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A Study on Segmentation Algorithms for Liver Disorder Analysis in Medical Images

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ABSTRACT

Computer aided algorithms plays vital role in the analysis of medical images for disease diagnosis and therapeutic planning. The role of segmentation and classification are vital for the analysis of region of interest. This research work analyzes segmentation algorithms based on user interaction for abdomen CT/MR/US images for liver disorder analysis. The tumor classification is done from the extracted ROI and compression algorithms based on ROI less computational complexity. The algorithms are classified into three categories; manual, semi-automatic and fully automatic.The related works in each category are discussed and the inferences are also highlighted.

Keywords; Algorithm, compression, classification , Region of interest, Segmentation,

I. INTRODUCTION

The rapid growth in enabling technologies has simplified the tasks related to collection, generation, accumulation and storage of volumes of data at an incredible pace across different systems and applications. Digital Image Processing (DIP) is a challenging area of research having widespread applications across variety of industries. Digital Image Processing focus on the techniques related to processing digital images by means of a digital computer [1]. Image processing algorithms plays vital role in disease diagnosis and therapeutic planning.The segmentation of liver is really a challenging task in CT/MR imaging, since there is variability in the size of liver. The figure 1 below depicts the three cases of liver data sets with variable liver size.

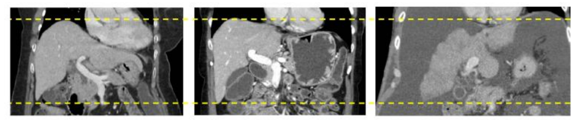

Figure 1: Typical liver shapes [1]

The above figure indicates that, choice of segmentation algorithm is vital, since the shape of liver varies and a universal algorithm cannot be used for all cases. The segmentation algorithms in general are grouped into manual, semiautomatic, fully automatic techniques. The semiautomatic technique involves less user interaction and fully automatic techniques are gaining importance for real time applications. Section 2 describes the related works in segmentation based on the nature of interaction with the user and finally conclusion is drawn in section 3.

2. RELATED WORKS IN SEGMENTATION

The segmentation techniques are broadly classified into 3 categories; manual, semi-automatic and fully automatic. Also based on the evolution of algorithms, they can be categorized into three generations as depicted in figure 2.

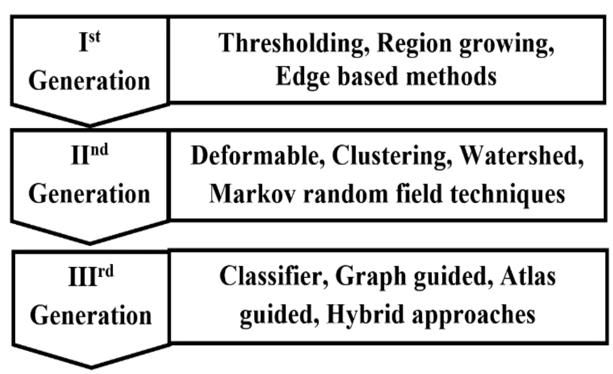

Figure 2; Classification of segmentation algorithms

2.1. Manual Segmentation

The manual segmentation involves much user interaction and it is time consuming. In liver segmentation, manual segmentation involves contour selection of pixels for the extraction of liver parenchyma on CT or MR data sets. After the extraction of liver, post processing is performed for the generation of liver volume. The problem in manual segmentation is that user variability in selection of ROI. The classical manual segmentation is not well suited in clinical practice, hence assisted contouring and in painting techniques are used in manual segmentation. The examples of assisted contouring techniques are active contours, live wire and shape interpolation [2 3 4]. The snake is a classical active contouring algorithm that extracts the ROI by the user defined set of points [5]. Many variation of classical snake models are there for the extraction of ROI. The input image should be preprocessed properly prior to segmentation and the parameter selection is crucial, since there is a chance of leakage in the object boundaries. The active contour algorithm is the basis for the software SliceOmatic created by Tomovision [6].

The live wire is a graph based approach in which the pixels are represented by graph vertices. The user chooses the seed point and free point that aids for the segmentation of liver. The 2D livewire algorithm is the basis for the software HepaVision created by MeVisLab [7].The shape interpolation enables the user to interpolate a 3D structure using contours. The shape interpolation was coupled with the live wire algorithm for a refined result. Smart paint is an assisted in painting algorithm for the extraction of liver parenchyma [8].

2.2 Semiautomatic Segmentation

The semi-automated techniques requires less user interaction when compared with the manual segmentation techniques and the best examples for semi-automated segmentation are intensity based approaches(seeded region growing) and graph cut techniques [9 10 11]. The intensity based approach does not have control over shape and sometimes result into over segmentation. The MR segmentation of the liver is a challenging task due to the heterogeneous structure of liver parenchyma. In graph cut technique, the user chooses the seed points for the extraction of foreground and background regions.

A comparative analysis of semiautomatic and manual segmentation algorithms for liver segmentation have been analyzed in [12] on MR images. The semi-automatic segmentation requires less manual intervention and statistical analysis has been performed on computation time of algorithms .A semi-automated 2D region growing algorithm was proposed for 3D CT images [13]. The time involved by the user to define the ROI was low and knowledge based features are used to estimate the shape and size of the tumor. The preprocessing was performed by median filter of kernel size 3 ×3, the results were not much satisfactory for lesions of low contrast.The liver volume analysis was done in [14] and a segmentation algorithm was proposed for the fat extraction on MR images. The segmentation was done by 2D active contour model and 3D reconstruction was performed. The statistical analysis was performed by anova and can be used for liver surgery preplanning.

A semi-automatic hybrid segmentation algorithm based on the multi scale filters with ride oriented region growing algorithm was proposed in [15] for the liver vessel segmentation on CT images. The morphological operations are used in the post processing stage and for validation hit rate, root mean square error are used. A comparative analysis of 3 segmentation algorithms ; 2D region growing based on knowledge parameters, propagation learning based 2D voxel classification and Bayesian rule based 2D region growing techniques on CT images [16]. The algorithms are compared based on the user interaction, computation complexity and segmentation error.An interactive algorithm was developed for the liver tumor analysis on CT/MR images, validation was performed by dice coefficient [17]. The hybrid algorithm is proposed in this work and it comprises of watershed with region merging procedure. Prior to segmentation, Gaussian filter was applied and sobel edge detector was applied. A computer aided 3D liver treatment planning system was proposed in [18], a semi-automatic algorithm was employed for tumor extraction, tumor size and its location was also determined for therapeutic application on CT and ultrasound images.

A hybrid algorithm comprising of thresholding with region growing was proposed for the extraction of liver and tumor regions [19]. The segmentation result was refined by morphological operations.The ROI was extracted from ultrasound liver images by partitioning technique; feature extraction was done by complete local binary pattern. For the classification of liver tumor, Support Vector Machine was employed [20]. In [21], a comparative analysis of various segmentation algorithms like thresholding, watershed, connected component labeling, clustering, neutrosophic and region growing are proposed for the segmentation of liver from abdomen CT images.

2.3. Fully Automatic segmentation

The fully automatic segmentation algorithms requires very less intervention and is widely used in clinical practices. In

[22], a 3D liver tumor model was proposed from the 2D MR parallel system images. The interpolation and extrapolation model relies on the shape model and morphological operations are also used. The Taubin's surface fairing algorithm was used for the smoothing of local surface irregularities. The generated 3D tumor models are used for preplanning in cryosurgery.

The neural network was coupled with the wavelet texture feature extraction for automatic classification and segmentation of liver diseaseson CT images[23]. The orthogonal wavelet features along with the statistical features are used for the training of probabilistic neural network to classify normal and fatty liver. An accuracy of 95% was obtained for the data base comprising of 100 images.A full automatic segmentation algorithm based on probabilistic model was proposed for the Non-contrast X-Ray Torso CT images[24]. The Gaussian function was employed for the probability density estimation of liver. The algorithm was tested on non-contrast CT images with performance evaluation have been done.A detailed study has been performed on semi-automatic and fully automatic methods for liver segmentation[25]. The fully automatic methods though is having many advantages, it has some challenges and issues to be addressed. A novel gray level based segmentation was proposed in this work and the data set comprises of normal, fatty, cirrhotic and tumors.

In [26], a segmentation model based on intensity analysis and anatomical information was proposed for liver segmentation on CT images. The algorithm comprises of expectation maximization, double thresholding and anatomy based rule for the extraction of ROI. The algorithm have been tested on MICCAI database and performance validation have been done. In [27], atlas based segmentation of spleen and liver was proposed for CT images. The initial segmentation was done by geodesic active contour, contrast enhancement was done and finally the segmentation was refined by the adaptive convolution technique and finally a normalized probabilistic atlas was constructed for segmentation. The performance evaluation was performed by dice coefficient and root mean square error. The multi class linear discriminant analysis was used for dimensionality reduction and probabilistic atlas was generated for segmentation on MR images[28]. The segmentation algorithm comprises of region growing and thresholding, finally border refinements are performed. The MR images are having segmentation challenges due to missing edges, motion artifacts and low signal to noise ratio.A 3D level set algorithm was proposed for the fully automatic liver segmentation in MR data sets[29]. Prior to segmentation, preprocessing was performed by 2D anisotropic diffusion filter and probabilistic map was generated. The segmentation performance was evaluated on fatty liver and non-fatty liver data sets.

A hybrid segmentation algorithm comprising of region growing and FCM was proposed for the tumor extraction and for classification, feed forward neural network was employed on CT images. The feature extraction by contourlet transform gives better results than wavelet based feature extraction [30].An automatic technique was proposed for the classification of liver disorders, for feature extraction, wavelet packet tree was employed and for classification, SVM was used on ultrasound images[31]. A detailed survey has been performed on the liver disorder segmentation and classification on CT, MR and ultrasound images. The algorithms are validated in terms of the performance metrics also[32].An object based 3D segmentation algorithm was proposed for the analysis of liver lesions [33]. Prior to segmentation, masking and feature extraction was done on CT images. The performance metrics evaluation yields efficient results and is used to find out the missed lesions after the examination by radiologist.

In [34], liver segmentation was done by improved fast marching algorithm, for blood vessel segmentation, maximum intensity projection (MIP) along with the 2D region growing technique with morphological operations are employed on CT images. For the segmentation of liver tumor, a user defined seed point was used. The liver, blood vessel and tumor segmentation aids the treatment planning. In [35],liver region was segmented by connected region growing, tumor was segmented by using Alternative Fuzzy C Means clustering algorithm on CT images. The contourlet transform features are extracted along with the first order and second order statistics. The probabilistic neural network was used for the classification of tumor stages. The probabilistic atlas was used for the initial segmentation of liver, for the segmentation of tumor, graph cut algorithm was applied on CT images[36]. The 3D features are extracted and for classification of tumor stages, support vector machine was applied.

The endoscopic ultrasound medical imaging modality provides detailed anatomy of the liver. In [37], different techniques are proposed for the endosonographic liver segmentation. The robot assisted thermal ablation of liver tumor was proposed in [38] on contrast enhanced CT images. The treatment planning module comprises of image registration, tumor segmentation and 3D visualization. The ultrasound imaging modality was found to be efficient for the detection of fatty liver disease on mice models [39].In [40], a detailed review was done on the different automatic segmentation algorithms on abdominal images. A 3D liver segmentation approach based on active contour model was proposed in [41]. The input image was replaced by a probability map derived from the statistical model of the liver. The segmentation result was refined by total variation dual approach. The liver biopsy is a classical technique to analyze non-alcoholic fatty liver disease [42]. A new quantitative ultrasound was proposed for the identification of steatosis in animal models. The results were found to be efficient, when compared with the MRI modality. In [43], three different neural networks are employed for the classification of fatty and cirrhosis liver disease on CT images. The Probabilistic Neural Network (PNN), Linear Vector Quantization (LVQ) Neural Network and Back Propagation Neural Network (BPN) are employed for the classification; performance metrics evaluation reveals that PNN is efficient for classification.

A hybrid segmentation technique comprising of spatial FCM and parametric deformable model was proposed for the segmentation on liver CT images [44]. Atlas based segmentation was employed for the extraction of liver and for the fat estimation, chemical shift base method was employed on MR images [45]. The statistical shape atlas was framed initially and is supplied to the deformable model for a refined segmentation. An automatic segmentation algorithm based on cascaded convolution neural network was employed for the segmentation of liver and for the segmentation of liver lesions; 3D conditional random field is used [46]. Efficient results are produced on abdomen CT data sets; quantitative analysis reveals the efficiency of the proposed segmentation approach. The classical thresholding was improved by the incorporation of fuzzy logic and Shannon entropy for the segmentation of tumor on CT images [47]. The tumor dimensions are determined and the fuzzy based Shannon entropy generates optimum threshold value with a segmentation accuracy of 93%.A hybrid segmentation algorithm comprising of watershed and active contour model was used for the fully automatic segmentation of liver on MR images [48]. The segmentation result was refined by the morphological operations and for evaluation, gold standard images are used.

A hybrid segmentation algorithm comprising of FCM with grey wolf optimization was proposed for the segmentation of liver from abdomen CT images [49]. For feature extraction, grey level concurrence matrix was used and for classification, Support Vector Machine was used. The segmentation accuracy of 96% was obtained for healthy liver classification and 97% for disease liver classification.The multilayer perceptron with 3D deformable model was employed for the segmentation of liver tumor on CT images [50]. The proposed algorithm was tested on 95 metastatic liver abdomen CT data sets. In [51], a detailed study has been done on the liver segmentation algorithms on the CT, MR images. The liver volume is estimated from the liver segmentation and

2.4 Inferences from the survey

The works related with the liver tumor segmentation and classification on different medical imaging modalities like CT, MRI and Ultrasound images have been analyzed. The works are analyzed based on user interaction and the algorithms are grouped into manual, semi-automatic and fully automatic techniques. In segmentation, CT is found to be better than MRI, because of high spatial resolution. The portal venous phase is more useful, since it depicts the liver parenchyma. The contrast agents are induced in the MRI modality for the enhancement that aids well for segmentation and analysis. The features of different segmentation methods are depicted in figure 3.

Technical approach		Reproducibility	Robustness	Time	Interactivity	Complexity of implementation
2D	Manual	↑	↑	↑↑	↑↑	↓↓
	Manual with assisted contouring	↑↑	↑↑	↑	↑	↓
2D and 3D	User-initialized & semi-automated	↑	↓	↓	↓	↑
	Fully automated segmentation	↑↑	↓↓	↓↓	↓↓	↑↑

Figure 3: Features of segmentation model [13]

The green color indicates that feature is favorable and red color indicates that feature is not favorable. The up arrow indicates the positive in the feature and down arrow indicates the negative in the feature. The number of arrows indicates the level of positive and negative feature. In the case of manual segmentation techniques, consistency will be there in the extraction of ROI from multiple slices of same data set, however since much user interaction is there, reproducibility and robustness will not be much good, so a single up arrow is used for those features. The computation complexity and user interaction is high for manual approaches; hence the features are represented by two up arrows. The algorithm complexity is very low in manual approach; hence the feature is represented by 2 down arrows. The features for manual assisted contouring are represented in second row. The features of semi-automatic and fully automatic algorithms are depicted in row 3 and 4. The choice of segmentation algorithm relies on various features; anatomical organ to be delineated, imaging modality etc. the parameters to be tuned in an algorithm also plays vital role, less number of parameter tuning is efficient, since the end users are physicians and radiologist. The computation time also should be low for an efficient segmentation algorithm.

3. CONCLUSION

This research work analyzes segmentation algorithms for liver disorder analysis. The algorithms are analyzed based on the nature of user interaction. Some of the related works in manual, semi-automatic and fully automatic algorithms are analyzed and the inferences are also made from the survey. The outcome of this research work will be an aid for those who are developing novel algorithms for segmentation taking into consideration of the bottle necks of the existing approaches.

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