Nodules Segmentation in Breast Ultrasound using the Artificial Neural Network Self-Organizing Map

Karem Daiane Marcomini and Homero Schiabel

***Abstract*— This work presents a proposal for localization and delimitation of suspicious masses in breast ultrasound images by selecting regions of interest. The presence of speckle noise, which is a characteristic type of ultrasound images, becomes a difficult task to delimit a lesion. Some techniques of digital processing were applied in 50 clinical images of breast ultrasound, in order to minimize the noise allowing posterior extraction of their contour. The segmentation technique used to extract the contour was performed by means of the artificial neural network Self-Organizing Map. Then three evaluation metrics were used to compare the proximity of the automatically obtained area with the manual outline of a radiologist, resulting in percent values of 91% to accuracy, 67% to sensitivity, and 97% to positive predictive value, approximately.**

***Index Terms*— artificial neural network, breast cancer, image processing, ultrasound.**

INTRODUCTION

BREAST cancer the second most incident type in the world and first among woman, being second cause of cancer death in woman [1]. In 2010, about 209.060 new cases were diagnoses and 40.230 deaths registered in the United States [2].

Aware of this, screening techniques which allow early diagnosis and treatment have been studied in order to increase the chances of survival, using less aggressive treatment [1], [3]. Currently, mammography is the imaging modality more effectively in the evaluation of breast abnormalities, and the most effective tool for early diagnosis [4] presenting high sensitivity (ranges around 85-92%), although its specificity is low. Therefore, the chances of a false-positive result lead to unnecessary biopsies are high. Besides the risk of radiation, uncomfortable process and failure in detecting lesions in dense breasts. Thus, it is necessary to investigate alternative methods for the detection of breast cancer [3].

With recent technological advances, the ultrasonography has proved to be useful in evaluation of abnormalities in the breast, and became the main adjunct tracking technical to mammography screening. This procedure aids in characterization of masses found in mammograms (efficiency around 95%), avoiding the achievement of unnecessary biopsies (reduction of about 25-35% when used as a complementary technique to mammography) and eliminating the need of mammography control [1], [4] - [6].

The anomaly detection in medical images can causing errors due to the high subjectivity. Trying to minimize these errors and to help in early detection of breast cancer, CAD (Computer-Aided Detection) schemes has been developed to improve the diagnostic accuracy and support radiologists in the interpretation and evaluation of structures of interest present in the image, trying to minimize these errors and to help in early detection of breast cancer [7].

One of the great difficult of CAD schemes for ultrasound (US) is the image presents low quality, being significantly degraded due to speckle noise, characteristic of ultrasound images. Therefore, the segmentation, which is the most important task, is difficulted and becomes the main cause of imprecision for many CAD systems. This process attempts to identify objects with similar characteristics, separating suspicious regions of the background. Another task of this process is the obtained an accurate representation of the boundaries, whose characteristics can be evaluated and used in classifying of the type of lesion [3].

Considering these difficulties, this paper presents the evaluation of segmentation by artificial neural network (ANN) SOM to automatic detection of nodules contour in regions of interest (ROIs) from clinical images of breast ultrasound.

IMAGE DATABASE

For this work, it was selected 50 cases of breast clinical of ultrasound containing a suspicious mass that were diagnosed with breast cancer, obtained at Integrated Center of Image Diagnostic, in the Santa Casa of the Misericórdia from São Carlos – São Paulo, Brazil.

The images were acquired by a Siemens G50 equipment, using a linear array transducer of 7.5 Megahertz (MHz) B-mode and video signal with 8-bits resolution (256 gray levels) for its capture.

For each ultrasound image obtained, an experienced radiologist determined the location of one or more suspicious masses and cut regions deemed necessary using the ImageJ 1.45 software. These cutouts selected are called regions of interest (ROIs) and have rectangular shape which include the lesion and adjacent tissues.

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DIGITAL PROCESSING

Many detection algorithms were tested about the selected ROIs to provide the most appropriate boundary of the suspicion mass. The digital image processing techniques were employed using the MATLAB 7.11.0 (2010b).

A. Application of Preprocessing Techniques

To assist the detection, pre-processing techniques were applied in order to remove redundant information or unwanted noise, allowing an improvement in the constituent data [6]. According to Micahilovich et al. [8] the application of pre-processing improves a significantly segmentation instead of process it directly in the original images.

Seeking to reduce the speckle noise present in ultrasound images, before the segmentation, the ROIs were initially submitted to wiener filtering [9] with neighborhood window size of 5x5, to minimize the additive noise. Then, the contrast has been increased by image equalization [10]. Finally, it was held the median filtering [11], with 7x7 neighborhood window, allowing the noise smoothing (removing of possible “bright points” that appeared in the image due to contrast enlargement).

B. Segmentation

ANNs are intelligent models grounded in mathematical functions developed to resemble the workings of brain, modeling the achievement of a particular task. Thus, we used the Self-Organizing Map (SOM) network, which does not have a fixed topology, being modified according to the problem and data distribution. It is composed of 10 neurons in its input layer, fully connected to the topologic square grid of size 10x10. This grid performs the calculation of mathematical functions and the necessary adjustments. These connections are associated with synaptic weights which stock the knowledge of the model serving as a mechanism of response to input received by each neuron [12].

The SOM network uses unsupervised learning, wherein only the pairs of input are supplied and there is not a desired output. It is characterized by learning through examples of the external environment, where the algorithm adapts the parameters for a given data set, seeking convergence to a solution [12].

The learning process occurs via the self-organizing of the topological map in a competitive way. The input pattern creates a dispute among neurons to be activated. The activated neuron is called "winning unit" and their weights will be updated in the training, as well as the weight of their neighbors.

Based on the model proposed by Haykin [12], whose algorithm is defined in five steps, we construct a neural model for image segmentation. The algorithm can be summarized as follows:

Initialization: assignment random values to the initial weights. These values comprise the connections between neurons of input layer and output.

- Sampling: two classes of samples are collected (values corresponding to the white color set at 255 and black at zero) and, during the training stage, the output data must converge.
- Similarity correlation and updating: find the winner neuron (the most similar to the patter presented). The convergence process should be carried out in a maximum of 1000 cycles. Then, the minimization of the Euclidian distance is performed, and finally, the winner neuron is found and its area of influence in relation to the neighborhood (update of the neurons involved in this radius).
- Training: an auxiliary network is created in order to restrict the process and to converge it in only two classes (according to those presented in the sample). Then, the network receives the input image and classifies them according to the values obtained in the previous step.
- Continuation: returns the sampling until no longer observe any significant changes on the map.

C. Post-Processing

Aiming to eliminate the remaining vestiges of segmentation, we applied a post-processing on the image. For this, we considered that each ROI has only one lesion and this is the region that has the larger area. Thus, all connected components were found and the region of highest area were checked, which was considered as a lesion. Then, it was verified the connectivity, being removed all pixels not connected to this region. Finally, we analyzed the occurrence of internal valleys, so these pixels will be added to the segmented area, forming a single region.

EVALUATION METHODS

Quantitative measurements were obtained in order to evaluate the accuracy of the segmentation technique. For this, a radiologist traced manually the lesion contour. The delineated area, denominated "ground truth" (GT), was compared with that obtained by the automatic segmentation method proposed. If the segmented region coincided with the GT, it was denominated as a true positive (TP), however if the region was considered negative by the classifier, it was counted as a false positive (FP). On the other hand, if the pixels not belong to the GT and were classified as such, were defined as a true negative (TN), but if they were present in the segmentation, were considered as a false positive (FP). From this, we can derive three metrics: accuracy, sensitivity and positive predictive value (PPV) [10], [13].

The accuracy measures the number of correct classifications in relation to the total of classified elements, according to (1).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \quad (1)$$

The sensitivity represents the proportion of elements in the GT that were correctly identified. The calculation is performed from (2).

$$Sensitivity = TP/(TP + FN) \quad (2)$$

The positive predictive value, finally, corresponds to the proportion of pixels correctly classified in the segmented region, as shown in (3).

$$PPV = TP/(TP + FP) \quad (3)$$

RESULTS

The processing of an ultrasound image is a challenge due to speckle noise interference and imprecision of the boundaries [9]. In order to minimize the noise problem, we applied three filtering techniques: wiener filter, image equalization and median filter. The result of these methods of pre-processing can be seen in Fig. 1.

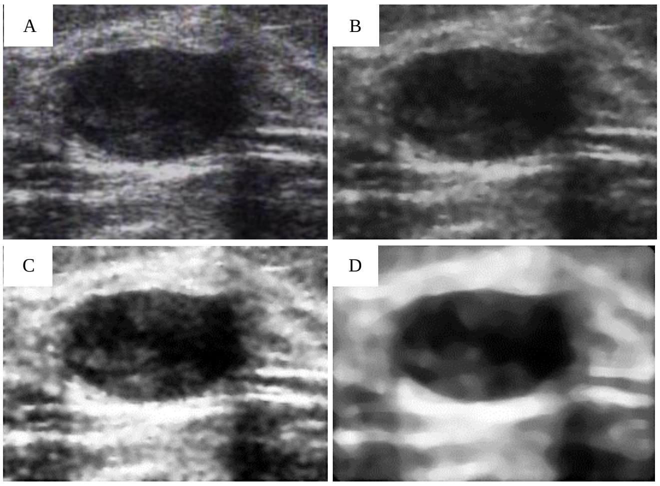

Fig. 1. ROIs of a breast clinical ultrasound image (a), processed by wiener filtering (b), equalization (c) and median filtering (d).

After minimizing the noise and increase the contrast between the background and the object, we apply the segmentation technique using an artificial neural network type self-organizing, in order to locate and delimit the lesion contour as accurately as possible. Trying to maintain just the suspicious mass on the segmented image, we used a post-processing algorithm to remove adjacent regions which not belong to the object of interest and junction of internal valleys. Finally, the contour obtained was overlapped on the input ROI for a qualitative visual evaluation, allowing verifying the consistence of the result presented by the proposed method and the lesion present in the image.

The result for segmentation, the process of removing remaining spurious and the overlapping of contour can be seen in the Fig. 2.

In order, to obtain a quantitative verification of the result the evaluation occurred mainly through the use of metrics. This is employees to reduce the subjectivity given by the visual process which is dependent of the observer. To make this possible, an experient radiologist delineated the lesions manually in 50 breast clinical ultrasound images, trying to achieve the highest accuracy as possible. Fig. 3 shows an example of contour traced on the original image and from which was extracted the lesion area.

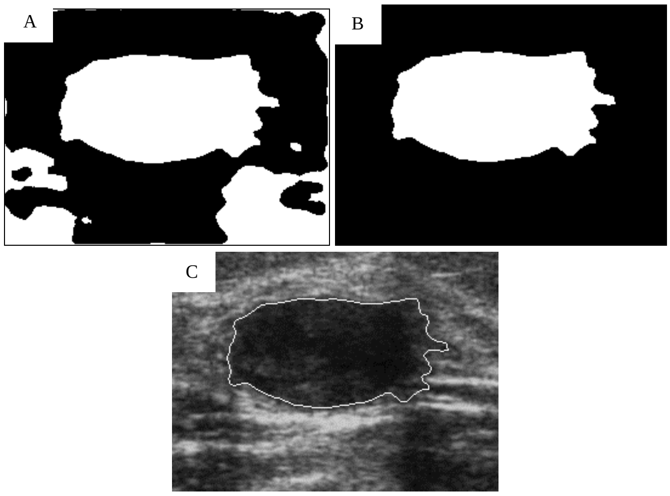

Fig. 2. Segmentation applied (a), removal the adjacent regions in the ultrasound image preprocessed (b), and the overlapping of contour in the original image (c).

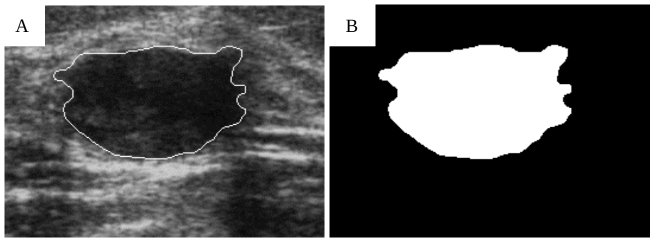

Fig. 3. A contour delimited by a radiologist (a) and marking of the lesion area extracted (b).

After obtaining the delineated area by the radiologist, this was compared with the proposed segmentation. The mean values obtained for the metrics used are shown in the Table I.

TABLE I
METRICS TO EVALUATION ABOUT SEGMENTATION WITH SOM

	Accuracy	Sensitivity	PPV
SOM	91,33%	67,45%	96,76%

CONCLUSION

The main idea of this work is to evaluate a segmentation technique capable of precisely defining the boundaries of lesions found on breast ultrasound images, automatically. However, this is a difficult task due to the presence of speckle noise, which significantly degrades the image quality and difficults the discrimination of some details [3]. Yap et al. [3] affirm that the proper functioning of a segmentation algorithm depends on the pre-processing of the image (enhancement and filtering) and selection of the appropriate model.

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The pre-processing techniques employed, in some cases, degraded the boundaries of the lesions, nevertheless allowed the enhancement of the contrast between the background and the object of interest, contributing to the subsequent detection.

The differential of the ANN to other process techniques is their learning ability, making it an algorithm that enables the occurrence of variations in the boundaries of the lesion if the image is submitted to a new training process because the corresponding values for the weights are given randomly, what modifies the convergence of the data. This network has some algorithmic complexity and its computational cost increases with the image size, considering the training and classification time. However, as we used just ROIs, the processing time is low.

The segmentation method proposed allows greater distinction between isolated points (noise) and the object of interest. Thus, the segmentation is more uniform, with accurate and smoother boundaries, besides to being not so susceptible to noise.

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