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Research Paper

AUTOMATIC CLASSIFICATION OF ULTRASOUND LIVER DISEASES BASED ON NEURAL NETWORKS

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Ultrasound Medical imaging is one of the famous technique for diagnostic application. This technique has been used for the detecting abnormalities related with abdominal organs like liver, kidney, uterus etc. Automatic liver disease classification from ultrasonic scans have been for long, the challenge for researchers, and has been made possible today by the availability of the easy and cost effective computing ways. In this paper the possibilities of classification of the ultrasound liver images into normal, cyst, cirrhosis, fatty liver using various features are explored. This paper analyses the effect of different filters in improving the quality of the liver ultrasound images before proceeding to the different phases of Segmentation, feature extraction and classification using Active contour algorithm ,Gray Level Run Length Matrix features and neural networks classifier respectively.

Keywords: Filters, Image segmentation, Feature Extraction, GLRLM, Classification, Neural Networks

INTRODUCTION

The Ultrasound Medical imaging technique is generally used for scanning various organs and soft tissues.

The use of ultrasonography as an imaging technique has become widely spread because of its ability to visualize all the organs with clear effects. The basic idea of ultrasound imaging is to send a fine beam of ultrasonic waves through the human tissues and then receive the echo reflections from the internal body structures to form the image.It enables the person to select the right image plane to display anatomy accurately into the organs like liver, kidney, pancreas etc [1].The main advantages of the ultrasound medical imaging is that it is cost effective and has exact characteristics[2]. Non-invasive diagnostic methods for liver diseases include Ultrasound, Computerized Tomography (CT) and Magnetic Resonance Imaging (MRI) [3]. Ultrasound liver texture can be used to classify a liver as normal, fatty, cyst, Haemangioma, metastases [4]. Liver diseases can be diagnosed by ultrasound by observing the characteristics of the liver .

Ultrasound image analysis finds its most usefulness in classifyingdifferent liver diseases as discussed.Casting the probability density

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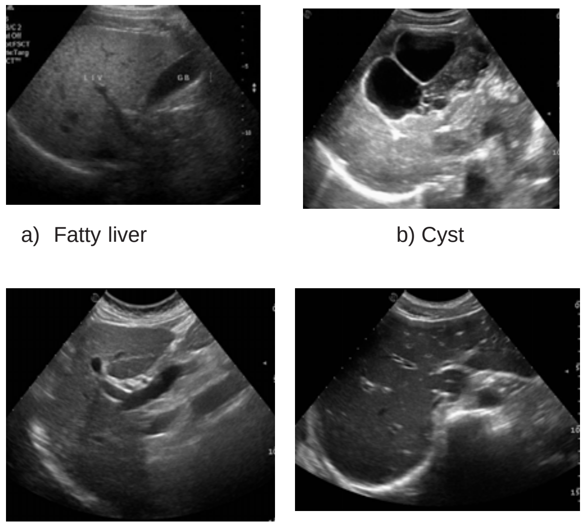
function (PDE) approach and adaptive filtering approach by YongjianYu et.al,who developed a new model for speckle reduction called as speckle reducing anisotropic diffusion (SRAD) method. SRAD filter is shown to generate images with better quality and excels over the traditional despeckle filters and the conventional anisotropic diffusion method in terms of speckle reduction, edge preservation and image clarity. Various combinations of noise removal, segmentation, features and classification techniques give varied results and these have been analyzed by different researches to find the best method. As a subset of this vast problem, the application of various filters in [9,10].Texture analysis methods are classified as statistical ,structural and spectral methods [11].Best statistical and spectral methods of feature extraction are ; the second order inter pixel relationship matrix known as grey level co-occurance matrix (GLCM),the grey level run length matrices (GLRLM) [13,14].

A characterization is performed between normal liver, bright liver, cirrhosis and carcinoma based on Region of Interest selected using gray level statistics. A series of feature extraction techniques and classification techniques are proposed in the literature [5].In 1992 developed a classification used an artificial neural network to method which diagnose diffuse liver diseases [15,16]. In 2002, Dokur et al. [17] proposed quantizer neural network for segmentation of ultrasound images. The quantizer neural network is an incremental neural network, which is trained by genetic algorithm. The quantizer neural network can be applied to any classification / recognition problem by modifying only the training set.At almost the same time Kadah et al. [18] proposed a new method for classifying diffuse liver diseases by means of an artificial neural network [19]. In our previous study [20], our system classified only the degree of progress of cirrhosis.

Moreover the exact classification can be done through various methods and also different filters can be used to classify. This technique proves one of the most effective way of distinguishing between the liver diseases as these diseases are being spread most frequently among many people in recent times.

Figure 1: Ultrasound Liver Images Used For Analysis



a) Fatty liver b) Cyst

c) Cirrhosis d) Hepatitis

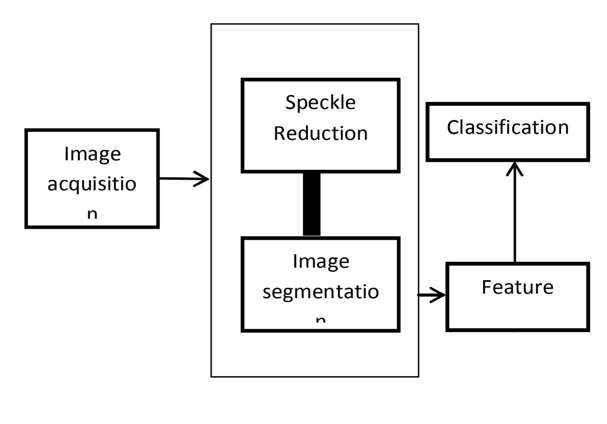
MATERIALS AND METHODS

A. System Outline

In this study, the liver disease images are got from the Sonoscan center in coimbatore and KMCH hospital on various patients taken from ultrasound machine.The overall system architecture is divided into 5 phases as depicted in Fig 2 .The first phase consists of image acquisition. This phase involves acquiring images from various sources. The acquired images are de-speckled and segmented using active contour method.

From the segmented image, the GLRLM features are extracted and presented to the neural networks for classification.

Figure 2: System architecture



B. Filtering Techniques

The medical imaging devices namely X-ray and Ultrasound produces images which are subsequently used by doctors for diagnosis. Every imaging system suffers from a common problem known as "Noise". Unwanted data which reduces the contrast and spoils the shape or size of objects thereby causing blurring of edges or dilution of fine details in the image is termed as noise. Noise corrupts the image and often leads to incorrect diagnosis. Each of the medical imaging devices are affected by different types of noise. This noise can be removed by using various filters.

Medical ultrasound imaging [20] has been used for effective diagnostics of diseases due to its non-invasive and accurate characteristics. The quality of ultrasound scan image is generally limited by the noise called speckle.. Especially, speckle noise occurs in the images of soft organs such as liver and kidney whose underlying structures are too small to be resolved by the large ultrasound wavelength.The speckle noise model [21] may be approximated as multiplicative and is given by equation (1).

$$f_{i,j} = g_{i,j}u_{i,j} + \alpha_{i,j} \qquad ...(1)$$

where $f_{i,j}$ is the noisy pixel $g_{i,j}$ represent the noise free pixel, $u_{i,j}$ and $a_{i,j}$ represent the multiplicative and additive noise respectively and *i*, *j* are indices of the spatial locations.

The speckle-reducing anisotropic diffusion is the replacement of the gradient-based edge detector $c_d(|\nabla g|)$ in an original anisotropic diffusion PDE with the instantaneous coefficient of variation that is suitable for speckle filtering $c_{srad}(|\nabla g|)$ from equation (2). A general function for the output image by extending the PDE of the de-speckle filter is

$$f_{i,j} = g_{i,j} + \frac{1}{\eta} div\,(c_{srad}(|\nabla|)\nabla g_{i,j}) \qquad ...(2)$$

The diffusion coefficient for the speckle anisotropic diffusion $c_{srad}(|\nabla g|)$ is given as equation (3).

$$C^2_{srad}(|\nabla g|) = \frac{\frac{1}{2}|\nabla g_{i,j}|^2 \frac{1}{16}(\nabla^2 g_{i,j})^2}{(g_{i,j}+\frac{1}{4}\nabla^2 g_{i,j})^2} \qquad ...(3)$$

Presently, most of the research work in this area aims at developing wavelet thresholding and threshold selection [22] (Hard threshold or Soft threshold) techniques for effective despeckling of ultrasound images, since wavelet provides suitable basis functions for separating noisy signal from image signal. There are two thresholding functions frequently used i.e. soft and hard threshold function proposed by Donoho [23], has been many works on finding suitable thresholds. Soft thresholding rule is chosen as suitable method over hard thresholding, since it is found to yield more visually pleasant images over hard thresholding. Many wavelet based thresholding techniques like Visu Shrink, Bayes Shrink and Sure Shrink [22] have proved better efficiency in image denoising.

C. Image Segmentation

Segmentation is a tool that has been widely used in many applications involving image processing and several techniques have been developed for this purpose. One such application is in medical image analysis for clinical diagnosis. The main goal of segmentation, which plays essential role in both qualitative and quantitative image analysis, is to divide an image into sets of regions that are visually distinct and uniform with respect to some property, such as grey level, texture or colour. One very efficient technique for image segmentation that is being used for high quality segmentation in many complex images is the active contour algorithm. Segmentation using active contours model (Snakes) was introduced by Kass et al[8]. The idea behind active contours, or deformable models, for image segmentation is quite simple. The user specifies an initial guess for the contour, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image.

Active contour model, also called snakes, is a framework for delineating an object outline from a possibly noisy 2D image. This framework attempts to minimize an energy associated to the current contour as a sum of an internal and external energy:

- The external energy is supposed to be minimal when the snake is at the object boundary position. The most straightforward approach consists in giving low values when the regularized gradient around the contour position reaches its peak value.
- The internal energy is supposed to be minimal when the snake has a shape which is supposed to be relevant considering the shape of the sought object. The most straightforward approach grants high energy to elongated contours (elastic force) and to bended/high curvature contours (rigid force), considering the shape should be as regular and smooth as possible.

D. Feature Extraction

Feature extraction is an integral part of the classification problem. Feature extraction techniques are mainly used for describing the characters of particular regions of the image. The aim here is to collect the measurements of characters from the various portions of the image and use it for recognition or classification of the image. This work primarily makes use of texture features for the task of classification as textures are prominent features in ultrasound images. Generally, the texture of an image [11] can be analyzed using two approaches:

- Structured Approach
- Statistical Approach

Structured approach is not generally suitable for ultrasound image processing because ultrasound images are rich in texture and textural processing works well with disease classification. Moreover structured approach is used only when there are objects to be identified in the image. Hence Statistical approach is used in this project as it is more simple and precise for the task of texture based classification. The statistical approach can be done in a number of ways. The current work makes use of GLRLM (Gray Level Run Length Matrix) method.

The proposed system presents a new approach of extracting local relative texture feature from ultrasound medical images using the Gray Level Run Length Matrix (GLRLM) based global feature. To adapt the traditional global approach of GLRLM-based feature extraction method. Local relative features are then calculated as the absolute difference of the global features of each segmented image. Performance of the proposed local relative feature extraction method has been verified by applying it in classifying ultrasound medical images of liver diseases. Besides, significant improvement has been noticed by comparing the proposed method with traditional GLRLM-based feature extraction method in terms of image classification performance. Feature extraction is a significant part of the classification problem. A new approach of extracting local relative texture features using the Gray Level Run Length Matrix is explained. The Gray Level Run Length Matrix (GLRLM) method [24] is a way of extracting statistical texture features. Galloway [25] introduced five statistical texture features to be extracted from the Gray Level Run Length matrices. These are: Short Runs Emphasis *(SRE)*, Long Runs Emphasis *(LRE),* Gray Level Non-uniformity *(GLN),* Run Length Non-uniformity *(RLN),* and Run Percentage *(RP)*:

$$SRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j\,|\,\theta)}{j^2} \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(4)$$

SRE: By dividing each run length value by the square of its length, short run lengths are emphasized. The denominator is the total number of runs in the image.

$$LRE = \sum_{i=1}^{G}\sum_{j=1}^{R} j^2\, p(i,j\,|\,\theta) \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(5)$$

LRE: Here we multiply each run length value by the square of its length, in order to give higher weight to the long runs

$$GLN = \sum_{i=1}^{G}\left(\sum_{j=1}^{R}p(i,j\,|\,\theta)\right)^2 \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(6)$$

GLN: High run length values will contribute most to this feature. The GLN feature will have its lowest value if the runs are evenly distributed over all grey levels.

$$RLN = \sum_{i=1}^{R}\left(\sum_{j=1}^{G}p(i,j\,|\,\theta)\right)^2 \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(7)$$

RLN: The RLN feature will have its lowest value if the runs are evenly distributed over all run lengths.

$$RP = \frac{1}{N}\sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(8)$$

RP: this is the ratio between the total number of observed runs in the image and the total number of possible runs if all runs had a length of one.

Two additional features were also introduced in [25]. They are Low Gray Level Runs Emphasis *(LGRE)* and High Gray Level Runs emphasis *(HGRE)*.

$$LGRE = \sum_{i=1}^{G}\sum_{j=1}^{R}\frac{p(i,j\,|\,\theta)}{i^2} \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R}p(i,j\,|\,\theta) \quad ...(9)$$

$$HGRE = \sum_{i=1}^{G}\sum_{j=1}^{R} i^2 p(i, j \mid \theta) \Bigg/ \sum_{i=1}^{G}\sum_{j=1}^{R} p(i, j \mid \theta) \qquad ...(10)$$

LGRE and HGRE: These features make use of the grey level of the runs and are introduced in order to distinguish textures that are similar according to their SRE and LRE features, but differ in grey level distribution of the runs.

Another 4 features were described in [25]. These are Short Run Low Gray Level Emphasis *(SRLGE)*, Short Run High Gray Level Emphasis *(SRHGE)*, Long Run Low Gray Level Emphasis *(LRLGE),* and Long Run High Gray level Emphasis *(HRHGE).*

Classification

Classification and *segmentation* have closely related objectives, as the former is another form of component labeling that can result in segmentation of various features. Image classification analyzes the numerical properties of various image features and organizes data into categories. Classification algorithms typically employ two phases of processing: *training* and *testing*. In the initial training phase, characteristic properties of typical image features are isolated and, based on these, a unique description of each classification category, *i.e. training class is created. In the subsequent testing phase, these feature space partition are used to classify image features*.. Sensitivity, the conditional probability of detecting a disease while there is a liver disease. Specificity, conditional probability of detecting as a normal liver while the liver is indeed a normal. In this proposed system, the classification of image is done using Artificial neural networks have proven themselves as proficient classifiers and are particularly well suited for classification. The performance of the classifier is evaluated by calculating accuracy, selectivity and specificity from the obtained confusion matrix. An ROC curve is also plotted, which is a plot of the true positive rate (Sensitivity) versus the false positive rate (1 - Specificity) as the threshold is varied. Here, Sensitivity=True Positive/Total Positive, Specificity =True Negative/Total Negatives and Accuracy = (True Positive + True Negatives)/Total Samples.

RESULTS AND DISCUSSION

The performance of the proposed system is evaluated with various test images. The work concentrates on commonly occurring liver diseases such as cyst, cirrhosis, fatty liver, haemangioma, metastases, hepatitis.

A. Noise Removal

The Results of speckle reduction are analysed using statistical measures such as Noise Mean Variance (NVM), Noise Standard Deviation, and Equivalent Number of Looks. This determines the quantity of the speckle in the image. If the quantity of speckle is less the Noise Standard Deviation (NSD) will be less. The formula for NSD is

$$NSD = \sqrt{\frac{\sum_{i=1}^{R}\sum_{j=1}^{C}(I_d(i, j) - NMV)^2}{R * C}} \qquad ...(15)$$

$$NMV = \frac{\sum_{i=1}^{R}\sum_{j=1}^{C} I_d(i, j)}{R * C} \qquad ...(16)$$

where I_d is the Despeckled image and R, C is the size of the image. To estimate the speckle noise level another assessment parameter known as ENL over a uniform region is used. A larger value of Equivalent Number of Looks (ENL) shows a better quantitative performance. The formula used to calculate ENL is

$$ENL = \frac{NMV^2}{NSD^2} \quad \text{...(17)}$$

SRAD filter suppresses speckle in terms of lower NSD values and slightly higher ENL values.

B. Active Contour Segmentation

By using Active contour algorithms, liver diseases were analyzed. The analysis was made by giving de-speckled images as input for segmentation. 400 iterations were made on analysis image and the results of contour segmentation were simulated.

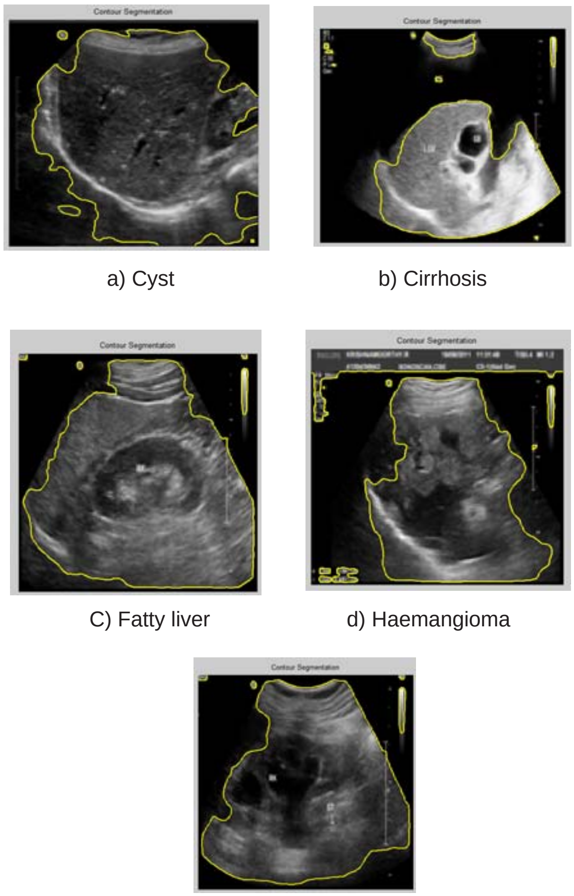
C. Extracted Features

The features [24, 25] are extracted from each segmented images which is obtained for every image in the dataset. With these features, the classifier was trained for all the images on the training set in each disease category namely, Cirrhosis, Cyst, Hepatitis, Fatty and HCC.

D. Neural Network Classification

We selected an ROI for each image shown in Fig.3. Then the system classified the image into different categories Cirrhosis, Cyst, Hepatitis, Fatty, HCC metastases and unknown. The term ‘unknown’ means that the output of the neural network belongs to none of above category

Figure 3: Segmented Images of Various Liver Diseases



a) Cyst

b) Cirrhosis

C) Fatty liver

d) Haemangioma

d) Metastases

Table 1: Extracted features for each disease

Features	Cirrhosis	Fatty	Metastases	Cyst	Haemangioma
SRE	0.5120	0.5129	0.6431	0.5277	0.5533
LRE	35.36	58.0983	63.51	72.065	48.92
RLN	1241	1091	1998	1317	1434
GLN	601.19	448.32	444.36	443.94	49.2
LGRE	0.09	0.1656	0.1198	0.09	0.1693
HGRE	38.4651	33.44	53.0316	52.01	36.1446
RP	0.29	0.2620	0.3113	0.291	0.3001

Table 2 Experimental Results For Possible outcome

Type	*tp*	*tn*	*fp*	*fn*
Cirrhosis	20	42	0	1
Cyst	18	45	0	0
HCC	17	40	0	0
Hepatitis	16	43	2	0
Fatty	20	44	1	1
metastases	18	42	2	2

Figure 4: Graph showing the possible outcomes of liver diseases

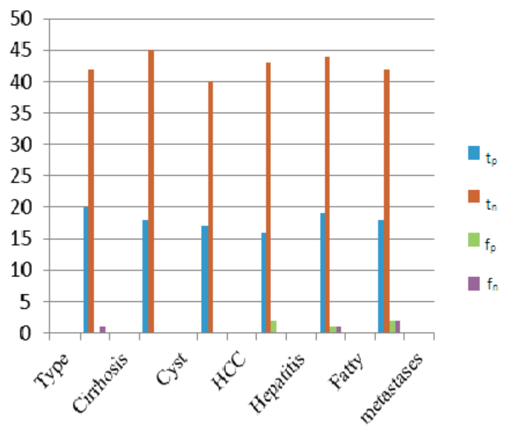


Table 3: Overall accuracy of the classifier

Disease	Total test images	Correctly classified	sensitivity	Specificity	Accuracy%	Overall accuracy
Cirrhosis	30	29	0.95	1	96.6	
Cyst	26	26	1	1	100	
HCC	22	21	1	1	96.6	98.3
Hepatitis	15	14	1	0.95	96.6	
Fatty	35	35	0.95	0.97	100	
Metastases	22	20	0.9	0.95	100	

classes. The neural network classifier then classifies the image according to the extracted features of the test image and comparing it with the already trained image features. In the test we evaluated the significance of the input parameters: that is, we changed the number input parameters and the choice of the parameter shown in Table 1. The parameter sets used are shown in each

Figure 5: Performance Analysis Graph

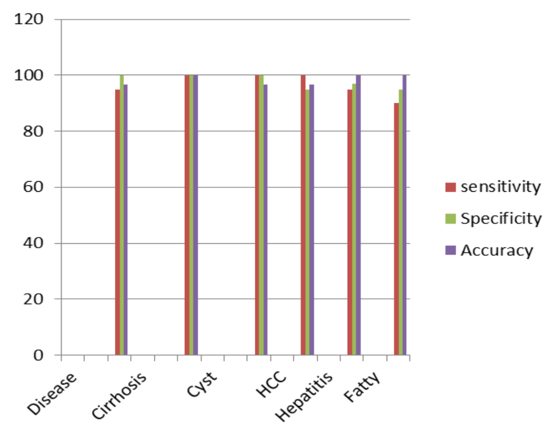


table. In these tables the relation between the correct pathology and the diagnosis by the neural network are shown in Table 2.

CONCLUSION

A new method is developed for the classification of ultrasound images using neural network for the diagnosis of liver diseases which provide accurate classification compared to other classification techniques. This method could establish a more objective diagnostic means to improve the clinical diagnostic accuracy, efficiency and repeatability, analyse liver disease quantitatively, and thus reduces misdiagnosis caused by the subjective judgment difference. As seen above the overall accuracy was found to be 98.3% approximately using neural network classifier.

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