BREAST ULTRASOUND SEGMENTATION USING EVOLUTIONARY PULSE-COUPLED NEURAL NETWORKS

E. Aceves and W. Gómez
Information Technology Laboratory/CINVESTAV-IPN, Ciudad Victoria, Mexico

e-mail: aaceves@tamps.cinvestav.mx

Abstract: In this article we present a segmentation algorithm based on computational intelligence paradigms for breast lesions on ultrasound. The parameter tuning of three different pulse-coupled neural networks (PCNN) models was performed through two distinct variants of differential evolution (DE) approach. To demonstrate the effectiveness of these hybrid models (i.e. evolutionary PCNN), a set of experiments was designed to compare the computerized segmentation outcomes with 51 breast tumors delineated by a senior radiologist. Since the proposed algorithm has a stochastic basis, 31 runs of the segmentation method were performed for every image in dataset. The segmentation performance was assessed in terms of accuracy (mean±standard deviation), which was computed from four metrics of area error: true positive, true negative, false positive, and false negative. Also, the percentage of outliers (i.e. atypical low accuracy values) was measured. The results pointed out that the simplified PCNN optimized by DE/rand/1/exp variant attached the best accuracy, 97.06±1.38 %, and the lowest percentage of outliers, 1.62 %.

Keywords: Breast ultrasound, segmentation, neural networks, differential evolution.

Introduction

Currently, breast cancer is the leading cause of death in women population around the world, regarding malignant neoplasm category [1]. Early detection and diagnosis is the key for breast cancer control to increase the success of medical treatment for saving lives.

Nowadays, mammography (MG) is the best screening modality for early detection and diagnosis of breast cancer. However, its accuracy depends mainly on the composition of glandular parenchyma; thus, MG could not detect breast lesions in women with dense tissue [2].

Currently, breast ultrasound (BUS) is the most important adjunct to mammography for patients with palpable masses and inconclusive mammograms [3]. The analysis of BUS images is performed visually by radiologists, whose observations are based on morphology and texture of tumors. Hence, their diagnosis depends on the experience and training that could lead to large variations inter-/intra-observer [4]. To overcome this problem, computer-aided diagnosis (CAD) systems have been emerged as “second observer” for analyzing BUS images using computational algorithms. BUS segmentation is a fundamental stage in the construction of CAD systems. The objective is to separate the breast lesion from the background and surrounded tissues. Then, from the segmented lesion, morphological and textural features are extracted to classify it as benign or carcinoma [4].

BUS segmentation is a difficult task, due to speckle artifact, low contrast, and blurry boundaries. Currently, the design and tuning of segmentation algorithms is still a rather lengthy, which goes through empirical trial-and-error stages, and whose effectiveness is mostly based on the skills and experience of the designer. The current tendency within medical images field is to apply paradigms of computational intelligence such as artificial neural networks and evolutionary computation.

The cortical models, as the pulse-coupled neural network (PCNN), have been applied efficiently to image segmentation in different image processing tasks [5]. However, the performance of these neural network models depends strongly on their parameter tuning. This inconvenient could be solved by optimization strategies, such as differential evolution (DE) approach. Therefore, the aim of this study is to propose a novel BUS segmentation algorithm based on PCNN, which parameters are tuning dynamically by DE.

Materials and Methods

The proposed segmentation approach is based on evolutionary pulse-coupled neural network (E-PCNN), which was performed in two main stages: image preprocessing and lesion segmentation.

Image Database – The image database used in this study consisted of 51 BUS images collected under diagnostic procedures acquired in the National Cancer Institute of Rio de Janeiro, Brazil. For each image, a senior radiologist cropped a rectangular region of interest (ROI) around the lesion. Thereafter, the tumor’s boundary was delineated manually using software designed for this purpose. The objective was to establish ground truth contours for comparing the outcomes of the proposed segmentation algorithm.

Image Preprocessing – BUS images have two main characteristics, the speckle artifact and low contrast
between different tissues, which difficult the accurate localization of the lesion boundaries.

Hence, there are three basic requirements when pre-processing BUS images: (i) it should suppress noise efficiently; (ii) it should preserve lesion boundaries and structure details; and (iii) it should enhance edge information [4]. Thus, the image preprocessing was divided in three basic steps: contrast enhancement, artifact speckle filtering, and lesion enhancement.

a) Contrast enhancement - First, the dynamic range of the ROI image, $I(x,y)$, is normalized to the gray-level range $[0,255]$. Next, the contrast-limited adaptive histogram equalization [6] (CLAHE) technique is applied to accentuate the lesion from surrounding regions to produce a contrast-enhancement image, $I_C(x,y)$.

b) Speckle filtering – The anisotropic diffusion filtering (ADF) is a non-linear technique, introduced by Perona and Malik [7], which has been widely used to reduce noise in images. It is capable of reducing the amount of noise without blurring the boundaries between homogeneous regions. The ADF is defined by the following partial differential equation:

$$ \frac{\partial I}{\partial t} = \text{div} \left[ c(\nabla I) \nabla I \right], $$

where $|\cdot|$, $\nabla$, and $\text{div}$, are the magnitude, gradient, and divergence operators, respectively, and the function $c(\cdot)$ is the diffusion coefficient expressed as:

$$ c(\nabla I) = \left[ 1 + \left( \frac{\nabla I}{\rho} \right)^2 \right]^{-1}, $$

where $\rho$ is a constant that controls the diffusion extension.

However, since BUS images do not present uniform intensities, due to low contrast and speckle presence, Aleman-Flores et al. [8] proposed texture descriptors for guiding the diffusion process in ADF method, by using the responses of a set of Gabor filters. The assumption is that different tissues have distinct textures.

In the frequency domain, a single Gabor filter becomes two shifted Gaussians at the location of the radial frequency, $\omega_0$, with a specific orientation (here $\theta = 0^\circ, 45^\circ, 90^\circ$, and $135^\circ$) outlined as:

$$ H(u,v) = \exp \left[ -2\pi \sigma^2 G(u - \omega_0) + \sigma^2 \nu^2 \right] + \exp \left[ -2\pi \sigma^2 G(u + \omega_0) + \sigma^2 \nu^2 \right], $$

where $u' = u \cos(\theta) + v \sin(\theta)$, $v' = v \cos(\theta) - u \sin(\theta)$, and the radial frequencies, $\omega_0$, are calculated in relation to image width, $N_c$, as:

$$ \omega_0 = \omega_1, 2\omega_1, 4\omega_1, ..., (N_c/4)\sqrt{2} \text{ cycles/image-width} $$

Besides, the Gabor filter scale, $\sigma = \sigma_{x} = \sigma_{y}$, is determined regarding the bandwidth, $b$, as:

$$ \sigma = \frac{\lambda}{\pi} \left[ \frac{\ln 2}{2} \frac{b^2 + 1}{2b^2 - 1} \right], $$

where the wavelength value is calculated as $\lambda = 1/\omega_0$.

By varying both $\omega_0$ and $\theta$, a set Gabor filters is created for attempting to filter specific frequencies, that means, to depict textures in spatial domain.

Then, to guide the diffusion process in equation 1, the diffusion coefficient term becomes $c(\nabla R)$, where $R$ represents the vector formed by the responses of Gabor filters. Therefore, the diffusion process depends on the gradient of the texture, $\nabla R$, which should be different for the lesion region and its background.

The contrast enhancement image $I_C(x,y)$ is filtered by the texture-oriented anisotropic diffusion filtering to obtain the smoothed image $I(x,y)$.

c) Lesion enhancement – The last step consists in attenuating distant pixels (far from the lesion) with intensity values similar to those of the tumor region. This is performed by multiplying the complement of $I(x,y)$ by a Gaussian constraint function, $G(x,y)$, concentric to the lesion, denoted as [4]:

$$ I_G(x,y) = G(x,y) \cdot I_C(x,y) $$

and $G(x,y)$ is computed as:

$$ G(x,y) = \frac{\exp \left[-\left( \frac{(x-\mu_x)^2}{2\sigma_x^2} + \frac{(y-\mu_y)^2}{2\sigma_y^2} \right) \right]}{2\pi\sqrt{\det K}}, $$

where the covariance matrix, $K$, is assumed to be diagonal,

$$ K = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_y^2 \end{pmatrix}, $$

and the standard deviations, $\sigma_x$ and $\sigma_y$, are defined from the manual estimation of lesion limits, by marking four points along the tumor width ($w_1, w_2$) and depth ($h_1, h_2$). These standard deviations are computed as

$$ \sigma_w = \frac{w_2 - w_1}{2}, \sigma_h = \frac{h_2 - h_1}{2}, $$

and the Gaussian function centroid ($\mu_x, \mu_y$) is calculated from the estimated lesion limits as:

$$ (\mu_x, \mu_y) = \left( w_1 + \frac{w_2 - w_1}{2}, h_1 + \frac{h_2 - h_1}{2} \right). $$

Segmentation – For segmenting BUS images we used the canonical PCNN model [9] and two variants, namely the intersecting cortical model (ICM) [10] and the simplified PCNN model (SPCNN) [11].

a) Canonical PCNN model and variants – The canonical PCNN is a bio-inspired neural network based on cat’s visual cortex and it was developed for high-performance biomimetic image processing. The PCNN has been widely applied to image segmentation, since presents attractive characteristics such as synchronous pulse burst, changeable threshold, and controllable parameters [12].
rate of convergence of DE as well as its accuracy can be improved by applying different mutation and selection strategies. In this study, we use two variants of DE for tuning the parameters of PCNN, ICM, and SPCNN models: (i) DE/rand/1/exp and (ii) DE/rand/1/bin. The description of this notation is: /rand, the perturbed vector is randomly selected from the population; /1, denotes the number of difference vectors considered to perturbation in mutation step; and /bin or /exp, stands for the type of crossover being used [13].

Herein, the hybridization of PCNN and DE is denoted as E-PCNN, as well as E-ICM and E-SPCNN. The goal is to adapt dynamically the responses of PCNN models for a particular BUS image, that means, it is created a specific model, defined by its parameters, to segment a single BUS image.

The fitness function used in our approach is an adaptation of the curve evolution defined in geodesic active contours theory [14]. A potential solution is given by the outcome of the hybrid model evaluated in the fitness map, by using the following fitness function:

\[ f(\phi_t^i) = \frac{1}{N} \sum_{i=1}^{N} g(\|\nabla I_c(\hat{\rho})\|\nabla \phi_t^i)|\kappa(\hat{\rho}) + \nabla g(\|\nabla I_c(\hat{\rho})\|)\nabla \phi_t^i, \]

where, \( \phi_t^i \) is the \( i \)th contour evaluated at generation \( t \), \( N \) is the number of points in \( \phi_t^i \), \( \|\nabla I_c(\hat{\rho})\| \) is the fitness map, \( \kappa \) is the curvature, and \( \hat{\rho} = (x,y) \). Ideally, if \( \phi_t^i \) is on the lesion border \( f(\phi_t^i) = 0 \), otherwise, \( f(\phi_t^i) < 0 \).

c) Fitness map - The basic idea of the fitness map comes from topography, where the image could be viewed as a topographic relief that represent a surface with features such as valleys and mountains, which represent objects borders and constant regions, respectively. To create the fitness map we used a scale-space representation, where a Gaussian kernel, \( h_\sigma \), with an increasing scale parameter, \( \sigma \), iteratively smooths \( I(x,y) \) for suppressing , fine-scale structures. Then, to extract the lesion surface, the gradient magnitude of the smoothed image is subject to a non-lineal transformation:

\[ g(\|\nabla I(x,y)\|) = \tanh(\alpha \|\nabla I(x,y)\| h_\sigma), \]

where, \( \alpha \) is a is a saturation constant. Finally the fitness map is normalized to the range \([0,1]\).

Performance Evaluation – The performance assessment defines the degree to which the computerized segmentation, Sc, agrees with manual delineation, Sm. It could be assessed in terms of area error, which involves four basic metrics: false positive (FP), denotes the area falsely identified by Sc compared to the reference, Sm; false negative (FN) expresses the area in Sm that was missed by Sc; true positive (TP), indicates the total area of Sm that was covered by Sc; and true negative (TN) denotes the total area in Sm that is truly not in the lesion that was also excluded by method Sc.
Then, from the aforementioned areas the accuracy is computed as $A_c = \frac{TP + TN}{TP + TN + FP + FN}$, i.e., how correct $Sc$ identifies the lesion region and excludes the background.

**Experimental Results**

In Figure 3 an example of the image preprocessing and lesion segmentation stages is shown. Figure 3a illustrates the original ROI image. Figure 3b shows the contrast-enhanced image with the CLAHE algorithm, whereas Figure 3c shows the filtered image with texture-oriented ADF. Figure 3d shows the lesion limits to define the variances of the constraint Gaussian function. Figure 3e is the result of multiplying the constraint Gaussian function by the complement of Figure 3c. Figure 3f illustrates the fitness map to be optimized. Figure 3g shows the manual segmentation performed by a senior radiologist. Finally, Figures 3h, 3i and 3j illustrate the results of the best solutions for E-PCNN, E-SPCNN and E-ICM algorithms, respectively.

To measure the performance of our segmentation method, 31 runs for each image in database were performed, since DE algorithm has a stochastic basis. The population of DE algorithm was set to 15 individuals or PCNNs, where each one is a potential solution.

The accuracy of each hybrid model (E-PCNN, E-SPCNN, and E-ICM) was computed by comparing their outcomes with the outlines drawn by a senior radiologist.

In Figure 4 presents the box-plots of the performance assessment. In Figure 4a, it is illustrated the comparison between E-PCNN, E-SPCNN and E-ICM models in relation to DE/rand/1/bin, whereas in Figure 4b the same comparison is made in relation to DE/rand/1/exp.

It is noticeable in both box-plots that all models presented an average accuracy above 90%. However, these models have outliers that represent those atypical segmentations with poor accuracy.

Tables 1 and 2 summarize the percentage of outliers below the lower whisker value (LWV), from Figure 4, and the accuracy value (mean±standard deviation) of each hybrid model. The best neural network model is marked in gray, that is, the one that presented the highest accuracy and the lowest percentage of outliers.

**Table 1: Values with respect to DE/rand/1/bin variant.**

<table>
<thead>
<tr>
<th>Model</th>
<th>LWV (%)</th>
<th>Percentage of outliers</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>E-PCNN</td>
<td>94.29</td>
<td>4.80</td>
<td>96.35 ± 3.72</td>
</tr>
<tr>
<td>E-SPCNN</td>
<td>94.99</td>
<td>2.25</td>
<td>96.99 ± 1.75</td>
</tr>
<tr>
<td>E-ICM</td>
<td>94.82</td>
<td>5.00</td>
<td>96.50 ± 3.82</td>
</tr>
</tbody>
</table>

**Table 2: Values with respect to DE/rand/1/exp variant.**

<table>
<thead>
<tr>
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<td>E-SPCNN</td>
<td>94.72</td>
<td>1.61</td>
<td>97.06 ± 1.38</td>
</tr>
<tr>
<td>E-ICM</td>
<td>94.56</td>
<td>3.70</td>
<td>96.62 ± 3.35</td>
</tr>
</tbody>
</table>
By comparing the best hybrid models from both Tables, one can note that SPCNN optimized by DE/rand/1/exp was the best approach for segmenting BUS images, since attached the best value of accuracy and the lowest percentage of outliers. All the algorithms and experiments were implemented in MATLAB 2012a® (The MathWorks, Massachusetts, USA), executed in a 2.6-GHz microprocessor and 4 GB in RAM.

Discussion and conclusions

In this work we proposed an evolutionary segmentation method, which combines the generalization of neural networks and the adaptability of differential evolution to segment complex images such as breast ultrasound.

The preprocessing procedure plays an important role in our approach, since prepares the image to the segmentation stage by enhancing the lesion region. This procedure is divided in three steps that combine different robust techniques describes in literature. First, the CLAHE [6] algorithm adjusts the contrast of ROI image. Next, the anisotropic diffusion filtering guided by texture descriptors filters, derived from the responses of a set of Gabor filters [8], reduces the speckle artifact and preserves fine details on lesion boundaries. Finally, the constraint Gaussian function, proposed by Horsch et al. [15], enhances the tumor region and attenuates pixels that are distant to the tumor region.

Two paradigms of computational intelligence were applied to preprocessed BUS images, which consisted in tuning the input parameters of the pulse-coupled neural network (PCNN) through differential evolution (DE).

The DE determined the optimal parameters of the PCNN by the maximization of the fitness function that evaluated the outcomes of PCNN (as well as ICM and SPCNN variants) on a fitness map. Moreover, two variants of DE were compared: DE/rand/1/bin and DE/rand/1/exp.

The performance of the evolutionary-hybrid models, E-PCNN, E-ICM, and E-SPCNN, was measured in terms of accuracy by comparing the manual delineations performed by a senior radiologist against the outcomes of the hybrid models.

The results displayed in box-plots, in Figure 4, show the behavior of each pulse-coupled neural network evolved by a particular differential evolution variant. However, to decide which hybrid model had the best performance, it is necessary to determine which one had the smaller amount of outliers and the highest accuracy. This analysis pointed out that the best hybrid model was SPCNN optimized by DE/rand/1/exp variant.

These outliers represent those atypical segmentations with poor accuracy, which could be produced by convergence to local minima solution, that means, the algorithm is trapped in a solution that do not corresponds with lesion boundary.

We believe that the most important contribution of this article is the use of evolutionary computation to optimize dynamically the parameters of distinct pulse-coupled neural networks models. The experiments demonstrated that these paradigms of computational intelligence are capable to segment BUS images accurately.

Encouraged by these results, the future work involves an analytical study of the influence of evolutionary segmentation in classifying breast ultrasound as benign or carcinoma by using a large BUS image dataset.

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