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A robust graph-based segmentation method for breast tumors in ultrasound images

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ABSTRACT

Objectives: This paper introduces a new graph-based method for segmenting breast tumors in US images.
Background and motivation: Segmentation for breast tumors in ultrasound (US) images is crucial for computer-aided diagnosis system, but it has always been a difficult task due to the defects inherent in the US images, such as speckles and low contrast.
Methods: The proposed segmentation algorithm constructed a graph using improved neighborhood models. In addition, taking advantages of local statistics, a new pair-wise region comparison predicate that was insensitive to noises was proposed to determine the mergence of any two of adjacent subregions.
Results and conclusion: Experimental results have shown that the proposed method could improve the segmentation accuracy by 1.5–5.6% in comparison with three often used segmentation methods, and should be capable of segmenting breast tumors in US images.

1. Introduction

Breast cancer is one of the leading causes of death in women. Medical ultrasound (US) imaging has been regarded as one of the gold standards for breast tumor imaging, since it is not only inexpensive and fast, but also noninvasive and accurate [1]. However, the manual US image diagnosis is subject to the radiologist's experience and skills. It has been recognized that computer-aided diagnosis (CAD) can increase the efficiency and reduce errors of breast cancer screening by using the computer as a second reader. Segmentation is the most essential and important step for further tumor analysis in CAD system [2].

In the past decade, a large number of segmentation methods including thresholding, neural network (NN), deformable shape model, etc. have been proposed in the literature [3,4]. However, due to the speckles and low contrast which are inherent in the US images, it is often difficult to segment the US images and the detection of boundaries or contours has become an important method to extract the tumor areas. Consequently, the active contour model (ACM) also called Snake [5] has become a popular segmentation method for US images and has been extensively used for breast [6–8], cardiopathy [9,10], carotid artery [11,12], prostate [13,14], thyroid [15,16], etc. For breast tumors in US images, Huang and Chen [6] automatically found the initial contour by the watershed transform for ACM to determine the contours of the tumor. Chang et al. [7] applied an anisotropic filter, a stick procedure and an automatic threshold method to find the initial contours for the Gradient Vector Flow (GVF) Snake, and finally extended this method to 3-D case. Jumaat et al. [8], however, made a comparison between Balloon Snake and GVF Snake in segmenting masses from breast US images and found that the average percentage area difference in the Balloon Snake was much lower than that in the GVF Snake.

The ACM methods deform in an iterative manner to get as close as possible to the contours of breast tumors. They still are sensitive to noises and heavily rely on the initial definition of object contours [6]. Because of the blurry boundaries inherent in the US images, it is difficult to find out an automatic scheme for defining the initial contours. A poorly defined initial contour apparently results in inaccurate segmentation of regions of interest (ROI). Currently used ACM methods require the initial contours to be defined by either manual delineations or some complexly auto -initialized methods. For real-time applications or sequentially processing a large number of images, the contour initialization should be computationally efficient.

In contrast to the ACM methods, clustering, an unsupervised learning technique is an alternative for image segmentation which requires less user participation. Clustering is an iterative method to find clustering centers which minimize the squared distances between sample points and the clustering centers [17]. The image points with varying intensities can be regarded as samples and hence can be grouped into different clusters, which denote non-overlapped regions in the image. Accordingly, the segmentation methods based on clustering techniques are regarded as region

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based methods. K-means clustering and fuzzy C means (FCM) clustering are the two basic and popular clustering methods [17]. The clustering based segmentation can be automatically performed without the need to set the initial contour. As a result, the K-means and FCM have been applied for segmentation of US images [18–20].

Region based segmentation methods based graph theory have also been proposed [21,22]. It is called graph-based (GB) segmentation method. Taking into account global image properties as well as local spatial relationships, a GB method results in a regional map that can be used for further processing, e.g. region merging or labeling. In the GB methods, an undirected graph $G = (V, E)$ where each vertex $v_i \in V$ corresponds to a pixel and an edge $(v_i, v_j) \in E$ connects v_i with v_j is constructed. The edge weights in the graph are often assigned with the difference of intensity, texture or other features between vertices. Consequently, the image segmentation can be converted into the graph segmentation in which each subgraph corresponds to a subregion.

One typical GB segmentation method called efficient graph-based (EGB) algorithm was successfully applied to various images [23]. It consisted of two steps, i.e. the graph construction for mapping an image to a graph, and the mergence of vertices in the graph. Intrinsically, the EGB segmentation method acted as a clustering method and expanded (or merged) regions according to the local spatial, in addition to the global information. Therefore, the regions with similar intensity levels but different locations could be well divided into different segments. Due to their simple structures and reliable theoretical basis, the GB representations and techniques have been refined and extensively applied to many segmentation problems, including medical image segmentations of laparoscopic images [24] and mammograms [25]. To the best of our knowledge, however, little attention has been paid to applying them to US image segmentation due to their significant sensitivity to noises.

Accordingly, we proposed to apply a new GB method to breast tumor segmentation in US images. Due to the complex image artifacts existing in US images, a preprocessing procedure for reducing the speckles and preserving the boundaries was performed before the segmentation. To make the segmentation more robust to noises, a new pair-wise region comparison predicate for our GB method was proposed to segment breast tumor regions. In the new predicate, we took into account the local statistics and the measures of signal-to-noise ratio (SNR) of US images. We designed a new metrics for evaluating the segmentation performance of difference techniques, and conducted experiments to make comparisons among the FCM, K-means, EGB and RGB methods. The new GB method was named as robust graph-based (RGB) algorithm because it was relatively insensitive to noises, could be applied with relatively smaller ranges of the parameters, and could improve the segmentation performance in comparison with the EGB method. In addition, we used the FCM and the RGB as the initial contour estimation methods and combined each of them with an ACM (Snake) method together to assess the performance of each algorithm.

The remainder of this paper is organized as follows. The next section describes the new GB method. Then, the experimental results on US images of breast tumor are presented. The final section gives a discussion, draws the conclusions and introduces our future work.

2. Methods

In a GB segmentation method [23], the image was firstly represented by a graph in which each vertex denoted a pixel. An edge existed between each pair of neighboring pixels. The edge weights varied according to some criterion, e.g. intensity difference. The vertices were regarded as the smallest subgraphs at the beginning of the segmentation. A larger subgraph could be generated by merging smaller subgraphs. By repeating the merging procedure, the image could be segmented into several larger homogeneous subregions which were represented by corresponding subgraphs.

In this study, a novel GB method making use of the statistical information of each subgraph (subregion) was proposed. The utilization of the statistics of each subregion could significantly improve the robustness of the proposed method to noises comparing to the EGB method [23]. Hence, it was named as robust graph-based (RGB) segmentation method in this paper.

2.1. Speckle reduction

It is well known that US image often contains plenty of artifacts and noises due to the complex imaging environment and imaging principle, such as speckles and low contrast. They greatly degrade the performance of conventional segmentation methods. To improve the robustness of the RGB method to noises, a preprocessing procedure for speckle reduction was required. A nonlinear anisotropic diffusion (NAD) model which has been proved to be an efficient method for the speckle reduction was used. In this paper, the parameters in the NAD model were set as suggested in [26] (i.e. 10 iterations with a time step $\Delta t = 2$ per iteration, $\alpha^* = 1$, $s = 20$, and $\beta^* = 0.2$).

2.2. Graph construction

In construction of the graph, each vertex $v_i \in V$ corresponded to a pixel in the image, and an edge $(v_i, v_j) \in E$ connected v_i with v_j which were neighbors. For monochrome images, the edge weight w_{ij} was the intensity difference between v_i and v_j, i.e.

$$w_{ij} = |I(v_i) - I(v_j)| \tag{1}$$

where $I(v_i)$ was the intensity of v_i.

In a conventional GB segmentation method, the graph was constructed in an 8-connected neighborhood, i.e. a pixel had eight edges connecting to its neighbors as illustrated in Fig. 1a. One might be wondering whether or not it was necessary to consider all edges connecting any of two neighboring vertices. To answer this question, we took into account three types of graph structure in which a pixel had less edges connecting to its neighbors, i.e. the 6-connected neighborhoods and the 4-connected neighborhoods as illustrated in Fig. 1b–d, respectively. The segmentation performance for the new types of graph was evaluated and an appropriate type of neighborhood was suggested for segmentation of US images. As the number of edges was reduced, the structure of the graph was simplified and the amount of computation was decreased, hence the algorithmic efficiency could be improved.

2.3. Pairwise region comparison predicate

Having constructed a graph in which each subgraph represented a single pixel, we needed to merge these subgraphs with similar intensity levels and form larger subgraphs (i.e. non-overlapped subregions). In this procedure, whether the boundaries

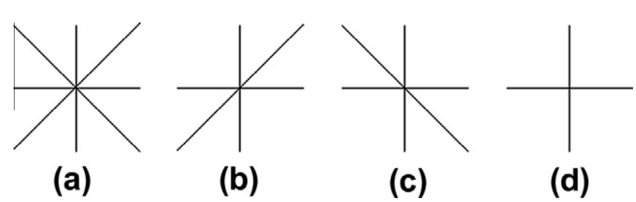

Fig. 1. Four different graph templates where the lines denote the edges, and the intersection point and the endpoints of edges denote the pixels. (a) 8-Connected neighborhood, (b) 6-connected neighborhood (left), (c) 6-connected neighborhood (right), and (d) 4-connected neighborhood.