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Local graph cut in the Image Segmenter app for breast ultrasound images segmentation

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Abstract
Breast cancer is among the most common cancers diagnosed in women globally. To help the breast cancer diagnosis, an important step is to accurately segment the breast lesion. To support clinicians in this important step, we analyze the performance of a semi-automated segmentation method based on the Local Graph Cut technique in the Image Segmenter application. Local graph cuts algorithm has the ability to segment more complicated shape by converting the image into a graph representation. It employs seed points set by the user and a cost function. The user identifies certain pixels as foreground and background. The region properties are identified from these pixels and they allow to specify the probability of a pixel belonging to the background or foreground. The graph cut formulation assigns each pixel to a node in the graph and incorrectly segmented pixels are re-assigned until the desired segmentation is completed. To evaluate the segmentation results, the Dice similarity coefficient and Fréchet distance were calculated between the ground truth images and the segmented images. Results show a Dice score of 0.7754 for malignant lesions and 0.8842 for benign lesions. The average Fréchet distance values were 303.28 for malignant and 290.80 for benign lesions, respectively. The experimental results show that the method achieves the best performance and gets the higher Dice score and Fréchet distance for breast benign lesions against malignant lesions.

Keywords: breast lesion; Local Graph Cut; Image Segmenter application; Dice score, Frechet distance

1. INTRODUCTION

Breast cancer is one of the most frequently diagnosed types of cancer among women. In 2022 it was estimated approximately 30% of newly diagnosed breast cancers in women. There has been a decline in the death rate since 1989, which is due to advances in treatment and earlier detection through screening [1].

Breast ultrasound imaging (BUS) is an inexpensive medical imaging technique that allows for an early detection of breast tumours. Accurate localization of regions of interest (ROIs) and lesion segmentation is a challenge for computer-aided diagnostic (CAD) systems for breast ultrasound images. The very first step in the diagnosis and analysis of breast cancer-based BUS is the tumour area localization. Segmentation is a difficult task and its results largely determine the performance of the CAD system. In semi-automatic segmentation methods, the user specifies a ROI that contains the lesion [2 ,3]. The BUS image segmentation procedure achieves the separation of the region of interest (ROI) from the background and other tissue structures [4].

A variety of approaches have been introduced in the literature for the ROI localization step.

Combining geometric features with segmentation of breast lesions from BUS images can be used to help doctors provide a correct diagnosis [5]. Moraru *et al.* [6] propose a segmentation technique for enhancing object edges that adapts image features to different forms of breast lesions. Various research methods to assist radiologists with breast mass classification and tumour mass segmentation in mammograms were presented in [7]. A CAD based on deep learning technique to detect, classify and segment the breast ROIs was proposed. This tool performs pre-processing to remove noise, artifacts, and muscle region in the image as they cause a high false positive rate. Two deep learning-based instance segmentation frameworks, i.e., DeepLabV3 and Mask RCNN were employed. The reported average precisions for the segmentation were 0.80 and 0.75, respectively, while the radiologists' accuracy was 0.80 and 0.88 for the two segmentation frameworks. Two convolutional neural networks, one having a Direct Acyclic Graph architecture and one with a serial architecture, were used for the segmentation of breast lesions in the study [8]. The ability to detect the contour irregularities of the lesions in BUS images was evaluated and the following average values were reported: 0.956 for global accuracy; 0.876 for IOU; 0.6877 for F-measure and 0.892 for Dice coefficient. Wang *et al.* [9] used AIDE (Annotation-efficient deep learning) as an open-source framework, to handle imperfect training datasets. AIDE is used for breast tumour segmentation on three datasets containing 11,852 breast images and produces segmentation maps comparable to those provided by experienced radiologists. The segmentation performance provided by AIDE is similar to that of fully supervised models. Mean Dice values of 0.690, 0.654 and 0.731 were obtained for the three data sets, respectively. The results showed that the proposed method can be a valuable tool in clinical practice, to help radiologists obtain a breast tumor segmentation. Daoud *et al.* [10] proposed a method for automatic segmentation of BUS images in two phases. In a first step, the image was decomposed into superpixels with a high boundary recall ratio. Then, they used both the edge- and region-based information techniques to outline the tumor. The evaluation of the segmentation performance was done on a database containing 160 BUS images and the obtained results proved that the method allows automatic and accurate tumor segmentation. An automatic multiscale superpixel method was proposed for the segmentation of breast ultrasounds in [11]. This method transforms the original image into multiscale images. An efficient superpixel boundary decomposition of multiscale images was created for these images. Then, the tumor region is generated using the segmentation method by the boundary graph cut. The results indicated a segmentation accuracy of 97.3% for benign tumors, 94.2% for malignant tumors, 96.4% for cysts and 96.7% for fibroadenomas. Huang *et al.* [12] proposed a new segmentation method based on the semantic classification and patch fusion. The results of the segmentation showed that the method provides competitive results compared to other conventional methods with a F1-score of 89.87% and the average radial error of 9.95%.

The proposed approach consists of the following steps: (i) segmentation of US images using the Local Graph Cut technique in the Image Segmenter application; (ii) analysis of breast mass segmentation performance using the Dice similarity coefficient and Fréchet distance. These metrics were calculated between the ground truth images and the segmented images.

The paper is organized as follows: section 2 presents the experimental database use in our study. Section 3 presents the proposed method. Section 4 presents the experimental results and the discussions and the section 5 presents the conclusions.

2. EXPERIMENTAL DATABASE

The experiments were carried out using ultrasound images that belong to the BUSI (Breast Ultrasound Image Datase) database [13]. BUSI is a publicly available database containing 780 images of which 133 are normal, 437 benign and 210 malignant, in .png format with an average size of about 500 x 500 pixels. The dataset also provides ground truth images that were generated by radiologists in collaboration with IT specialists. Images were acquired from 600 women between the ages of 25 and 75 using a LOGIQ E9 and LOGIQ E9 Agile ultrasound scanner. They were collected by Baheya Womenś Hospital for Early Detection and Treatment of Cancer (Cairo, Egypt) (Fig. 1).

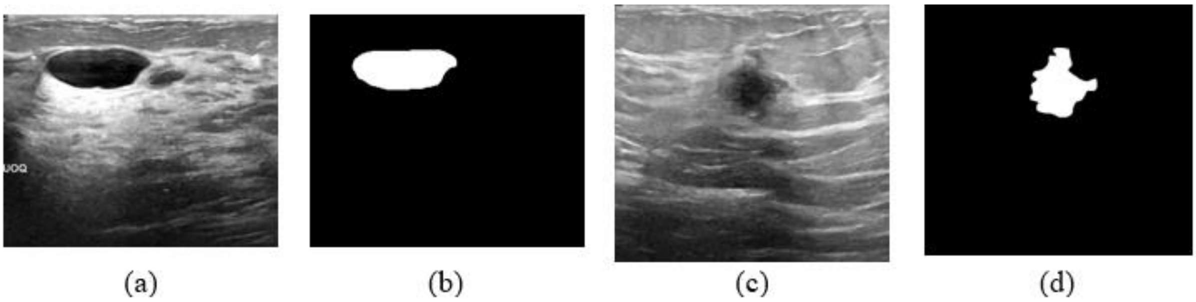

Fig. 1. Breast ultrasound images of BUSI dataset. (a) Gray scale image of a benign lesion; (b) Ground truth for benign lesion; (c) Gray scale image of a malignant lesion; (d) Ground truth for malignant lesion [13].

3. METHOD

Image segmentation is the process of dividing an image into regions based on the characteristics of the pixels in the image. One way to find regions in an image is to detect the sharp discontinuities in pixel values, which usually indicate edges, which can define regions. We analyze the performance of a semi-automated segmentation method based on the Local Graph Cut technique in the Image Segmenter application. Local graph cuts algorithm has the ability to segment complicated shape by converting the image into a graph representation. It employs seed points set by the user and a cost function. The user identifies certain pixels as foreground and background. The region properties are identified from these pixels and they allow to specify the probability of a pixel belonging to the background or foreground. The graph cut formulation assigns each pixel to a node in the graph and incorrectly segmented pixels are re-assigned until the desired segmentation is completed. Breast mass segmentation is initiated by drawing the region of interest. The region of interest framing will determine the selection of the area to be segmented. To draw a region of interest, two diagonal points are selected.

To evaluate the segmentation results, both the Dice similarity coefficient and Fréchet distance were calculated between the ground truth images and the segmented images. The Dice coefficient measures the degree of overlapping between the result predicted by the Local Graph Cut technique and the actual segmentation performed by the radiologists and it is as [14 , 15]:

$$Dice = \frac{2 \times (X \cap Y)}{X + Y} \tag{1}$$

where, X and Y represent the region of the ground truth and the region generated by the Local Graph Cut technique, respectively. The Dice similarity coefficient values are subunit and values close to 1 indicate a high segmentation performance.

The Fréchet distance evaluates the similarity between geometric objects [9]:

$$Frechet = max(\max_{a \in S(y`)} \min_{b \in S(y)} \|a - b\|, \max_{b \in S(y)} \min_{a \in S(y`)} \|b - a\|) \tag{2}$$

where S(y′) and S(y) indicate the boundary points on the predicted and on the reference boundaries.

The flowchart of the proposed approach is showed in Fig. 2.

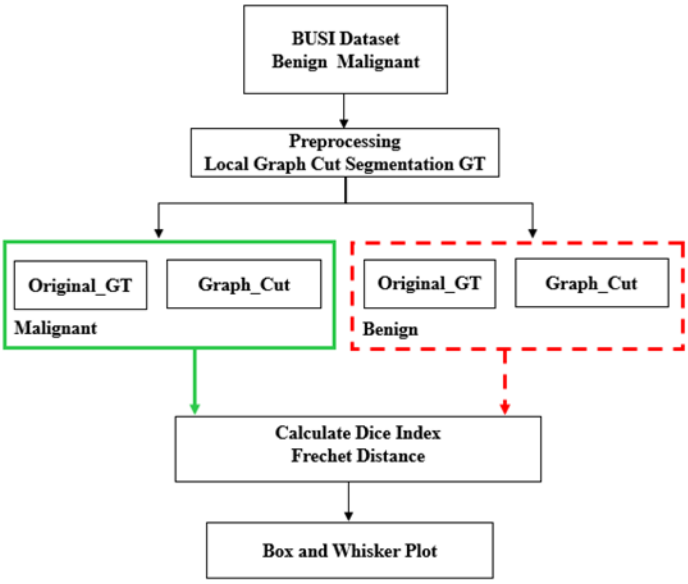

Fig. 2. The framework of the proposed approch.

4. RESULTS AND DISCUSSION

An important step in the correct diagnosis of breast cancer is the segmentation precision of the breast lesion. To achieve this goal, the Local Graph Cut technique is employed to segment breast lesions from BUS images of the BUSI database. Then, for each segmented image the Dice similarity coefficient and the Fréchet distance between the ground truth images and the segmented images are determined.

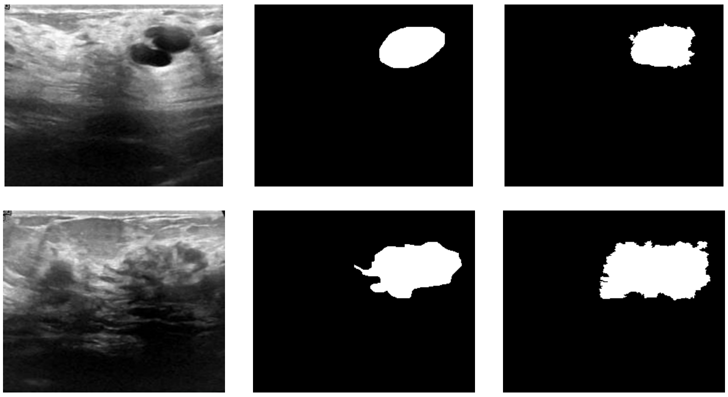

Fig. 3. Segmentation results. From left to right, they are the original image, segmentation ground truth provided by radiologists and segmentation result of Local Graph Cut. The top row is for a benign lesion and the bottom row is for a malignant lesion.

Figure 3 displays a visualization of the segmentation results by Local Graph Cut technique. On the top row is an example of benign lesion image corresponding to the original image, ground truth provided by radiologists, and the segmentation result provided by the Local Graph Cut algorithm. On the bottom row is shown a malignant image.

To evaluate the segmentation results, the Fréchet distance between the extracted contours of the ground truth images and the segmented images has been calculated (Fig. 4). To demonstrate the efficacy of the segmentation, the overlapping contours used to determine the Fréchet distance are presented in Figure 4e.

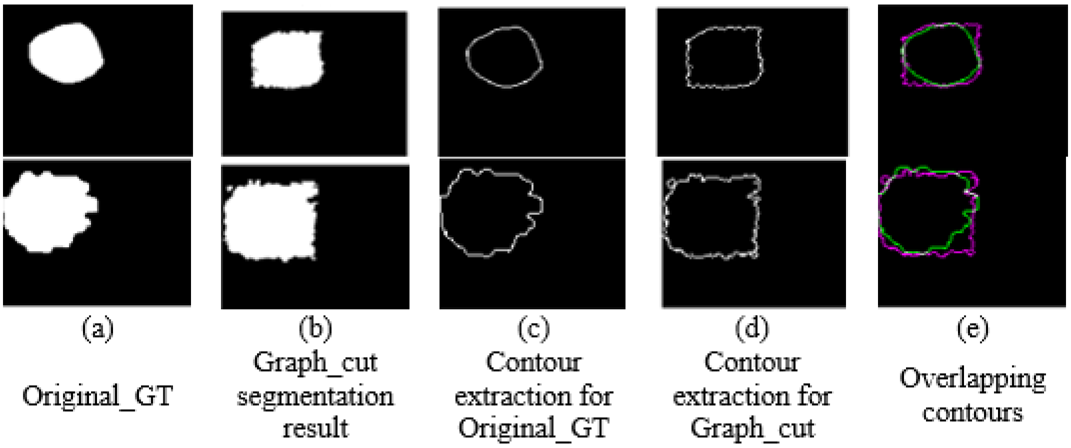

Fig. 4. The top row shows a benign image (from left to right correspond to segmentation ground truth provided by radiologists, segmentation provided by Graph cut algorithm, outer contour estimation for ground truth provided by radiologists, outer contour estimation for segmentation result based on Graph cut algorithm and overlapping contours of the ground truth and segmented images). The bottom row shows a malignant image.

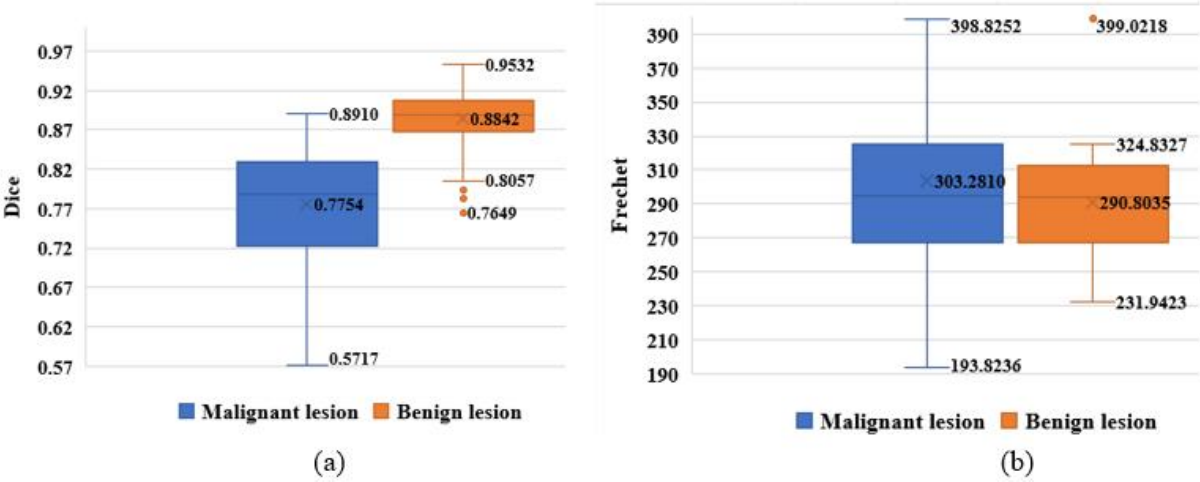

Fig. 5. Comparison of the performance of Local Graph Cut segmentation algorithm. (a) average Dice score; and (b) average Fréchet distance. The central lines indicate median values, the boxes the interquartile range and the whiskers the smallest and largest values for Dice score and Fréchet distance value, respectively

Figure 5 shows the quantitative evaluation of the performance of breast lesion segmentation in terms of similarity between the overlapping contours extracted from the ground truth images and segmented images using the Local Graph Cut algorithm. As it can be seen, the segmentation method achieved the highest score of Dice score and Fréchet distance for benign breast lesions. This finding clearly indicates that Local Graph Cut method can segment the benign lesions more precisely. The segmentation performance degrades when more irregular shape and spiculated contour are targeted. The reported results indicate that the success of disease monitoring mainly depends on the accuracy of the segmentation algorithm. Both the Dice score and the Fréchet distance show that the proposed semi-automatic segmentation method could be used by radiologists for the delineation of lesions in BUS images and to obtain a fast and accurate segmentation of the breast tumors.

5. CONCLUSIONS

Breast cancer is the most serious disease that can affect women's health. Both the diagnosis and treatment at an early stage of evolution has as result a mortality rate decreasing. In this framework, we have analyzed the efficacy of Local graph cut algorithm the breast lesion segmentation. The approach was validated using a similarity analysis between the results provided by proposed segmentation tool and the ground truth image segmented by radiologists. The experimental results show that the method achieves the best performance for breast benign lesions against malignant lesions.

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