Computational Sciences and Engineering 1(1) (2021) 51-56

University of Guilan

Computational Sciences and Engineering

journal homepage: https://cse.guilan.ac.ir/

Assessment of Mass Segmentation Methods in 3-D Ultrasound Images

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ARTICLE INFO

Article history:
Available online 02 May 2021

Keywords:
Breast Cancer
Mass
3D automated breast ultrasound
Segmentation

ABSTRACT

Breast cancer is the most common cancer between women worldwide. Although it is the leading cause of cancer death of women in the world, it can be prevented if it is detected and diagnosed at the early stages. There are various ways of detecting breast cancer varying from mammography to some basic clinical tests and procedures. Automated 3-D breast ultrasound (ABUS) is one of the most advanced breast cancer detection systems which is used as a complementary modality to mammography for early detection of breast cancer. However, it is notable that screening mammograms is so difficult and time consuming for radiologists due to the large variety in shape, size, and texture of 3-D masses in these images. Hence, computer-aided detection (CADe) systems could be considered as a second interpreter in order to assist radiologists to increase accuracy and speed. In this paper, we assess different approaches that have been implemented to segment masses in ABUS images. These approaches vary from pure image processing methods to deep neural networks based on which limits, advantages and disadvantages over each other have been compared.

1. Introduction

Breast cancer is the most common type of cancer among women, and it also is the main reason of women's death [1]. The main reasons causing this cancer are age increasing and getting old, not enough mobility, obesity and drinking alcohol [2]. Breast cancer is an important disease for women and it is the first factor of women's death between the age 20 to 59 [3].

The most effective way to confront breast cancer is the early diagnosis that allows doctors to identify and cure this illness is its early stages. Nowadays, the imaging modalities are continuesly under

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http://dx.doi.org/10.22124/cse.2021.19328.1006

development and one of the newest methods is Automated 3-D breast ultrasound (ABUS); the advantages of this method over mammography which is the most common method of imaging are as follows [4]: 1) the ultrasonic waves used in ABUS are less dangerous than the X-ray which is used in mammography. 2) mammography can lead to more false positives than ABUS. 3) mammography is less sensitive to dense breasts while ABUS is not like that.

Handle held ultrasound (HHUS) is a complementary modality besides mammography. Despite of its positive points it has limitations such as its high dependence on the operator [5]. Hand held ultrasound's limitations can be removed by using ABUS such that a transducer can automatically rotate around the breast and embed two dimensional slices until it can make up a volumetric three dimensional image [6].

2. Computer-aided ABUS Imaging

3-D ABUS imaging solves 2-D imaging-related issues. As mentioned before, a transducer is moved around or along the breast automatically and produces 2-D images which later will be used to make volumetric 3-D images and these images represents the corresponding breast volume. Some cross-sections of breast volume have been illustrated in Figure 1. The red arrow in the slices indicates the location of the mass contained in the breast.

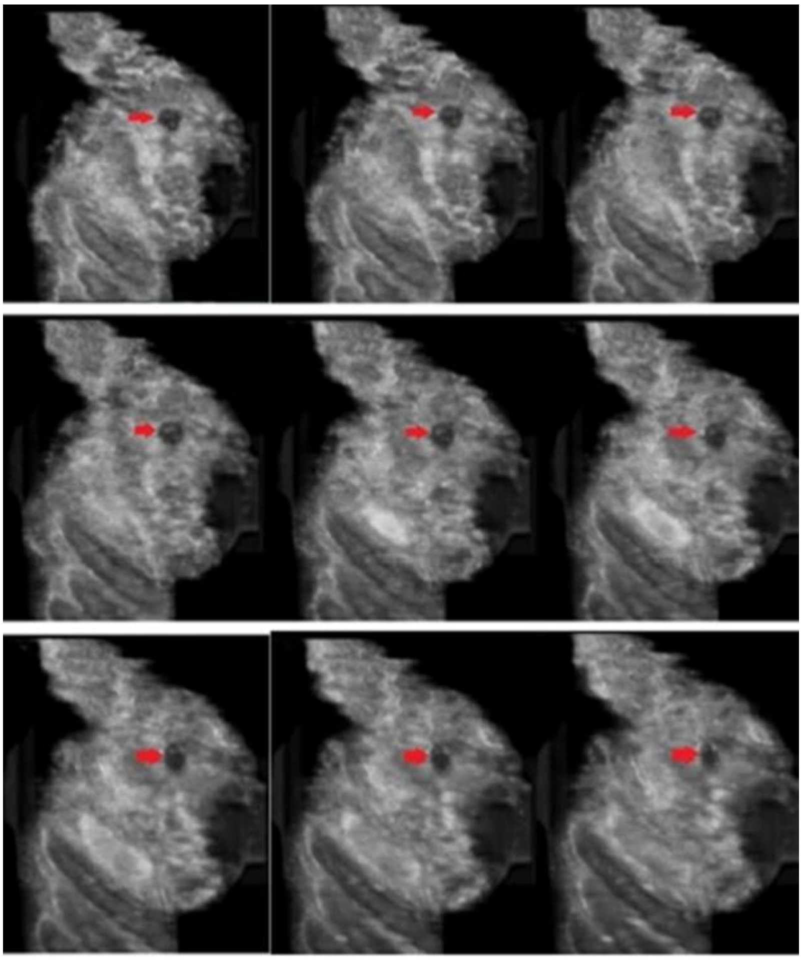

Figure. 1. Some consecutive cross-sections of a 3-D volume in coronal view [7]

3. Mass segmentation in 3-D ABUS images

The purpose of mass segmentation is the extraction of mass' boundary [7] and altogether, the following methods are used for mass segmentation [8]: 1-Thresholding based methods, 2-Clustering based methods, 3-Watershed based methods, 4-Graph based methods, 5-Active contour-based methods, and 6-Neural network-based methods. Active contour is the crucial factor of ABUS imaging-based methods. This method is used to determine the boundaries of objects in images [9]. In this way, an energy function is defined, which is the sum of internal energy (contour-wise related) and external energy (image-wise related) and the purpose is to minimize the function. Kuo et al. [10], used an active contour based model for mass segmentation. To this end, the Radial Gradient Index (RGI) method was used to produce an initial contour for mass boundary estimation. they used equation (1) as an RGI for each contour and concluded the Dice factor of 0.70. This model was first developed in 2005 by Lee et al. [11].

$$RGI_{3D} = \frac{\sum_{d\Omega} \vec{_G}(x.y.z) \cdot \overset{\wedge}{_r}(x.y.z)}{\sum_{d\Omega} |\vec{_G}(x.y.z)|}, \quad (1)$$

Tan et al. [6] improved a dynamic programming technique called spiral scanning for incorporating the mass boundary position. This technique was originally developed by Wang et al. [12] for lung nodule detection in CT images.

Deformable models are used for mass segmentation. Deformable models represent contours or surfaces which change under the influence of internal and external forces. Geometric deformable models are divided into two categories: Region-based and edge-based models [9]. Kozegar et al. [9] developed an edge-based model since region-based deformable models were not applicable to their problem. They used a technique called Distance Regularized Level Set Evolution (DRLSE) [13] for mass segmentation in 3-D ABUS images. They used a three-stage method in their next work [9] which was used for semi-automatic segmentation (the term "semi-automatic" means that the system used the regional location of the mass which is predefined before the classification begins). This three-stage method consists of noise reduction, pre-segmentation, and 3-D deformable models for accurate segmentation of the masses.They used an adaptive region growing algorithm at the first stage of this paper [9] and also a Gaussian mixture model(GMM) which works based on the volume and circularity of the training masses. At this part of the procedure, a Gaussian mixture model (GMM) is constructed using circularity and volume information of training samples. This GMM acts as a probability density function (PDF) which can be used to indicate the probability of the new samples being a mass [9]. In the next step of the segmentation, they used deformable models with an energy function (equation 2) as mentioned below [9]:

$$E = E_{DRLSE} + E_{shape}, \quad (2)$$

In the second stage of this procedure, a novel geometric edge-based deformable model is introduced using the results of the previous stage as the initial contour. In order to implement their algorithm, they used a dataset that was collected using the "ACUSON S2000" imaging system which is developed by the SomoVu company. Their dataset consisted of 50 samples (38 malignant and 12 benign lesions). They achieve a mean dice of 0.74 ± 0.19 by implementing their algorithm on the mentioned dataset. They also used the Optimized Bayesian Non-Local Mean (OBNLM) filter for reducing speckle noise impact and denoising.

4. Mass segmentation in 3-D ABUS images using Deep Learning based approaches

Ciresan et al. [14] used deep learning for the segmentation of neuron structures in electron microscope images for the first time. In 2015, Ronneberger et al. [15] introduced the U-net architecture which unlike the model that Circen and his colleagues introduced that only labeled one pixel, labeled a number of pixels simultaneously. In 2016, Çiçek et al. [16] introduced 3-D U-net, which was the improved version of U-net and you can see the model’s architecture in the figure (2). This architecture has a contraction path and an expansion path. 3-D U-net has three skip connections that help to extract data.

In 2018, Fayyaz et al. [4] introduced a method based on deep learning that used 3-D U-net neural network architecture for mass segmentation. In order to implement their algorithm, they used a dataset that was collected using the ACUSON and SomoVu imaging systems. Their dataset consisted of 50 samples (38 malignant and 12 benign lesions).

Fayyaz et al. faced two important issues in their research, the first problem was the huge size of the windows due to the big size of the mass samples that were approximately 80×270×270 pixels and this leads to many problems such as learning procedure being time-consuming of the and also the need to strong and cutting edge hardware. The other problem they faced was the unbalanced dataset they were working on. There were 1000 negative voxels for each positive one. In order to overcome this issue, instead of using the whole image as the input to the network, they chose a limited window around the mass, in other words, they use windows with a fixed size of 32×80×80 and the mass as it’s center. In addition, in order to improve the learning quality, they used techniques such as Up-sampling and Down-sampling, image rotation, and inversion.

Fayyaz et al. [4] introduced another method that was based on postprocessing. The mentioned algorithm is as follows:

1- The volume that has to be segmented, would be given to the network’s input in a 3D window.

2- The network’s output will be received based on the given input to the network.

3- The number of positive labels will be calculated in the voxels of the volume’s septum in the output of the network.

4- If the number of positive labels in the voxels of the volume’s septum was more than the given threshold, the input’s desired volume that is downsampled with the next scale will be given to the network and we will be back at the step number 2.

5- If the number of positive labels in the voxels of the volume’s septum was less than the given threshold, the network’s output will be enlarged and would be considered as the network’s answer.

Fayyaz et al. [4] used Adam optimizer for learning their network and also used 5-fold cross-validation for evaluating their outputs and used DSC (equation 3) for checking their network's accuracy.

$$DSC = \frac{2TP}{2TP + FP + FN}, \tag{3}$$

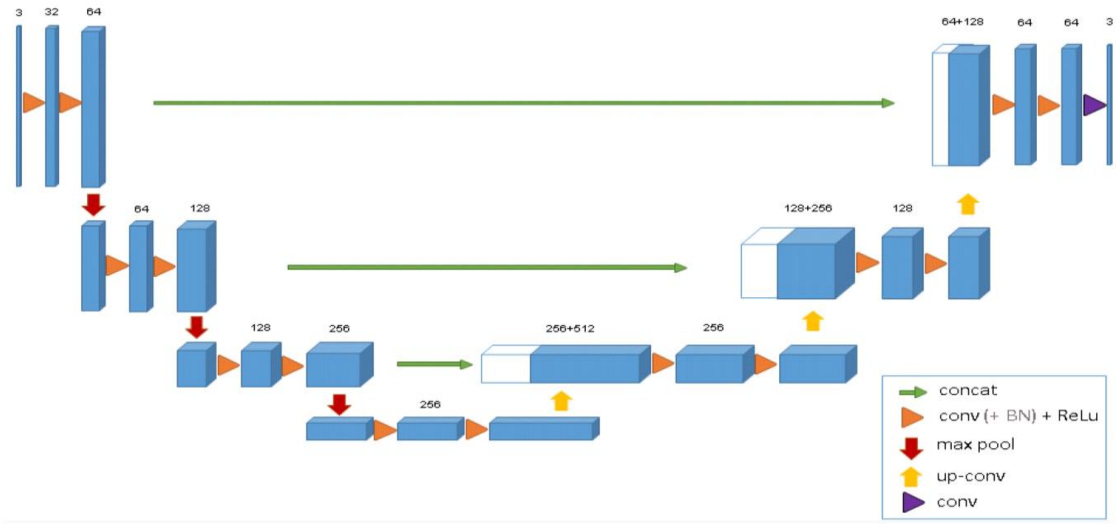

Figure. 1. 3D U-net neural network architecture [15]

5. Comparison of the results

In this section, we gloss over the comparison between the results of different researches regarding to segmentation of mass in ABUS images. Table 1 summarizes the accuracy of different methods in terms of Dice coefficient.

Table 1. The comparison between the results of different researches for mass segmentation in ABUS images

Author(s)	Date	Samples	Benign samples	malignant samples	mean dice
Fayyaz et al. [4]	2018	50	12	38	**0.77 & 0.59**
Kuo et al. [10]	2013	94	-	-	**0.70**
Kozegar et al. [13]	2017	50	-	-	**0.52**
Kozegar et al. [9]	2018	50	38	12	**0.74±0.19**
Tao et al. [6]	2016	78	-	-	**0.73±0.14**

6. Conclusion

In this survey, it was attempted to bring some light to the methods of imaging ABUS, also methods of imaging breast cancer and the pros and cons of aforementioned state-of-the-art methods compared to each other; furthermore, the researches regarding to segmentation of mass using base methods as well as methods based on deep learning and 3-D U-net neural networks architecture were studied.

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