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Ultrasound Image Segmentation Methods: A Review

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Abstract. Breast cancer is one of the leading causes of death in México and among the world. This is mainly due to late diagnosis and the price of cancer treatment. Ultrasound (US) is one of the most used tools for image-based assessment of this disease, since it can help discriminate solid vs. cystic masses, as well as between benign or malignant masses. However, ultrasound imaging depends largely on the radiologists experience. A detection not depending on such experience should produce better diagnosis; therefore, it is necessary to develop automatic detection systems for US images. These systems are based on the image segmentation, which is an image processing technique used to analyze and group pixels by their features. US image segmentation represents important challenges due to the complicated appearance of healthy and tumoral tissue in the ultrasound image that includes speckle pattern, low contrast, blurred boundaries, etc. In this work, we provide a review of tests and comparisons of various segmentation methods that had helped to detect lesions in US images, we present some visual examples to compare this methods and we evaluate their performance in order to develop computer-aided diagnostic systems that help radiologists to do better diagnoses.

Keywords. Segmentation, breast ultrasound images, breast cancer, ultrasound.

INTRODUCTION

Breast cancer is one of the main causes of death in Mexico and around the world. In Mexico, the adoption and improvement of different techniques for early cancer detection has been promoted. Recent statistics show that in 2009, only between 5 and 10% of cases cancer was detected in an opportune way. Late diagnosis difficult the treatment, reduces the likelihood of success and makes it more costly [6].

X-ray mammography is the only imaging modality that has been shown to lead to a reduction in mortality when implemented in screening programs in asymptomatic women. Ultrasound imaging can help increase the detection power of X-ray mammography in women with radiologically dense breasts. Also, ultrasound imaging can help differentiate cysts from solid masses.

One of the key steps in the analysis of ultrasound images of breast masses is the definition of its borders. This step is known as segmentation and this is a processing technique employed to analyze and to group pixels according to their features. Segmentation in ultrasound is very challenging due to the characteristics of the images, the speckle pattern, low contrast, fuzzy borders, etcetera.

A lesion segmentation tool that does not depend on the experience of the radiologist should reduce the subjectivity of breast ultrasound. It is necessary to develop automatic or semi-automatic detection systems for ultrasound images. Therefore, the goal of this work was to review the state of the art of segmentation methods for breast ultrasound images, and to report our initial experience implementing these methods in a public database.

METHODS

Image segmentation is one of the most important stages of image processing and analysis, with the goal of partitioning a region of interest (ROI) following certain characteristics and attributes [2].

There are plenty of segmentation methods effective in specific kinds of images. In the case of ultrasound images, traditional methods sometimes do not work satisfactorily because of noise or speckle patterns, complicating the visualization of lesion boundaries.

Thresholding

Thresholding [11] is the most basic segmentation method, consisting in setting an intensity value as a threshold, such that objects will be separated according to their intensity. If the image has a resolution of 8 bits and intensity value at some

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pixel is higher than the threshold, a value of 255 (foreground) will be assigned, otherwise its value is set to 0 (background), generating a binary image. This method does not consider pixel location, only its intensity. The method works fine for images with clearly different regions; since features in ultrasound images are not easy to distinguish, the choice of a threshold is difficult, often giving a poor segmentation. (Figure 1.c). In [9] the thresholding method with a variant is applied to ultrasound images. Due to the flexibility of their method, the segmentation was close to the ideal one.

In the case of ultrasound images, several tests have been performed with thresholding, but due to the speckle pattern they have, and the low contrast among different tissues, it is very difficult to determine the correct threshold, since information can be removed from the region of interest or leave a lot of information that is not relevant to the case study.

Clustering

This method partitions a data set, in this case an image, into *k* clusters depending on characteristics shared by the pixels. In contrast to the thresholding method, it does consider the pixel location, and segmentation is accomplished for pixels having similar intensities and placed close together.

In medical images the k-means method is employed for image segmentation and classification. In the case of ultrasound images, new clustering [7] methods have been developed where a region of interest is first selected, to restrict analysis within that region, discarding a large portion of the speckle pattern, Shan et al [7] created an algorithm that filters the image in the spatial-frequency domain, calculating the phase accumulation along the maximum energy orientation. Thereafter they used a variant of the k-means method, obtaining satisfactory results. This approach generated highly accurate borders in some lesions, but as it can be seen, it was not effective for many new ultrasound images, giving rise to other alternatives, as described next.

Active Contours

The active contours methods are based on physical characteristics and employed to delineate borders by using simulated elastic curves deformed under the influence of external forces, defined by image features, and by internal forces corresponding to the evolution of the curve itself [2]. This method requires of the definition of an initial curve to initiate the definition of the active contours.

Active contours are useful in the analysis of ultrasound images since the ROI segmentation does not depend anymore on the experience of the radiologist analyzing the image. The only requirement is for the physician to have a rough idea of the shape of the lesion, to initiate the application of the active contours. (Figure 1.e, image 4).

Neural Networks (NN)

The goal of a neural network is to classify the contents of the data, in this case an image. Neural networks separate one region of the image form another based on the importance of several features among the regions. These networks imitate the learning way of the human brain. NN methods are based on defining a pattern recognition algorithm based on training it with a data base. This algorithm is composed of an input layer, an output layer, and several hidden middle layers. In lesion segmentation problems, the *backpropagation neural networks* have been applied adjusting their synaptic connection weights. The connection weights are adjusted based on the of the resemblance of the output data to the output expected from the training data set. Another kind of networks are the self-*organizing maps* (SOM), which produce a feature vector from the main data characteristics. In the same way, the *hierarchical ANN*, interconnect several neural networks in a tree structure in order to extract further characteristics [2].

An advantage of this method is its high accuracy for lesion segmentation, making the method adapted for dealing with images, through its variant known as *convolutional neural networks CNN*. A disadvantage of this method is that it requires a lot of data in order to train the network and learn what is required for accurate segmentation of almost any input image. (Figure 1.f)

PRELIMINARY TESTS

In this work a database [10] with 210 images of malignant breast lesions is used to evaluate the segmentation methods presented. They were acquired with LOGIQ E9 ultrasound and LOGIQ E9 Agile ultrasound system in Baheya Hospital for Early Detection & Treatment of Women's Cancer, Cairo, Egypt. For each image there is a region of interest labeled by an expert. We present next a brief overview and comparison among the most employed methods.

- The images were resized to 512x512 pixels.
- The threshold for thresholding method was variable, it was calculated in MATLAB [12] for each image.
- The clustering method used was k-means, with k=2 (injury and background).
- The initial contour to active contour method was a circle in the center of the possible injury.
- The training dataset for neural network method was of 189 images and 21 images were tested. The CNN used was a U-Net [13] architecture with 23 convolutional layers.

RESULTS

To assess the segmentation accuracy, we compared the segmentation methods with the expert segmentation. We quantified the true positive segmentation pixels (lesion pixels in both images), true negative segmentation pixels (background pixels in both images), false positive segmentation pixels (lesion pixels in test images, background pixels in the expert images) and false negative segmentation pixels (background pixels in test images, lesion pixels in expert images).

Figure 1 shows the results of applying various segmentation methods on 6 different breast ultrasound images. Columns show, from left to right, the original B-mode image, results from expert segmentation (performed by the radiologist), thresholding, clustering, active contours, and neural network.

Table 1 shows the results in percentage of the quantitative analysis of segmentation performance in the 6 images presented in Figure 1. In general, the best performance was obtained with NN, while the poorest performance was obtained with thresholding method.

Table 2 summarizes the performance of each method applied to 112 images by showing the overall accuracy, precision, sensitivity. The considered ground truth value was the expert segmentation.

Image 1

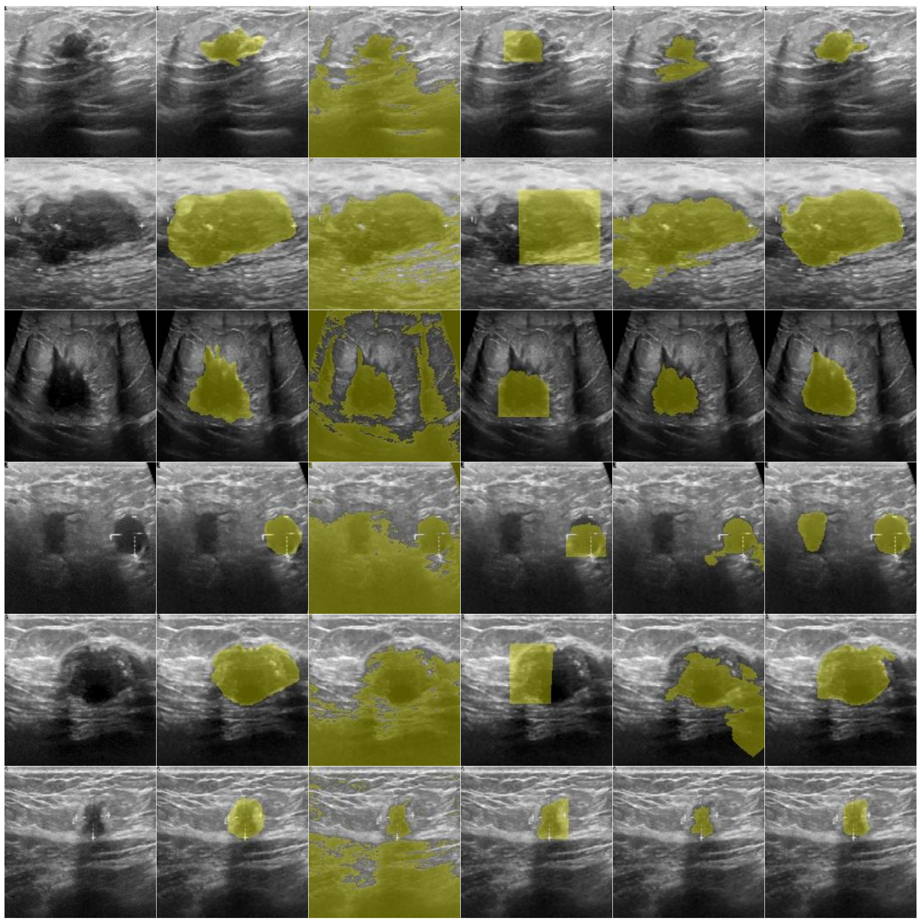
Image 2

Image 3

Image 4

Image 5

Image 6



(a) (b) (c) (d) (e) (f)

FIGURE 1. (a) Original image (b) expert segmentation (c) thresholding based method (d) clustering segmentation (e) active contour segmentation (f) neural network segmentation

TABLE 1. Quantitative analysis of segmentation methods on images of Figure 1

Image	Expert seg. area in pixels	Thresholding area (%)		Clustering area (%)		Active contour area (%)		CNN area (%)	
		TP	TN	TP	TN	TP	TN	TP	TN
1	15914	58.74	42.57	56.01	98.34	40.74	97.16	67.85	99.85
2	85626	88.97	49.46	60.98	90.34	82.05	87.07	88.36	99.18
3	33421	72.68	49.18	69.26	99.57	56.12	99.99	81.22	99.72
4	12900	87.04	43.32	74.51	98.77	77.99	98.23	94.22	95.52
5	45124	82.17	47.4	42.72	95.34	61.69	85.61	82.46	98.51
6	13341	47.76	53.34	73	99.22	37.91	100	67.14	99.99

TABLE 2. Metrics comparison

Metric	Thresholding	Clustering	Active contour	CNN
Accuracy	0.3484	0.9789	0.9693	0.9802
Precision	0.0488	0.6247	0.5600	0.7660
Sensitivity	0.9128	0.5429	0.7389	0.6583

DISCUSSION AND CONCLUSIONS

In our preliminary tests comparing different breast ultrasound segmentation methods, we observed that the most basic segmentation method of thresholding is not good enough for the ultrasound images. This result agrees with those reported on [3]. This poor performance could be attributed to the fact that thresholding does not consider information from neighboring pixels. The clustering methods, active contours and CNN showed better accuracy and sensibility indicating that, for the specific data inputs used here, the best segmentation is achieved with CNN. The reason why the sensitivity was lower compared to active contours is the low number of data examples for network training. This is evident in Figure 1(f), image 4, where some features were incorrectly classified, lowering the performance of the method.

The best methods for performing ultrasound image segmentation have proven to be deformable models and neural networks, although as mentioned, a disadvantage of the former is that a good manual initialization of the curve is needed for it to work properly, unless another method is previously used to establish the initial contour. On the other hand, CNN have been shown to be very good for classifying all kinds of information and, in our case, achieving a good segmentation of the image, but their great disadvantage is that a lot of data is needed for them to have a good training and work better.

At both, the Institute of Physics and the Institute of Applied Sciences and Technology at UNAM, work is underway to develop an automatic segmentation tool for breast ultrasound images, with the aim of creating an online segmentation system for these images that will help radiologists make more accurate image interpretation.

Although a few hospitals mostly in urban areas have very advanced ultrasound equipment that can even filter the image very well and segment the images themselves, smaller clinics and imaging services in rural areas still have equipment that delivers very poor quality images, which is a problem for physicians because it takes longer to mark the image and requires more experience on the part of the radiologists to be able to analyze them correctly. Having an online tool available can help them to be more accurate in their diagnoses and save them time, by helping them define the location of the lesion.

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