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Researching of Image Compression Based on Quantum BP Network

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Abstract

The encoding time of traditional fractal image coding method is too long.Aiming at this problem, a quantum BP network algorithm is proposed in the paper. By using a neuronal *model with quantum input and output, combined with the theory of BP in image compression and the complex BP algorithm, a model for image impression with 3-layer quantum BP is built, which implements image compression and image reconstruction. The simulation results show that QBP can obtain the reconstructed images with better quantity compared with BP in spite of the less learning iterations.*

Keywords: *quantum BP network, image compression, signal reconstruction, quantum neural network, convergence rate*

1. Introduction

With the development of multimedia technology and the wide application of digital image information, the issues of massive data's storage and transmission are the biggest challenge in the field of electronic information technology, and the image data compression technology is the key to solve this problem. The image compression can use as little as possible bits representative image or the information of images included. High quality and efficiency compression technology means a better visual effect, a faster transmission rate and a smaller data amount of storage.

Based on special topology structure and learning algorithm, artificial neural network has massive processing capability of parallel distributed information, it also can realize image compression quickly and economically, which has been widely used in the field of image compression [1-3]. However, with the depth promotion of the application and the constantly emerging of the practical problems, the limitations and deficiencies of the neural network used for image compression are also gradually revealed. With powerful computing capacity of quantum computing gradually appearing, many scholars began to consider combining quantum theory and neural network to improve the computing performance of neural network in essence, which is Quantum Neural Networks (Quantum Neural Networks, QNN).

Quantum Neural Networks has the potential to be an important means of information processing in the future, which can combine quantum computing and artificial neural network. This article is on the basis of the study of Kouda [4, 5], proposed a quantum neuron model including quantum state input and quantum state output, which based on the principle of BP network for image compression, to construct a method for image compression layers 3 QBP network model (QBP: Quantum Back-Propagation Network), researched the network learning algorithm and performance in-depth, and realized image compression and image reconstruction. The simulation results show that, in the case of the same compression ratio, QBP network not only get better reconstructed image quality, but also less than in the number of iterations on the best learning rate.

2. Quantum BP Neural Network

2.1. Quantum Neuron Model

Quantum gate is the basis of the physical implementation of quantum computing, quantum gates group network can be constituted by quantum gates. This paper's basic

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computing unit is composed of a phase-shift gate and two controlled not gate, as the activation functions of neural network to form a new quantum neuron model [6-8]. To facilitate the application, new quantum neuron model use the plural form of quantum state and general quantum logic gate group.

Quantum bit and classical bit difference: a quantum bit is in the state | 0 > and | 1> coherent superposition state.

$$|\psi\ >=\alpha\ |0>+\beta\ |1> \tag{1}$$

And here the α and β are plural, means probability amplitude, meet the normalization requirements of $|\alpha|^2+|\beta|^2=1$. A complex function to describe the state of the quantum states, the representation of complex function:

$$f(\theta)=e^{i\theta}=\cos\theta+i\sin\theta \tag{2}$$

$i=\sqrt{-1}$ represents the imaginary unit, θ represents the phase of the quantum state. $|0\rangle$ probability amplitude with the real part of the complex function representation, $|1\rangle$ probability amplitude with imaginary part representation. A quantum state can be described as follows:

$$|\psi\rangle=\cos\theta|0\rangle+\sin\theta|1\rangle \tag{3}$$

According to the definition of the formula (2), the quantum neuron model based on a phase shift gate and two controlled not gate is shown in Figure 1. Its input use in the form of a superposition of multiple quantum states, processed by three quantum gates on the amplitude and phase of the input quantum state to obtain the output of the superposition of multiple quantum states.

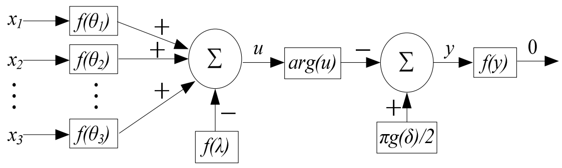

Figure 1. Quantum Neuron Model

In Figure 1, $x_i\left(i=1,2,\cdots n\right)$ represents the i-th input to the neurons of the quantum state, $\theta_i\left(i=1,2,\cdots n\right)$ is phase transfer coefficient for weight, λ is the threshold coefficient, δ is the phase control factor, O for the output state; $\arg(u)$ is the complex extraction phase, that is $\arg(u)=actag(\mathrm{Im}(u)/\mathrm{Re}(u))$. Among them, $\mathrm{Im}(u)$ is the imaginary part of complex u, $\mathrm{Re}(u)$ is the real part of complex u; the definition of *f* function as formula (2); $g(x)$ is the sigmoid function. Here I_i that *i* input to the neurons was set to quantum state x_i' phase, the quantum neuron output in formula expressed as follows:

$$u=\sum_{i=1}^{n}f(\theta_i)f(I_i)-f(\lambda) \tag{4}$$

$$y=\frac{\pi}{2}g(\delta)-\arg(u) \tag{5}$$

$$O = f(y) \quad (6)$$

There are two types of parametric form in this quantum neuron model, one is corresponding to the phase shift of the phase of the weights θ_i and threshold parameters λ; another flip control parameters δ corresponding to the control gate. Different from the traditional neuron, the result by multiplying value $f(\theta_i)$ and the input $x_i = f(I_i)$ in quantum neurons is realized by the phase shift gate to neuron state phase shift.

2.2. Quantum BP Neural Network Image Compression Model

Based on the quantum neuron model proposed above, with the help of BP artificial neural network [9] for image compression theory and network structure established the quantum BP neural network for image compression. In order to reduce the run time of the system and improve the efficiency of the network, artificial BP neural network structure established by quantum BP network for image compression is only one hidden layer, the network structure as shown in Figure 2. From the figure we can see that its network structure is the same as the traditional three-layer BP network, only one hidden layer, and no connection between neurons of the same layer, each between layer and layer neurons are all connected. The difference is that its input and output is the superposition of a plurality of quantum states and the structure of neuron.

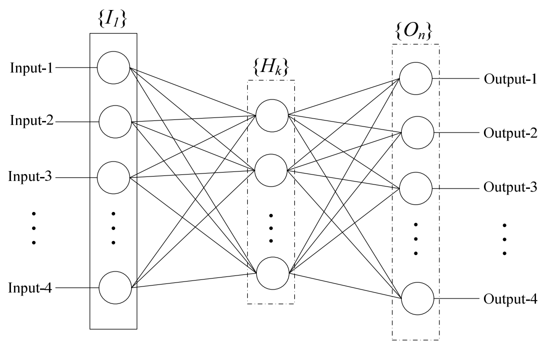

Figure 2. QBP Three Layers Neural Network of Image Compression

Principle of quantum BP neural network realized image compression is the same as BP network, both of them are made of hidden layer neurons number less than the input and output layer. After the image data is input to the input layer, which is forced through the slender waist of the hidden layer to achieve the purpose of image compression, then realized the image's decoding and reconstruction from hidden layer to output layer. Therefore, three QBP network shown in Figure 2, the input and output layers of the network are taken equal number of neurons N, the size of N's original image is determined during the course of compression according to the specific situation, each neuron corresponding to a pixel; the number of hidden layer neurons is K, and K <N, the size of K is determined depending on the different compression ratio, each layer relationship between the input and output as the following description.

When the input data is input to the input layer, each neurons of input layer will make [0, 1]'s input value convert to phase values between quantum states $[0, \pi/2]$, and its phase modulation by the quantum state will be output from the input layer neurons. Expression is as follows:

$$y_{1l} = \frac{\pi}{2} I_l \quad (7)$$

$$IO_l = f(y_{1l}) \tag{8}$$

The expression of each neuron in hidden layer output is as follows:

$$u_{1k} = \sum_{l}^{N} f(\theta_{1k,l}) \times IO_l - f(\lambda_{1k}) \tag{9}$$

$$y_{2k} = \frac{\pi}{2} g(\delta_{1k}) - \arg(u_{1k}), \quad k = 0,1,\cdots K \tag{10}$$

$$H_k = f(y_{2k}) \tag{11}$$

$\theta_{1k,l}$ is the phase rotation factor that from input layer *l* neuron to hidden layer *k* neuron, λ_{1k} is hidden layer of *k* neuron's threshold coefficient, δ_{1k} is the phase control factor of hidden layer *k* neuron, H_k is *k* neuron of hidden layer output.

The output of each neuron in output layer's expression is as follows:

$$u_{2n} = \sum_{k}^{K} f(\theta_{2n,k}) H_k - f(\lambda_{2n}) \tag{12}$$

$$y_{3n} = \frac{\pi}{2} g(\delta_{2n}) - \arg(u_{2n}) \tag{13}$$

$$OP_n = f(y_{3n}) \tag{14}$$

$\theta_{2n,k}$ is the phase rotation factor that from hidden layer *k* neuron to output layer *n* neuron, λ_{2n} is output layer of *n* neuron's threshold coefficient, δ_{2n} is the phase control factor of output layer *n* neuron, OP_n is *n* neuron of hidden layer output.

Among quantum neuron, the quantum state $|1\rangle$ is equivalent to the active state of the neuron, the quantum state $|0\rangle$ is equivalent to the inhibition of the neurons state, so arbitrary neuron's quantum state is defined as superposition state of activation state and inhibit state, the final output value is the active state probability. So the final output of the BP neural network output layer neuron is as follows:

$$O_n = \left|\mathrm{Im}(OP_n)\right|^2 \tag{15}$$

2.3. Training Algorithm

In order to train three layers quantum BP neural network, with the help of plural BP algorithm, back propagation in the network is defined quantum back propagation algorithm (QBP algorithm). This algorithm uses the approximate mean square error of the steepest descent algorithm [10], to adjust network phase rotation coefficient θ, threshold coefficient λ and phase control factor δ, to make the training error of the mean less than the expected goal.

Mean square error function is defined E, and its expression is as follows:

$$E = \frac{1}{2} \sum_{n}^{N} (t_n - O_n)^2 \tag{16}$$

t_n is output layer of *n* neuron's desired output, O_n is the actual output of the *n* neurons in the output layer. By the network's input/output formula, it can be seen that the final output error of the network are the phase rotation factor θ of each layer, the threshold factor λ and the phase control factor function δ, so error E can be changed through adjusting them. Quantum BP network back-propagation training process is as follows:

First, compared the error value whether is less than the target error, if not less than, then the error will spread reversely. Based on the steepest descent method, layers parameters will be adjusted reversely layer by layer.

(1) Parameter adjustment of output layer of each neuron

After the adjustment of the hidden layer *n-th* neuron's phase controlling factors δ_{2n} turns into as follows:

$$\delta_{2n}^{new} = \delta_{2n}^{old} + \eta \frac{\pi}{2}(t_n - O_n)\operatorname{Im}\left(f'(y_{3n})\right)g'(\delta_{2n}) \tag{17}$$

Among them, η is the learning coefficient, it reflects the learning rate in the training. Its selection has a great influence on the neural network training speed and precision of the parameter. Error is not implicit explicit function of the layer, so using the chain rule of calculus to calculate partial derivatives.

The phase rotation coefficient of the output layer $\theta_{2n,k}$, the threshold factor λ_{2n} can be adjusted as follows:

$$\theta_{2n,k}^{new} = \theta_{2n,k}^{old} - \eta d_n \arg'(u_{2n}) m_n \tag{18}$$

$$\lambda_{2n}^{new} = \lambda_{2n}^{old} - \eta d_n \arg'(u_{2n}) s_n \tag{19}$$

Among them:

$$m_n = \frac{\cos(\theta_{2n,k} + y_{2n})\operatorname{Re}(u_{2n}) + \sin(\theta_{2n,k} + y_{2n})\operatorname{Im}(u_{2n})}{\left(\operatorname{Re}(u_{2n})\right)^2} \tag{20}$$

$$s_n = \frac{-\cos(\lambda_{2n})\operatorname{Re}(u_{2n}) - \sin(\lambda_{2n})\operatorname{Im}(u_{2n})}{\left(\operatorname{Re}(u_{2n})\right)^2} \tag{21}$$

$$d_n = 2(t_n - O_n)\operatorname{Im}(OP_n)\operatorname{Im}\left(f'(y_{3n})\right) \tag{22}$$

(2) Parameter adjustment of the hidden layer

$$\delta_{1k}^{new} = \delta_{1k}^{old} - \eta \frac{\pi}{2} \sum_{n}^{N} d_n \arg'(u_{2n}) m_n g'(\delta_{1k}) \tag{23}$$

$$\theta_{1k,l}^{new} = \theta_{1k,l}^{old} + \eta \sum_{n}^{N} d_n \arg'(u_{2n}) m_n \arg'(u_{1k}) m_{1k} \tag{24}$$

$$\lambda_{1k}^{new} = \lambda_{1k}^{old} - \eta \sum_{n}^{N} d_n \arg'(u_{2n}) m_n \arg'(u_{1k}) s_{2k} \tag{25}$$

Among them:

$$m_{1k} = \frac{\cos(\theta_{1k,l} + y_{1l})\operatorname{Re}(u_{1k}) + \sin(\theta_{1k,l} + y_{1l})\operatorname{Im}(u_{1k})}{\left(\operatorname{Re}(u_{1k})\right)^2} \tag{26}$$

$$s_{1k} = \frac{-\cos(\lambda_{1k})\,\mathrm{Re}(u_{1k}) - \sin(\lambda_{1k})\,\mathrm{Im}(u_{1k})}{\left(\mathrm{Re}(u_{1k})\right)^2} \tag{27}$$

Then, using the new parameters compute for the three layers quantum BP network's input and output, because there are no parameters in the input layer, the prior calculation can start from the hidden layer. Error calculation can be done after getting the final output value of the network, if the error value is still less than the target error value, it need repeat reverse propagation, and then adjust the parameters. This cycle continues until the error value is less than the target error.

3. Quantum BP Neural Network for a Small Image Compression

In order to verify Figure 2 the three layers QBP network whether has image compression capability, this paper use this network on a 8×8 Pixel image compressed (Figure 3(a) below). The reasons for selecting 8×8 small image due to it can be clearly seen the changes in each pixel, and also more easily distinguish network compression reconstruction capacity. The QBP network of the input layer and output layer neuron number is 64, because of the number of hidden layer neurons determines the ability of the network compress image, the number of optional hidden layer neurons are 16, 8 and 4, and network training adopts QBP algorithm. In the process of image compression, if the error E does not exceed the target error E_{lower} , then the training is over, and the network has a convergence. If the learning iteration number has exceeded a fixed value, but error E is still no less than E_{lower} , then the training end, the training of this net work does not have convergence. If the network target error is set to 0.001, the maximum number of iterations is 5000. During network training process, the size of the learning coefficient of the network η affects the average number of iterations and the convergence speed, in order to obtain a minimum average number of iterations, the learning coefficient η is different values of $[0.1, 6.0]$. In order to obtain a stable average number of iterations, each learning coefficient trained 20 times. Network learning coefficient η depends on the average number of iterations and the convergence rate.

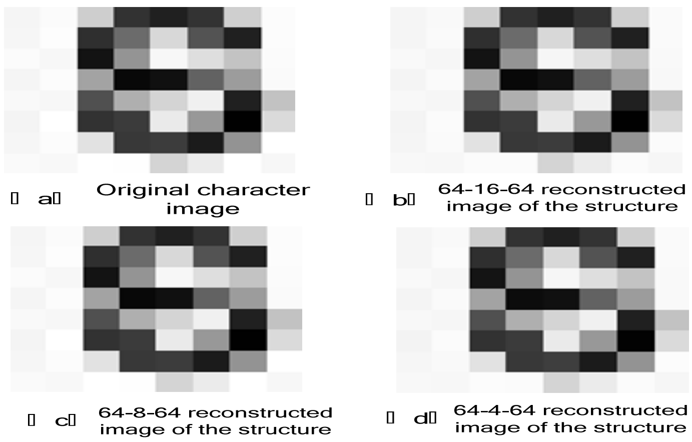

Figure 3. Reconstruction Characters Image

Figure 3 shows the different QBP network structure in Figure 3(a) the compression of image reconstruction. Whatever using any kind of network structure, the reconstruction of image compression effect is good, the human eye can hardly identify unzip each pixel of the image and original image is the difference between each pixel, so the quantum BP network has a good reconstruction ability of image compression. Figure 4 and Figure 5 shows a part of the learning coefficient for different η_Q values, different network structure has the average number of iterations and the convergence rate.

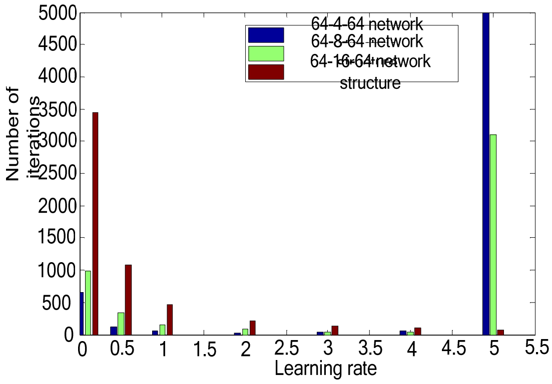

Figure 4. Average Number of Iterations when η_Q are Different

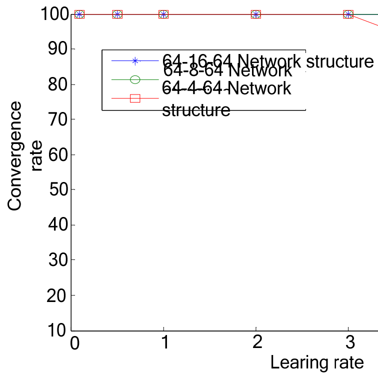

Figure 5. Network Convergence Rate when η_Q are Different

As can be seen from Figure 4 and 5 that QBP average number of iterations decreases with the increase of the learning coefficient η_Q, when η_Q located between 0.1 and 4.0 the learning iteration number does not exceed 500 times will reach convergence. When the number of hidden layer neurons 8 and 4, the average number of iterations are not more than 120 times to convergence, and with the compression rate increased, the number of hidden layer neurons decreased, network convergence need less number of iterations. For 64-16-64 network structure, when η_Q = 5.0, the minimum average number of iterations is 56 times, for 64-8-64 network structure, when η_Q = 3.6, to obtain a minimum average number of iterations is 34 times; for 64-4-64 network structure, when η_Q = 2.1, to obtain a minimum average number of iterations is 28 times.

From the above analysis results, it is not difficult to see QBP network has excellent image compression reconstruction ability; and with the compression ratio improved, it not only reduce the size of the network, accelerate the network learning convergence speed, but also has a better visual fidelity in reconstructed image. This is because the QBP network in the image compression process of training, the end of each iteration, the information is not only stored in the network weights and thresholds, but also retain the parameters phase shift, so the information capacity of the network is increased, the loss less data in compression process. Moreover, QBP trains data of real and imaginary parts at the same time, which not only greatly improve the computational efficiency, and more close to the original value, and choose the appropriate learning coefficient η_Q can also reduce the number of iterations network, improve the network convergence rate.

4. Conclusion

This paper mainly studied quantum neuron model which used quantum gate group (that is, the phase-shift gate and controlled not gate) as the basic cell, and with plural BP learning rule and BP network for image compression principle, build QBP for image compression and used in image compression. The experimental results show that image compression QBP compared with BP network, shows faster learning rate, and has a better image compression ability than BP network.

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