A Survey on CAD System for Liver Cancer Diagnosis

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Abstract--Hepatic cancer is the fifth most common cancer in the world and the majority of patients with liver cancer as a result will die within one year. Computer Aided Diagnosis (CAD) systems help a great deal in aiding the detection and diagnosis of cancer. They serve as an effective second opinion. Computed Tomography (CT) is one of the commonly used imaging modalities in the cancer domain since it gives the intrinsic details of the tissues. Recent developments in Computed tomography have been very helpful to avoid the effect of radiation during the scanning process. The four major steps in the computer aided diagnosis are the pre-processing of the images, segmentation of the regions of interest, feature extraction and classification. This paper gives a brief summary of the recent developments in the segmentation of the region of interest and the classification of liver diseases using the Computed Tomography images and the results of the existing methodologies.

Keywords: CAD, Segmentation, Classification, Liver Tumor, CT

I. INTRODUCTION

The liver, having a wide range of functions, including detoxification, protein synthesis, and production of bio chemicals necessary for digestion is considered as a vital organ. Located in the right upper quadrant of the abdominal cavity, resting just below the diaphragm, it does a multitude of functions. The liver is prone to many diseases because of the chemicals it deals with. Primary liver cancer is globally the sixth frequent cancer, and the second leading cause of cancer death. Liver resection, in which the diseased liver tissue is surgically removed completely by the doctors is the only available cure for liver cancer at present. For the development of the automated CAD system, segmentation and classification are used. Due to the similarity of the intensities of the adjacent organs in the abdominal CT scan, segmenting the liver from the CT scan is considered to be too difficult. Selection of the features plays a vital role in the classification process. The present non-invasive techniques in the medical imaging include X-rays, Computed Tomography scans and Magnetic Resonance Imaging. Of all the internal imaging procedures available to physicians, the CT scan is the most detailed, and can give a doctor the most complete picture of what’s happening inside a patient’s body. They are particularly useful and widely used in diagnosing cancer. The paper gives a brief summary on the existing techniques in the segmentation and classification of the liver and liver tumors automatically from the CT scan images.

II. RECENT CAD SYSTEMS FOR ROI SEGMENTATION

Guodong Li et al(2015)[1] proposed a method for developing and validating an automated method to segment livers in CT images. This method has three steps: pre-processing, initialization and segmentation. Firstly, the statistical shape model was constructed based on the principal component analysis and smoothening was done using curvature anisotropic diffusion filtering. Then, the mean shape model was moved using thresholding and Euclidean distance transformation to obtain a coarse partition in the test image. Finally, the deformable graph cut was proposed to effectively integrate the properties of inter-relationship of the input images and initialized surface. The validation was done on 50 CT scan images. The results showed that the proposed method was effective and accurate for detection of the liver surface. The proposed method accurately detected the hepatic surfaces and also provided results sans over-segmentation and under-segmentation.

Changyang Li et al(2013)[2] proposed a novel level set model incorporating the likelihood energy with the edge energy. The minimization of the likelihood energy was calculated by approximating the density distribution of the target and the multimodal density distribution of the background which can have multiple regions. The edge detector was used for preserving the ramp associated with the edges for weak boundaries during the edge energy calculation. The proposed method was compared with the existing Chan-Vese and the geodesic level set methods and also the manual segmentation methods which were performed by the clinical experts. The results on 18 clinical datasets showed that the proposed algorithm had a Jaccard distance error of 14.4 ± 5.3%, relative volume difference of –8.1 ± 2.1%, average surface distance of 2.4 ± 0.8 mm, RMS surface distance of 2.9 ± 0.7 mm, and the maximum surface distance of 7.2 ± 3.1 mm. The validation showed that the proposed approach was able to segment the tumors with heterogeneous densities that follow the finite Gaussian distribution.

Ina Singh et al(2015)[3] proposed a k means method based on ant colony optimization. This helped in reducing the initial clusters problem of k-means clustering. The contours of the liver region were improved using the proposed level set methods. This method for automatic and unsupervised liver does not need training data for its functioning. It proved
efficient in segmenting livers with high accuracy. The proposed method was found to have less computational time and robust in finding the region of interest automatically. When compared with the existing k-means method, the hybrid k-means had better results in quantitative and qualitative analyses. The G-accuracy was improved and also there was a decrease in the computational time.

Kaiping Wei et al.[2007][4] proposed a novel segmentation method for CT brain images. The skull’s boundary was searched using the row scanning approach. The intra-cranial area was extracted accurately using the morphological operator. The 2D Otsu threshold segmentation method was used to find the regions of interest wherein the threshold was calculated using the PSO. The proposed algorithm helped in tackling many challenges present in medical imaging and was also efficient and automated.

Ina Singh et al.[2015][5] proposed a hybrid method combining K-Means, ACO and Level set method. This method greatly helped to find the match between the donor and recipient liver automatically. The K-Means algorithm was used to cluster the data. This was done in an intelligent way because different location gave different results. For optimizing the K-Means, ACO was used. Then, the level set method was used for the segmentation. The hybrid K-Means with ACO and level set performed better than the existing K-means and level set on both quantitative and qualitative basis. The F-measure and sensitivity was found to be high in the hybrid K-Means method. This method greatly helped during surgeries.

Marius George Lingurar et al.[2012][6] proposed a method for automated liver segmentation. The local shape across organs was compared using a 3-D affine invariant shape parameterization. Regular sampling of the organ’s surface were collected and it was very helpful in comparing features of closed 3-D surfaces point-to-point and also devoid of the common problems. Probabilistic location information was helpful during liver segmentation. The segmentation of liver in abnormal images was taken care of by the geodesic active contours. The proposed method had better qualitative results when compared with the existing methods. The volume overlaps, the average surface distance all favoured the proposed method. The downside of the proposed method was the time for registration and segmentation.

Xing Zhang et al.[2010][7] presented a method for automated liver segmentation from CT images based on integrating the statistical shape model with optimal-surface-detection-strategy. The method had a total of three steps. Initially, 3-D generalized Hough transform was used for localisation of the average liver shape model. Then, the initialization of the subspace of the SSM was done by using intensity and gradient profile. The optimal surface detection strategy based on graph theory was used to deform the shape model for adapting to the liver contour. The segmentation errors that occurred at long and narrow regions of liver in this method was taken care of by employing more landmark points. The scale and rotation of the object required high parameter space and computational cost.

E-Liang Chen et al.[1998][8] presented a CT liver image diagnostic classification system. The liver boundary was extracted automatically from the CT scan using a detect-before-extract system. The normalized fractional Brownian motion model was applied followed by a deformable contour model to find an initial liver boundary. There were numerous iterations used in the deformable contour model. This system did not perform well in all the images and was object-oriented. The components in the system were easily replaceable by other better components, if any.

Hossein Badakhshannoor et al.[2011][9] proposed a novel approach for the accurate segmentation of organs in the CT scans. The knowledge of the organ was utilized for validating a large number of potential outcomes generated by the generic segmentation method rather than using the organ’s prior information directly in segmentation process. The principal component analysis approach was used to collect information about the organ space. The volumetric overlap error, relative volume difference, average symmetric surface distance, symmetric RMS surface distance and maximum symmetric absolute surface distance were measured for the liver segmentation process. The unique way to choose the segmentation parameters automatically which lead to the best results were provided by statistical information. The proposed model stood among the top four automatic segmentation models at the time of publication.

Xinjian Chen et al.[2012][10] proposed a model combining the active appearance model, liver wire and the graph cuts for segmentation in the abdominal CT scans. The model building, object recognition and delineation were the main parts of the model. In model building phase, AAM was constructed and the LW cost function and GC parameters were trained. The multi object strategy was utilized in object initialization. The shape-constrained Graph Cut method was the core part of the whole system during delineation. The proposed method slightly under segmented the organs due to the asymmetrical nature of the shape term that was designed. The whole data set and all organs’ average localization error was found to be 7.3 mm, which was accurate enough for clinical use. The multithreading methods were suggested to reduce the running time which was about 5 minutes.

Shraddha Sangewar et al.[2013][11] proposed a novel liver segmentation model using K-Means segmentation. The low contrast, blurred edges, the variations in shape were overcome with a variational model based on intensity probability distribution propagation and region appearance propagation. This helped to focus on the region of interest amidst all complexities. The method combined K-Means with a local contouring algorithm. The proposed method required less user interaction and also provided fast and efficient liver segmentation. Five separate regions were identified during the segmentation process.

Nader H. Abdel-massieh et al.[2010][12] proposed an automatic liver segmentation with no user interaction. Contrast enhancement was applied to the slices of segmented liver. Thresholding of the tumor in the slice was done using the Isodata after the Gaussian smoothing had been applied.
Rule based on diagnostic knowledge on liver tumor shape was applied to make the errors go off. Then, a consistency check was performed. The segmentation metrics calculated were volumetric overlap, relative absolute volume difference, average symmetric absolute surface distance, symmetric RMS surface distance, and maximum symmetric absolute surface distance. The proposed method provided better results when compared with the existing methods.

Chunming Li et al [2010] [13] proposed a model where the regularity of the level set function was intrinsically maintained in the evolution of the level set. The conventional level set irregularities were corrected using re-initialization wherein the signed distance function periodically replaced the degraded level set function. A unique forward and backward diffusion effect was defined for the potential function which helped to maintain the shape of the desired level set function. This novel distance regularized level set evolution let go off numerical fallacies. This model used large time steps and so it reduced the number of iterations and computation time significantly. But this method sometimes resulted in under segmentation and over segmentation.

Nuseiba M. Altarawneh et al [2015] [14] proposed a modified liver segmentation model based on the distance regularized level set. The existing levels et model did not work well for the weak edges and blurred edges. This proposed model added a new balloon force which aimed to slow down the direction of the evolution of the contour in the regions of weak and blurred edges. This model helped greatly in reducing the over segmentation and under segmentation fallacies. This model greatly controlled the direction of evolution of the contour.

III. RECENT SYSTEMS FOR CLASSIFICATION

Turid Torheim et al [2014] [15] proposed a method which aimed to develop a system that could correctly predict the cervical cancer from the Brix parameters derived from the pre-chemoradiotherapy DCE--MRI. The texture analysis was done by gray level co-occurrence matrix construction from the maps. The explanatory variables used by the support vector machine classification were the first and second order features. The leave-one-outcross model validation was used for the validation process. The first order features could not differentiate between cure and relapsed patients which the second order did with around 70% accuracy. The spatial relations within the tumor that were quantified by texture features were found to be more fit for outcome prediction than first order features.

Xiabi Liu et al [2015] [16] proposed a new Fisher criterion and Genetic optimization based feature selection method. The feature subsets were evaluated using Fisher criterion and the optimal features were selected from the set of candidates by developing a new Genetic optimization algorithm. The regions of interests were selected with the help of the classifiers support vector machines, bagging, Naïve Bayes, K-nearest neighbour and AdaBoost and the selected features. The new method performed better than the feature selection based on classification accuracy rate and genetic optimization. It was highly effective in the recognition process. Some additional pre-processing steps would have increased the accuracy.

Miltiades Gletsos et al [2003] [17] proposed a method for feature selection and classification of hepatic cancer using neural networks in CT images. The gray level average and 48 texture parameters derived from the region of interests of the spatial gray level co-occurrence matrices were calculated for the feature extraction. Three sequentially placed feed-forward neural networks were part of the classification module. The first neural network classifier classified the liver into normal and pathological region. The second classified the pathological regions into cyst or other diseases. The third classifier classified the other disease into hepatocellular carcinoma or hemangioma. The method showed that the lower dimensional feature vectors and increased classification performance were possible by genetic algorithms. The method showed the acceptability of co-occurrence texture features, the high performance of genetic algorithms for selection of features in comparison to sequential search methods and the NN classifiers' high performance.

Yehonatan Sela et al [2011] [18] presented a method for the classification and grading of fibrosis automatically based on changes in the hepatic hemodynamic along with hyperoxia and hypercapnia. The learning method was supervised and it automatically created the classification and grading liver fibrosis grading model from training datasets. It constructed a statistical liver fibrosis model by evaluating the local variance in T2*-W scans and signal intensity time course. The experimental results on 162 slices and 34 mice yielded 96.9% accuracy in the separation of healthy and histological based fibrosis graded subjects with the hierarchical multi class Binary SVM classifier. The overall accuracy was 75.3 for healthy subjects. The proposed method outclassed all the existing methods. The proposed method cannot adapt easily to the human liver. This method enabled the automatic non-invasive grading of liver fibrosis.

IV. CONCLUSION

In this article, a brief summary of the existing methods used in the diagnosis of liver diseases and hepatic tumors have been discussed. The methods used for detecting tumors in lung and brain CT or MRI have also been discussed since they can serve as a benchmark for the future developments in this domain. This automatic system increases the accuracy and efficiency of the diagnosis and detection of liver tumors and help serve as a reliable second opinion. In the future, diagnostic efficiency and time can be further improved manifold with the enormous development of the CAD technology.

V. FUTURE SCOPE

The usage of the proposed system can be further improved by increasing the CT image feature set to include the various orientations of the CT scan and also 3D CT scans.
This will greatly improve the laboratory results. Better segmentation and classification algorithms will highly improve the accuracy of the automated system. The process can further be speeded up by keeping the feature set as small and concise as possible.

REFERENCES


