International Journal of Emerging Technology in Computer Science & Electronics (IJETCSE)
ISSN: 0976-1353 Volume 22 Issue 1 – MAY 2016.

AUTOMATED SEGMENTATION TEXTURE BASED ANALYSIS AND IDENTIFICATIONOF DIFFUSE PARENCHYMA LUNG DISEASES

S. SABARIA, M.SIVASANKARI

M.E(CS) Dept. of CSE,ARM Engineering College, Chennai, India

M.E (CS) Dept. of CSE,ARM Engineering College, Chennai, India

***Abstract* - In this paper, survey has been made on the applications of computer aided diagnosis techniques for diagnostic sciences in biomedical image classification. Computer aided diagnosis (CAD) systems aiming to increase radiologist confidence and identification of the extent and characterization of the type of present disease patterns. This study gathers representative works that exhibit how CAD is applied to the solution of very different problems related to different diagnostic science analysis. It also detects the methods to solve the special problems of medicine. SVM neural network, Artificial neural network, Decision tree, Minimum distance are used in almost all imaging modalities of medical image classification. Similarly fuzzy C means, fuzzy + GA, water-shed and improvements to it are important tool in segmentation of lungs images. GLCM Based, Textural features, Wavelet features are also commonly used for feature extraction and feature selection.**

Keywords: SVM- Support vector machine, ANN- Artificial neural network, GA- Genetic Algorithm, GLCM - Gray Level Co-occurrence Matrix, CAD-computer aided diagnosis.

I. INTRODUCTION

Digital Image Processing is currently a hot research area in medicine and it is believed that they will receive extensive application to biomedical systems in the next few years. In recent years, considerable and serious efforts have been made toward the development of computer aided diagnosis (CAD) system in diagnostic radiology. CAD system has been developed to assist doctors to diagnose precisely. It is used to improve the accuracy and consistency of radiological diagnosis to reduce the rate of false negative cases. The typical architecture of a CAD system includes selection of training samples, image pre-processing, segmentation features extraction and selection, classification and identification.

CAD is fundamentally based on highly complex pattern recognition. It is used to determine an estimate of the probability of disease. The most important process involved in CAD schemes are: (1)Image segmentation – a stage where the pixels are grouped into regions based on image features.

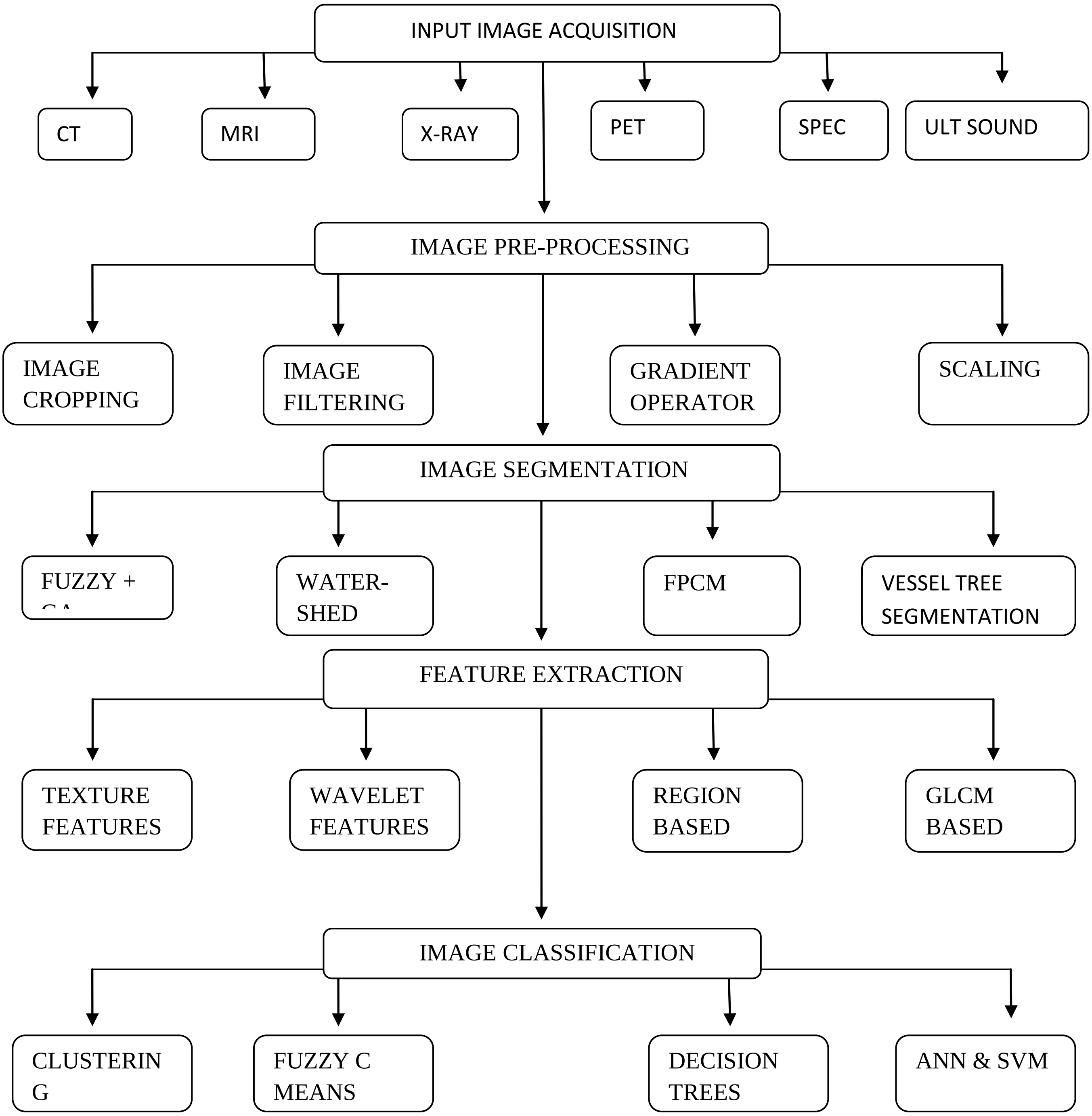
Segmentation partitions an input image into its constituent parts or objects. The output of the segmentation stage usually contains raw pixel data. Boundary representation and regional representation has to be considered. (2) Image classification– a stage where features are extracted and categories of normal or abnormal patterns. Recognition is the process that assigns a label to an object based on information provided by its descriptors.

The efficiency of the CAD system is based on the following parameters:(1) Sensitivity – It measures the proportion of actual positives which are correctly identified. The hit rate (sensitivity) can be up to 90% depending on system. A correct hit is termed a True Positive (TP), while the incorrect marking of healthy sections constitutes a False Positive (FP). (2) Specificity - Specificity measures the proportion of negatives which are correctly identified. The less FPs indicated, the higher the specificity. (3) Efficacy –the results of different treatments can be more properly evaluated and validated.

A.Segmentation

Segmentation partitions an input image into its constituent parts or objects. The output of the segmentation stage usually contains raw pixel data. Boundary representation and regional representation has to be considered. The preprocessing step of most Computer-Aided Diagnosis (CAD) systems for identifying the lung diseases is lung segmentation. In this paper, various segmentation techniques such as fuzzy + GA, water-shed, fuzzy + MLP and vessel segmentation is used.

Fig1. Various approaches in Biomedical image processing.



B .Feature Extraction

Choosing a representation is only part of the solution for transforming raw data into a form suitable for subsequent computer processing. A method must also be specified for describing the data so that features of interest are highlighted. Description also called feature selection, deals with extracting features.Feature selection: This is the technique, commonly used in machine learning of selecting a subset of relevant features for building robust learning models. Texture features, wavelet features, GLCM are various techniques to extract the features of lungs.

C.Recognition and Interpretation

Recognition is the process that assigns a label to an object based on information provided by its descriptors. Interpretation Involves assigning meaning to an ensemble of recognized objects, interpretation attempts to assign meaning to a set of labeled entities. Thus the classification techniques involve clustering, fuzzy c means, ANN and SVM. Artificial Neural Networks (ANN) are nonlinear information processing devices interconnection of neurons. The development of the ANN started in 1943 by McCulloch and Pitts and is still growing rapidly. The advantages of ANN include adaptive learning, self organization, parallelism, fault tolerance etc., Applications involve in knowledge extraction, pattern recognition, forecasting, clinical diagnosis, security systems and still wider.

In this paper, survey is made on applications of Neural Networks to diagnostic science. Basic approaches and techniques in medical image analysis at various phases are highlighted in Fig.1.

II. METHODS

A) Segmentation

Anna N. Karahaliou suggestedan automated scheme for volumetric quantification of interstitial pneumonia (IP) patterns, using a multidetector CT (MDCT) training set. Initially, lung-field segmentation is done by 3-D automated gray-level thresholding combined with an edge-highlighting wavelet preprocessing step, followed by a texture-based border refinement step [1]. Fully automatic method foridentifying the lungs in three-dimensional (3-D) pulmonary X-ray CT images proposed by Eric A. Hoffman [5]. The automated vessel tree segmentation scheme is proposed, adaptedto the presence of pathologies affecting lung parenchyma is purely discussed by Cristina Kalogeropoulou, Anna N. Karahaliou [2].The capable of segmenting the lung's air and its soft tissues followed by estimating the lung's air volume and its variations throughout the image sequence. This technique involves using the image sequence's combined histogram to obtain a reasonable initial guess for the lung's air segmentation thresholds is proposed by Ting-Yim Lee, Rajni V. Patel[10]. The segmentation of lungs with such high-density pathologies is consists of two main processing steps. First, a novel robust active shape model (RASM) matching method is utilized to roughly segment the outline of the lungs. Second, an optimal surface finding approach is utilized for segmentation result to the lung. Left and right lungs are segmented individually is proposed by Christian Bauer, and Reinhard Beichel*[11].

A (CAD) system proposed (Gomathi & Thangaraj) for detection of lung cancer with Fuzzy Possibilistic C Mean (FPCM) algorithm was used for segmentation because of its accuracy. The automatic segmentations are evaluated by comparing them to manual segmentations in terms of volumetric overlap and border positioning measures proposed by Mathias Prokop, and Bram van Ginneken[12]. The method to segment mammogram image using a self-organizing neural network based on spatial isomorphism. The method used is a modified version of the algorithm proposed by Venkatesh and Rishikesh to extract object boundaries in an image[13].There is considerable overlap between image processing techniques that seek to identify and to quantify abnormalities of the lung parenchyma, but it is the accurate quantification of abnormal lung that is so crucial for the investigation of structure-function relationships in lung disease is suggested by David M. Hansell [15]. This diagram is discussed in the paper, vessel tree segmentation by Cristina Kalogeropoulou, Anna N. Karahaliou [1]. (a) And (c) 3-D representation and (b) corresponding axial slice of segmented LF, provided by the first stage of the algorithm. White arrow indicates LF under-segmentation. (d) Corresponding axial slice of segmented LF after application of the lung border refinement step, respectively.

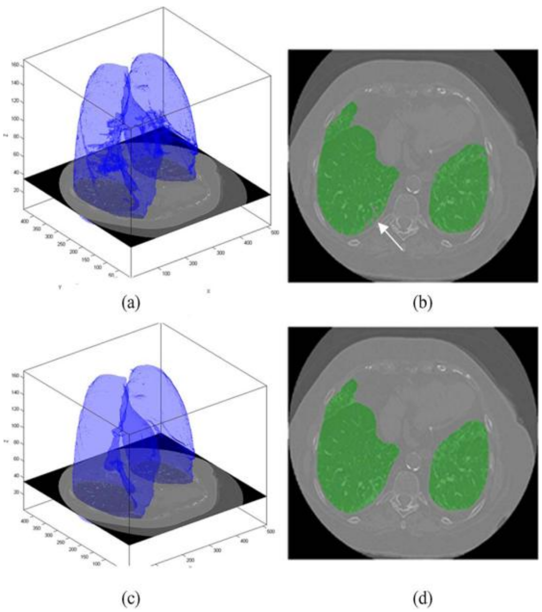


Fig 2: Lung field (LF) segmentation example.

INPUT IMAGES	SEGMENTED LEFT LUNG	SEGMENTED RIGHT LUNG

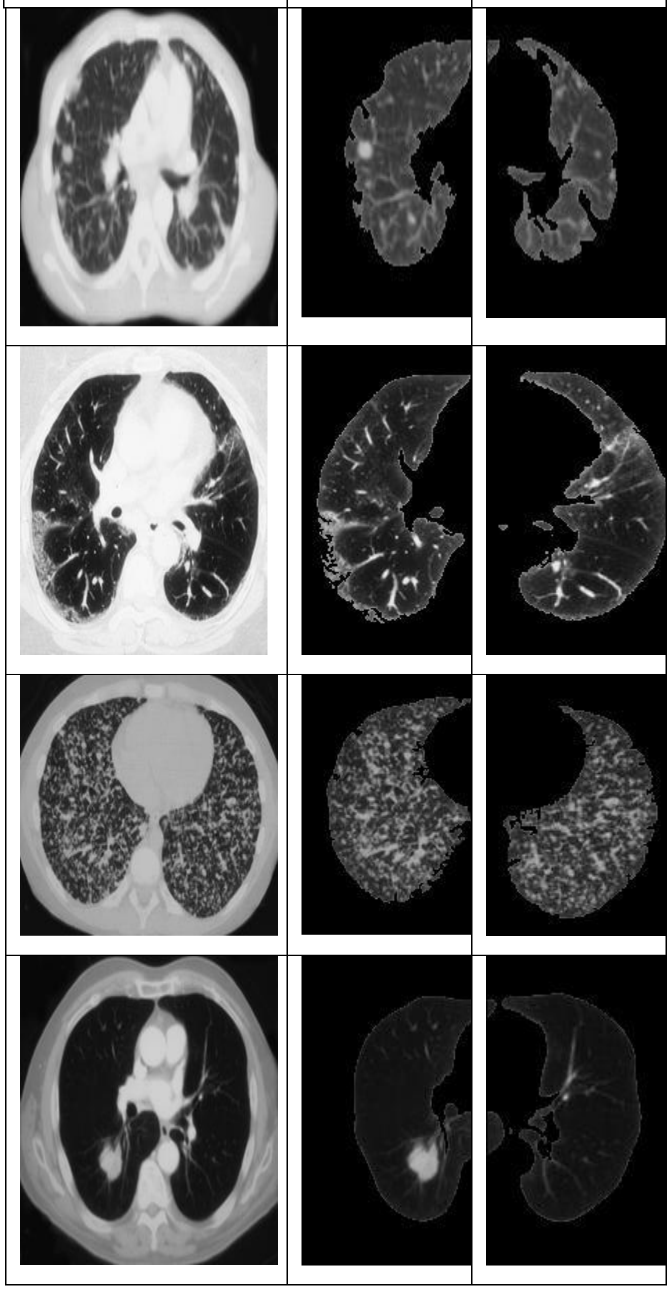


Fig 3: The segmentation of the left and right lungs.

Fig 4: Example image for carcinoma.

Fig 5: Example image for lung cancer.

B.Feature Extraction

Numerous systems were reported for detecting lung nodules on chest X-ray images. Many kinds of features have been proposed for discriminating between normal tissues and abnormal ones. However, there have been a few researches on comparing the effectiveness of those features. Computer-aided diagnosis (CAD) has been proven to be a very effective approach as assistant to radiologists for improving diagnostic accuracy. The numbers of features used in those researches are not sufficiently large. The purpose of our research is to find the optimal feature set from a large number of features which enable a CAD system for lung cancer screening to take large step toward a practical application.

A Computer Aided Diagnosis (CAD) system for the characterization of hepatic tissue from Computed Tomography (CT) images presented by (Mougiakakou et al.)[14], includes five distinct sets of texture features extracted using the following methods: first order statistics, spatial gray level dependence matrix, gray level difference method, Laws' texture energy measures, and fractal dimension measurements. If the dimensionality of a feature set is greater than a predefined threshold, feature selection based on a Genetic Algorithm (GA) is applied. The textural information obtained from the extracted tumor using Fast Discrete CurveletTransform (FDCT) is used to train and classify the liver tumor into hemangioma.

3-D Co-occurrence Features: The Gray Level Co-occurrence Matrix (GLCM) is a well-established tool for characterizing the spatial distribution (second order statistics) of gray levels in an image, and has been extensively exploited in lung image analysis.[15].The mean and range of each feature over the 13 co-occurrence matrices (corresponding to 13 directions) was calculated, comprising a total of 26 GLCM-based features for each distance.

Feature Selection: A statistical approach, the stepwise discriminant analysis (SDA) is employed to reduce themdimensions of the feature vector.

ILD CAD schemes [8]–[11] exploit texture analysis for the identification and characterization step, while incorporated preprocessing stages, such as lung field (LF) and vessel tree segmentation are often developed to deal with normal lung anatomy.The heuristic algorithms such as a genetic algorithm, a forward stepwise and a backward stepwise selections which need much smaller computational loads. These algorithms give not a really optimal feature set but a sub-optimal one because only a part of possible combinations of features are evaluated. The sub-optimal feature set is referred to as the optimal feature set for simplicity.

Thus the 3-D texture based analysis involves first-order statistics is used to extract the features [19], filter-based features is most common techniques to extract [16], [18], co-occurrence matrices [19], run length matrices [19], 3-D local histograms, and fractal features is more accurate to analysis the characteristics [19],

[20,21,22] uses measures on co-occurrence matrices, measures on run-length matrices, moments of the attenuation or intensity histogram, and also fractal dimension as features. Sluimer et al. [23] used a filter bank of Gaussians and Gaussian derivatives.

C.Classification

SVM classifier was applied to study on training set of chest mages with classification accuracy of 93%. SVM was applied to classify the diseases using gray level and co-occurrence matrix features and region-based shape descriptors, calculated from regions of interest (ROIs), as input (Chien)[24].SVM is used to classify vessel tree candidate voxels into vessel or ILD patterns, thus the two-class pattern recognition problem has to be solved. The main aim of the SVM classifier is trained to be able to separate one class from the othersuggested by Anna N. Karahaliou [1]. The extent of the ground-glass opacities as classified by the radiologist, the neural network (density mask) reached a sensitivity of 99% (89%), specificity of 83% (55%), positive predictive value of 78% (18%), negative predictive value of 99% (98%), and accuracy of 89% (58%) is discussed in thepaper[25]. The main advantage of NNs lies in their ability to use some *a priori* unknown information hidden in the data [26]. the task of the first NN is to classify intohealthy and pathological regions. If the estimation of NN1 is the pathological region, the second NN (NN2) is activated in order to classify the region into cyst (C2) or "other disease." If the diagnosis is cyst, the procedure is terminated, else the third NN (NN3) is activated in order to classify into hemangioma (C3) or hepatocellular carcinoma (C4) is discussed in the paper [14].

III.CONCLUSION:

In this paper, a survey has been made on the applications of CAD for diagnostic sciences in biomedical image classification. The various features using the computing techniques have been brought out in this paper with their advantages and limitations. The future work is to develop certain new algorithms based on these computing techniques for diagnostic science applications, because of various emerging medical systems which is still under research and, enabling the better delivery of healthcare.

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