for Medical Electronics, College of Engineering , Guindy, Anna University,Chennai, TamilNadu, India(raviguru@annauniv.edu).

Biopsy is a usual method for finding the type of tumors, but there is a very high risk of post biopsy hemorrhage [2]. It is very difficult, even for an experienced clinician, to diagnose the existence, type, and the level of a disease in liver. Therefore, a reliable non invasive method for early detection and differentiation of these diseases is clearly desirable.

Texture feature refers to the spatial inter relationships of the basic elements of an image [3].Texture Methods can be classified as Statistical, Structural, Model based and Signal Processing techniques [4]. Multi-scale filtering methods such as Gabor wavelet has shown significant potential for texture description, where the advantage is taken of the spatial frequency concept to maximize the simultaneous localization of energy in both spatial and frequency domains [5]. Ahmadian compared Dyadic and Gabor wavelet and showed that the Gabor wavelet achieves higher classification rate since it is rotation-invariant and eliminates the DC component of an input image [6].

Mona Sharma compared five different feature extraction methods on Meastex database [7]. The results showed that the Law's method and co-occurrence matrix method yield the higher recognition rate. Haralick reviewed various approaches and models for texture [8]. He concluded that for micro textures, the statistical approach works well and for macro textures, histograms of primitive properties and co-occurrence can be used. Kyriacou et.al classified normal, fatty, cirrhosis and hepatoma ultrasonic liver images and found that Fractal Dimension and Spatial Gray level dependence Matrices gave higher accuracy than Gray level Run Length Statistics [9]. Law used Brodatz textures and other images to compare his masks with Co occurrence based features and found that his method had high success rate [10].

In this paper, features from Law's Method, Autocorrelation Method Edge Frequency method and Gabor wavelet are extracted and their recognition rate in classification of abnormalities is compared by using Back Propagation Network.

II. MATERIALS AND METHODS

In this study, the ultrasound images have been taken using curvilinear transducer array of frequency 4 MHz. These algorithms are applied on 25 samples of normal, benign and cyst images on 10 x 10 pixel region of interest (ROI) with an 8 bit resolution. The Features extracted from these methods are further processed to obtain optimal features which represent the most discriminating pattern space for classification. These optimal features are given as input to the neural network for classification.

A. Feature extraction methods

In the feature extraction module features are extracted from the samples for classification.

The algorithms used are:
i)Laws' Texture Energy Measures

The texture energy measures developed by Kenneth Ivan Law have been used here [11].

Laws' texture measures are computed by first applying small convolution kernels to the image, and then combining statistics (e.g. energy) of the resulting images to extract texture features. The 2-D convolution kernels typically used for texture discrimination are generated from the following set of five one-dimensional convolution kernels of length five [12]. Each 1-D array is associated with an underlying microstructure and labeled using an acronym accordingly.

$$
\begin{aligned}
L5 &= [\ 1\ \ 4\ \ 6\ \ 4\ \ 1\ ] \\
E5 &= [\ -1\ -2\ \ 0\ \ 2\ \ 1\ ] \\
S5 &= [\ -1\ \ 0\ \ 2\ \ 0\ -1\ ] \\
W5 &= [\ -1\ \ 2\ \ 0\ -2\ \ 1\ ] \\
R5 &= [\ 1\ -4\ \ 6\ -4\ \ 1\ ]
\end{aligned}
$$

Where L performs local averaging, E is an edge detector, S detects spots and the W and R vectors act as wave detectors. The texture energy of the filtered images is used to extract 14 texture features. The obtained features are normalized.

Table-1 Laws' Texture Features

Feature (P,Q)	IMAGE TYPE		
	NORMAL	BENIGN	CYST
EL	0.069 ± 0.006	0.09535 ± 0.006	0.224 ± 0.0164
ER	0.036 ± 0.0021	0.04831 ± 0.002	0.110 ± 0.0110
SE	0.007 ± 0.0009	0.01082 ± 0.0009	0.0251 ± 0.0037
WE	0.005 ± 0.0008	0.00815 ± 0.0008	0.0202 ± 0.0027
SS	0.003 ± 0.0005	0.00116 ± 0.0002	0.0125 ± 0.0020
EE	0.012 ± 0.0015	0.02043 ± 0.0015	0.0516 ± 0.0068

The above table shows the normalized optimal parameters extracted from the Laws' method. The texture energy obtained for cyst method is large when compared to the normal and benign images due to large difference in gray level values. The values show that the cyst image has well defined edges and spots in horizontal direction.

ii) Autocorrelation based texture features

The textural character of an image depends on the spatial size of texture primitives. An autocorrelation function can be evaluated to measure this coarseness [13]. This function evaluates the linear spatial relationship between primitives. If the primitives are large, the function decreases slowly with an increasing distance whereas it decreases rapidly if texture consists of small primitives. The set of autocorrelation coefficients shown below are used as texture features:

$$C_{ff}(p,q) = \frac{MN}{(M-p)(N-q)} \frac{\sum_{i=1}^{M-p} \sum_{j=1}^{N-q} f(i,j) f(i+p, j+q)}{\sum_{i=1}^{M} \sum_{j=1}^{N} f^2(i,j)} \qquad (1)$$

Where *p, q* is the positional difference in the *i, j* direction, and *M, N* are image dimensions. In this study we vary the (p, q) from (0, 0) to (9, 9) giving us a total of 100 features.

Table-2 Autocorrelation based Texture Features

Feature (P,Q)	IMAGE TYPE		
	NORMAL	BENIGN	CYST
7,3	0.971 ± 0.014	0.898 ± 0.028	0.556 ± 0.099
7,4	0.97 ± 0.014	0.89 ± 0.028	0.562 ± 0.102
7,5	0.97 ± 0.014	0.888 ± 0.029	0.56 ± 0.11
7,6	0.97 ± 0.014	0.88 ± 0.031	0.56 ± 0.111
7,7	0.97 ± 0.014	0.88 ± 0.034	0.56 ± 0.11
7,8	0.97 ± 0.014	0.87 ± 0.039	0.551 ± 0.11
7,9	0.97 ± 0.015	0.866 ± 0.0389	0.54 ± 0.11
8,5	0.97 ± 0.015	0.88 ± 0.031	0.557 ± 0.10
8,6	0.97 ± 0.016	0.882 ± 0.030	0.557 ± 0.11
8,7	0.97 ± 0.016	0.878 ± 0.032	0.556 ± 0.11

The table shows that autocorrelation co-efficients decreases slowly with increasing distance which implies that the images are composed of coarse texture. Since there is a large variation in gray level values of the pixels in the cyst and benign images, the co-efficients show low value when compared to co-efficients of the normal images.

iii) Gabor Texture Parameters

An important desirable feature of Gabor filter is optimum joint spatial/spatial-frequency localization, orientation selectivity. The spatial /frequency analysis has played a central role in feature extraction as it combines the two fundamental domains. An important property of the Gabor transform is that its coefficients reveal the localized frequency description of a signal (or) an image, instead of the global frequency information as provided by the coefficients of Fourier Transform [14]. Basically, a 2-D

Gabor filter is a complex sinusoidally- modulated Gaussian function of some frequency and orientation [15].

A 2-D Gabor filter is given by

$$g(x,y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left(\frac{-1}{2}\left(\frac{x^2}{\sigma_x{}^2}+\frac{y^2}{\sigma_y{}^2}\right)+2\pi jW_x\right) \quad (2)$$

Where W is the frequency of sinusoid.
σ_x and σ_y characterize the spatial extent and bandwidth of the filter in x and y directions respectively.

An input image I(x, y) is passed through a set of Gabor filters to obtain the set of filtered output. The Gabor Mean, Standard deviation, Skewness, Kurtosis and Variance are calculated as texture parameters from the magnitude of the transformed coefficients.

Table-3 Gabor Wavelet Features

Image Type	Scale value	Gabor Mean	Gabor S.D	Gabor Variance	Gabor Skewness	Gabor Kurtosis
	Orientation=0º					
Normal	1	1.08	0.297	0.088	-0.071	3.144
	2	2.803	0.131	0.017	-0.014	1.775
	3	1.499	0.75	0.562	0.012	3.217
	4	0.727	0.653	0.427	-0.089	3.1
Cyst	1	0.45	0.127	0.016	0.276	2.958
	2	1.147	0.084	0.007	0.031	1.997
	3	0.817	0.371	0.138	-0.03	3.103
	4	0.625	0.446	0.199	-0.27	2.817
Benign	1	1.249	0.359	0.129	-0.188	2.978
	2	3.194	0.149	0.022	0.016	1.804
	3	2.364	0.747	0.558	-0.013	3.12
	4	1.147	0.821	0.673	-0.442	3.473

Table-3 shows the optimal Gabor texture parameters. The Gabor parameters depend on the variation of gray levels in pixels. The Gabor mean appears to be less for cyst than benign and normal images. They have less gray level variation and it nearly appears to be homogeneous. The Gabor mean is larger for benign than cyst and normal images. So it is found that the benign image appears to be inhomogeneous. The normal images are intermediate between these two types.

iv) Edge-frequency based texture features

A number of edge detectors can be used to yield an edge from an original image. An edge dependent texture description function E is calculated as follows [16]

$$E(d)=|f(i,j)-f(i+d,j)|+|f(i,j)-f(i-d,j)|+|f(i,j)-f(i,j+d)|+|f(i,j)-f(i,j-d)| \quad (4)$$

This function is inversely related to the autocorrelation function. Texture features can be evaluated by choosing specified distances *d*. Varying the distance *d* parameter from 1 to 30 giving us a total of 30 features. Here features are based on distance-related gradient [17]. Micro edges can be detected using small distance operators and macro edges need large size edge detectors. Dimensional of texture description is specified by the number of considered distance.

Table-4 Edge Frequency Features

Feature D	IMAGE TYPE NORMAL	BENIGN	CYST
1	63.5 ± 10.2	49.05 ± 9.82	7.28 ± 5.59
2	114.5 ± 18.4	84.59 ± 17.99	12.00 ± 9.14
8	155.1 ± 22.5	106.89 ± 20.78	13.74 ± 10.12
14	155.7 ± 21.7	108.88 ± 21.01	14.41 ± 11.52
21	158.4 ± 23.8	109.53 ± 21.04	14.56 ± 10.86
29	227.5 ± 36.7	152.40 ± 32.81	14.94 ± 12.78
30	261.8 ± 44.2	171.38 ± 39.39	15.45 ± 13.43

The table shows the optimal features that are extracted in which the distances have a small variation to detect the micro edges. The distances are varied to find the gray level differences between a pixel and its neighboring pixel at various distances. The results show that the gray level differences increase as the distance increase. It implies that the gray level differences are large for normal images than tumor and cyst images.

v) Optimal Feature Sets

The optimal features selected from these methods correspond to a total of 27 features.

Table -5 Optimal Features in each Texture Algorithm

Feature Extraction Methods	No. Of Features
Autocorrelation Method (ACF)	10
Law's Method	6
Gabor Wavelet Method	4
Edge Frequency Method	7

Table-5 shows the optimal number of features extracted from each of the methods. They are selected in a way to show wide variation among all types of images useful in discriminating various types of liver abnormalities. The optimal features are selected from the total number of features obtained from each method (ACF - 99, Laws – 14, Gabor -24, Edge frequency – 30 features).

III. CLASSIFICATION

Hiroshi Fujita showed that the BPN had provided good classification performance for mammograms [18]. A three layered feed forward Back propagation network is used for classification to show the performance. The reprehensive features obtained from above methods are presented to the network. These features are normalized and given as input to the neural network.

A total of 25 image samples from normal, benign and cyst are considered in which the random set of 50% are used as training data set. The remaining is used as testing data set. The neural network is trained with 2000 learning epochs. Each learning epoch corresponds to the entry of complete set of training data.

IV RESULTS AND DISCUSSION

The performance evaluation of the four texture methods is based on the ability of the classifier to recognize the abnormalities. The texture method that gives the best recognition has high recognition rate.

The aim of this paper is to find which of the feature extraction methods give high recognition rate in classifying abnormalities of liver images. Table 7 shows that high recognition rate is obtained for features extracted from Gabor wavelet followed by Laws' method, Autocorrelation method and Edge Frequency method.

Table -7 Recognition rate of Texture algorithm

Texture Method	Recognition Rate
Laws' Method (LM)	76%
Gabor Wavelet Method(GW)	79%
Autocorrelation Method(AC)	70.83%
Edge Frequency Method (EF)	68.25%

From the table it is seen that the Gabor wavelet classifies better when compared to other methods since it analyses the image in both time and frequency domain simultaneously. But since the ultrasound image is degraded by speckle noise and the appearance of lesion overlaps enough with the sonogram, the result is less in ultrasound liver image.

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