# Abdominal Liver Cyst Segmentation of CT Images Using Neural Network Classification

Vijaya Tharani A
*Department of Electrical and Electronics Engineering*
*Anna University Regional Campus, Tirunelveli, Tamilnadu, India*

Vinolia Anandan
*Department of Computer Applications*
*Anna University Regional Campus, Tirunelveli, Tamilnadu, India*

**Abstract - Computing techniques are useful for medical diagnosis because they provide additional information that cannot be obtained by clinical presentations and radiologic imaging. This work reports the quality analysis of Computed Tomography (CT) images. CT is highly accurate for diagnosing liver diseases. Often liver diseases are identified using gray scale images. This project, segments the gray scale liver CT image to extract the liver cyst region based on anatomic knowledge of the liver, Adaptive Threshold Decision (ATD), histogram analysis and morphological operations. The statistical texture features are extracted from the liver region using wavelet. The extracted features are optimized by the Sequential Forward Floating Search (SFFS) and Genetic Algorithm (GA). Finally, the optimized features are given as the input to the neural network classifier to classify the disease as liver cyst.**

**Keywords – PNN, LVQ, BPNN, Biorthogonal wavelet transform, Medical diagnosis.**

## I. INTRODUCTION

**L**iver diseases are considered acutely as it plays vital role to the life of the human. The liver is one of the leading organs in the body, placed in the upper right portion of the abdomen [3]. The liver has many important functions, include clearing toxins from the blood, produce blood proteins and bile which assists digestion. However, there are many unlike problems that can occur in the liver and some can cause enduring damage. These conditions include virus infections, reactions due to alcohol, cyst, hereditary conditions. Visual interpretations of medical images are used for the early detection and diagnosis of diseases. The evaluation is based on visual interpretations which depends on the ability of the physicians to discriminate certain patterns or shape of the image. As a result, Computer Aided Diagnosis (CAD) [24] has become one of the most important investigative subjects in medical imaging. This work focuses on the development of Probabilistic Neural Network (PNN) [8], Learning Vector Quantization (LVQ) [13] Neural Network, Back Propagation Neural Network (BPNN) [17] for classification of liver cyst from CT abdominal images[15]. Neural networks are preferred for recognizing diseases from the features extracted from the liver image. Preprocessing of liver images, segmentation, feature extraction and feature selection are made using image processing techniques. **A** cyst is a closed, saclike structure that contains liquified, gas, or semisolid material and is not a normal part of the tissue where it is located. Cysts are familiar and can occur anywhere in the body of people of any age. Cysts vary in size; they may be visible only under a microscope or they can grow so large that they displace normal organs and tissues [32]. The outer wall of a cyst is called the shell. Liver cyst, also known as a hepatic cyst, a simple liver cyst is a thin-walled bubble, a fluid-filled in the liver typically produces signs.

## II. PROPOSED ALGORITHM

The data used in this work were collected from the CT image database of http://ctisus.com/teaching files.

### A. *Liver extraction from CT abdominal image –*

CT abdominal image contains the descriptions of the liver and other organs like spleen and stomach. Normally, the liver region is positioned in the upper left side of the abdomen and takes up the largest area among the various organs integrated in the image and the liver image maintains a stable intensity throughout. But a fixed threshold is not possible to extract liver region because, the intensity differs according to the patient, slice and the CT machine. Therefore, adaptive threshold is chosen for each slice based on histogram analysis. Then, the histogram is drawn and analyzed. The intensities demonstrating background (dark) and bone values (brightest) are removed by making pixel counts to zero. Generally, liver lies in between 100 and 225 intensities range. Since liver area is large compared to other adjoining organs and has constant intensity throughout, the maximum pitch corresponds to the liver area. Hence, an intensity range with maximum count pixels plus certain margin to accommodate any variance in the liver region pixels is adaptively obtained for every slice. This range represents the liver region pixels. The pixels in the adaptive threshold range are extracted. The output looks similar to spotted sand. It is converted to an object with real area by morphological closing and opening operations [11]. The liver is extracted alongside with the fragments of other organs located near to it and with intensity same as that of liver. Since these fragments can affect accurate diagnosis, they can be removed based on area. The area of the liver is large when compared with the fragments of other organs. After removing the fragments, the liver area obtained is complemented and multiplied by the original image to get the segmented liver in the CT abdominal image.

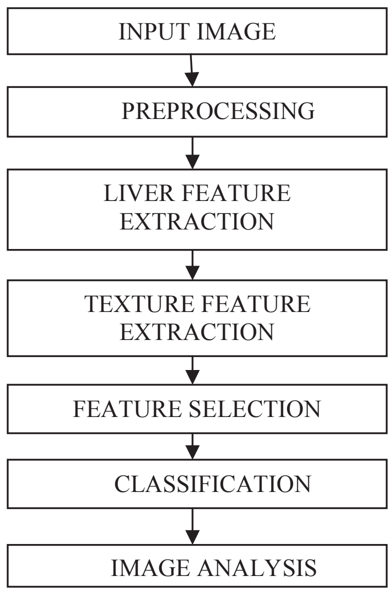

Figure 1. workflow diagram

*B. Biorthogonal wavelet based statistical texture feature extraction-*

From the smallest level of pixel representations, one can gather useful information through a process called feature extraction. Texture is one of the most used characteristics in medical image interpretation, and is applicable to a wide variety of image processing problems. The co-occurrence matrix or Spatial Gray Level Dependence Method(SGLDM) is defined for an image with a countable number of gray levels. SGLDM is used to extract the texture features of the liver cyst region and first order and second order features could be used for further analysis. The first order features are mean, energy, entropy, skewness and variance. The second order features are angular second moment, inertia, correlation, inverse difference and maximum probability.

The feature values are normalized by subtracting lowest value and dividing by maximum value minus minimum value. Maximum and minimum values are calculated based on the training dataset. In the test data set, if the feature value is less than minimum value, it is set to lowest value. If the feature value is greater than maximum value, it is set to maximum value. After that values are normalized and are optimized by feature selection algorithm.

*C. Feature selection*

The feature selection difficulty involves the selection of a subset of 'd' features from a total of 'D' features, based on a given optimization condition. The D features are denoted uniquely by distinct numbers from 1 to D, so with the intention of the whole set of D features may be written as,

$$S = \{1, 2, . D\}. \qquad (1)$$

X denotes the subset of selected features and Y denotes the set of residual features. So, S = X U Y at any time. J(X) denotes a function evaluating the performance of 'X'. 'J' depends on the particular application. Here J(X) denotes the classification performance of liver region as liver cyst using the position of features in 'X'. In this work, Sequential Forward Floating Search(SFFS) and Genetic Algorithm (GA) techniques are used.

*C.1 Sequential Forward Floating Search (SFFS)-*

1. $X=\phi$ ;
2. $Y=\{i \mid 1 \le i \le D\}$;
3. K=0 ; // *Initialization*
4. While (K<d) {

Find the most significant feature 'y' in 'Y' and add to 'X'
Find the least significant feature 'x' in 'X'
While $(J(X_k - \{x\}) > J(X_{K-1}))$
{
$X_{k-1} = X_k - \{X\}$;
K-1;
Find the least significant feature X.
}
}

The most and least significant feature is selected based on the classification performance, J(X), of PNN classifier for identifying cyst liver.

*C.2. Genetic algorithm*

```
GA_select ()
{
Initialize population P;
Repeat{
        Select two parents p1 and p2 from P;
        Offspring = crossover (p1,p2);
        Mutation (offspring);
        Restore (P, offspring);
                  }
until (stopping condition);
}
```

A binary digit represents a feature, values where 1 and 0 denotes selected and removed, respectively. The initial population is generated by random function.

Initial population:
for (i = 1 to |P|)
for(each gene 'g' in ith chromosome)

if (random () < d/D) g = 1; else g = 0;

A chromosome represents a selected feature subset, ‘X’, and the estimation function is clear. In order to force a feature subset to satisfy the given subset size necessity, the size value, d, is taken as a constraint and a penalty is imposed on chromosomes breaking this limitation. The fitness of a chromosome ‘C’ is defined as,

$$fitness(C)=J(Xc)-penalty(Xc) \quad (2)$$

where ‘Xc’ is the corresponding feature subset of C, and penalty(Xc) = w × (|Xc| − d) with a penalty coefficient ‘w’. The chromosome selection for the next generation is done on the centre of fitness. The selection mechanism should ensure that fitter chromosomes have a higher probability survival. If the mutated chromosome is superior to both parents, it replaces the similar parent. ‘I’ fits in between the two parents, it replaces the inferior parent. Otherwise, the most inferior chromosome in the population is replaced. The selected feature set based on the test dataset is used to train the PNN classifier for classifying the liver diseases to select the optimum feature set.

*D. Neural network classifiers-*

In this work, three classifiers namely PNN, LVQ and BPNN. These three classifications has high accuracy. The first one PNN is predominantly a classifier, map any input pattern to a number of classifications and can be forced into a more general function approximator. Then, the second one is LVQ is a neural net that combines competitive learning with supervision. It can be used for pattern classification and finally, the BPNN is a multilayer feed forward network trained according to error back propagation algorithm and is one of the most widely applied neural network models are considered for classification of the diseases [8,13,17].

*E. Classification performance evaluation-*

If both diagnosis and test are positive, it is called True Positive (TP). The probability of a TP to occur is estimated by counting the true positives in the sample and dividing it by the sample size. If the diagnosis is positive and the test is negative it is called a False Negative (FN). False Positive (FP) and True Negative(TN) are defined similarly. Accuracy is given by Eq. (2).

$$Accuracy=TP+TN/(TP+TN+FN+FP) \quad (2)$$

The values described are used to calculate different measurements of the quality of the test. The first one is sensitivity, SE, which is the probability of having a positive test among the patients who have a positive diagnosis.

$$SE=TP/TP+FN \quad (3)$$

Specificity, SP, is the probability of having a negative test among the patient who has a negative diagnosis.

$$SP=TN/FP+TN \quad (4)$$

Two other measurements that can be used are the Positive Predicting Value (PPV) and Negative Predicting Value (NPV).

$$PPV=TP/TP+FP \quad (5)$$

$$NPV=TN/TN+FN \quad (6)$$

## III. EXPERIMENT AND RESULTS

**T**he data used in this work were collected from medical image database of http://www.ctisus.com/teaching files. This image is in Digital Imaging Communications in Medicine (DICOM) format and it is converted to binary image i.e bitmap file.

The liver area extraction was carried out successfully based on the above method. For most of the slices, the liver area was completely extracted, although there were some erroneous cases where other organs adjacent to the liver were also extracted. This is because of adding certain intensities to the middle intensity of the liver region while fixing adaptive threshold. However, most of the cases did not influence much on the recognition because entire liver volume affected by diffused liver diseases is contributing for recognition. The segmentation method is simple and accurate in extracting the liver boundary in most of the slices because of the morphological operations, preserving the shape of the liver. Hence the liver boundary is correctly captured. Adaptive threshold decision solves the problem of varying intensity for patient and CT machine parameters. Also, it is easy to implement compared to the methods discussed by other researchers. The results are compared with the existing results. Most of the images are noise free. If the image contains noise because of the protocol settings, then preprocessing is done to remove noise by applying gaussian filtering technique.

Feature selection algorithms SFFS and GA are used to optimize the feature set. Based on the experiments conducted with the available data, SFFS is taking less time and perform the same sequence of operations and always produce the same results. On the other hand, GA executes a different sequence of operations from one to another, and produces a different solution on each occasion. If more CPU time is allowed, GA can produce better solutions. A simple way of giving more time to a GA is to increase the generation number or the population size. Since these algorithms repeatedly add and remove features, it is possible that the same subsets are reevaluated. By book keeping the already evaluated subsets and their performance data, we can avoid duplicate computations and speedup the algorithms. Since the classification accuracy of 95% is obtained with the features Contrast, Entropy, Angular Second Moment and Homogeneity extracted from images and are giving optimal performance in this application domain, the cost of classifier is reduced. Also, the biorthogonal wavelet transform for the depth n = 2 is applied and features are analyzed. There is no improvement in the classification performance other than increase in computations.

To justify the choice of wavelet domain, for the same dataset, without applying biorthogonal wavelet transform, in the gray level domain, the four features are extracted and the performance of the neural networks. it is clear that PNN neural network outperforms LVQ and BPN in accuracy i.e. recognition rate. Also performance of classifiers in wavelet domain is better than in gray level domain. Hence PNN is chosen as a good classifier in this application domain for classifying liver cyst.

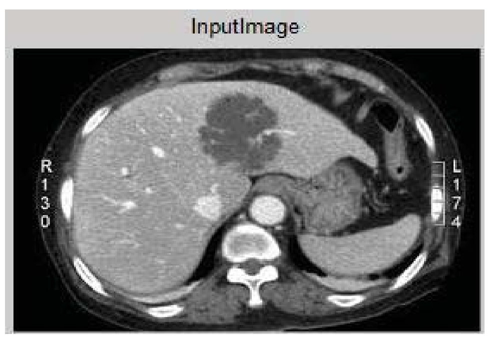


Figure 2. CT abdominal image (cyst)

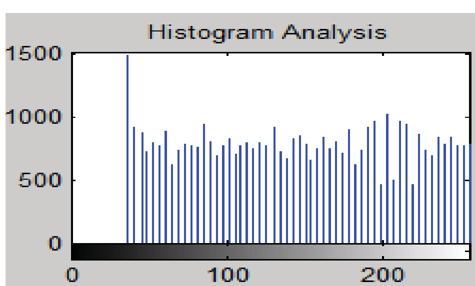


Figure 3. histogram for the filtered image

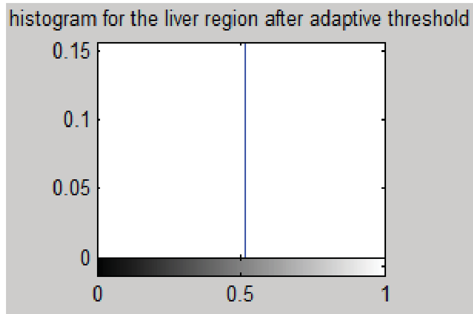


Figure 4. histogram for the liver region after adaptive threshold decision

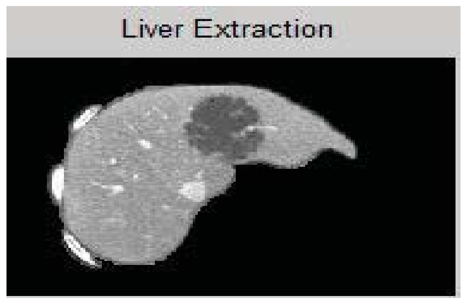


Figure 5. segmented liver

## IV.CONCLUSION AND FUTURE WORK

The segmentation method is simple and accurate in liver cyst image from CT abdominal images because of the morphological operations preserving the shape of the liver. Adaptive threshold solves the problem of varying intensity for patient and CT machine parameters. Experimental results show that the PNN is a good classifier, giving an accuracy of 98% for classifying liver cyst using wavelet based on statistical texture features. The sensitivity is 97% and specificity is 94%. Hence it is concluded that the neural network supported by conventional image processing operations can be effectively used for liver disease diagnosis.

The proposed system can be extended for other types of liver diseases like ascites, liver cancer, and steotosis and also for other types of medical images like Dual CT and MRI.

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