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Classification and Analysis of Ultrasound Liver Images

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Abstract—*Ultrasound imaging is considered to be one of the most cost-effective, real-time imaging capabilities and non-invasive techniques for conclusive diagnosis in some cases and preliminary diagnosis.Tissue characterization attempts to provide quantitative information about the state of disease or health of tissue interrogated by an ultrasound beam. Liver is an important organ since it plays a vital role in human life. Liver tissue is having major diseases than any other tissues, so ultrasound images of liver tissue are collected for this project. The performance of preprocessing method in this paper is to remove speckle noise. Preprocessing was proposed by comparing the MSE and PSNR values of SRAD denoising and Log-Gabor filter, since SRAD denoising gives smooth edges. To enhance contrast and edge Log-Gabor filter is used. The ultrasound liver images are characterized using Moment Invariant Features; which are invariant to translation, size and rotation. Extracted are based on moments, image partition. The main use of moments is for optical character recognition and shape identification. In this paper we propose a Neuro-Fuzzy classifier for classification of liver image categories. Neuro-Fuzzy algorithm was applied to selected medical images for classification .The good performance of the method is a promising indicator that it can be used, to provide reliable information about the liver disease staging.*

Index Terms—Ultrasound liver image, Preprocessing, Log-Gabor filter, SRAD denoising, Moment Invariant Feature Extraction, Neuro-Fuzzy Classifier.

I INTRODUCTION

ULTRASOUND (US) imaging enables effective, real-time, and non-invasive tissue classification in many diagnostic and prognostic applications. Conventional US B-mode images have been analyzed to extract texture features for prostate tissue classification. Moreover, spectral analysis has been employed to quantify tissue at scales finer than the resolution of B-mode imaging using the frequency content of radio-frequency (RF) signals. Texture and spectral analyses have been used, both separately and combined, for cancer detection. Ultrasound also is used as a tool for tissue characterization in terms of the tissue response to static mechanical stimuli.

Ultrasonic imaging has gained widespread acceptance as an effective diagnostic tool to visualize organs and soft tissues in human abdominal wall with no deteriorating effects. It enables the operator to rapidly select the ideal right image plane to display normal or pathological anatomy accurately and it is safe and cost effective.

Ultrasonic echoes from human tissues, when displayed as a B-scan image, form a texture pattern that is characteristic of both the imaging system and the tissue that is being imaged. This image texture represents the acoustic properties of human tissues and provides very useful tissue signature regarding their soft structure.

One application of diagnostic ultrasound is liver imaging. The most useful tissue differentiation techniques are based on the investigation of B-scan images.

Liver diseases are taken seriously because of the liver's vital importance to the life of the patient. The liver is a large, meaty organ that sits on the right side of the belly. The liver's main job is to filter the blood coming from the digestive tract, before passing it to the rest of the body. The liver also detoxifies chemicals and metabolizes drugs. As it does so, the liver secretes bile that ends up back in the intestines. The liver also makes proteins important for blood clotting and other functions.

Preprocessing is done to remove speckle noises and to enhance the contrast and edge. A comparative study of SRAD and Log-Gabor filter are done, and as a result Log-Gabor filter is used for the preprocessing method. Moment Invariant Features (MIF) are used to extract the features. MIF are invariant to translation, scaling and rotation.

In the existing sytems they used SVM classifiers [1], statistical and neural classifiers [2] and K-nearest neighbour classifiers were used [3].

A classifier system is a machine learning system that learns syntactically simple rules to guide its performance in an arbitrary environment. For tissue classification Neuro-Fuzzy classifier employed. Neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic. Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks.

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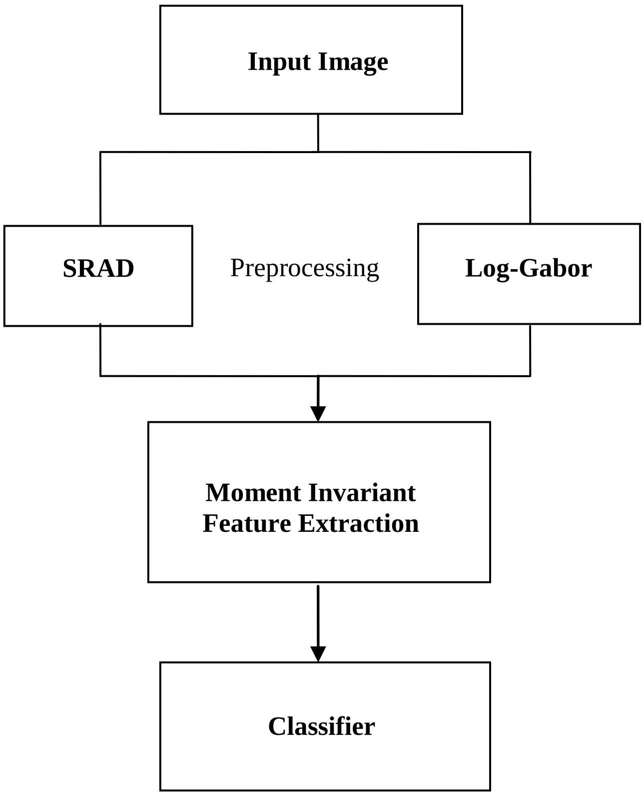

Fig.1. Flow Diagram

Preprocessing,Moment Invariant Feature Extraction steps are carried out as in Fig.1

II MATERIALS AND METHODS

The work presented in this study consists of three major modules: 1) collection of ultrasound liver images, 2) Preprocessing,3) Feature Extraction and 4)Classifier.

1. *Collection Of Ultrasound Liver Images*

An abdominal ultrasound can test for many liver conditions, including cancer, cirrhosis, or problems from gallstones. The medical ultrasound frequency ranges from 1MHz to 15MHz.A sound wave is typically produced by a piezoelectric transducer; the wave travels into the body and comes into focus at a desired depth. The sound wave is partially reflected from the layers, the return sound wave vibrates the transducer, and the transducer turns the vibrations into electrical pulses that travel to the ultrasonic scanner where they are processed and transformed into digital image.

Transforming the received signal into a digital image may be explained by using a blank spreadsheet as an analogy. The ultrasound liver images of abnormal condition livers and normal condition livers of patients were collected.

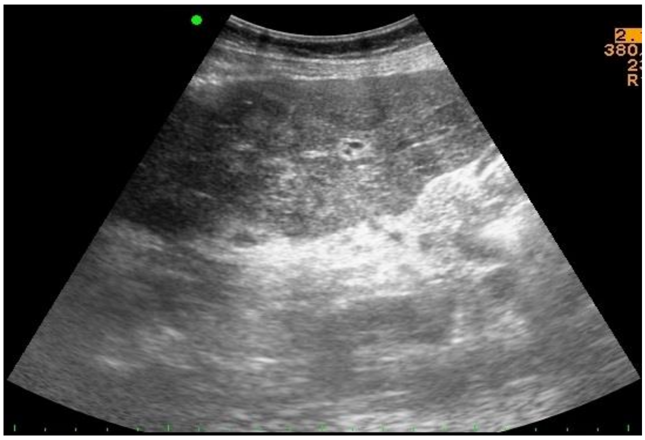

Fig.2.An ultrasound liver image of liver cancer patient

2. *Preprocessing*

The preprocessing removes the speckle noises in high frequency images. Speckle noise is caused by coherent processing of backscattered signals from multiple distributed signals. Speckle differs from other types of noise in the sense that it is a deterministic artifact, meaning that two signals or images, acquired under exactly the same circumstances, will experience exactly the same speckle corruption pattern but if some or all of the circumstances differ, the speckle corruption pattern will be different. To remove speckle noise, adaptive and non-adaptive filters can be used. Preprocessing enhances the contrast and edge detection of image. A comparative study of SRAD Denoising and Log-Gabor Filter were done here.

A. Speckle Reducing Anisotropic Diffusion (SRAD)

In the case of diffusion filtering the direction and strength of the diffusion are controlled by an edge detection function. SRAD is a nonlinear diffusion based method. SRAD emphasizes edge-enhancement more than visualization improvement.

SRAD removes speckle by preserving edges and enhancing edges. It removes speckles and at the same time enhances the edges. It removes speckles by modifying the image via solving a Partial Differential Equation. SRAD is proposed for speckled images without logarithmic compression. If the edge is not detected, the edge will not be enhanced and even smoothed. And if the noise is detected as edges, the noise will not be smoothed and even enhanced.

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SRAD exploits the instantaneous coefficient of variation, which serves as edge detector in speckled images. The function exhibits high values at edges and produces low values in homogeneous regions. Thus it ensures the mean preserving behavior in the homogeneous regions and edge preserving and edge enhancing at the edges. The performance of SRAD is sensitive to the selection of threshold value. Although SRAD has a dynamic threshold value, its precision of edge detecting is not so good in experiment.

B. Log-Gabor Filter

Images are better coded by filters that have Gaussian transfer functions when viewed on the logarithmic frequency scale. Gabor functions have Gaussian transfer functions when viewed on the linear frequency scale [15]. Log-Gabor filters basically consist in a logarithmic transformation of the Gabor domain which eliminates the annoying DC-component allocated in medium and high-pass filters. Log-Gabor filters can be constructed with arbitrary bandwidth and the bandwidth can be optimised to produce a filter with minimal spatial extent. Log-Gabor implementation is non-orthogonal, which implies a considerable increasing of computational and memory costs.

There are two important characteristics :-

Firstly, log-Gabor functions, by definition, always have no DC component, and secondly, the transfer function of the log Gabor function has an extended tail at the high frequency end. Field's studies of the statistics of natural images indicate that natural images have amplitude spectra that fall off at approximately 1/w. To encode images having such spectral characteristics one should use filters having spectra that are similar. Field suggests that log Gabor functions, having extended tails, should be able to encode natural images more efficiently than, say, ordinary Gabor functions, which would over-represent the low frequency components and under-represent the high frequency components in any encoding.

Another point in support of the log Gabor function is that it is consistent with measurements on mammalian visual systems which indicate we have cell responses that are symmetric on the log frequency scale.

On the linear frequency scale the Log-Gabor function has a transfer function of the form

$$G(w) = e^{(-\log(w/w_o)2) / (2 (\log(k/w_o)2)}$$

3. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be notoriously redundant (e.g. the same measurement in both feet and meters) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called *feature extraction*. If the features extracted are carefully chosen it is expected that the features set will extract the relevant information from the input data in order to perform the desired task using this reduced representation instead of the full size input.

Feature extraction involves simplifying the amount of resources required to describe a large set of data accurately. When performing analysis of complex data one of the major problems stems from the number of variables involved. Analysis with a large number of variables generally requires a large amount of memory and computation power or a classification algorithm which overfits the training sample and generalizes poorly to new samples. Feature extraction is a general term for methods of constructing combinations of the variables to get around these problems while still describing the data with sufficient accuracy. **Moment Invariant Feature Extraction used,** since it is invariant to scale, rotation and shape.

A. GLCM Feature Extraction

The Gray Level Coocurrence Matrix (GLCM) method is a way of extracting second order statistical texture features.

Haralick et all first introduced the use of co-occurrence probabilities using GLCM for extracting various texture features. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, θ) contains the second order statistical probability values for changes between gray levels 'i' and 'j' at a particular displacement distance d and at a particular angle (θ). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, θ). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of gray levels is often reduced. GLCM matrix formulation can be explained with the example illustrated in fig 2.1 for four different gray levels. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixels).

$g_{ij} = (i, j)^{th}$ entry in GLCM

The following features are used:-

1) Energy:
   $$\text{Energy} = \sum_i \sum_j g_{ij}{}^2$$
2) Entropy:
   $$\text{Entropy} = \sum_i \sum_j g_{ij} \log_2 g_{ij}$$
3) Contrast:
   $$\text{Contrast} = \sum_i \sum_j (i-j)^2 g_{ij}$$
4) Variance:
   $$\text{Variance} = \sum_i \sum_j (i-\mu)^2 g_{ij}$$
5) Homogeneity:

$$\text{Homogeneity} = \sum_i \sum_j \frac{1}{1+(i-j)^2} g_{ij}$$

6) Correlation:

$$\text{Correlation} = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y}$$

7) Cluster Prominence:

$$\text{Prom} = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \{i + j - \mu_{x-} \mu_y\}^4 \text{ X P(i.j)}$$

B. Moment Invariant Feature Extraction

Moment functions have a broad spectrum of applications in image analysis, such as invariant pattern recognition, object classification, pose estimation, image coding and reconstruction. These new features compute moments from a point shifted to a distance from the image centroid [4]. By doing so, the new moments show improved ability to represent symmetrical and noisy images. A set of moments generally represents global characteristics of the image shape and provides information about different types of geometrical features of the image. Regular moments are the first of these moment functions to find applications since they are algorithmically and computationally simple. Moment Invariant feature extraction becomes a classical tool for object recognition. It represents global characteristics of the image shape. It provides information about different types of geometrical features of the image [19].

Derived the seven famous invariants to the rotation of objects.

$$ø_1 = \mu_{20} + \mu_{02}$$

$$ø_2 = (\mu_{20} - \mu_{02})^2 + 4\mu^2_{11}$$

$$ø_3 = (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2$$

$$ø_4 = (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2$$

$$ø_5 = (\mu_{30} - 3\mu_{12})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) + (3\mu_{21} - \mu_{03})(\mu_{21} + \mu_{03}) \text{ X } (3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)$$

$$ø_6 = (\mu_{20} - \mu_{02})((\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2) + 4\mu_{11}(\mu_{30} + \mu_{12})(\mu_{21} + \mu_{03})$$

$$ø_7 = (3\mu_{21} - \mu_{03})(\mu_{30} + \mu_{12})((\mu_{30} + \mu_{12})^2 - 3(\mu_{21} + \mu_{03})^2) - (\mu_{30} - 3\mu_{12})(\mu_{21} + \mu_{03}) \text{ X } (3(\mu_{30} + \mu_{12})^2 - (\mu_{21} + \mu_{03})^2)$$

where

$$\mu_{pq} = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - x_c)^p (y - y_c)^q f(x, y) \, dx \, dy$$

is the central moment of the object $f(x, y)$ and (x_c, y_c) are the coordinates of the object centroid.

4. *Classifier*

A classifier system is a machine learning system that learns syntactically simple rules to guide its performance in an arbitrary environment. For tissue classification Neuro-Fuzzy classifier employed. Neuro-fuzzy refers to combinations of artificial neural networks and fuzzy logic.

Neuro-fuzzy hybridization results in a hybrid intelligent system that synergizes these two techniques by combining the human-like reasoning style of fuzzy systems with the learning and connectionist structure of neural networks. Neuro-fuzzy hybridization is widely termed as Fuzzy Neural Network (FNN) or Neuro-Fuzzy System (NFS) in the literature. Neuro-fuzzy system (the more popular term is used henceforth) incorporates the human-like reasoning style of fuzzy systems through the use of fuzzy sets and a linguistic model consisting of a set of IF-THEN fuzzy rules. The main strength of neuro-fuzzy systems is that they are universal approximators with the ability to solicit interpretable IF-THEN rules.

The strength of neuro-fuzzy systems involves two contradictory requirements in fuzzy modeling: interpretability versus accuracy. In practice, one of the two properties prevails. The neuro-fuzzy in fuzzy modeling research field is divided into two areas: linguistic fuzzy modeling that is focused on interpretability, mainly the Mamdani model; and precise fuzzy modeling that is focused on accuracy, mainly the Takagi-Sugeno-Kang (TSK) model.

Although generally assumed to be the realization of a fuzzy system through connectionist networks, this term is also used to describe some other configurations including:

- Deriving fuzzy rules from trained RBF networks.
- Fuzzy logic based tuning of neural network training parameters.
- Fuzzy logic criteria for increasing a network size.
- Realising fuzzy membership function through clustering algorithms in unsupervised learning in SOMs and neural networks.
- Representing fuzzification, fuzzy inference and defuzzification through multi-layers feed-forward connectionist networks.

Fuzzy classification is the task of partitioning a feature space into fuzzy classes. A fuzzy rule gives a meaningful expression of the qualitative aspects of human recognition. Based on the result of pattern matching between rule antecedents and input signals, a number of fuzzy rules are triggered in parallel with various values of firing strength.

The proposed neuro-fuzzy approach is better than neural network classifiers in the sense that prior knowledge about the training data set can be encoded into the parameters of the neuro-fuzzy classifier.

III RESULTS

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Computer simulations were carried out using MATLAB. Experimental results are conducted on ultrasonic B-mode images.

Comparative study of SRAD and Log-Gabor filter were conducted on the collected ultrasound liver images and calculated the MSE (Mean Square Error) and PSNR (Peak Signal-to-Noise Ratio) in dB.

Table 1 Comparative study of SRAD and Log-Gabor filter performance for normal liver image and abnormal liver images

Filters	**Normal Images**		**Abnormal Images**	
	MSE	**PSNR**	**MSE**	**PSNR**
SRAD	0.00015507 to 0.00023352	84.4475 dB to 86.225 dB	0.00010423 to 0.00026654	83.8731 dB to 87.9506 dB
Log-Gabor	0.348899 to 0.713970	49.594 dB to 52.7038 dB	0.416771 to 0.898337	48.5964 dB to 51.9318 dB

The performance of SRAD and Log-Gabor filters shows that Log-Gabor filter is best suited to remove speckle noise and enhances the contrast. SRAD filter has high PSNR values and it takes more CPU time. PSNR value should be in range of 30 dB -60 dB, values indicate the quality of the image The Log-Gabor filter gives good images quality and PSNR values ranges from 45-55dB.

IV DISCUSSION

We propose neuro-fuzzy classifier to find whether a liver image is in normal or abnormal condition.

A comparative study of SRAD denoising and Log-Gabor filter were done. The performance of SRAD and Log-Gabor filters shows that Log-Gabor filter is best suited to remove speckle noise and enhances the contrast. SRAD filter has high PSNR value it ranges from 83-87dB and it takes more CPU time. PSNR value should be in range of 30 dB -60 dB, values indicate the quality of the image. The Log-Gabor filter gives good images quality and PSNR values ranges from 45-55dB.Finally for preprocessing Log-Gabor filter chosen, for good quality of image and the processing time is less than SRAD filter.

V CONCLUSION

We have presented a technique, which is able to process large number of ultrasound liver images. Calculated the PSNR and MSE values of SRAD and Log-Gabor filter. The PSNR value of Log-Gabor filter ranges from 45-55dB. Finally Log-Gabor filter used for preprocessing method, since the PSNR value ranges from 30-60dB indicates the quality of images. A novel approach for ultrasound liver images classification based on extracting features using GLCM and moment invariant feature extraction. Moment-invariants are invariant to translation, size and rotation. They are able to compute moments from a point shifted to a distance from the image centroid, and the image at any rotation, and the images at any size. The result of this project shows the classification of the liver images, means the liver is in normal condition or in abnormal condition.

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