Recent Advances and Future Potential of Computer Aided Diagnosis of Liver Cancer on Computed Tomography Images

Megha P. Arakeri and Ram Mohana Reddy G.

Department of Information Technology
National Institute of Technology Karnataka, Surathkal, India
{meghalakshman,profgrmreddy}@gmail.com

Abstract. Liver cancer has been known as one of the deadliest diseases. It has become a major health issue in the world over the past 30 years and its occurrence has increased in the recent years. Early detection is necessary to diagnose and cure liver cancer. Advances in medical imaging and image processing techniques have greatly enhanced interpretation of medical images. Computer aided diagnosis (CAD) systems based on these techniques play a vital role in the early detection of liver cancer and hence reduce death rate. The concept of computer aided diagnosis is to provide a computer output as a second opinion in analysis of liver cancer. It assists radiologist's image interpretation by improving accuracy and consistency of radiological diagnosis and also by reducing image analysis time. The main objective of this paper is to provide an overview of recent advances in the development of CAD systems for analysis of liver cancer. Medical imaging system based on computer tomography will be focused as it is particularly suitable for detecting liver tumors. The paper begins with introduction to liver tumors and medical imaging techniques. Then the key CAD techniques developed recently for liver tumor detection, classification, case-based reasoning based on image retrieval and 3D reconstruction are presented. This article also explores the future key directions and highlights the research challenges that need to be addressed in the development of CAD system which can help the radiologist in improving the diagnostic accuracy.

Keywords: Computer Aided Diagnosis, Computed Tomography, Image Retrieval, Liver Cancer, Medical Imaging.

1 Introduction

For years, cancer has been one of the biggest threats to human life. It is expected to become the leading cause of death over the next few decades. Based on statistics from World Health Organization (WHO), deaths caused by cancer are projected to increase in the future, with an estimated 11 million people dying from cancer in the year 2030 [1]. Hence detection of this cancer in early stages becomes important to cure deadly disease. Currently, the only confirm diagnosis for the liver cancer is the needle biopsy which is an invasive technique and generally not recommended. Various imaging techniques like Computed Tomography (CT), Medical Resonance Imaging (MRI) and Ultra-Sonography (US) exist for acquiring the images of the liver [2]. Among all

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these techniques CT has been identified as accurate noninvasive imaging modality in the diagnosis of liver cancer. The medical images interpreted by radiologists provide only about 75% of diagnostic accuracy. The advancements in image processing and artificial intelligence techniques have lead to the development of CAD system to ease image analysis task of radiologists. The components that can be made as part of CAD to provide complete assistance to the physician in diagnosis of liver cancer include segmentation, classification of tumor, image retrieval for case based reasoning and 3D reconstruction of tumor.

The aim of this paper is to provide an overview of recent advancements in the development of CAD systems for analysis of liver cancer and to present the major challenges in development of CAD.

This paper is organized as follows: Current techniques and related issues in different phases of CAD are discussed in section 2. Section 3 explores the various feature descriptors used in medical image retrieval systems. Finally, in section 4, the future research challenges are highlighted.

2 Computer Aided Diagnosis

A system for computer aided diagnosis of liver tumor on CT image is shown in Fig.1 . In the first step of CAD, suspicious regions of liver are detected. Next, the features such as texture, gray level intensity, shape and size of tumor are extracted which then assist the radiologist in classifying the suspicious liver region as benign or malign tissue.

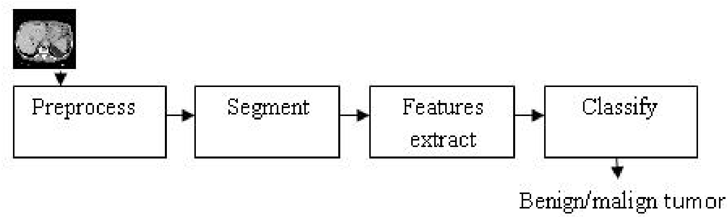

Fig. 1. Computer Aided Diagnosis System

2.1 Preprocessing

The noise can mask and blur important features in the image. Therefore, filtering techniques like median [3], wiener [4], and ICA [5] are proposed in the literature for noise elimination. However, the main problem of liver tumor detection from CT images is related to low contrast between tumor and liver intensities. Thus, contrast enhancement also should be done as part of CT image preprocessing through histogram processing as presented in [6].

2.2 Segmentation

The important task the radiologist face in medical image analysis is delineation of boundary of anatomical structures called segmentation. Kumar *et al.* [7] proposed a method that obtains a liver segmentation by using optimal gray level threshold within the mask area. The region growing is performed by extracting all pixels connected to the initial seed with intensity values within the threshold. Megha P A *et al.* [8] developed an algorithm to overcome the drawback of semi-automatic region growing by determining threshold and seed value automatically. The use of conventional watershed algorithm results in over segmentation. Jianhua Liu *et al.* [9] addresses the problem by combining watershed segmentation with region merging. H P Nagh *et al.* [10] demonstrated the use of *k*-means algorithm in clustering the medical images into several regions of interest.Mala *et al.* [11] extracts the liver tumor from liver region by applying fuzzy C-means clustering (FCM). Fuzzy membership function allows varying degree of membership and it require huge computational time. The deformable models or snake approach to image segmentation uses closed curves that deform under internal and external forces to delineate object boundaries. Rui Lu *et al.* [12] manually placed initial boundry outside the tumor region. Then the snake deforms to the tumor boundary with the minimization of energy function. The contour does not deform to the exact boundaries in the presence of blurred edges. Chetankumar *et al.* [13] formed initial contour of the snake using edge detection technique.

2.3 Feature Extraction

A reliable diagnosis of the cancer can be provided assisting the physician with computerized tissue classification. Yu-Len Huang *et al.* [14] extracted texture features on non enhanced liver CT image with 85% classification accuracy. Stavroula G *et al.* [15]improved the accuracy of the diagnosis of liver on CT images using three distinct feature sets extracted using first order statistics, spatial gray level dependence matrix and gray level difference method. The most robust features were derived from the original set using forward sequential search method. Tryphon Lambrou *et al.* [16] developed a CT liver image diagnostic system which extracts first and second order texture statistics from different scale wavelet transform coefficients and used leave-one-out method for feature selection. The feature set dimensionality can be reduced by popular methods like Principal Component Analysis (PCA) [17] and Independent Component Analysis [18].

2.4 Classification

The neural networks with their remarkable ability to derive meaning from complicated data can be used to extract patterns that are too complex to be noticed by humans. Megha P A *et al.* [19] used probabilistic neural network on CT abdominal images in conjuction with Co-occurrence texture features extracted from the segmented region and classified liver tissue as benign and malign with an accuracy of 94.6%. Chien Cheng Lee *et al.* [20] proposed classification of different types of liver tumor using support vector machine(SVM). Since SVM algorithm performs binary classification, it takes more time when many patterns have to be classified. The concept of neural network can be combined with fuzzy rules to provide fuzzy neural network [21].

3 Content Based Image Retrival

Medical image retrieval is a very demanding application since it is expected to provide the physician a decision support for diagnosis by retrieving relevant cases. Most of the image retrieval methods used are text-based. This technique has its own disadvantages because the rich features present in an image cannot be described by keywords completely. The most effective method is content based image retrieval (CBIR) where images are retrieved based on visual similarity rather than keyword search [22].

Local features are more important than global features in medical image. Winnies Tsang *et al.* [23] used both local and global texture descriptors for tissue identification of CT abdominal images of liver and also experimented with several similarity measures. He achieved precision of 91.57% with combination of local features and Jeffery divergence similarity measure. Ajitha Gladis *et al.* [24] retrieves medical images based on image signature obtained by color histogram, texture and patterns of medical images by performing three level wavelet analyses with 97% retrieval accuracy. Pei-Cheng Cheng *et al.* [25] fills the gap between low level and high level semantics by considering the relevance feedback from the user and adjusting image weights. A comparative assessment of the performances of the medical CBIR systems is not possible as there is a lack of common database to evaluate different systems. The Image-CLEF med, is one of the few platforms to evaluate and compare different systems. The IRMA, the med-GIFT, and the VisMed projects are participants of Image-CLEF med [26]. Also,3D model of the tumor can be built for volume analysis [27].

4 Future Challeges

The future challenges in development of CAD system to assist the physician in making more accurate and reliable diagnostic decisions include:

(i) Development of fully automatic, accurate, robust and fast segmentation methods which can detect cancer in early stage. (ii) A reliable diagnosis with 100% classification should be achieved by feeding the more discriminative features of the tumor to the classifier and also by incorporating expert knowledge. (iii) There is a need to develop CBIR system which produces more meaningful results at faster retrieval rate (iv) 3D reconstruction methods that bring improvements in computation time and surface smoothness.

5 Conclusions

The use of quantitative image analysis tools, in conjunction with the experience of the physician, can improve diagnostic sensitivity and specificity and reduce interpretation time. This paper has provided extensive survey on CAD systems that have been proposed and developed in the recent years and also highlighted the future research challenges to develop more effective and efficient CAD systems that help in early diagnosis of liver cancer on computed tomography images.

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