Brief Review on Liver segmentation using Image Processing

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Abstract :
Liver cancer is one of the most popular cancer diseases and causes a large amount of death every year. The chances for liver cancer in men and women have increased to 40% and 23% respectively. Segmentation of liver from images of the abdominal area is critical for diagnosis of tumor and for surgical procedures. Accurate detection of the type of the liver abnormality is highly essential for treatment planning which can minimize the fatal results. Accurate results, however, can be obtained only through computer aided automated systems. Besides being accurate, these techniques must converge quickly in order to apply them for real time applications. Many reports claim its work to be superior, but a complete comparative analysis is lacking in these works. In this survey paper, an extensive comparative analysis is performed to illustrate the merits and demerits of various available techniques. This work also explores the applicability of the techniques in liver segmentation from Computed Tomography images. The main objective of this work is to highlight the position of various automated techniques which can indirectly aid in developing novel techniques for solving the health care problem of the medical sector.

Keywords – Image Processing, Liver Cancer, Liver segmentation, Kmeans

I. Introduction

Liver cancer is one of the most common internal malignancies also one of the leading death causes. Medical image analysis is an important biomedical application which is highly computational in nature and requires the aid of the automated systems. The image analysis techniques are often used to detect the abnormalities in the human bodies through scan images. In the area of Computer-Aided Diagnosis (CAD), accurate and robust segmentation of liver tissue from medical images is a prerequisite for detecting the tumor and its extent. But, due to the highly varying shape of liver and weak edges between some adjacent organs (e.g., heart, stomach, and muscles), liver segmentation becomes a challenging task that has attracted research attention recently. Further, the low contrast between the intensities of the liver and its nearby organs hinders the accurate segmentation. Liver sometimes presents in different dimensions and makes the detection and segmentation even more difficult. The imaging techniques such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or positron emission tomography (PET) are the standard instruments for the diagnosis of liver pathologies such as cirrhosis, liver cancer, and fulminant hepatic failure. Among these techniques, CT images are often preferred by diagnosticians since they provide more accurate anatomical information about the visualized structures. The Computer aided diagnosis system consists of two major steps: (a) Image segmentation & (b) Image classification. The liver segmentation process Imtlates with a preprocessing stage and is followed by the actual segmentation. There are several approaches for the segmentation of liver. Some of them are semi-automatic and a few others are fully automatic. Semi- automatic methods require user intervention to outline the region of interest before leaving to the computer for processing. Whereas, fully automated segmentation method segments without the aid of user intervention. The various approaches used for liver segmentation are based on Threshold, Model, Level Set, Region, Active contour, and clustering. The manual segmentation of the liver is very time consuming, and hence we concentrate on automatic segmentation.

II. Literature Review

The image segmentation is to partition an image into meaningful regions with respect to a particular application. In the medical sector, segmenting the liver is difficult since the image includes intensity homogeneities of other organs like kidney, spleen, and pancreas. A few prevailing segmentation techniques include Level Set method, Active Contour, Clustering algorithm, Histogram based approach and Gray level methods.

a) Model Based Approaches

The statistical shape model based method has the best performance among all the approaches in the grand challenge workshop [1]. Most of the model-based approaches utilize the Statistical Shape Model (SSM) that includes shape correspondence, shape representation, and search algorithms. The shape-model construction process, establishes landmark point's correspondence among all shapes of training sets [2]. Statistical shape model for the liver introduced by Lamecker built the SSM of liver from 20 manually

segmented individual CT datasets. They proposed a geometric approach based on minimizing the distortion of the mapping given a few user- defined feature points where a user defines the feature points by decomposing the surface into patches. The patch boundaries were constructed by specifying only a few points on the surface and then computing the shortest path between them. The mean of the two 3D-shapes, were computed using a mere translation to align the gravity centers of the shapes and a rigid transformation computed by mean least squares (MLS). Principal Component Analysis (PCA) was used to analyze the variability over a set of training data to the set of corresponding liver surfaces [3]. The drawback of the SSM method is that, it does not promise good results if the number of training datasets is very small. Similarly, although many applications in computer vision that used active contour technique and some actually achieved good results, but for the application where segmentation serves as a preprocessing step, such as where it is used for content based image retrieval (CBIR), it requires a lot of time to execute. Statistical deformable model for the segmentation of liver CT volumes by Hermann trained the SSM on 35 training datasets to model the expected shape and appearance. The underlying SSM consists of 2,500 landmarks. Subsequently, a local search similar to the Active Shape method was used to initialize the main components of this approach which was a deformable mesh that strives for equilibrium between internal and external forces. The internal forces describe the deviation of the mesh from the underlying SSM, while the external forces model the fitness to the image data. They also employed a graph-based optimal surfuce detection during the calculation of the external forces. But this technique is image dependent. Automatic liver segmentation using a statistical shape model with optimal surface detection method combines three steps: First, localization of liver shape model using 3-D Generalized Hough Transform (3D-GHT) under translation and isotropic scaling. Second, subspace initialization of the statistical shape model through intensity and gradient profile. Third, deform the shape model to adapt to liver
contour through an optimal surface detection approach based on graph theory. The main drawback of 3D-GHT is scale and rotation of the objects are handled in a brute force manner that requires 6-D parameter space and high Computational cost. In subspace initialization of the step the candidate points searching proceeds iteratively and takes most of the time. In final optimal surfuce detection step graph nodes are sampled in all columns with the same sampling distance [4]. Segmentation of liver Vasculature from contrast enhanced CT images using Context – Based Voting describes segment and identify the liver vasculature using region based features and vessels are classified by multiple feature point voting mechanism [5].

b) Active Contour Based Approaches

The GVF snake used for semi-automatic liver segmentation, the first step of this algorithm was enhancing and denoising the images by histogram equalization and anisotropic diffusion filtering. Then several manually chosen points were connected using hermite-splines curve for the initial snake boundaries. Finally, fine segmentation was performed based on generalizing the GVF snake [6].GVF for liver segmentation used the canny edge detector to generate an edge map. A new maximum force angle map is introduced to evaluate the direction variability of the GVF forces. The segmentation was done in a slice-by-slice fushion [7].Segmentation of the Liver Using the Deformable Contour Method on CT Images for unsupervised liver segmentation algorithm consists of three steps. In the preprocessing, to simplify the input CT image by estimating the liver position (ELP) using a prior knowledge about the location of the liver and by performing multilevel threshold on the estimated liver position. The proposed scheme utilizes the multiscale morphological filter recursively with region-labeling and clustering to detect the search range for deformable contouring. The final contour is found by using the labelingbased search algorithm on the gradient-label map [8]. C.Platero proposed for Liver segmentation for hepatic lesions detection and characterization based on 3D anisotropic diffusion processing without any control parameter combination of edge detection techniques, histogram analysis, morphological processing, and evolution of an active contour have been applied to the liver segmentation [9].

c) Gray level Based Approaches

An adaptive hybrid segmentation algorithm using Bayesian classification on volume intensities [12], the process starts with a single user-defined pixel seed inside the liver. The mean and the variance of a rectangular neighborhood around this pixel is computed as the initial parameter values of the liver class. Then, a voxel classification with a smoothed MAP rule is applied to produce a segmentation label map. The identification of the liver region is done using an adaptive morphological adjustment to remove the disconnected regions outside the liver and to fill the holes inside the liver. Finally the liver volume is corrected by a level-set method. These three steps are repeatedly applied to the image until no further change occurs. In this novel algorithm a good distribution samples needed for constructing model is the one main demerit. Another gray level based approach the liver regions are estimated using both gray levels of the image and the spatial relationship among neighboring voxels [13]. The liver volume was refined by employing a 3D region growing.

d) Histogram Based Approach

Fully automatic liver segmentation using histogram tail threshold algorithm to segment the liver region by eliminating neighboring abdominal organs of the liver, such as the pancreas, spleen, and kidneys[10]. Otsu's method using threshold the histogram using maximum, minimum, median intensity of ROI to detect the location of the liver from the Region of Interest [11].

e) Clustering Based Approach

Enhanced k-means clustering algorithm for liver segmentation implemented in [14]. The system combines Kmeans is one of the simplest unsupervised learning algorithms that classify a given dataset into certain number of clusters. The main idea is to define K - centroids one for each cluster. The drawback of this K- means clustering, cyst region was not extracted properly. To improve its performance morphological opening -by- reconstruction operation is applied on the output of K-mean clustering algorithm. The main advantage of this approach is enhanced k-means clustering method better performance than region growing for cyst area segmentation in liver images. Fuzzy C means FCM clustering method for liver tumor segmentation is not very effective with noisy or outlying points and with clusters of different volume and unequal sample sizes. To overcome these problems, an alternative FCM clustering algorithm is used. Alternative Fuzzy C Means (AFCM) is a segmentation algorithm that is based on clustering similar pixels in an iterative way, where the cluster centers are adjusted for all iterations [15].

f) Level set based Approaches

The level set method has been successfully used for medical image segmentation. The advantages of the level set approach handle topological changes and define the problem in one higher dimension. The main dis advantages of this method are time consuming and they produce over segmentation [16]. The Segmentation using level set method that evolves according to a speed image that is the result of a scanning technique based dynamic programming implemented by [17]. The main limitations is I e v e I set method adjusts this first segmentation using a speed function obtained from a pixel classification algorithm. The accuracy is only sufficient in a small number of cases. In this core of the algorithm is a level set function that has the availability to manage separating and joining liver boundary routinely. The liver level set (LLS) is separated into two stages which a preprocessing stage and a level set with a hybrid energy minimization algorithm. The drawback of this approach is the hybrid energy is reformulating in level set framework in a looping manner, thus allowing to inherent the topology changes from previous image [18]. First attempt to segment the liver using level set is done by Pan introduced an accumulative level-set speed function which varied by time to improve the detection sensitivity of weak edges. It al so incorporated prior liver location based on anatomy knowledge to help in the segmentation process. Pan's 2D algorithm begins by initializing the curve through putting a small circle inside the liver region for each slice. Thus, if a disconnected region occurs in the current slice, a user needs to initialize a circle for each disconnected regions [19].

III. Conclusion

In this work, the merits and demerits of various automated techniques for Liver segmentation is analyzed in detail. The suitability of the techniques for various applications is also illustrated in this survey. Several novel hybrid approaches may be developed through the ideas conveyed in this report. This report also aid in highlighting the significant contributions of engineering theory to the medical field.

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