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Automated Segmentation of CT Liver Images: A Review

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Abstract—Segmentation of liver region from CT abdominal images has attained a massive importance in the field of medical imaging, Segmentation is the fundamental process for the identification of tumor present in the liver and also used to identify the various other diseases present in it. volume measurement of the Liver and its rendering also one of its major applications. Various automated methods for segmenting the liver images are reviewed in this paper and proposed a literature review. In general, segmentation techniques for Liver images can be semi-automatic and fully automatized in nature. In this paper, various approaches, applications and its related problems has been explained for the fully automatized techniques of liver image segmentation.

Keywords— CT liver Segmentation, Liver decease, Artificial Neural Networks, Machine Learning, Clustering based Methods.

I. INTRODUCTION

Liver disease is one among the foremost serious health diseases that cause death worldwide. Due to this reason, the liver image segmentation has attained importance in medical imaging field. The advances in digital image processing techniques have attracted various researchers towards the event of processed ways of automatic liver analysis. It's the primary and essential step for identification of liver tumors, liver surgical designing system which is a system for liver transplantation and 3D liver volume rendering. Manual segmentation of liver is feasible. However, it will take an immense time and intensive task an it is depending on variability of the operator Various techniques based on Machine learning are combined with the image processing techniques to get a semi-automatic and automatic techniques for the segmentation of liver images more effectively. However, liver image segmentation from abdominal images is a tough task due to the following three major reasons. First one is the appearance of low distinction and bleary edges of the liver. Secondly, the intensity of pixels in liver region is analogous and overlapped in nature with the nearer organs and tissues which are present in abdominal image area. Third reason is the liver is in non-rigid form and variant in position and it's terribly advanced. Due to these facts, the problem of the liver image segmentation task is substantially increased. In this paper, the author has a tendency to review the various segmentation techniques that uses the main automatic in nature. It conjointly highlights the numerous contribution of machine learning techniques in the field of medical imaging. Rest of the paper is organized as follows. Summary of automatic segmentation techniques is bestowed in section two. Totally different automatic ways that are delineated are briefly summarized in the section three and eventually the paper is terminated in section four.

II. SEGMENTETION OF LIVER IMAGES

Generally, liver image segmentation techniques may be divided in 2 categories [1]: It is semi-automatic, wherever the user interaction is needed and the automatic, wherever whole segmentation method is machine-controlled, and no user intervention is needed. A lot of Details of automatic segmentation techniques are given in next section.

A. Automated lung image Segmentation Methods

In automatic based method, the complete process is automatic, and these strategies are unit enforced with no user intervention. These strategies are typically most well-liked by clinicians as these give quick segmentation and it will be free from user errors. These strategies operator is freelance and conjointly in nature for saving the time. Next, numerous automatic liver image segmentation techniques are delineated.

1) Neural Network Based Methods:

Liver area was extracted from abdominal pictures of neural network is depicted in [2]. The various advantages of supervised based learning method are mentioned in [3]. The authors utilized an unattended way of learning the complete lung image segmentation. The authors planned an automatic methodology for segmenting totally different organs including the lung texture along with Hopfield neural network. Firstly, the image is scaled all the way down to grey scale levels. Secondly, order-based mathematics texture transforms (Haralick transforms) are applied for calculating the texture options of the image. The overall lung scan and texture image is then given as input towards the Hopfield neural network and therefore the image is clustered into varied organs. This proposed method is tested for various images and performance of the proposed methodology is very low. A back propagation which is primarily based on neural network is proposed in [4] for the purpose of machine-controlled segmentation of liver region from X-ray CT pictures of abdomen. A collection of values is calculated nfor every image during a window of size 5X5 which is centred at that overall image. Neural network is trained for these options for each and every image. Output of the network is binary image in nature wherever the entire pixels happiness to liver region are set to bright and the remaining pixels are set to dark.

Neural network is employed for distinctive segmentation of liver and abnormal liver region is given in [5]. This methodology consists of four main process such as image pre-processing, feature extraction from image, feature choice and classification of the given image. Throughout the feature extraction process, the step five is the set of methods which are extracted are applied using mathematics based, intensity-based approach, morphological based, frequency domain based and wave domain-based methods. Principal part Analysis is employed for feature choice. A feed- forward Multi-Layer Perceptron neural network is trained by back propagation rule for the chosen methods to require call of normal or abnormal in nature.

Combination of watershed method, and neural network has been proposed in [6]. This methodology includes two sequential steps: pre-processing and liver image extraction rule. Throughout pre-processing, edge preserved noise reduction is completed by applying mathematical morphology (morphological smoothing, intensity threshold and morphological gradient). Watershed based method is applied to gradient image to partition it to some regions. The feed forward neural network trained with back propagation rule is employed to liver extraction. These methods are employed in liver recognition.

Work of [6] is extended by applying combination of unvaried watershed rule and neural network for the automated segmentation of liver from database images in [7]. First, morphological smoothing, gaussian filtering and morphological gradients are used for noise reduction and edge improvement. When enhancing the image, watershed method is applied on scaled and thresholded gradient image. Ten biggest regions are designated among the divided regions by watershed-based method. Six shape-based methods are extracted for every region. Identical methods are extracted from the images of six totally different multilayer perceptron neural networks which are trained using the backpropagation method. For every region, the methods are iteratively extracted by watershed and neural network. All the methods which are extracted from each way are compared and therefore the overall error is employed to regulate the desired parameters mechanically. Consecutive, parameters are adjusted in many iterations. The liver region is finally extracted by the output of watershed rule with the optimum parameter.

2) Support Vector Machine Based Methods:

Automatic liver image segmentation uses the Support Vector Machine has been used in [8]. For providing stronga nd correct segmentation, they initially analyzed the various texture options of image so that they can use the combination of pixel-wised classifier and shape-wised trained worker. Three major steps square measure utilized in this approach. Firstly, the texture analysis method is applied for the purpose of extraction images in the input abdominal CT picture element level options. Ripple remodel is employed in [9] can be used as a texture descriptor. These texture descriptors are used as square measure input to support vector machine to classify the info into picture element wised liver space and non-liver space. SVM classification results misclassified pixels each inside the liver outside of the liver. Therefore, shape-wised trained worker i.e., set of morphological operations square measure are used to refine the results of SVM classification to urge correct delineation of liver.

A technique almost like higher than mentioned method is employed by authors in [10]. They initially used the texture descriptor, then combination of support vector machine classifier and form skilled worker i.e., set of morphological operations. However, in this paper, they used each Haralick descriptor and moving ridge rework as texture descriptor and compared outcomes of each of those and well-tried that use of moving ridge work as texture descriptor provides higher results than haralick texture descriptor.

The authors in [11] planned machine-driven liver image segmentation method using the support vector machine and texture description. Segmentation method started with texture classification. Moving ridge-based model is employed to drive input to support vector machine that classified pixels in liver and non-liver region. The divided liver using SVM classification isn't that much clear. For refinement of results authors used region growing methodology. For purification of holes and broken areas inside liver, dilation is employed. Misclassified pixels outside liver are removed by erosion. Even once these operations edges isn't so clear. For smoothness of edges, region growing is employed. Results are compared with manual segmentation.

3) Clustering Based Methods:

The clustering-based methods are described by the authors of [12] which is completely an unique and standard segmentation methodology that consists of an automatic shift based methodology which is supported by the complete detection of low-contrast dataset set which is present in the database which is in the form of a liver. This method consists of three stages i.e. pre-processing, classification and post-processing. Pre-processing consists of removal of fat tissue, the spine and ribs, right excretory organ removal and finding smallest potential region of interest (ROI). For removing fat tissue, which is associated in averaging, filter is applied, and its gradient is calculated. Modification of the gradient filter from negative to positive is taken into account as world minima that find a lobe that corresponds to fat tissue. For removing the spine and therefore the ribs, first off image is thresholded and its value of is 258. Row and Column projections of the entire image square is calculated and analyzed. These projections build a frame through spine direction and therefore the spine and ribs are excluded by dilating this frame. Right excretory organ is far from primary excretory organ and its removed by the K means algorithm. When removing the fat, the correct excretory organ, the spine and therefore the ribs, image is resized, and region of interest is chosen for reducing the computation quality. Second step is liver classification wherever the classifier is chosen supported knowledge dependent and automatic shift mechanism. Just in the case of different dataset, K-means is employed otherwise, for low images and a typical liver size, Multi-layer Perceptron (MLP) is employed. Results of segmentation method is improved through the post-processing process wherever a series of operations are applied.

Authors propose various automated segmentation techniques for low-contrast based pictures in [13]. Initial image was chosen and divided manually. Intensity mean, and variance of this divided images are chosen as previous data. In order to support this previous data, K-means clustering based methodology is employed to sight liver(object) and non-liver(background) areas. Graph cut is utilized to section liver region from these detected areas. Most contribution of this technique is that liver and non-liver regions may be obtained mechanically by K-means clustering in each low-contrast slice of volume. Associatively improved fuzzy c-means clustering which is an improved method, that categories things consistent with intensity and previous data has been projected in [14]. This technique composed of four major steps. Firstly, liver's location is roughly obtained by quick walking technique. Results of this method is maintained by broken-backed Hull algorithmic rule. To refine the segmentation result, associatively improved the fuzzy clustering which supported the previous data for combining with a multiple cycle process is intended. Throughout the third step, the liver is visualized by walking Cube methodology.

Modified K-means clustering rule is employed for liver image segmentation in [15]. K-means divides given dataset to variety of clusters. In K-means method, K-centroids are outlined one for every cluster. The most disadvantage is that hooked up organs don't seem to be removed properly. So, the authors have used morphological opening-by-reconstruction to enhance the performance. Authors compared their methodology with region growing and showed that increased K-means provides higher results than region growing. FCM based clustering methodology is used for the segmentation of liver tumor isn't terribly effective with clattery and with clusters of various volume and unequal sample sizes. Another FCM clustering rule is employed. Various Fuzzy C means algorithms suggests that the proposed (AFCM) may be a segmentation rule that's supported clustering which is similar pixels in AN unvaried manner, wherever the cluster centers are adjusted for all iterations [16].

4) Hybrid based methods:

Authors obtained promising results by applying multimodule neural network for various organ identification in [17]. This multimodule based network is predicated on grey levels and discourse data. When this method discourses neural network, morphological operations square measure applied to pictures to erase the noise. To deal with the difficulties related to form and position variations, seven spacial fuzzy rules square measures are utilized. Organ boundaries and its square measures are refined for supporting the relationships among the organ shapes in sequent pictures. This technique additionally has some limitations. The probabilities of failure accumulated in cases wherever the grey level of desired region is thus on the brink of the adjacent tissue that even a doctor couldn't delineate it.

Authors of [18] projected a combination of neural network and fuzzy primarily based technique, improved fuzzy cellular neural network and applied it to liver CT image segmentation. A new liver image segmentation algorithmic rule combining fuzzy C-means and multi-layer perceptron neural network is proposed in [19]. The initial image is chosen from series of liver CT databases. Threshold technique is employed for enhancing the standard of image. Fuzzy c-mean cluster and morphological reconstruction filter square measure to delineate the initial liver boundary. This metameric initial image is taken as sample image square measure to train the multilayer perceptron neural network. Neural network trained in this manner is employed for adjacent slice image segmentation. This method can be used for all the slices. During this technique, the initial image has got to be chosen due the ultimate results rely upon this image.

An automatic segmentation technique for liver resonance (MR) pictures supported by the self-organizing map (SOM) and hierarchical clustering-based technique is proposed in [20]. Initially, the first cut of four edges are away to decrease computation load. Median filter is applied on resized image to de-noise it. Native square measures are extracted for each picture. These square measure method acts as a feed to the input to Self-Organizing Map. The output prototypes square measure then filtered with the hits map and a hierarchical cluster technique is applied to the prototypes to pick the simplest segmentation for a quantitative image analysis index. This technique has some limitation as final metameric liver pictures don't seem to be sleek.

III. DISCUSSION

Liver image segmentation could be a terribly troublesome task owing to low distinction and blurred edges in liver pictures. Moreover, neighboring organs might need similar intensity levels. Manual segmentation is feasible, however it is operator dependent and a long task. So, various authors have planned many automatic ways to hurry up the method and to avoid wasting the time. Support Vector Machine is taken into account as best pixel-based classifier and provides smart results. However, the results of support vector machine would like more refinement. In clustering-based ways, initial image is to be chosen rigorously as a result of accuracy of ultimate segmentation depends there on image. In neural network-based techniques, grey levels are accesses by supervised learning of grey level options. But, supervised learning requires a large training information set. Neural network supported unsupervised learning ways for recovering the results. Although unsupervised techniques might give quicker segmentation, however accuracy of those ways continues to be poor as parameters of those ways might vary among completely different patients. Combination of various machine leaning techniques provides higher results than individual techniques. Although, individual ways have their own advntages and disadvantages. Various researchers in [1,21,22] reviewed many techniques for liver CT image segmentation. However, none of them provides the complete contribution of machine learning techniques in liver image segmentation. All the ways mentioned higher than are summarized in table 1.

TABLE 1 VARIOUS SEGMENTATION METHODS AND ITS RESULTS

Reference	Segmentation Methods	Data Set Used
[2]	Feed-forward based NN	Fifteen slices of three patients
[3]	Combination of Hopfield NN and Texture	CT image of two Patient s
[4]	NN	CT images of 10 patients

[5]	Feed-Forward NN	650 images of Liver CT images
[6]	Combination of Feed-Forward NN and Watershed based methods	60 Abdominal MR images
[7]	Combination of Multi-Layer Perceptron and Iterative Watershed based methods	120 Abdominal MR images
[8]	SVM based method	Contrast Enhanced CT images
[11]	SVM based method	Data set of 28 CT images
[12]	K-means Clustering	20 Data Sets consist of 12 bit DICOM images
[17]	Combination of Multi-module Contextual NN and spatial Fuzzy Rules	Lung CT images of 10 patients
[18]	Combination of Fuzzy C-means and Multi-Layer Perceptron NN	Lung CT Images
[20]	Hierarchical Agglomerative Clustering and SOM	Lung MR images

IV. CONCLUSION

In this paper, the suitable machine learning ways for automatic liver image segmentation, their merits and demerits are reviewed. Though various machine learning techniques such as neural network, support vector machine, clustering is projected for automatic segmentation however the matter of liver image segmentation continues to be open. Supervised learning methods requires a set of training and supervised based information which is initially and finally to be chosen properly. Unattended learning ways could provide higher results. However, the overall accuracy could vary among the completely different patients. Some methods want the previous data of overall liver dataset form and placement. Further, most of the methodologies need many by the way of experimentation calculated parameters that build the method computationally advanced. Many novel and advanced hybrid approaches is also developed for correct segmentation.

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