Medical image segmentation based on Memristor neural network

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ABSTRACT

To alleviate the workload associated with image segmentation and enhance segmentation performance, there are still many details to be improved in the specific application of image segmentation. In particular, the Pulse-Coupled Neural Network (PCNN) presents challenges, such as determining the optimal selection of connection coefficients. Then an enhanced model known as the Memristor Pulse-Coupled Neural Network (M-PCNN) is proposed. This model integrates the connection coefficients from the traditional PCNN with resistance selection mechanisms. Firstly, the two memristor are operated in parallel to enhance the stability and fault tolerance of the model. If one memristor fails, the other can continue to work normally to ensure the stable operation of the system. Subsequently, the parallel configuration directly replaces the connection strength in the traditional model, and the interaction of two parallel memristors can extract the lesion area more effectively, making the segmentation result more accurate. Finally, the lesion region of the image was magnified and analyzed using both models. Experimental results demonstrate that, compared to the traditional PCNN model, the connection coefficients in the M-PCNN model are simpler to select, significantly reducing the workload associated with the segmentation task. Additionally, the M-PCNN model is more accurate in extracting targets from images. For some complex structures, M-PCNN model can better extract lesions. In this paper, four objective evaluation metrics are selected. Through the precise comparison of data, it is demonstrated that all M-PCNN models take better values to further improve the accuracy of medical diagnosis.

Keywords: Image segmentation, pulse-coupled neural network, Memristor, connection coefficient, objective evaluation index

1. INTRODUCTION

Medical image segmentation is a considerable technology in medical image analysis, and its main purpose is to accurately localize and identify structures and tissues in medical images, so as to provide a reliable basis for disease diagnosis, treatment planning and disease monitoring [1]. However, medical image segmentation faces many challenges. Traditional image segmentation methods basically lean upon essential features such as color and texture to segment images [2-4]. These methods often have limitations in processing images such as manual parameter selection leads to over- or under-segmentation of images, blurred boundaries and the like. As a result, there is a need for constantly explore more effective image segmentation algorithms.

The Pulse-Coupled Neural Network (PCNN), a neural network model that simulates the activity mechanisms of biological neurons, reveals strong biological realization and is widely used in the field of image processing [5-6]. In the PCNN model, the connection strength is determined by manual settings or simple fixed rules, which often fail to make full use of image feature information resulting in poor accuracy and stability of the segmentation outcomes.

Memristors are designed inspired by biological synapses and have the property of memorizing the resistive state [7]. It dynamically adjusts the connection strength based on the local features and global information of the image, while the PCNN model uses this historical information to adjust the parameters. In medical image segmentation, local and global features are crucial for accurate segmentation.

The aim of this paper is to investigate the application of the memristor-based Pulse-coupled neural network (PCNN) image segmentation technique in medical image segmentation [8-9]. By combining neural networks and biological concepts, an innovative image segmentation method is proposed. This method introduces a way to set up the connection strengths in the traditional PCNN model by replacing the memristors to improve the effect and stability of image segmentation. By dynamically adjusting the connection strength, PCNN model can better adapt to different types of medical imagesand and optimally adjust the parameters using historical information during processing.

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Through this research, we can not only promote the technical development in the field of image segmentation and improve the accuracy and efficiency of image processing, but also deepen the understanding of neural network models and biological mechanisms, and provide new ideas and methods for research in interdisciplinary fields. In addition, The PCNN image segmentation technique based on memristors has strong potential for engineering applications, and is expected to be widely used in the fields of medical image analysis and intelligent monitoring systems.

2. INTRODUCTION TO MEMRISTOR NEURAL NETWORKS

Memristors and synapses are structurally similar in that both consist of two main parts, a receiver and a transmitter. In a memristor, the receiving end is a device with nonlinear resistive properties, while the transmitting end is a controller capable of controlling the state of the resistance. This structure allows the memristor to achieve nonlinear resistance modulation without the use of transistors, thus simulating the synaptic behavior in neural networks. The computer neural network system is analogous to a biological neural network, the memristor is analogous to a biological synapse, and the doped and non-doped layers in the memristor are equivalent to the pre- and post-synaptic membranes of the synapse, whereas the oxygen atoms in the titanium oxide thin film can be thought of as neurotransmitters capable of storing and transmitting information.

The PCNN model forms a feedback-type network composed of interconnected neurons, each of which operates based on three main components: the receptive domain, the tuning component, and impulse generation. Determining the connection strength of PCNN models for image segmentation poses a significant challenge, requiring consideration of factors such as specific application contexts and task requirements. For the complex structure and rich features of medical images, the confirmation of connection strength needs to consider the correlation and weight assignment among numerous features. Additionally, the connection strength has a large range of values, which requires trial and error in a large parameter space to finalize a suitable value. Memristor neural network is a new type of network structure that integrates a memristor into a pulse-coupled neural network (PCNN). In this study, the two parallel-connected memristor replace conventional connection strengths. According to the adaptive learning ability of the memristor, the connection strength can be adjusted more flexibly according to the characteristics of the image and the requirements of the segmentation, so as to improve the accuracy and adaptability of segmentation. The parallel-connected memristor can enhance the local connectivity in the neural network, which makes the information transfer between neurons more localized and refined, and improves the segmentation accuracy and detail expression ability. The M-PCNN model is shown in Figure 1.

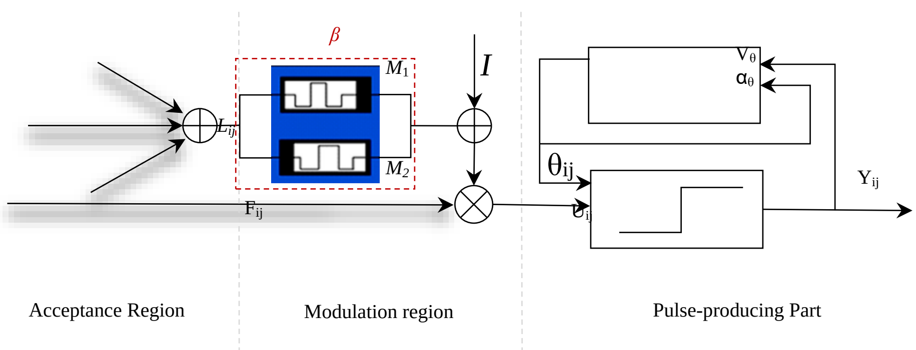

Figure 1. M-PCNN Model

The iterative Eq.1 for the improved M-PCNN is obtained by taking the two memristor as M_1 and M_2 respectively, to replace the value of β in the conventional PCNN model as follows.

$$
\begin{aligned}
&F_{ij}(n) = S_{ij} \\
&L_{ij}(n) = V_L \sum W_{ijkl} Y_{kl}(n-1) \\
&U_{ij}(n) = F_{ij}(n)\left[1+\left(\frac{M_1 M_2}{M_1+M_2}\right)L_{ij}(n)\right] \\
&\theta_{ij}(n) = \exp(-\alpha_\theta)\theta_{ij}(n-1) + V_\theta Y_{ij}(n-1) \\
&Yij(n) = \begin{cases} 1, (U_{ij}(n) \succ \theta i_j(n-1) \\ 0, \left(U_{ij}(n) \le \theta_{ij}(n-1)\right) \end{cases}
\end{aligned} \tag{1}
$$

Due to the properties of memristor, the maximum resistance value and the minimum resistance value of the memristor are respectively selected to be connected in parallel instead of the β-value, which can effectively solve the drawbacks of manually selecting the connection strength and achieve the best effect of image segmentation.

3. EXPERIMENTAL PROCEDURE

In order to verify the applicability and generalization ability of our model, various medical images were collected, and finally in this paper, breast MRI images and bladder stone CT images were selected for image segmentation. Each image was uniformly set to have a resolution of 96 and pixels of 256 × 256. In this paper, the lesions in each image were zoomed in advance, so that the detailed features of the lesions could be observed and compared more clearly in order to more accurately assess the performance of the improved model in the segmentation task.

The initial set of images consists of segmented images of left breast carcinosarcoma. Specifically, in Figure 2, R1(a), R1(b), R1(c), and R1(d) depict the original image, labeled image, segmentation image using the PCNN model, and segmentation image using the improved M-PCNN model, respectively. From a holistic perspective, the improved M-PCNN model performs better than the traditional PCNN model in processing the background image, and it is able to effectively ignore the regions other than the lesion and highlight the features of the lesion more accurately. From the framed position of image R1(c), it can be seen that the traditional PCNN model has some limitations in segmenting the soft tissue part of the background other than the lesion, and fails to achieve ideal segmentation results. In contrast, the M-PCNN model is able to highlight the lesion region more intuitively, providing clearer visualization results. In addition, the traditional PCNN model also shows deficiencies in dealing with edge regions, failing to effectively ignore the edge regions, which may have a negative impact on the accuracy of medical diagnosis. The M-PCNN model, on the other hand, not only improves the segmentation effect on the background soft tissues, but also effectively reduces the interference of the edge regions on the lesion feature extraction through its advanced multi-scale feature extraction and fusion mechanism.

According to the objective evaluation indexes in Table 1, it can be seen that the extraction of lesion features in the segmentation results of the PCNN model is not excellent, and through the comparison of the Dice Similarity Coefficient (Dice), Intersection Over Union (IOU), and Relative Volume Difference (RVD) indexes, it can be observed that the M-PCNN model shows higher performance in the image segmentation task compared with the PCNN model. It can cover the background information more effectively, while the PCNN model still has a lot of residual background information in the segmentation result, which fails to extract the lesion features effectively. From the comparison of Precision (Pre), the M-PCNN model improves the segmentation accuracy by 11% compared to the PCNN model, which is enough for the improved model to more accurately capture the lesion region and exclude the background, making the segmentation results clearer and more accurate. By comparing the Dice, IOU and RVD metrics, it can be observed that the M-PCNN model has the ability to match the lesion region more accurately when performing the image segmentation task.

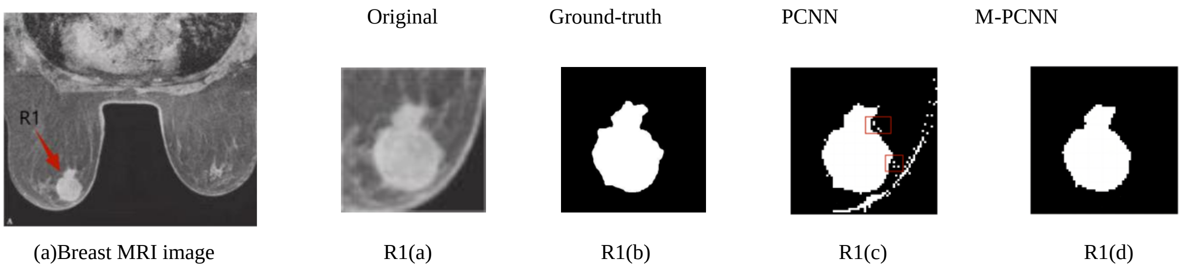

Figure 2. Breast fibroadenoma lesion segmentation image

Table 1. Breast fibroadenomatosis test results

Evaluation Index	Model	R1
Dice	PCNN	0.8791
	M-PCNN	**0.9099**
Pre	PCNN	0.8273
	M-PCNN	**0.9321**
IOU	PCNN	0.7843
	M-PCNN	**0.8347**
RVD	PCNN	0.1337
	M-PCNN	**-0.0463**

The second set of images are bladder stone segmentation images. P1(a), P1(b), P1(c) and P1(d) in Figure 3 are the original image, labeled image, PCNN model segmentation image and the improved M-PCNN model segmentation image respectively. From the overall view of Figure 3, after the zoom-in operation on the lesion region, it can be found that when segmentation is performed, the traditional PCNN model results in over-segmentation of the lesion when segmenting certain locations with fuzzy edges. For instance, from the comparative analysis of the regions framed in images P1(b), P1(c) and P1(d), the PCNN model appears to be over-segmented when performing segmentation, resulting in the non-lesion regions being incorrectly extracted as target regions as well. This phenomenon may be caused by the poor performance of its segmentation algorithm in the presence of blurred boundaries. In contrast, the M-PCNN model is more efficient in dealing with fuzzy boundaries and is able to segment the lesion regions more accurately.

According to Table 2, the Dice, Pre and IOU metrics reach 0.9738,0.9569 and 0.9481 respectively in the M-PCNN model. The above data further confirms that the M-PCNN model is more accurate in segmenting the lesions with a higher degree of similarity and overlap with the original image, indicating that it is more accurate in segmenting the fuzzy boundaries for the extraction of the target compared to the traditional PCNN model. Evaluation using RVD reveals that the RVD value of the M-PCNN model is almost close to 0, which indicates that the volume predicted by the model almost completely overlaps with the actual volume, reflecting its advantage in reducing the mis-segmentation of non-lesion regions. Combining the IOU and Dice metrics, it can be seen that the M-PCNN model performs well in the medical image segmentation task, especially when dealing with fuzzy boundaries, demonstrating higher accuracy and significantly improving the segmentation of lesion regions.

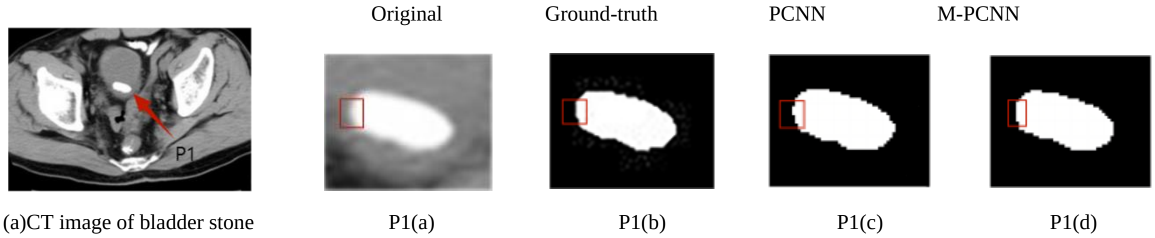

Figure 3. Segmentation image of kidney stone lesion

Table 2. Results of kidney stone lesion test

Evaluation Index	Model	P1
Dice	PCNN	0.9504
	M-PCNN	**0.9738**
Pre	PCNN	0.9071
	M-PCNN	**0.9569**
IOU	PCNN	0.9037
	M-PCNN	**0.9481**
RVD	PCNN	0.1001
	M-PCNN	**0.036**

4. CONCLUSION

This paper proposes an image segmentation technique based on memristor neural network, and the improved model performs better in dealing with image edges and complex structures. Leveraging the adaptive learning capability of memristors enables dynamic adjustment of connection strengths, thereby enhancing the accuracy and robustness of image segmentation. This adaptive capability allows real-time adjustments based on image features and background noise during segmentation. For medical images, characteristics and lesions may vary considerably from organ to organ in the human body, and the adaptive learning ability of the memristor can help the neural network to be dynamically adjusted and optimized according to different situations, so as to improve the segmentation ability for certain complex structures and lesions. The segmented images obtained using the proposed improved model demonstrate significant enhancement in image segmentation tasks compared to the traditional PCNN model, as evidenced by objective evaluation metrics such as Dice coefficient (Dice), Precision, and Intersection over Union (IOU).

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