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Segmentation of Liver from Abdomen CT Images Using Classification and Regression Tree

T.R. Nisha Dayana[1], A. Lenin Fred[2*]

[1]Dept. of CSE, Bharathiar University, Coimbatore, India
[2]Dept. of CSE, Mar Ephraem College of Engineering and Technology, Marthandam, India

Corresponding Author: leninfredip@gmail.com,

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Abstract— Segmentation role is inevitable in image processing for the extraction of the desired region of interest. This work proposes decision tree for the segmentation of liver from abdomen CT images. Prior to feature extraction and segmentation, feature extraction was performed by the median filter. The hybrid feature extraction comprising of GLCM and LBP is used and training phase comprises of 20 DICOM CT abdomen images. The morphological operations are performed in the post processing phase for the refinement of output. The algorithms are developed in Matlab 2010a and tested on real time abdomen CT images.

Keywords—Decision tree; Segmentation; Classification, regression tree,

I. INTRODUCTION

Image segmentation is an important process to extract information from complex medical images. Segmentation has wide application in the medical field [1]. The main objective of image segmentation is to partition an image into mutually exclusive and exhausted regions such that each region of interest is spatially contiguous and the pixels within the region are homogeneity with respect to a predefined criterion [2]. Widely used homogeneity criteria include values of intensity, texture, color, range, surface normal and surface curvatures. Several diagnostics are based on proper segmentation of the digitized image [3].

Segmentation of medical images is needed for applications involving estimation of the boundary of an object, classification of tissue abnormalities, shape analysis, contour detection. Image segmentation is basically dividing the image into different regions. That is, separating objects from the background and labelling them (give them individual id numbers) so that information about them can be extracted [4].

Jyoti Deshmukh and Udhav Bhosle proposed an association rule based algorithm for the analysis of mammogram images. The filtering of input image was performed by the median filter and preprocessing stage also apply morphological operation for the elimination of artifacts. The enhancement stage comprises of contrast stretching algorithm and for the extraction of ROI, region growing and thresholding is used. The texture features are extracted from ROI and association rules are framed for the tumor classification [5].

A. Anguera et al used data mining algorithms for the analysis of stabilometric and electroence phalographic series data. A novel data mining algorithm termed as knowledge discovery in databases (KDD) was proposed for the medical data analysis. For EEG database, the accuracy of classification was 99.86 % and 98.11% for two class epilepsy detection. For stabilometry series data classification accuracy of 99.4% and 99% for sports application [6].R. Bharat Rao et al performed a detailed study on the mining of medical images. The health disorders, different types of medical imaging modalities and challenges of data mining are also highlighted in this work [7].

Amjad khan and zahid Ansari conducted a detailed study on the soft computing techniques in medical image mining applications. The widely used soft computing algorithms are fuzzy sets, rough sets, neural network and genetic algorithms [8]. Data mining Techniques gains importance in the analysis of mammogram images for breast tumor classification. The preprocessing stage comprises cropping and histogram equalisation, feature extraction was performed by first order and second order statistics like mean, variance, skewness, and kurtosis. The association based classification algorithm generates better results than back propagation neural network [9].

The segmentation algorithms play a vital role in medical image mining, two algorithms are proposed for the extraction of the corpus callosum in MR brain images [10] [11]. The thresholding algorithm was used for the removal of artifacts and for the extraction of region of interest, Spectral segmentation and graph based approach was used. The algorithm was used on a database comprising of 76 MR brain images representing musicians and non-musicians [12]. In [13], a survey has been performed on image mining, its techniques, and applications, the merits and issues in image mining techniques have also been analysed.

In [14], three data mining algorithms logistics regression, artificial neural network, and decision tree (c5.0) have been proposed for the prediction of diabetics based on the risk factors. In the dataset 735 subjects have diabetics and 752 subjects are normal. In the prediction models, 12 variables are used as inputs the validation was performed by accuracy, sensitivity, and specificity. The decision tree model was found to have the best classification accuracy followed by the logistics regression and the ANN. For clinical data analysis, predictive models like logistics regression, artificial neural network, decision tree, and nearest neighbour. The dataset comprises the physiological information of 3220 subjects. The neural network and logistic regression with kernel functions yield efficient results [15]. The neural network approach was found to be effective in the prediction of heart diseases based on 13 attributes. An accuracy of 94%, sensitivity of 92%, and specificity of 92.5% were achieved by the neural network [16].

II. METHODOLOGY

A. Materials and Methods

The abdomen CT images used in this work are obtained from Metro Scans and Research Laboratory, Trivandrum.

B. Classification and Regression Tree (CART)

The goal of segmentation is to extract the desired region of interest. Image segmentation is typically used to locate objects and boundaries (line curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

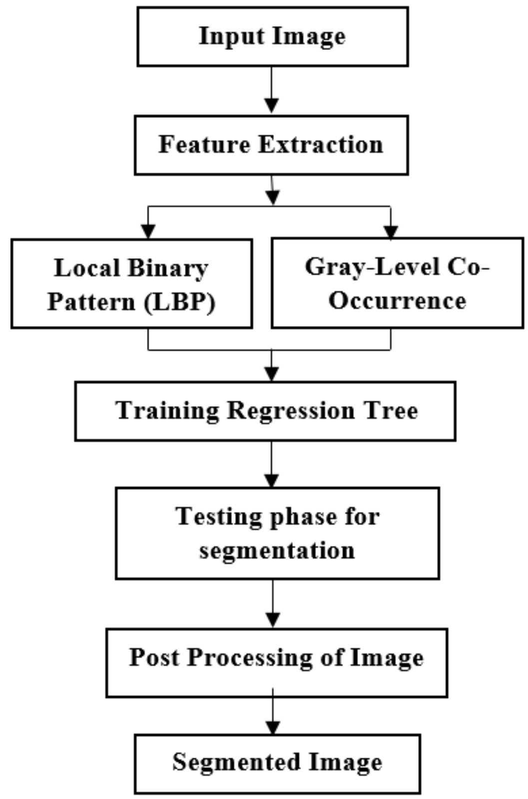

Figure 1: Flow chart of liver segmentation

CART is a classification method which uses historical data to construct so-called decision trees. Decision trees are then used to classify new data. Decision trees are represented by a set of nodes which splits the learning sample into smaller and smaller parts. CART algorithm will search for all possible variables and all possible values in order to find the best spilt – the question that splits the data into two parts with maximum homogeneity. The process is then repeated for each of the resulting data fragment.

CART can easily handle both numerical and categorical variables. Among other advantages of the CART method is its robustness to outliers. Usually, the splitting algorithm will isolate outliers in individual node or nodes. An important practical property of CART is that the structure of its classification or regression trees is invariant with respect to monotone transformations of independent variables. One can replace any variable with its logarithm or square root value, the structure of the tree will not change.

C. Feature Extraction

The feature selection process usually is designed to provide a means for choosing the features which are best for classification optimized against on various criteria. This research work proposes hybrid feature extraction comprising of Local binary pattern (LBP) and Gray-Level Co-Occurrence Matrix (GLCM).

D. Local Binary Pattern

Local Binary Pattern is a simple but very efficient texture operator which labels pixels of an image by thresholding neighbourhood of each pixel and considers the result as a binary number [17].

$$LBP(R,P) = \sum_{P=0}^{P-1} s\left(g_n - g_c\right)2^P \qquad (1)$$

Where P is the number of pixels in the neighbourhood, R is the radius of the neighbourhood, g_n is the gray value of the neighbours and g_c is the gray value of the centre pixels.

The neighbourhood is formed by 'P' set of pixels on a circle of radius 'R'.

$$s(x) = \begin{cases} 1 & if \quad x > 0 \\ 0 & otherwise \end{cases} \qquad (2)$$

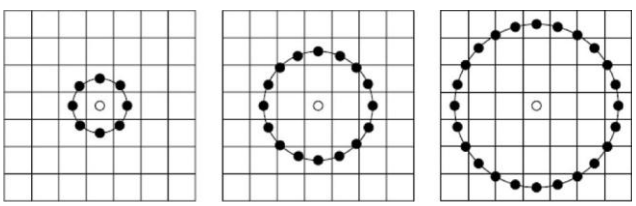

Figure 2. Determination of LBP for neighborhood connectivity R=1, 2, 3

The LBP is calculated for each pixel, which is labelled as '0' (gray value of neighbour is less than centre pixel gray value) and otherwise, it is assigned a value of '1'.

E. Gray-Level Co-Occurrence Matrix

A statistical method of examining texture that considers the spatial relationship of pixels is the Gray-Level Co-occurrence Matrix (GLCM), also known as the gray-level spatial dependence matrix [18]. The GLCM function characterizes the texture of an image by calculating how often pairs of the pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and the extracting statistical measures from this matrix.

$$Entropy = \sum_{mn}^{N-1} -\ln\left(I_{mn}\right)I_{mn} \qquad (3)$$

$$Energy = \sum_{mn}^{N-1} I_{mn}^2 \qquad (4)$$

$$Contrast = \sum_{mn}^{N-1} I_{mn}\left(m-n\right)^2 \qquad (5)$$

$$Homogenity = \sum_{mn}^{N-1} \frac{I_{mn}}{1+\left(m-n\right)^2} \qquad (6)$$

$$Correlation = \sum_{mn}^{N-1} I_{mn} \frac{\left(m-\mu\right)\left(n-\mu\right)}{\sigma^2} \qquad (7)$$

F. Operation of CART

Training of CART is done by giving integer values corresponding to features of an image that are extracted using LBP and GLCM. These integer values are compared with some threshold values. If the integer value is less than the threshold value it will come under the non-liver region and if it is greater than the threshold value it will come under the liver region. After the training phase is over CART can easily segment any query input images.

CART methodology consists of three parts:

- Construction of maximum tree
- Choice of the right tree size
- Segmentation of image using constructed tree

G. Construction of maximum tree

Building the maximum tree implies splitting the learning sample up to last observations, i.e. when terminal nodes contain observations only of one class

Let t_p be a parent node and $t_{1,}$ t_r -respectively left and right child nodes of parent nodet_p. Consider the learning sample with variable matix X with M number of variables x_j and observations. Let class vector Y consist of N observations with the total amount of K classes.

Where,

$t_p, t_{1,}$ t_r - Parent, left and right nodes

x_j - Variable j (Feature value)

x_j^R - best splitting value of the variable

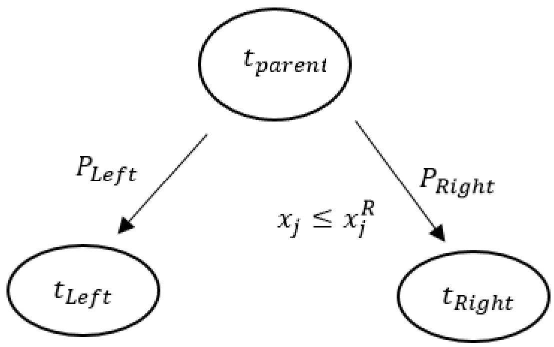

Figure 3: Construction of decision tree

Maximum homogeneity of child nodes is defined by so-called impurity function *i(t).* Since the impurity of the parent node t_p is constant for any of the possible splits $x_j \leq x_j^R$, $j = 1 \ldots \ldots M$, the maximum homogeneity of left and right child nodes will be equivalent to the maximization of change of impurity function$\Delta i(t)$.

$$\Delta i(t) = i\left(t_p\right) - E\left[i\left(t_c\right)\right] \quad (8)$$

Assuming that the $P_1, P_r -$ probabilities of right and left nodes, we get:

$$\Delta i(t) = i\left(t_p\right) - P_1 i\left(t_1\right) - P_r i\left(t_r\right) \quad (9)$$

Therefore, at each node, CART solves the following maximization problem:

$$Max_{j=1,..M} \Delta i(t) = i\left(t_p\right) - P_1 i\left(t_1\right) - P_r i\left(t_r\right) \quad (10)$$

H. Choice of the right tree size

Maximum trees may turn out to be of very high complexity and consist of hundreds of levels. Choosing the right size of the tree means cutting off insignificant nodes and even subs trees.

In this case, the splitting is stopped, when the number of observations in the node is less than the predefined required minimum N_{min}.Obviously the bigger N_{min} the parameter, the smaller the grown tree. On the one hand, this approach works very fast, it is easy to use and it has consistent results. But on the other hand, it requires the calibration of the new parameterN_{min}. In practice N_{min} is usually set to 10% of the learning sample size. While defining the size of the tree, there is a trade-off between the measure of tree impurity and complexity of the tree, which is defined by total number of terminal nodes in the tree T.

With the increase of the tree parameter N_{min} , on the one hand, the impurity increases (for $N_{min} = 15$, impurity is equal to 0.20238 and for $N_{min} = 30$ impurity is equal to 0.21429). On the other hand, the complexity of the tree decreses (for $N_{min} = 15$, number of terminal nodes T is equal 9 and for $N_{min} = 30$, T=6).for the maximum tree, the impurity measure will be minimum and equal to 0, but number of terminal nodes T will be maximum. To find the optimal tree size, one can use a cross-validation procedure.

I. Segmentation of image using constructed tree

As the classification or regression tree is constructed, it can be used for classification of new data. The output of this stage is an assigned class or response value to each of the new observations. By set of constraints in the tree, each of the new observations will get to one of the terminal nodes of the tree. A new observation is assigned with the dominating class/response value of terminal node, where this observation belongs to.

J. Post processing of image

Post processing of an image means performing some morphological operations to the image. Morphological operations apply a structuring element to an input image, creating an output image of the same size. In morphological operation, the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighbours. By choosing the size and shape of the neighbourhood, construct a morphological operation that is sensitive to specific shapes in the input image.

The most basic morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, while erosion removes pixels on object boundaries. The number of pixels added or removed from the objects in an image depends on the size and shape of the structuring element used to process the image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image. The rule used to process the pixels defines the operation as dilation or erosion. These operations are used to define the clear boundaries of segmented output image.

III. Results and Discussion

The algorithms are developed in Matlab2010a and tested on real time abdomen CT images. Prior to feature extraction, the pre-processing was performed by the median filter of kernel size 5×5. For LBP feature extraction, eight neighbourhood connectivity is considered. The kernel size of 11×11 is used for the feature extraction and during the training process, features are extracted and stored.

Based on the features extracted, the decision tree is constructed and is depicted in figure 4. The correct classification percentage for liver segmentation is depicted in figure 5. In the testing phase, the features are extracted from the query image and tried to match for the liver or non-liver regions. The training phase comprises 20 DICOM CT images.

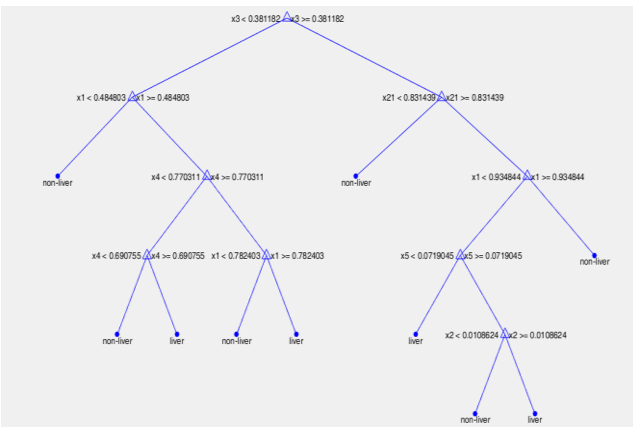

Figure 4: Decision tree generated for liver segmentation

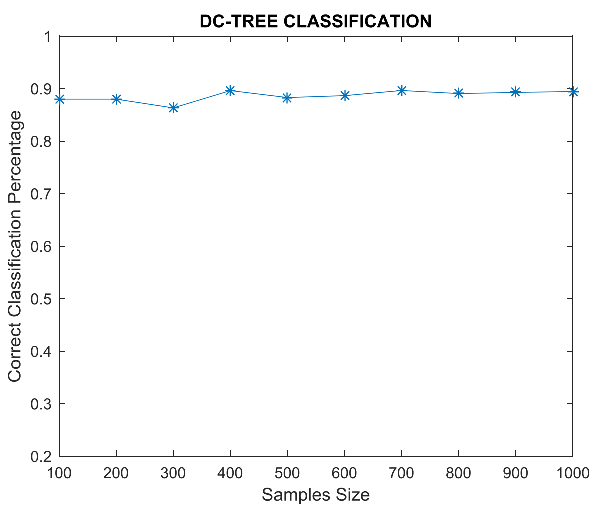

Figure 5: Correct Classification percentage for the liver segmentation.

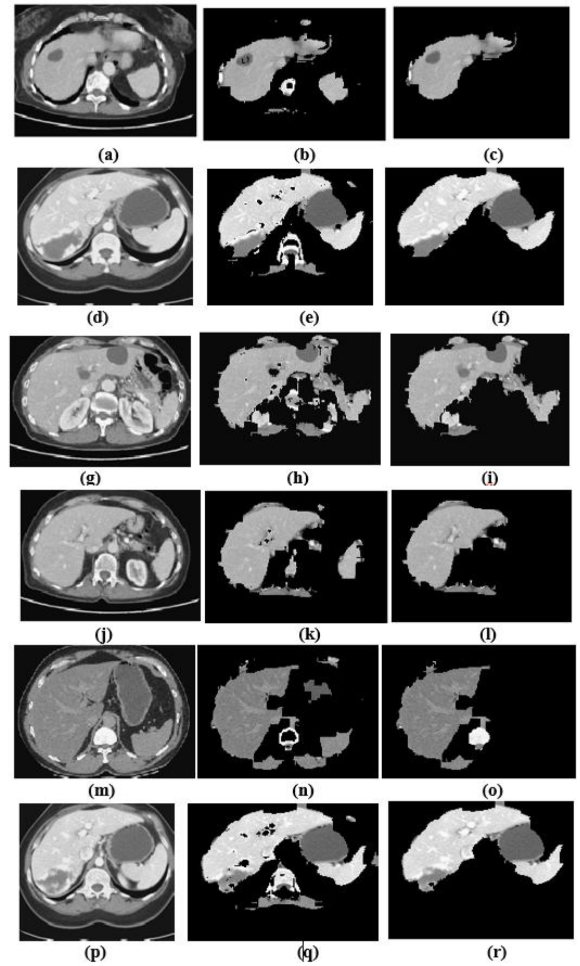

Figure 6: the First column represents the input images, Second column represents the decision tree segmented image and the third column represents the post processed image.

IV. Conclusion

This research work proposes decision tree based segmentation of liver from abdomen CT images. The pre-processing was performed by the median filter and hybrid feature extraction comprising of GLCM and LBP is used. The CART was employed for the segmentation of liver from abdomen CT images and the results were found to be satisfactory. The future work is multiview decision tree for segmentation of medical images.

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Authors Profile

A. Lenin Fred received his B.E degree in Computer Science and Engineering from Madurai Kamaraj University in 1995, M.E degree in Computer Science and Engineering from Madurai Kamaraj University in 2001, Doctoral Degree in Computer Science and Engineering, specialized in Digital Image Processing from ManonmaniamSundaranar University, Tirunelveli, India. His area of research includes Medical Image Processing, Biometrics and Multimodal Biometrics. He is working as Principal in Mar Ephraem College of Engineering Tamilnadu, India and have 21 years of teaching experience. He is an active life member IEEE, ISTE, IET and ISRD. He is the Principal Investigator of several government funded projects

T.R. Nisha Dayana is currently Research Scholar in the department Computer Science and Engineering at Bharathiar University, Coimbatore, India.

