QIBDS Net: A Quantum-Inspired Bi-Directional Self-supervised Neural Network Architecture for Automatic Brain MR Image Segmentation

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Abstract. A Quantum-Inspired Bidirectional Self-Organizing Neural Network (QIBDS Net) architecture operated by Quantum-Inspired Multi-level Sigmoidal (QIMUSIG) activation function suitable for fully automatic segmentation of T1-weighted contrast enhanced (T1-CE) MR images, is proposed in real time. The QIBDS Net architecture comprises input, intermediate and output layers of neurons represented as *qubits* and inter-connected by second order neighborhood based topology. The inter-connections between the intermediate and output layers are effected by means of counter propagation of quantum states without any training or external supervision. Quantum observation is carried out at the end to obtain the segmented tumor from the superposition of quantum states. The proposed self-supervised network architecture has been tested on T1-CE MR images from publicly available data sets and is found to be very efficient while compared with other state of the art techniques.

Keywords: Quantum computing · QBDSONN · SOFM · CNN

1 Introduction

Brain tumour segmentation, isolating the brain lesions from MR images, is one of the tedious tasks owing to wide variations in structure and gray-levels present

The original version of this chapter was revised: Titles that were originally not visible in the reference section are now displayed properly. The correction to this chapter is available at https://doi.org/10.1007/978-3-030-34872-4_64

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in MR images. Efficient knowledge based fuzzy clustering [1,2] and assisted techniques [3] offer to distinct the abnormal cells in MRI images. Owing to inherent parallel and adaptive computing properties, fuzzy logic inspired Artificial Neural Networks (ANN) [4–6] gained popularity among the computer vision researchers for MR image segmentation. Notable examples include a multi-class artificial neural network (ANN) classifier by Kumar *et al.* [5] for $T1-CE$ MR images segmentation and Self-Organizing Feature Map (SOFM) contributed by Ortiz *et al.* [6]. However, to obtain anatomically correct MR image segmentation, ANN architectures are assisted by complex back-propagation algorithm and explicitly rely on intensity and spatial feature information.

The large scale of redundant intensity and spatial feature information prevalent in MR images have been avoided using Convolutional Neural Networks (CNNs) which revolutionized the field of computer vision. A shallow CNN comprising with two convolution layers is proposed by Zikic *et al.* [7] for brain tumour detection. Of late, a complete tumour detection framework using a binary CNN is also suggested by Lyksborg *et al.* [8]. In addition, to avoid the effect of over fitting, Pereira *et al.* [9] developed a CNN assisted by small kernels (3×3). However, in contrast to automated MR image segmentation, the Convolutional Neural Network based approaches often suffer due to lack of labeled MR images for training and high computational complexities and hence fully automatic MR image segmentations received much attention.

The inherent properties of quantum computing enables the quantum-inspired artificial neural networks to evolve in the field of pattern recognition. A quantum back-propagation algorithm assisted Quantum Multi-layer Self-organizing Neural Network (QMLSONN) architecture is proposed by Bhattacharyya *et al.* [10,11] for fast and efficient binary image segmentation. In contrast to the complex quantum back-propagation algorithm employed in QMLSONN, Konar *et al.* [12,13] resorted to quantum counter propagation of the network states and developed a Quantum Bidirectional Self-Organizing Neural Network (QBDSONN) Architecture characterized by a bi-level sigmoidal function suitable for binary image segmentation. Hence, the QBDOSNN architecture motivates the authors to apply on gray scale MR images with functional modification of the bi-level activation function to a multi-level sigmoidal activation function in quantum environment.

2 Basic Concepts of Quantum Computing

A *qubit* [14] is the normalized superposition of classical bits 0 and 1 and is the constituent unit of quantum processing represented as:

$$|\psi\rangle = \gamma_0|0\rangle + \gamma_1|1\rangle = \begin{bmatrix} \gamma_0 \\ \gamma_1 \end{bmatrix} \tag{1}$$

where, $|\gamma_0|^2 + |\gamma_1|^2 = 1$, γ_0 and γ_1 are complex quantities.

Quantum computation is realized by quantum rotation gate which is the basis of quantum algorithms and is reversible in nature. The operation of a quantum rotation gate applicable on a single *qubit* can be shown as:

$$\begin{bmatrix} \gamma_0' \\ \gamma_1' \end{bmatrix} = \begin{bmatrix} \cos\omega & -\sin\omega \\ \sin\omega & \cos\omega \end{bmatrix} \times \begin{bmatrix} \gamma_0 \\ \gamma_1 \end{bmatrix} \tag{2}$$

The set of superimposed quantum states $|\psi_i\rangle$ with $0-1$ basis forms a Hilbert Hyperspace and the quantum system is defined using the wave function ϕ as

$$|\psi\rangle = \sum_{k}^{n} p_k |\phi_k\rangle \tag{3}$$

On quantum observation, the quantum systems interacts with the physical system and the true outcome is obtained.

3 Quantum Inspired Bi-Directional Self Organizing Neural Network (QIBDS Net) Architecture

The proposed QIBDS Net architecture replicates the Quantum Bi-Directional Self Organizing Neural Network (QBDSONN) architecture [12,13] with functional modification in the form of a novel quantum inspired multi-level sigmoidal activation (QIMUSIG) function targeted to address the gray levels pertaining to MR Images. Three layers of neurons viz.,input, hidden and output are composed of *qubits* in the suggested QIBDS Net architecture as illustrated in Fig. 1. The QIBDS Net employs the rotation angle for the interconnection strength and the threshold, represented as Φ and ν respectively. The activation $|\tau\rangle$ can be interpreted as

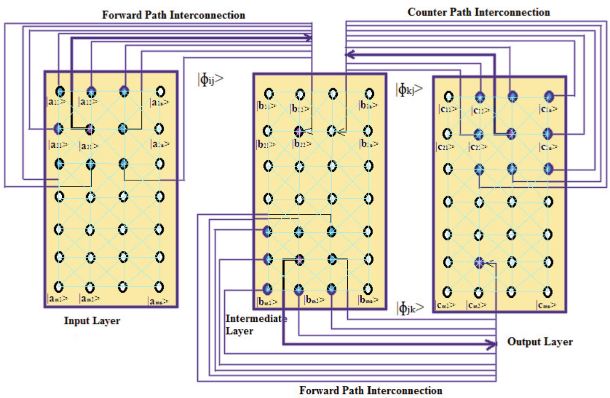

Fig. 1. Quantum Inspired Bi-Directional Self-Organizing Neural Network (QIBDS Net) architecture (Few Inter-layer connections are provided for visibility).

$$|\tau\rangle = \begin{bmatrix} cos\nu \\ sin\nu \end{bmatrix} \tag{4}$$

Without exploring the imaginary section of *qubits*, the input-output dynamics of the network layers is defined as

$$|z\rangle = f_{QIBDSNet}(\sum_{l}^{n} x_l \langle \Phi_l|\tau_l\rangle) = f_{QIBDSNet}(\sum_{l}^{n} x_l cos(\alpha_l - \nu)) \tag{5}$$

where, x_l is input to the quantum neuron. The activation function, $f_{QIBDSNet}(x)$ is defined as:

$$f_{QIBDSNet}(x) = \frac{1}{\rho_\omega + e^{-\mu(x-\theta)}} \tag{6}$$

where, the steepness factor μ and activation θ are represented by *qubits*. The multi-level class response (gray level intensity) is exhibited by ρ_ω and is defined as

$$\rho_\omega = \frac{B_N}{\beta_\omega - \beta_{\omega-1}}, 1 \leq \omega \leq L \tag{7}$$

where ω is class index; β_ω, $\beta_{\omega-1}$ are class outputs and the summation of the 8-connected neighborhood gray-scale pixels contribution is denoted as B_N. The QIMUSIG activation function with varying steepness factor μ is shown in Fig. 2. Owing to wide variation of image pixel intensities and pertaining to MR images, four distinct adaptive activation schemes have been introduced in the suggested network architecture over 8-connected neighborhood pixels [15]. These are

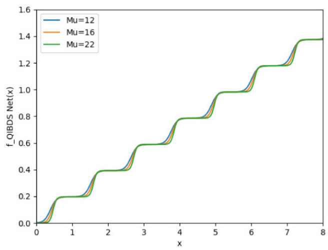

Fig. 2. Multi-class response of QIMUSIG activation function $f_{QIBDSNet}(x)$ for $\mu = 12, 16, 22$ and class $L = 8$

1. Activation based on ϱ-distribution (θ_ϱ)
2. Activation based on skewness (θ_χ)
3. Activation based on heterogeneity (θ_ξ)
4. Activation based on fuzzy cardinality estimate (θ_ν).

Suppose, the response of the intermediate and output layers neurons are denoted as $|In_j\rangle$ and $|Ou_i\rangle$ respectively. In addition, the inter connection weights between input to intermediate layer and intermediate to output layer are expressed as $|\Phi_{kj}\rangle$ and $|\Phi_{ji}\rangle$ respectively with the activations $|\tau_j\rangle$ and $|\tau_i\rangle$ at the intermediate layer and output layer, respectively. The input-output relation of a quantum neuron can be defined as [12]

$$|Ou_i\rangle = f_{QIBDSNet}(\sum_j^N y_j \langle \Phi_{ji}|\tau_i\rangle) =$$
$$f_{QIBDSNet}(\sum_j^N f_{QIBDSNet}(\sum_k^L x_k \langle \Phi_{kj}|\tau_j\rangle)\langle \Phi_{ji}|\tau_i\rangle) \quad (8)$$
$$i.e., |Ou_i\rangle = f_{QIBDSNet}(\sum_j^M f_{QIBDSnet}(\sum_k^L x_k cos(\alpha_{kj} - \nu_j))cos(\alpha_{ji} - \nu_i))$$

Quantum observation allows to evaluate the error incurred by QIBDSNet at the output layer and guided by α and ν as:

$$\xi = \frac{1}{2}\sum\{\vartheta(t+1) - \vartheta(t)\}^2 \quad (9)$$

The inter-connection weights $|\Phi(t)\rangle$ (represented as *qubits*) are transformed into $\vartheta(t)$ at a particular epoch (t) on quantum observation.

4 T1-Weighted CE MR Image Segmentation Using QIBDS Net

The input MR image pixels are received at the input layer of the suggested QIBDS Net as normalized fuzzy intensities and subsequently transformed into quantum states $[0, \frac{\pi}{2}]$ as

$$x_k = \frac{\pi}{2} \times I_k \quad (10)$$

where, normalized MR image pixels are designated by I_k and the transformed quantum states are described by x_k. The proposed QIBDS Net is implemented on $T1$-weighted CE brain MR images from the available data sets [16] in PARAM SHAVAK super computer provided by CDAC, India. In the experimental set up, the steepness hyper-parameter, μ is tailored between 0.24 to 0.25 with step size 0.001 and the three distinct sets $F_{\lambda_{\omega L}} = \{c_1, c_2, c_3\}$ of class level, $L = \{8\}$ are used. A tiny cluster, considered as tumour is erroneously exposed as outcome after the segmentation and hence to remove these small clusters with threshold $(\sigma = 4)$, a post processing operation has been performed.

5 Results and Discussion

In the current experiments, in comparison to QIBDS Net, a CNN [9] is trained with 1200 MR images from the same data set [16] allowing maximum 100 epochs. 800 T_1-weighted CE MR images are used for validation and testing. Four different types of empirical goodness evaluation metrics (PPV, SS, ACC, DSC) [1] are used in the experiments. A similar post processing technique has been applied on the segmented output images obtained using SOFM [6], fuzzy-clustering method [1] and CNN [9]. Figure 3 shows the input skull-tripped sample MR slices

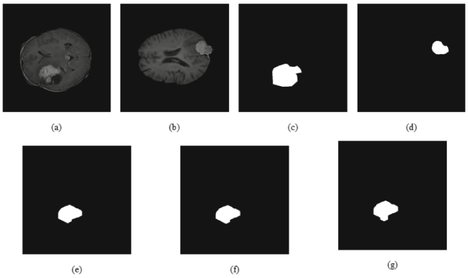

Fig. 3. Skull stripped input MR images (a) slice no: 5 (b) slice no: 68 manually segmented tumor for (c) slice no: 5 and (d) slice no: 68 [16]. Segmented tumours followed by post processing using (e) fuzzy-clustering [1] (f) SOFM [6] and (g) CNN [9] from slice no. 5

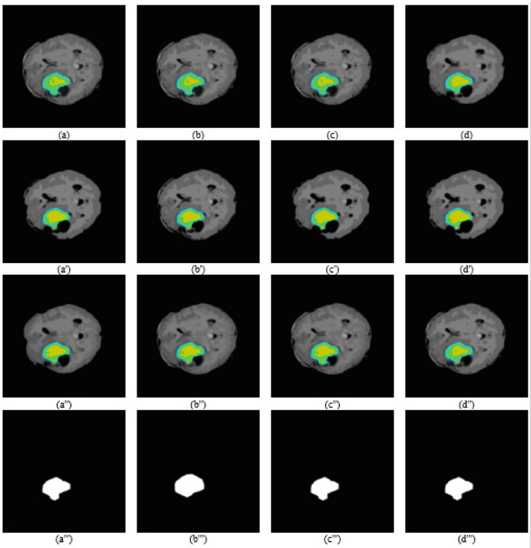

Fig. 4. $(a-d)$ QIBDS Net segmented and followed by post-processing with color map images (Yellow-enhanced tumor region, Green-non-enhanced tumor region and Sky blue-edema region) for slice no. 5 using $L = 8$ transition levels with four different thresholding schemes θ_ϱ $(a-a'')$, θ_χ $(b-b'')$, θ_ξ $(c-c'')$ and $\theta_\nu(d-d'')$ for the three distinct level sets c_1 $(a-d)$, c_2 $(a'-d')$ and c_3 $(a''-d'')$ (Color figure online)

with the manually segmented ground truth images and the segmented tumour using the state of the art methods. The proposed QIBDS Net segmented output MR images with the post processed tumour regions are demonstrated using the class levels $L = 8; \{c_1, c_2, c_3\}$ and four distinct activations θ_ϱ, θ_χ, θ_ξ and θ_ν, as shown in Fig. 4.

The evaluation metrics: average accuracy (ACC), dice similarity (DSC), positive prediction value (PPV) and sensitivity (SS) using the suggested QIBDS

Net with the class level $L = 8$ and activation (θ_ξ) for three distinct level sets c_1, c_2, c_3, SOFM, CNN and fuzzy-clustering method are reported in Table 1. It is evident from the results that the proposed QIBDS Net outperforms supervised SOFM and unsupervised fuzzy-clustering with respect to evaluation metrics and reports similar accuracy as the supervised CNN. However, the average DSC reported using CNN is superior to the QIBDSN Net which is demonstrated using Box plots as shown in Fig. 5.

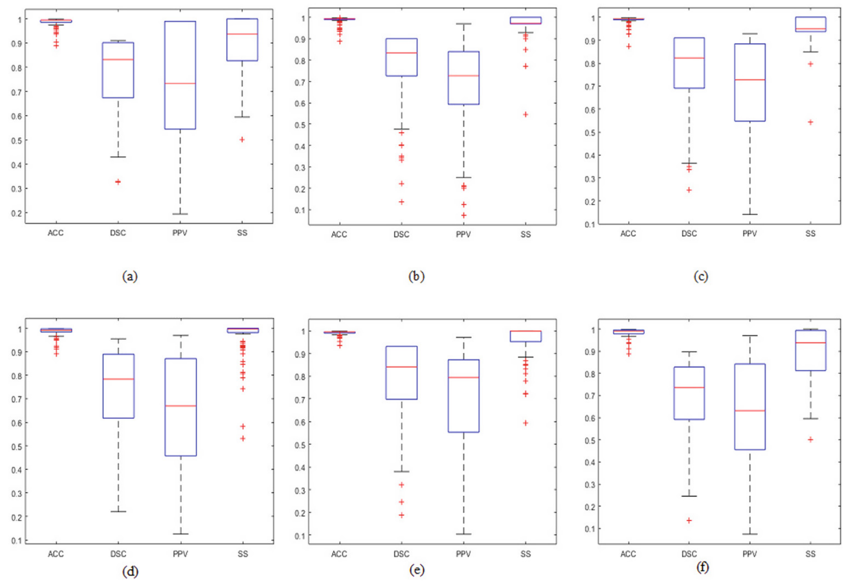

Fig. 5. Box plot of the proposed QIBDS Net with the fixed class level $L = 8$ and class level sets $(a)c_1, (b)c_2$ and $(c)c_3$ and using (d) SOFM (e) CNN and (f) Fuzzy-clustering.

Table 1. A comparative analysis among the proposed QIBDS Net with activation (θ_ξ), Fuzzy-Clustering, SOFM and CNN with one sided two sample KS test (significance level $\alpha = 0.05$ and values marked in bold

Method	Set	ACC	DSC	PPV	SS
QIBDS Net	c_1	0.985	**0.765**	**0.720**	0.906
	c_2	0.984	**0.763**	0.665	**0.970**
	c_3	**0.990**	**0.763**	0.675	0.955
SOFM [6]		0.984	0.738	0.637	**0.962**
CNN [9]		**0.998**	**0.792**	**0.706**	**0.961**
Fuzzy-Clustering [1]		0.982	0.690	0.624	0.898

6 Conclusion

In this paper, a novel quantum-inspired bi-directional self-supervised neural network architecture referred to as QIBDS Net, has been evolved for fully automatic segmentation of MR images. To show the effectiveness of the suggested QIBDS Net, experiments have been performed on $T1$-weighted CE MR images and a comparative analysis with unsupervised fuzzy clustering, supervised self-organizing feature map (SOFM) and convolutional neural network (CNN) has been demonstrated on the same data set. It may be noted that QIBDS Net outperforms SOFM and fuzzy clustering based MR segmentation in terms of all evaluation metrics and yields similar accuracy as CNN in spite of being a self-supervised network architecture. However, it is a subject of investigation to demonstrate the effectiveness of QIBDS Net on BRATS data sets and authors are focusing in this direction.

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