Ultrasound Image Segmentation based on Information Diffusion Model

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Abstract - Medical image segmentation is one of the fundamental and classic problem in computer aided diagnosis. Among different segmentation techniques, graph theoretical approaches attracted much research attention since it have many good features in practical applications. This work is an attempt in this direction. In this article a graph based approach for segmentation on ultrasound image is proposed. It makes use of information diffusion model in social networks. Proposed method is tested on a set of real ultrasound images and the result is compared with other graph based approaches. Computational complexity of this approach is comparatively less.

Keywords -Ultrasound Image Segmentation, Graph Based Image segmentation

I. Introduction

In clinical routine, computer assisted diagnostic processing has already become an important part [1]. It has increased much interest in the use of methods and tools for the management, analysis and communication of medical image data. As a result medical image analysis has experienced an immense growth as an interdisciplinary research field, attracting the research efforts from diverse area such as Applied Mathematics, Computer Sciences, Physics and Medicine. One of the fundamental and classic problems in image analysis is *segmentation*, which is the process of partitioning an image into disjoint, highly correlated, more manageable and meaningful homogeneous regions with respect to certain properties. Image segmentation plays a crucial role in understanding and managing image content for diagnosis and for mining in medical image database. Since the introduction of ultrasound imaging in clinical practice, accurate measurements of anatomical structures have been required. It is usually carried out by manual segmentation of the region of interest. This wearisome and error-prone practice is now supported by segmentation algorithms. A large variety of segmentation methods have been proposed over the past decade, see for example [2], [3], [4], [5], [6], [7], [8]. Typically, two design approaches are adopted in these image segmentation algorithms. One approach is user interactive and the other approach is automatic. In the former approach the segmentation is controlled by some degree of interaction with the user. For instance, the identification of the area of interest in the image is controlled by the user input. In the later approcah the segmentation is realized without any human intervention. As the criteria for segmenting the image varies from image to image and on the image aquisition methods, a reliable and accurate segmentation of an image, in general, is very difficult to achieve by purely automatic means. Despite many years of research, the problem of reliable automatic segmentation method is still very challenging, with the increasing amount of image data acquired from modern imaging devices. More over fast and accurate semi-automatic segmentation is still very much desirable due to the inevitable human oversight required in health care practice. As mentioned earlier semi-automatic segmentation techniques require a certain level of user interaction. For example in graph cut methods user selects initial seed points where as in active contour level set methods an initial contour is placed and in the region growing method user clicks a starting point. Interactive segmentation algorithms have become quite popular and mature over the past decade; see,[9], [10], [11].

Many segmentation methods are computationally complex, especially when run on large medical datasets. But many medical image applications require fast and accurate segmentation of data in order to be useful in decision making. Furthermore, the amount of data available for any given patient is steadily increasing which makes fast segmentation algorithms even more important. This work concentrates on segmentation methods on ultrasound medical images. In comparison with other medical images, ultrasound images have more noise, less grey-scale contrast and blurred boundaries of tissue. These features of ultrasound images degrades the performance of the common threshold and edge detection segmentation methods on such images. Several segmentation algorithms have been proposed for analysing medical ultrasound images [12]. Among different segmentation techniques, graph theoretical

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approaches have many good features in practical applications. In recent years, with the development of complex networks theory, the graph-based methods attracted much attention and it is widely using in image segmentation [2], [13]. This work is an attempt in this direction. In this article graph based approach for segmentation on ultrasound image is proposed. It makes use of information diffusion model in social networks. The rest of the article is organized as follows. The next section gives a brief description to graph based image model and social network analysis along with other basic concepts in image processing. Section III describes the methodology in detail and the results are analysed in Section IV. Section VI concludes the article.

II. Basic Concepts

An image is basically a two dimensional function of spatial coordinates, f(x, y), and amplitude of this function at a given coordinate gives the intensity value of the image. Digital image processing is application of various algorithms on the image to improve the quality of the image by removing noise and other unwanted pixels and also to obtain more information on the image. Among the various image processing techniques image segmentation is a very crucial step to analyse the given image.

A. Graph model for images

In graph based methods, image is modelled as an undirected weighted graph. A node in the graph represents a pixel and the edge weights measure the similarity or dissimilarity between nodes. Now the image segmentation problem can be reduced to problem of partitioning a graph into disjoint meaningful parts. Graph based segmentaion methods use the superpixel as the basic operating unit in order to reduce the image complexity. The image boundaries are first extracted via superpixels.

With the immense growth of information science in the last two decades, social networks analysis are gaining much importance. Since social networks form an efficient platform for the interchange of ideas and information, the process of information interchange attracted much attention on such systems. In social networks, the process is termed as information diffusion, where information is spread via the connected nodes. The independent cascade (IC) model and the linear threshold (LT) model are two commonly used diffusion models for social networks. The IC model assumes that a node can be activated independently by any one of its neighbours, while the LT model assumes that whether a node will be activated depends on the aggregation of its neighbours activations. Diffusion models are defined with the notion of neighbourhood. The neighbours with direct connections to a node could exhibit different forms of influence depending on their connectivity in the social network. In this paper, an extended IC model is used.

III. Methodology

There are several factors or artefacts that significantly reduce the accuracy of conventional segmentation methods and ultimately cause difficulty in interpretation. Most prominent artefacts inherent in the ultrasound images, such as speckles and low contrast, make it difficult to segment the ultrasound images. In situations where automatic segmentation is difficult and cannot guarantee correctness or reliability interactive methods are best opted. In this work an interactive graph based segmentation method is used which takes the advantage of reliability under users control.

To generate an initial segmentation Simple Linear Iterative Clustering algorithm is used. It segments the input image into multiple uniform and small compact regions called superpixels [14]. Superpixels of the image is used to reduce the complexity of the graph representation in pixel level. Simple Linear Iterative Clustering which is based on a spatially localized version of k-means clustering. It uses a very simple and efficient method similar to mean shift to decompose an image in to visually homogeneous regions. Each pixel is associated to a feature vector

$$\psi(x,y) = \begin{bmatrix} \lambda_x \\ \lambda_y \\ I(x,y) \end{bmatrix}$$

where $\lambda = \frac{rl}{rz}$. Simple Linear Iterative Clustering algorithm takes two parameters, first one is rz which is the nominal size of the superpixels and the second one is rl which is the strength of the spatial regularization. The input image is divided into a grid with size rz. The centre of each grid tile is then used to initialize the corresponding k-means and the segmentation of image is obtained by refining the k-means centres and clusters by applying the Lloyd algorithm. The procedure is as follows, the image is initially divided into a regular grid with $M \times N$ tiles and a superpixel is initialized from each grid centre x_i, where

$$M = \lceil \frac{I_w}{rz} \rceil \quad N = \lceil \frac{I_h}{rz} \rceil$$

$$x_i = roundi\frac{I_w}{rz} \quad y_i = roundj\frac{I_w}{rz}$$

Here, I_w, I_h are the image width, height respectively. The centers are then moved in a 3×3 neighbourohood to minimize the edge strength

$$edge(x,y) = \|I(x+1,y)I(x-1,y)\|_2^2 + \|I(x,y+1)I(x,y-1)\|_2^2$$

Then the superpixels are obtained by running k-means clustering, started from the centers,

$$C = \{\Psi(x_i,y_j), i = 0,1,,M-1 \quad j = 0,1,,N-1\},$$

thus obtained. Features and contours in the image are preserved by adjusting the iterations and region size. Graph modelling using superpixels reduces the complexity of the graph representation from hundreds of thousands of nodes to only a few hundred nodes. The next step is to represent the image by an undirected graph $G = (V;E)$. Each node $v_i \in V$ corresponds to a superpixel, and adjacent nodes are connected by edges $e_{i,j} \in E$. Each edge $e_{i,j} \in E$ has a corresponding nonnegative weight $w_{i,j}$. The edge weight is a measure of the similarity between neighbouring superpixels v_i and v_j in terms of the average pixel intensity and the variation in local speckle noise distribution.

The next step is to select the seed point for region of interest and background. Final segmentation method is modelled as an information spread over the network. The simplest model to predict the spread of an information over a network is the SIR model [15], [16], [17], [18]. The SIR model is originally used in epidemiology to compute the amount of susceptible, infected and recovered people in a population during an epidemic spread. The SIR model has three classes; Susceptible(S), Infected(I) and Recovered(R). It is assumed that the entire population N, is initially in susceptible state S. When an information burst out, members who are currently in state S have access to the information from their immediate neighbours and they changed to the infected state I. At the end of a certain time period, the information becomes old and is no longer propagated, thus the population recovers from its affect and is in recovered state R. In the proposed method a similar approach as that of information diffusion model is used to obtain the final segmentation from the initial seed points.

In this model the superpixels are initially in susceptible state S. A superpixel changes from state S to state I if it believes in the information spread from its immediate neighbour. The information acceptance rate of a superpixel in $S\chi$ is

$$(\lambda S\chi), \quad (0 < \lambda(S\chi) < 1),$$

that is, an S superpixel is infected with probability $\lambda(S\chi)$ if it is adjacent to a superpixel in state I. An S superpixel is adjacent to one or more I superpixels with probability $\theta(t)$ at time t. Thus, the infected probability for an S pixel at time t is

$$\lambda(S\chi)\theta(t).$$

Assume new superpixels are susceptible. As time passes, some superpixels lose interests in spreading information with rate μ to become inactive. Initially, just a few infected superpixels and most superpixels are in S state. As the information spreads, S superpixels become I superpixels gradually. Thus, the initial condition of the model is

$$I\chi(t_0) > 0, S\chi(t_0) = 1 - I\chi(t_0),$$

and

$$R\chi(t_0) = D\chi(t_0) = 0,$$

where $t_0 = 0$. Specifically, the problem is defined as follows.

Algorithm	
Step 1:	Generate initial segmentation of input image into superpixels using Simple Linear Iterative Clustering algorithm.
Step 2:	Construct a weighted graph corresponding to these superpixels. Adjust edge weight based on the average intensity variation and local speckle pattern
Step 3:	Select initial background and object seeds, store corresponding information, and set all the seeds in active state.
Step 4:	For each superpixel x in active state perform the steps 5 and 6
Step 5:	Spread information to immediate neighbour y with a probability based on the edge weight
Step 6:	If y is already carrying the information with a high probability, do not respond to x other wise accept the information and remain in active state
Step 7:	After each iteration if no neighbour responds, then set state of x as inactive.
Step 8:	If at least one superpixel is in active state then perform step 4 for next iteration otherwise stop

Initially object and background seeds are selected and all the background seeds are assumed to be affected by negative information and the objects seeds are assumed to be stored the right information. In this stage all these superpixels are in active state. At any point of time an active superpixel spread the information to its immediate neighbour, say x with a probability p. if x is already affected by the negative or right information it will not respond to the activity. Otherwise x is also affected by the negative information or store the right infromation based on the probability by which the negative information is spread from its neighbour or the probability by which the right information is spread. x become active and started to spread its state. If all the neighbours of x are either already affected by the information they may not respond to the activity of x and eventually x lose interest in spreading the information and it moves to inactive state. This process iteratively progresses until all the superpiexels become inactive. Now an image segmentation is obtained by the nature of information stored in the superpixels.

IV. Result and Analysis

Experiments are conducted to analyse how well the above mentioned segmentation method performs on a wide range of real ultrasound images, including test cases. The ground truth set for each of these test cases are used as a basis for the efficient evaluation of the performance of the proposed segmentation method. Experimental results of the proposed method for image segmentation is presented in figure 2. It shows that the proposed method achieves better results among other graph based methods for ultrasound image segmentation. The result is compared with two dataset on ultrasound images with manually annotated ground truth.

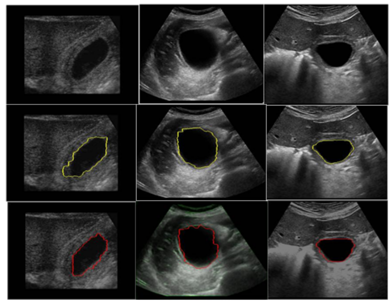

Fig. 1. Segmentation Result

Initially the experiments were conducted by adjusting the edge weight based on the average pixel intensity. Then the edge weights are adjusted by considering the local speckle pattern also. The results are shown in Figure 1. Evaluation of the proposed method is done by considering the area of overlapping of the region of interest obtained and ground truth area. The following parameters are analysed to arrive at a conclusion. True Positive (TP), which is the pixels belonging to the region of interest of the ground truth classified correctly by the proposed segmentation method. True Negative (TN) are those pixels outside of the region of interest of the ground truth that are classified correctly. False Positive (FP) is the set of pixels not belong to the region of interest of the ground truth but wrongly classified as region of interest by the proposed segmentation method. The False Negative (FN) denotes the pixels that are inside the region of interest of the ground truth but are incorrectly classified as out of the region of interest by the proposed segmentation method. These parameters are used to estimate accuracy (ACC), sensitivity (SEN), specificity (ESP), positive predictive (PDP) and negative predictive (PDN) as follows.,

$$ACC = \frac{TP + TN}{FN + FP + TN + TP} \quad (1)$$

$$SEN = \frac{TP}{TP + FN} \quad (2)$$

$$ESP = \frac{TN}{TN + FP} \quad (3)$$

$$PDP = \frac{TP}{TP + FP} \quad (4)$$

$$PDN = \frac{TN}{TN + FN} \quad (5)$$

Usually all of the measures $(1) - (5)$ are used to compare segmentation results. For a simple and efficient comparison combinations of these measures such as the Efficiency (EFI) and Youden index (Y-index) are used, which are computed as follows.

$$EFI = 1/2(SEN + ESP) \quad (6)$$

$$Y - index = (SEN + ESP - 1). \quad (7)$$

These measures are used to compare the efficiency of the proposed method with that of other graph based approaches such as graph-cut and modularity based methods. The comparison result is shown in Figure 2

	Proposed	GraphCut	Modularity
ACC	0.98887988	0.9528408	0.95489681
SEN	0.84234508	0.671468	0.80387694
ESP	0.99649533	0.9675907	0.96625394
PDP	0.92587646	0.745995	0.8307376
PDN	0.99184488	0.9625813	0.96391887
EFI	0.9194202	0.8195293	0.88506544
Y-index	0.83884041	0.6604587	0.79323089

Fig. 2. Comparison

V. DISCUSSION

Since the speckle pattern in an ultrasound image also hold some useful information for analysing the organ under observation, it is sometimes referred as texture. In this experiment the speckle pattern is also considered as an artefact and the speckle pattern in the image is also used to modify the edge weight in the graph representation of the image. For a better evaluation ground truth is used for comparison with the result of the proposed algorithm and the degree of error is evaluated by using valid measures such as accuracy (ACC), sensitivity (SEN), specificity (ESP), positive predictive (PDP) and negative predictive (PDN). The Youden index was suggested by W.J. Youden in [19] as a way of summarising the performance of a diagnostic test. Its value ranges from -1 to 1, and has a zero value when a diagnostic test gives the same proportion of positive and negative results, i.e the test is useless. A value of 1 indicates that there are no false positives or false negatives, that is the test is perfect. In this experiment it is observed that the Y-index value is more closer to 1 compared to other methods. Clearly the proposed method give more accurate results in comparison with other methods.

VI. CONCLUSION

Motivated by the importance of segmentation in many applications and in particular in the medical ultrasound images, experiments were conducted to analyse the graph based approaches for segmentation. It is observed that due to the challenges such as low contrast and inherent speckle noise in ultrasound images many of the segmentation algorithms results in poor performance on ultrasound images. Efficiency and simplicity of graph based approaches become a driving force to conduct experiment using graph model for representing the ultrasound image. Instead of using pixel level modelling, a superpixel level mapping is used to improve the robustness to noises and to reduce the computational complexity. Graph modelling using superpixels is less complex compared to pixel mapping. Initially interaction of user is used to control the quality of the segmentation. Then a final segmentation is obtained by using a modelling similar to information diffusion in social networks. In this study no human interaction is used in performance evaluation instead valid measures are used. Results produced by the proposed image segmentation algorithm is tested in a simpler way. The correctness is tested depending on whether or not it is consistent with the segmentations results in the ground truth. For this purpose the parameters such as True Positive, True Negative, False Positive and False Negative are used to measure the area of overlapping of the region of interest obtained by the proposed method and that of the ground truth area. Comparison of the proposed method with that of the other graph based approaches such as graph-cut and modularity based approaches are done by estimating accuracy, sensitivity, specificity, positive predictive and negative predictive. By computing Y-index the result analysis can be summarized and it can be concluded that the proposed method give more accurate results since Y-index values are more closer to 1 compared to the other graph based approaches.

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