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Evolutionary pulse-coupled neural network for segmenting breast lesions on ultrasonography

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ABSTRACT

Purpose: This paper presents an evolutionary segmentation approach for breast lesions on ultrasound (BUS) based on the pulse-coupled neural network (PCNN) model and an adaptive differential evolution algorithm (JADE). *Methods*: First, a despeckle method based on anisotropic diffusion filtering is applied. Thereafter, to attenuate distant pixels that do not belong to the tumor, the filtered image is multiplied by a constraint Gaussian function. The resultant preprocessed image is segmented by a population of PCNNs whose parameters are evolved iteratively by JADE algorithm. Three population sizes are tested with 10, 20, and 50 individuals. The average radial derivative (ARD) function is used as a fitness function to be maximized. The experiments are performed on a BUS dataset with 100 ultrasonographs, which were delineated manually by a senior radiologist for defining ground-truth lesion outlines. The Matthews correlation coefficient (MCC) measures the accuracy of the proposed method, which evaluates the agreement between both the ground-truth and the computerized segmentations. Additionally, from segmented lesions, five morphological features are extracted and the local Fisher discriminant analysis (LFDA) classifier is trained. The 0.632+ bootstrap method is used for evaluating the classification performance in terms of the area under ROC curve (AUC). *Results*: The experimental results point out that segmentation accuracy is unaffected by the population size for attaining similar segmentation solutions, where the median MCC value is about 0.85. Moreover, the classification performance increased from manual delineation to PCNN segmentation (from AUC=0.907 ± 0.032 to AUC=0.920 ± 0.022). *Conclusion*: The evolutionary segmentation approach is capable of accurately segmenting and classifying BUS images with respect to ground-truth data. This behavior is because the JADE algorithm self-adapts the search procedure for finding adequate PCNN parameters that maximizes the ARD function.

1. Introduction

Currently, breast ultrasound (BUS) is the most important adjunct to mammography for patients with palpable masses and normal or inconclusive mammograms. Radiologists perform BUS image analysis by observing morphological and texture characteristics of breast lesions [1,2]. Hence, the diagnosis depends on their expertise and training. This subjectivity can lead to large variations of inter/intraobservers image interpretation, and, consequently, to distinct clinical conduct recommendations [3,4]. To overcome this problem, computer-aided diagnosis (CAD) systems have emerged as a "second reader" for analyzing medical images. Then, specialists can take the CAD outcome as a second opinion and make a more conclusive diagnosis for reducing unnecessary biopsies in benign cases [5]. Commonly, CAD systems for BUS images involve four stages [6]: (i) image preprocessing, (ii) lesion segmentation, (iii) feature extraction, and (iv) classification.

BUS segmentation is a difficult task, owing to the variance in lesion shapes, speckle artifact, low contrast, and blurry boundaries [7]. Moreover, it is a critical stage within CAD systems, whereby the lesion should be separated accurately from the background and other structures. Afterward, textural and morphological features are extracted for tumor classification as benign or malignant [6].

Several classical techniques have been applied to segment BUS images, which include gray-level histogram thresholding [8], region growing [9,10], active contour models [11–15], watershed transformation [16–18], and split-and-merge techniques [19,20]. These approaches provide effective solutions in limited domains, such as well-defined lesion contours, quasi-homogeneous textures, or well-contrasted regions. However, the current challenge is to cope with irregular lesion shapes and different variations in sonographic features, such as low contrast, shadows, and heterogeneous textures. Therefore, more sophisticated approaches have

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been proposed recently, such as graph-based techniques [21,22], cellular automata models [23], or normalized cuts [24].

The distinct aforementioned segmentation techniques attempt to determine the best lesion margin among several possible solutions. In this context, the term "best" is related to the solution that depicts the lesion margin as realistically as possible (i.e., accurately) . Hence, this problem could be addressed by paradigms of the computational intelligence (CI), which involves techniques inspired by nature that exhibit an ability to learn or adapt to new situations in complex and changing environments. CI techniques have been applied to deal with distinct BUS segmentation tasks such as clustering, parameter tuning, or pixel classification by using the following paradigms [25]:

- Fuzzy logic (FL) describes uncertainty and vagueness of human reasoning [26,27].
- Artificial neural networks (ANNs) model the properties of biological neural systems and the functions of adaptive learning [28–31].
- Swarm intelligence (SI) models the collective behavior of simple organisms (individuals) in swarms [32–35].
- Evolutionary computation (EC) mimics processes from natural selection, where the main concept is survival of the fittest [36–38].

Regarding ANNs, the pulsed-coupled neural network (PCNN) has been applied to BUS segmentation because it presents attractive characteristics such as synchronous pulse burst, changeable threshold, and controllable parameters [29,39]. Shi et al. [30] used a simplified model of PCNN (denoted SPCNN) for segmenting BUS images, whose parameters are sequentially changed (inside a predefined range) following an evaluation of an improved fuzzy mutual information (IFMI) criterion. Then, the lesion contour that maximizes the IFMI is selected as the best-segmented one. Similarly, Jing and Yuanyuan [31] used the abovementioned SPCNN-based technique to generate a presegmented lesion (i.e., an initial contour), which is iteratively deformed up to the final lesion boundary by using an active contour model.

The PCNN segmentation performance depends strongly on its parameter tuning, that is, setting adequate values for attenuation time constants, voltage potentials, and linking coefficients [40]. Moreover, because of the large variance in breast lesions shapes and low contrasts produced by shadows, echo features and blurry or ill-defined boundaries, the PCNN parameters used for segmenting a particular BUS image do not necessarily perform well in a different one. Hence, such parameters should be automatically adapted to cope with specific characteristics of the image.

The task of automatically tuning the PCNN parameters could be addressed as an optimization problem, where an optimization algorithm guides the search procedure for finding adequate parameters that maximize (or minimize) a suitable cost function. For adjusting the PCNN parameters, population-based metaheuristics have been widely used, which are often based on SI and EC paradigms such as particle swarm optimization [41], differential evolution [42], artificial immune system [43], bacterial foraging optimization [44], fruit fly optimization [45], and genetic algorithm [46,47]. These approaches have been proposed to segment arbitrary images by maximizing an entropy criterion; however, in BUS images, finding the lesion contour that maximizes the intensity gradient between the tumor region and the background is desirable.

Hence, in this paper, we propose an evolutionary BUS segmentation approach, which evolves a population of potential PCNN to find the boundary that best fits a particular tumor shape. In this sense, we used an adaptive differential evolution algorithm to optimize the parameters of the PCNN, where the average radial derivative (ARD) is used as fitness function. The basic genetic operators (mutation, crossover, and selection) are used to maintain candidate solutions (i.e., potential lesion contours) over subsequent generations. To our knowledge, this evolutionary PCNN segmentation approach applied to BUS images is original.

2. Methods

2.1. Pulse-coupled neural network

Eckhorn et al. [48] proposed the linking field network (LFN), which is a bio-inspired neural model based on cats' visual cortex. The authors discovered that the cat's midbrain presents an oscillatory behavior (i.e., synchronous pulse bursts) that creates binary images from visual impressions. From a computational point of view, if a digital image is applied as input data to the LFN, then the image pixels are grouped based on spatial proximity and brightness similarity. By doing so, Johnson and Ritter proposed the pulse-coupled neural network (PCNN), which is a modification of the LFN to adapt its functioning for image processing algorithms [49]. This neural network is a 2D single layer, laterally connected network of integrate-and-fire neurons, with a 1-to-1 correspondence between the image pixels and network neurons. Also, the PCNN does not require any training, but adequate parameters adjusting. The output images at different iterations typically represent some segments or edges information of the input image.

The structure of a single pulse-coupled neuron (PCN) has three well-defined sections (Fig. 1) [49]: (1) input field, receives stimulus signals (pixel intensity S_{ij} and weighted surrounding PCN outputs); (2) modulation field, integrates both linking, L_{ij}, and feeding, F_{ij}, signals to create the internal activity, U_{ij}; and (3) pulse generator, the neuron fires when U_{ij} is larger than a threshold T_{ij}.

The behavior of a single PCN is described iteratively as [39]

$$F_{ij}[t] = e^{-\alpha_F} F_{ij}[t-1] + V_F (W * Y[t-1])_{ij} + S_{ij}, \tag{1}$$

$$L_{ij}[t] = e^{-\alpha_L} L_{ij}[t-1] + V_L (W * Y[t-1])_{ij}, \tag{2}$$

$$U_{ij}[t] = F_{ij}[t](1 + \beta L_{ij}[t]), \tag{3}$$

$$Y_{ij}[t] = \begin{cases} 1 & \text{if } U_{ij}[t] \geq T_{ij}[t] \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

$$T_{ij}[t] = e^{-\alpha_T} T_{ij}[t-1] + V_T Y_{ij}[t], \tag{5}$$

where ij is the position of the PCN in the network, with $1 \leq i \leq M$, $1 \leq j \leq N$, and M and N represent the height and width of the PCNN (i.e., the same size as the input image), "$*$" denotes the convolution operator, and $W = \{w_{pq}\}$ is the synaptic weight matrix whose entries are computed as [39]

$$w_{pq} = \begin{cases} 0 & \text{if } p = q \\ 1/r & \text{otherwise,} \end{cases} \tag{6}$$

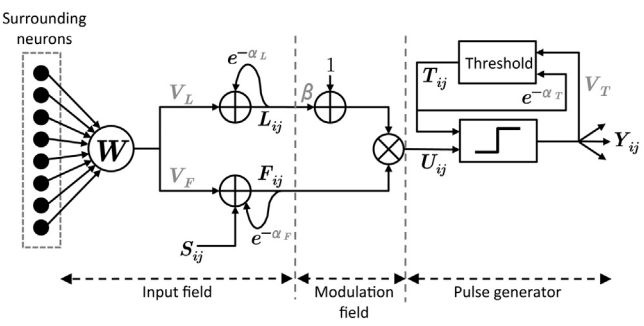

Fig. 1. The structure of a single PCN. In grey, the neuron parameters.