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Survey on Liver Segmentation Schemes in CT Images

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ABSTRACT

In the field of medical image processing, the segmentation of liver in computed tomography images are of enormous significance. Dividing schemes into two categories that are semi-automatic and fully automatic schemes. Both classes have some techniques, approximation, related queries; some drawbacks will be described and clarified. To obtain a liver segmentation, there is an analysis on methods for segmentation of liver as well as techniques using computed tomography images are shown. Following the relative study for liver segmentation schemes various measurements, scoring for liver segmentation are given; advantages and disadvantages of techniques will be emphasized carefully. Several faults and difficulties of the suggested methods are still to be focused.

I. INTRODUCTION

Now a day, in an area of medical image processing, the segmentation of liver in computed tomography images have enormous importance. It is the start and an important action for detection of liver diseases, liver volume measurements and 3D liver volume rendering. To bring out the liver data or information, a manual process and visual inspection are used, which is very time consuming process and process of ideas to fix a problems. Dividing the methods of liver segmentation into two categories that is methods of semi-automatic and methods of fully-automatic segmentation of liver. The image processing and machine learning theories gives the more knowledge about these two methods of liver segmentation. Furthermore, it is not an easy task because of low level contrast and indistinct boundaries which are used to identify the computed tomography images. The above features are generated by the partial volume effects because of spatial averaging, patient movement, and beam hardening. In addition, same types of gray levels may be used by neighbor organs in the body like spleen, liver, and stomach. For now, same type of gray levels cannot use the same organ related to the same topic. All these characteristics, difficulty with huge diversity of liver shapes enhances the problem in the liver segmentation task.

II. LIVER VOLUME SEGMENTS

Basically, segmentation of liver by CT images is divided into two different classes that are partially/semi-automatic method and automatic liver segmentation method.

2.1 Semi-automatic scheme for segmentation of liver

In these schemes, it needs a little user involvement which is used to complete the task. The involvement for this task is changes from chosen of seed pixels manually to a manual refinement of a binary mask for the liver. The latest Semi-automatic methods for segmentation of liver are obtainable, and according to image processing techniques, these methods are predetermined.

2.1.1 Graph based semi-automatic schemes

Images are handling by weighted and undirected graphs, where pixels called the vertices, and neighboring pixels are view as connected vertices. The weights of the edges in the graph calculate the likeness among two connected vertices. The involvement of user used in the methods of segmentation of liver via the operation for the selection of seed points and via steps for modification. Normally, the live wire algorithms as well as the graph-cut segmentation algorithms are used under this class.

Barrett and Mortensen (1997) to remove edges in medical images, they planned an algorithm for live wire segmentation. To find the least cost paths among seed points which are already by the user is calculated by the algorithm of live wire segmentation. The weighted sum of Image features such as the gradient value, gray value, gradient direction, and Laplacian zero-crossing are used to compute the cost of the path. Firstly, initial seed point will be selected by the user which lies on the boundary of the organ, after that the opening from the elected seed point (already classified by the user in the image), then Dijkstra's search algorithm or dynamic programming algorithms are used to calculate all possible least-cost paths. User will select the boundary of the image.

Schenk et al. (2001) expand the above liver-wire method for segmentation of liver in computed tomography images, also helps to decrease the users communication and calculation period. The cost function is calculated via determining the liver shape from the nearest adjacent slice in the body which is already segmented. User has capability to manage the process of segmentation which is supported by algorithm of liver-wire segmentation. Job of the user will be restricted by choosing the seed points and selecting the most wanted edges where as the processor will manage the details

Beichel et al. (2007) used in their research the graph cut segmentation algorithm. They anticipated in computed tomography images depending on the method of graph cut segmentation, 3D interactive liver segmentation approach.

2.1.2 Region-growing based semi-automatic schemes

This technique is based on reality in which the common gray values are shared by close pixels. Generally, this method is used in an iterative or replication manner in which the whole organ is segmented inside the liver at distinct areas. Manually recent pixels are added to the seed area as intensity of a surrounding area is below that of seed intensity under given limited value. Beck and Aurich (2007) engaged in their approach region- growing algorithm of interaction liver segmentation. They anticipated three dimension region-growers through nonlinear coupling criterion. User manually corrects the leaked regions or missing parts. By calculating the convex hull within restricted local regions around the boundary, the segmentation proceeds. This process is called post processing step.

2.1.3 Level sets based semi-automatic schemes

In this technique, user illustrates a rough contour from inside or outside the object, and then the contour will contract/enlarge. This algorithm comes under image segmentation problem. The process of contracting/enlarging will be terminated, when contour meets the object boundary. The major function managing the way of contour contracting/enlarging also determining the terminate point of this process is done by speed function. Liver segmentation methods under semi-automatic are classified into two groups, that are 2D level sets methods and 3D level sets methods.

2.1.4 Atlas matching semi-automatic schemes

Probabilistic atlases are established from huge number of anatomical images by a manual segmentation. By using affine transformations, pictures have been submitted into a standard space. These images as well as corresponding segmentations are then averaged and engaged into a Bayesian frame for constructing a probabilistic Atlas,. For every pixel, the randomness for a particular organ is calculated. At last, to bring out the needed organ which depends on the later probability a simple thresholding or conditional mode algorithm is used. The probabilistic atlas requires a lot of training data can be gathered and physically fragmented which is its main disadvantage.

2.2 Fully-automatic liver segmentation schemes

By "fully automated" we mean that without any user involvement, segmentation process of liver will be applied. Normally, fully-automatic liver segmentation methods are highly valued by radiologists and also release by udders faults and partiality, as well as there is difficult and wastage of time plus save the operator from this drawbacks.

2.2.1 Deformable model based automatic schemes

Gao et al. (1998) proposed a liver and right kidney parameterized 3D models as well as explain the technique which adjusts them to abdominal computed tomography images. To calculate the matching between the image gradient direction and the deformable model unit surface, they will identify the term energy function. When the energy function reaches the least value, an optimal match is attained. Outcome of the segmentation of liver can be calculated via a radiologist, whereas to calculate the segmentation of right kidney, objective measurements will be used. Some Researchers in Montagnat and Delingette (1996) and Soler et al. (2001) intended to overcome these drawbacks; they merged this method and the method of an elastic registration by using a hybrid method.

2.2.2 Statistical shape model based automatic schemes

This model is constructed which gives a more instances of a contour. Every contour is characterized by set of n labeled landmark points. The instances of the labeled training are line up into a shared co-ordinate frame by the using reproduce analysis. For reducing the amount of squared distances to the mean of the set, it rotates, translates, and scales every training shape.

Lamecker et al. (2004) to attain a grand robustness to noise and outliers, he planned schemes for the segmentation of liver which depends on a SSM. This model is developed by using a semi automatic mapping procedure. Client or user involvement wants to spot the matching points on all liver training data. To confine the liver shape variations, the principle component analysis (PCA) is used. The statistical shape method is permitted after that to collapse inside the captured space of variation via best-matching profile technique expressed by Cootes et al. (1994).

2.2.3 Probability atlas based automatic schemes

Rikxoort et al. (2007) proposed a liver segmentation method which is based on pixels classification in grouping with a multi atlas registration. To present every pixel inside an automatically perceived area as liver tissue or background, K nearest neighbor (kNN) classifier is used. Firstly, every image is resampled to isotropic pixels in case of preprocessing. For detecting as well as correcting the rotations regarding the Z-axis, bones are noticed by thresholding and by applying different rotations X-direction is maximized. Then by thresholding, lungs are detected as well as the area of potential liver is restricted to a fixed height about the lower lung rim. (Rueckert et al. 1999) By using an affine transform followed by B-spines methods in multiple resolutions, the twelve selected training scans are listed to the current image. For this principle, a stochastic gradient optimizer optimizes a negative mutual information cost function which is presented by Mattes et al. (2003). To plan individual training segmentations to the current image, the resulting transformation fields are used. (Rohlfing et al. 2005) the three spatial features are based: they represent the percentage of the probabilistic segmentation above, left, and behind the pixels, this results probabilistic atlas segmentation. By using smoothing and morphological operations the outcomes are post-processed, when classifying each pixel in the area of the mask with a 15-nearest-neighbor classifier.

2.2.4 Rule based automatic methods

Chi et al. (2007) use dedicated scripting language: describe protocols which are utilized to remove dissimilar organization from that images which are already tested. Order of extraction is: background air, lungs and other intra body air, subcutaneous fat and muscle layer, bones within muscle layer, aorta, spine, heart, and liver. Image analysis is done when organization uses the previous detected structure during each removal step. These protocols can also include information regarding neighborhood relations, intensity distributions, geometric features, etc. An area of seed is selected by threshold the right side of the CT slice below the heart after containing the removed listed organization up to the heart, until an item conforming definite size criteria is perceived. A process related to region growing is initiated by using this seed region. With no use of supplied training information and factors which have not been systematically evaluated, all rules are defined.

2.2.5 Gray-level based automatic schemes

Gray-level based automatic methods depend on a statistical analysis for computed tomography segment that are physically segmented to calculate the liver gray levels. Several schemes make use of histogram analysis which depend on a previous data regarding the liver intensity range for the calculating the liver gray levels. The calculated values are used with a straightforward or cyclic process of thresholding to construct a binary map which characterized the liver and then this image processed morphologically to remove connected organs. The existing segmented image gives the information employed as a support for segment the present image or picture. Lastly, make use of active contours or B spines it assists to smoothing the edges of every computed tomography images

Seo and Park (2005) they proposed a scheme for segmentation of liver in contrast enhanced computed tomography images which depends upon algorithm of left partial histogram threshold (LPHT). The left partial histogram threshold removes other neighboring organs apart from the pixels variations. A multi-modal threshold follows histogram transformations that are used to find the ranges of gray level. Lastly, morphological filtering is managed to smoothing the edges of the image and removes the unwanted things.

The extraction of liver in computed tomography images and also used in computer aided liver analysis system; this scheme is planned by Pil et al. (2006). Measured the liver distribution, also employed to choose the region of interesting. Once the probability crossed 50%, the window will allocated as region of interesting when compared to the liver's value of existing probability. Then, to mine the liver regions, the watershed segmentation algorithm is used. The areas which are fragmented can be combined into the momentous areas which are used for optimal segmentation. Lastly, area of liver is chosen by previous data regarding the anatomic information of the liver.

III. COMPARATIVE STUDIES

Automatically fragmentation of liver, troubles are still there. The techniques for liver shape model repeatedly fail. When there is a complex shaped liver, the techniques for liver shape model always failed. Other methods also go through the common fault, the organs which are attached to the liver are failed to split. In computed tomography slice, the connected organs have an alike intensity exterior. A relation between the different techniques is not important because of the need of a common data and a distinctive calculation. Also distinct techniques and methods are experienced on little data sets also techniques performance is calculated which depends on self selected fault functions.

Heimann et al. (2009) calculated sixteen automatic scheme and interactive scheme for segmentation of liver. A much larger standard deviation of the ending scores can be examined by automatic methods when linking to the automatic and the interactive segmentation approaches. The large standard deviation occurs because faults form on outliers. Although, in the comparison of automatic method and interactive have same several successful outcomes in the comparison study of interactive methods, normally the consistency of automatic methods is yet poorer. Troubles occur at distinct test images and areas. Even though several regions cause more fault than additional regions, all methods are fail not even in a single region. When evaluating performance, this observation together with the great variation of results over different test images supports the call for a large and diverse collection of test. With the exactness of created outcome, methods are calculated. Segmentation with great exactness will be observed.

IV. CONCLUSION

The two schemes for the segmentation of liver that are semi-automatic and automatic liver segmentation using computed tomography images related techniques and suggestions have been examined. Even though, many methods for segmentation are tested, troubles always lie there. In reviewed methods, the level of gray based methods are used to achieve the optimistic results, but for database variation they are not that much strong. The high variability of CT intensity values does not examined by gray level estimation. When multifaceted and large data sets are used, the performance could decreases significantly. In addition, several methods needs physical involvements and also need some serious parameters to be experimentally estimated, robustness method is affected by all these facts. Methods of learning are based on the training set, and should select watchfully. There is requirement for plenty of information can be accurately gathered, also can be physically fragmented to create structure, the model based techniques and probabilistic atlases go through the some difficulty; this is because the training set as well as faults of users and unfairness are strongly affects the obtained model. Starting assignment changes the outcome of the segmentation. The algorithms will be unsuccessful while dealing with non standard liver shapes. It is hard to describe an accurate speed function and its factors are the main limitation. In addition, a relation between the different techniques is not important because of the need of a common data and a distinctive calculation. Furthermore, used datasets in mostly investigators are extremely little.

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