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A method for compressing computer-generated hologram using genetic algorithm optimized quantum-inspired neural network

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ABSTRACT

A method for compressing computer-generated holograms (CGHs) using genetic algorithm optimized quantum-inspired neural network is proposed. Genetic algorithm is a global optimization algorithm, which can provide better initial weights for the quantum-inspired neural network. The global optimization ability of genetic algorithm is combined with the local optimization ability of the quantum-inspired neural network enables the network to achieve better convergence effects. Under different compression ratios, CGHs are compressed by the genetic algorithm optimized quantum-inspired neural network and the quantum-inspired neural network respectively, and Fresnel transform technology is used to reconstruct the decompressed CGHs. The experimental results show that the genetic algorithm optimized quantum-inspired neural network can obtain better quality reconstructed images than the quantum-inspired neural network while using fewer learning iterations.

Keywords: Computer-generated hologram, compression, quantum-inspired neural network, genetic algorithm

1. INTRODUCTION

In computer holography, the computer-generated hologram contains a large amount of original object information, including the object amplitude and phase information [1]. So it is necessary to adopt a method to compress the hologram data in order to transmit the hologram quickly, keep the information of the hologram undamaged and have a better reconstruction quality.

Ref.1 proposed a quantum neuron model with quantum state input and quantum artificial neural network theory, which proved that the quantum-inspired neural network (QINN) has faster learning speed and better reconstruction results than the ordinary artificial neural network in compressed image application. Genetic algorithm was proposed by John Holland in the 1970s [2]. It is a random search algorithm based on biological natural selection and genetic mechanisms. By simulating the phenomena of reproduction, crossover and mutation in nature, a set of candidate solutions are retained in each iteration, and better individuals are selected from the solutions based on a certain index. These individuals are combined by gene operators to generate a new generation of candidate solutions, and the process is repeated until the requirements are met.

A quantum-inspired neural network has been found to offer more powerful quantum parallelism with quantum superposition and has higher efficiency for ordinary image calculations [3, 4]. Therefore, some researchers have used QINN to improve the efficiency of compressed image [5, 6]. The network has a strong dependence on the initial weights, the essence of training is to optimize the weights of the network to get better network performance [7]. However, the steepest gradient descent method is usually used in network training, when the weights of the network are not appropriate, the quantum neural network is easy to fall into local optimum [8].

The quantum neural network is optimized by genetic algorithm, which combines the global search ability of genetic algorithm with the local search ability of quantum-inspired neural network, effectively solving the problems of QINN's difficulty in escaping from local extremes, slow convergence speed, and oscillation effects. Therefore, finding a suitable set of weight distributions is very important for QINN.

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In this paper, the Fresnel transform technology (FTT) is used firstly to make a CGH training set [9].Then obtain a set of initial weights of the quantum neural network through the genetic algorithm, and use genetic algorithm optimized quantum-inspired neural network (GAQINN) to compress and transmit CGHs. Finally, FTT is used to reconstruct image and PSNR is used to evaluate the quality of reconstructed images.

2. PRINCIPLE OF COMPUTER-GENERATED HOLOGRAM

The hologram uses the interference phenomenon of light to record the amplitude and phase information of the object wave in the form of interference fringes. According to the method of calculating a hologram using off-axis reference light proposed by Leith and Upatnieks [1], the amplitude and phase transmittance of the hologram can be expressed as

$$\begin{aligned} I(x,y) &= [r(x,y)+a(x,y)][r(x,y)+a(x,y)]^* \\ &= |R(x,y)\exp[j\phi(x,y)] + A(x,y)\exp[j\psi(x,y)]|^2 \\ &= R(x,y)^2 + A(x,y)^2 + 2R(x,y)A(x,y)\cdot\cos[\phi(x,y)-\psi(x,y)], \end{aligned} \tag{1}$$

where the object wave with amplitude $A(x,y)$ and phase $\psi(x,y)$ is expressed as $a(x,y)=A(x,y)\exp[j\psi(x,y)]$. The reference wave with amplitude $R(x,y)$ and phase $\phi(x,y)$ is expressed as $r(x,y)=R(x,y)\exp[j\phi(x,y)]$.

3. QUANTUM-INSPIRED NEURAL NETWORK

3.1 Quantum neuron

In Ref. 5, the expression of the quantum state is

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

θ is the phase of the quantum state, and the values of the real part and imaginary part correspond to the probability amplitudes of $|0\rangle$ and $|1\rangle$ respectively.

The quantum neuron is the basic unit of QINN. Quantum neuron is composed of 1bit rotating quantum gate and 2bit control NOT gate. The calculation process of the quantum neuron is as follows

$$u=\sum_{i=1}^{L} f(\theta_i)f(I_i)-f(\lambda), \tag{3}$$

$$y=\frac{\pi}{2}g(\delta)-\arg(u), \tag{4}$$

$$O=f(y), \tag{5}$$

where $g(x)=1/[1+\exp(-x)]$, $\arg(\cdot)$ represents the phase of the complex number, L is the number of input quantum neuron, O represents the output of the quantum neuron, the phase parameter θ and the threshold λ corresponds to 1-bit rotation gates, and the reversal parameter δ corresponds to the 2-bit CNOT gate [11].

3.2 Quantum-Inspired neural network structure

Normalize the input data to [0, 1], and then convert it into a quantum state phase [0, π/2], the input I_l of the network is represented as

$$I_l=\frac{\pi}{2}input_l, \tag{6}$$

In the quantum neuron model, any neuron state can be described as the coherent superposition state of two qubits. The output value of the nth neuron of the last layer of the network is expressed as the probability that the observation is $|1\rangle$, expressed as

$$output_n=|O_n|^2. \tag{7}$$

4. QUANTUM-INSPIRED NEURAL NETWORK OPTIMIZED BY GENETIC ALGORITHM

4.1 Genetic algorithm optimizes QINN parameters

The quantum neural network structure of compressed hologram needs to be determined, including the number of neurons in input layer, hidden layer and output layer.

The first step of genetic algorithm is to generate initial population. Because of the advantages of high precision, wide range and fast operation, floating-point coding is adopted. The coding length of parameter gene is equal to the sum of the weights and thresholds of QINN.

According to the principle described in Ref. 12, the fitness function is a function that measures the adaptability of the chromosome and is a criterion for driving the evolution of the algorithm and selecting individuals based on the objective function. The fitness function of QINN optimized by genetic algorithm is based on the total error function of the network, which is defined as

$$Fitness = \frac{1}{E}, \tag{8}$$

$$E = \frac{1}{2}\sum_{n=1}^{N}(target_n - output_n)^2 , \tag{9}$$

$target_n$ and $output_n$ represent the expected output and actual output of the nth output layer neuron respectively, N is the number of output layer neuron. Calculate the evaluation function of each individual and sort them, then select the individual by the following probability value

$$p_i = \frac{Fitness}{\sum_{i=1}^{N} Fitness_i}. \tag{10}$$

The genetic algorithm finds the individual with the best fitness value by performing selection, crossover, and mutation operations, then decode this individual and save it. Finally, QINN training begins, and the optimal individuals obtained by genetic algorithm are transferred to the QINN network as its initial weights θ, λ, and δ.

4.2 CGH Compression with Optimized Quantum-Inspired Neural Network

Construct a three-layer QINN network to compress CGH. Before compression, normalize the pixel value of the hologram from [0, 255] to [0, 1]. Then divide the CGH (e.g., $X\times Y$ pixels) into sub-blocks (e.g., $x\times y$ pixels, $N=(X\times Y)/(x\times y)$), and then convert the sub-blocks to a column vector (e.g., $L\times 1= x\times y$) as the input data of the network. The CGH from the input layer to the hidden layer is the process of encoding, and from the hidden layer to the output layer is the process of decoding. The number of input and output quantum neurons is equal. The number K of hidden quantum neurons is less than the number L of input quantum neurons to achieve the purpose of CGH compression. The output value of the hidden quantum neuron is the result of CGH compression. The output value of the output layer quantum neuron is the reconstructed image.

5. EXPERIMENTS RESULTS AND ANALYSIS

5.1 Quality Evaluation of Reconstructed Image

In order to evaluate the image quality of the reconstructed CGH, four indexes compression ratio, mean-squared error (MSE), and peak signal-to-noise ratio (PSNR) are used.

$$\mathrm{CR} = \frac{S_c}{S_o} = \frac{K}{L}, \tag{11}$$

$$\mathrm{MSE} = \frac{1}{X\times Y}\sum_{x=1}^{X}\sum_{y=1}^{Y}| f(x,y) - \overline{f}(x,y)|^2 , \tag{12}$$

$$\mathrm{PSNR} = 10\log_{10}\frac{x_{peak}^{2}}{\mathrm{MSE}}, \tag{13}$$

where S_c is the size of the compressed hologram, S_0 is the size of the original hologram, $f(x,y)$ is the reconstructed CGH image, $\bar{f}(x,y)$ is the original CGH image, and x_{peak} is the peak-to-peak value of the image data.

5.2 Comparison of QINN and GAQINN

The experiment uses QINN and GAQINN to compress CGH respectively, and the two methods are compared in terms of compression speed and reconstructed hologram quality.

The experiment uses holograms with a 256 grayscale value of 256×256 pixels. The original hologram is normalized, and the pixel range is converted from [0, 255] to [0, 1]. In the experiment, $K = 8$ is selected. The hologram is divided into 8 × 8 pixels and converted into 1024 vectors with the length of $L = 64$ as the input of the network, so the number of input and output quantum neurons of the network is 64. The number of hidden layer quantum neurons is set to 32, 16, 8 and 4 respectively, and the image compression ratio (CR) corresponding to each network structure is 0.5, 0.25, 0.125, and 0.0625.

The weights of QINN network are initialized randomly, while GAQINN uses genetic algorithm to initialize the weights. Corresponding to the four network structures, the number of individuals of genetic algorithm S should be equal to the sum of all weights. Set the population number to 1000, adopt the floating-point coding method, according to the range of QINN weight, controlling the floating-point coding range to [-1, 1]. ArithXover crossover method is used, and the crossover probability P is random in this method. The selection operation uses the normGeomSelect, and the mutation operation uses the nonUnifMutation. Population size is 500. Set the genetic algebra as 200 to optimize the weights, and four sets of network initialization weights are obtained.

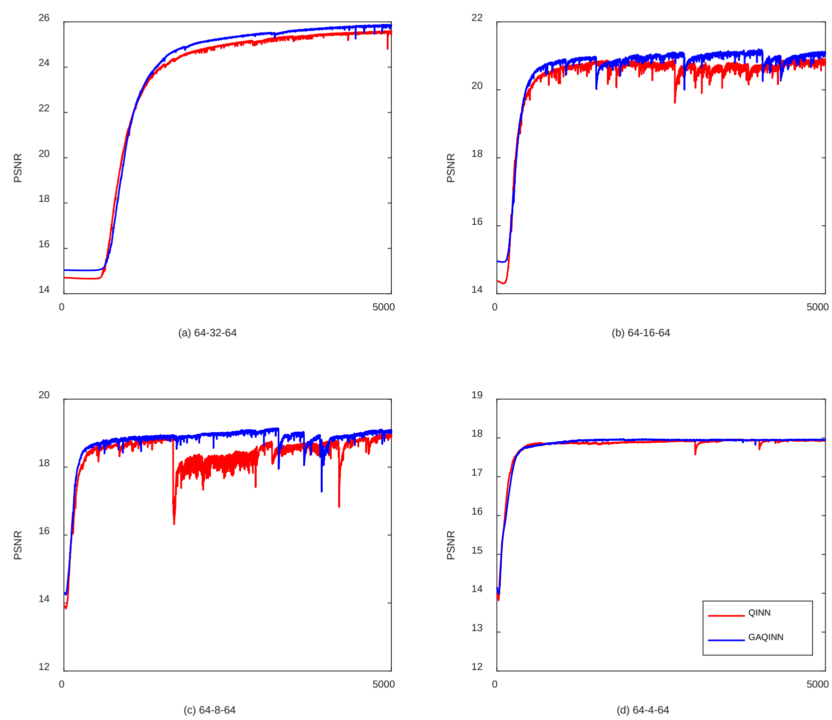

Fig.1 The PSNRs of the reconstructed images of CGH changes with the increase of training iterations. The horizontal coordinate represents the number of iteration steps. Here, "64-32-64" stands for the network structure (input layer width—hidden layer width—output layer width, respectively).

Figure 1 shows the PSNR values of the reconstructed CGH at different compression ratios. When K = 32, 16, and 8, GAQINN can reach the PSNR value when QINN converges before QINN. The PSNR value at GAQINN convergence is greater than the PSNR value at QINN convergence. When k = 4, it is found that the CGH reconstruction results of the two methods are similar. This is because the number of hidden neurons and network parameters of the network is less than other network structures. The network structure is the decisive factor affecting the reconstructed image quality, and the optimization of the initial value has little effect on improving the network performance.

The QINN is trained for 5000 steps with different learning rates, and the E are set to appropriate values respectively. When the training reaches the maximum training steps or the loss value is less than E , stop training. Since the initial value of the optimization is random, in order to obtain a more stable optimization results, both method are performed 10 times, and the average value of evaluation indexes is taken.

Table1 Comparison of convergence steps between GAQINN and QINN

K	CR	E_{max}	GAQINN		QINN	
			Iterations	lr	Iterations	lr
32	0.5000	0.00038	2548	0.25	3283	0.2
16	0.2500	0.00150	477	0.4	765	0.3
8	0.1250	0.00210	957	0.45	1618	0.3
4	0.0625	0.00270	444	0.1	525	0.1

Because the learning rate determines the convergence rate of the network, the higher the learning rate, the faster the convergence rate, but the final convergence effect will be worse. Table 1 lists the learning rates used to achieve similar PSNR values for the two methods, and the number of iterations required for both methods when the loss value reaches E_{max}. Take K = 32, for example, loss converges to 0.00038, QINN uses 3283 steps, and GAQINN only uses 2548 steps.

Table2 Quality evaluation of reconstructed image

K	CR	GAQINN			QINN		
		Err	PSNR(dB)	Iterations	Err	PSNR(dB)	Iterations
32	0.5000	0.0003464	25.7651	4969	0.0003607	25.4576	4974
16	0.2500	0.0011924	21.1964	3985	0.0012141	20.9287	4942
8	0.1250	0.0019868	19.1431	3267	0.0020495	18.9847	4999
4	0.0625	0.0025408	17.9924	4825	0.0025442	17.9309	4882

The PSNR values of compressed CGH reconstructed images are compared between GAQINN and QINN at different compression ratios. When CR = 0.5, The PSNR value for GAQINN is 25.7651, corresponding to 4969 iterations. The PSNR value for QINN is 25.4576, corresponding to 4974 iterations. The number of training steps of GAQINN is less than that of QINN. Therefore, as can be seen from Table 2, GAQINN always converges to a smaller error than QINN, which means that GAQINN can always find a better solution under the optimal learning rate of the two methods. The PSNR of CGH reconstructed by GAQINN method is better than that by QINN method.

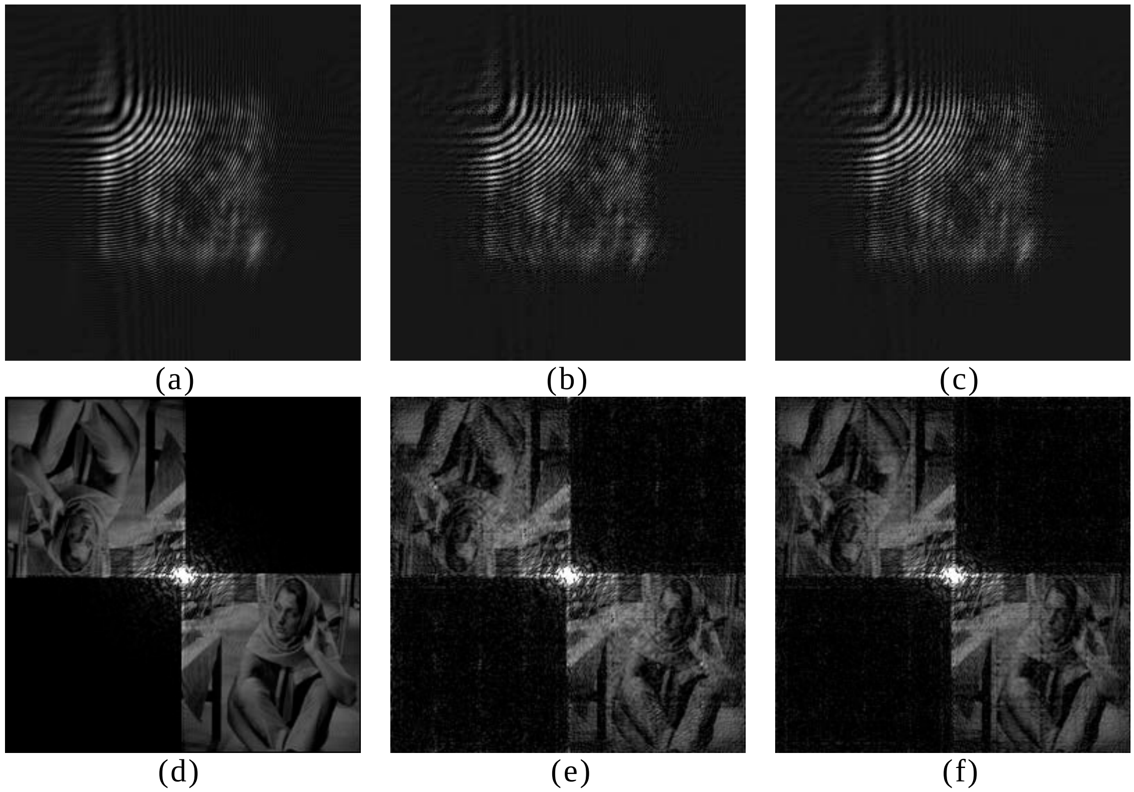

Fig. 2 Comparison of CGHs and their reconstructed images with CR=0.5. (a) CGH without compression, (b) CGH compressed with QINN, (c) CGH compressed with GAQINN, (d) reconstructed image of (a), (e) reconstructed image of (b), and (f) reconstructed image of (c).

6. CONCLUSION

We propose a genetic algorithm to optimize the quantum-inspired neural network method to compress Fresnel CGHs. Compared with QINN, GAQINN starts training from a better initial value, which can speed up the compression of CGHs. The combination of the global optimization ability of genetic algorithm and the local optimization ability of quantum neural network improves the quality of CGH after decompression. At the same time, a better quality reconstructed original image is obtained.

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