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Method of computer-generated hologram compression and transmission using quantum back-propagation neural network

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Abstract. A method for computer-generated hologram (CGH) compression and transmission using a quantum back-propagation neural network (QBPNN) is proposed, with the Fresnel transform technique adopted for image reconstruction of the compressed and transmitted CGH. Experiments of simulation were conducted to compare the reconstructed images from CGHs processed using a QBPNN with those processed using a back-propagation neural network (BPNN) at the optimal learning coefficients. The experimental results show that the method using a QBPNN could produce reconstructed images with a better quality than those obtained using a BPNN despite the use of fewer learning iterations at the same compression ratio. [DOI: 10.1117/1.OE.56.2.023104]

Keywords: computer-generated hologram; image processing; image reconstruction techniques; quantum optics; quantum information and processing.

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1 Introduction

In computer holography, a computer-generated hologram (CGH) contains a large quantity of information, including the amplitude and phase information of an object.[1,2] Therefore, it is necessary to find an appropriate method to effectively compress and quickly transmit an object's information. Our goal was to find a way to reduce the holographic fringe information of a digital hologram (DH) for 3-D image real-time display.

Several studies have been conducted on DH compression. In Ref. 3, the holographic bandwidth was compressed using spatial subsampling. In Refs. 4 and 5, a sparse matrix representation was used. In Refs. 6 and 7, the joint photographic experts group baseline encoding technique was applied. In Refs. 8–10, an artificial neural network was adopted. These studies were based on an electronic holographic hardware display system. However, we have generated a DH that depends on an optical table. The experimental requirements of the DH are very rigorous. To simplify our experiments and verify the rationality of our scheme, we adopted a CGH to replace a DH because they have similar properties and they all are complex function (i.e., the amplitude function and phase function).

According to Refs. 1 and 2, we can know a CGH is an interference fringe pattern with a nonlinear intensity distribution. This intensity distribution contains the 3-D information of an object. Artificial neural networks have been widely used in the nonlinear field,[8] and they can be adaptively and intelligently adjusted to overcome the hologram information distribution problem.[9] A back-propagation neural network (BPNN) has proven to be effective for CGH compression.[10] However, the processing speed of a BPNN is lower than that of other methods used for processing large amounts of information, and the memory capacity is limited.[11]

In research, we have found that a quantum back-propagation neural network (QBPNN) offers a more powerful quantum parallelism with quantum superposition compared with other networks, which is suitable for processing large amounts of data. According to the principle of quantum computation, an n-bit quantum register can simultaneously save 2^n n-bit binary numbers (from 0 to $2^n - 1$), where each number has a certain probability. A quantum system can exponentially increase the storage capacity and handle all 2^n numbers of an n-bit quantum register at high speed.[11,12]

Because of these advantages, several researchers have used a QBPNN to compress images.[13–16] CGH is an image that contains the amplitude and phase information of an object. Therefore, a QBPNN can be adopted to process a CGH. A method for compressing, transmitting, and reconstructing a CGH using a QBPNN and the Fresnel transform technique (FTT) is proposed, as shown in Fig. 1.

2 Principle of Computer-Generated Hologram

Based on the holographic principle of Leith and Upatnieks with regard to off-axis reference beam holograms,[17] a Fresnel hologram of a 256 gray-scale Lena image was generated by a computer. The amplitude and phase transmittance of a hologram recorded under ideal conditions are as follows:

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

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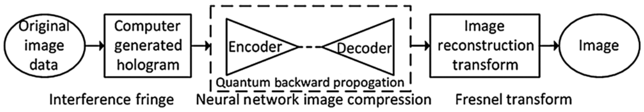

Fig. 1 CGH compression, transmission, and reconstruction using QBPNN and FTT.

where $r(x,y) = R(x,y)\exp[j\phi(x,y)]$ represents the tilted reference wave and $a(x,y) = A(x,y)\exp[j\psi(x,y)]$ represents the object wave. $I(x,y)$ is the resulting intensity variation of the interference pattern between the object wave and the reference wave. In the experiments of simulation, the position of the reference wave $r(x,y,z)$ was $r[0{,}0{,}1500(\text{mm})]$ and the position of the object wave $a(x,y,z)$ was $a[-0.2208, 0.2208{,}1500(\text{mm})]$. Using Eq. (1) and Table 1, a CGH was generated using a computer, as shown in Fig. 2.

3 Quantum Back-Propagation Neural Network

3.1 *Quantum Neuron Model*

According to the principle described in Ref. 13, in quantum computing, a quantum bit state $|\phi\rangle$ maintains a coherent superposition of states $|0\rangle$ and $|1\rangle$, which can be described as

$$|\phi\rangle = \alpha|0\rangle + \beta|1\rangle, \tag{2}$$

where α and β are complex numbers called probability amplitudes. That is, the quantum state $|\phi\rangle$ collapses into either the $|0\rangle$ state with probability $|\alpha|^2$ or the $|1\rangle$ state with probability $|\beta|^2$, where $|\alpha|^2 + |\beta|^2 = 1$.

To express the quantum states, a representation of the quantum state using complex numbers can be expressed as

Table 1 Experimental data of a Lena for a CGH.

Parameters	Value
Wavelength	633 nm
Original image size	128×128 pixels
Pixel size	0.00345×0.00345 mm
Hologram size	256×256 pixels

$$f(\theta) = e^{i\theta} = \cos\theta + i\sin\theta, \tag{3}$$

where $i = \sqrt{-1}$ is the imaginary unit and θ is the phase of the quantum state. This equation connects the probability amplitude of $|0\rangle$ with the real part and that of $|1\rangle$ with the imaginary part. According to Eq. (3), a quantum state can be described as follows: $|\phi\rangle = \cos|0\rangle + \sin|1\rangle$. The quantum neuron model was described in Ref. 13.

The quantum neuron output is given by

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

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

$$O = f(y), \tag{6}$$

where $f(\cdot)$ has been described in Eq. (3), $g(\cdot)$ is the sigmoid function, $\arg(u)$ represents the phase extracted from a complex number u, $x_i (i = 1{,}2, \ldots, M)$ is the i'th input to the neurons of the quantum state, $I_i (i = 1{,}2, \ldots, M)$ is the phase of quantum state x_i, $x_i = f(I_i)$, and O is the output state.

This quantum neuron model has two kinds of parameters: the phase parameter of weight connection $\theta_i (i = 1{,}2, \ldots, M)$ and threshold λ for the phase of the 1-bit rotation gate and the reversal parameter δ for the 2-bit controlled-NOT gate.[18,19]

3.2 *Structure of Quantum Back-Propagation Neural Network*

The structure of the QBPNN is nearly the same as that of a conventional 3-layer BPNN. The difference is that all the neurons are quantum neurons in a QBPNN, and the QBPNN input and output are the super positions of multiple quantum states. In a QBPNN, L, K, and N are the numbers of neurons in the input, hidden, and output layers, respectively. Further details are provided in Ref. 16.

When the data [i.e., $\text{input}_l (l = 1{,}2, \ldots, L)$] are input into the network, the input layer converts the normalized input value [0, 1] into the phase $[0, \pi/2]$ in quantum states and outputs this to the hidden layer as follows:

$$I_l = \frac{\pi}{2}\text{input}_l, \tag{7}$$

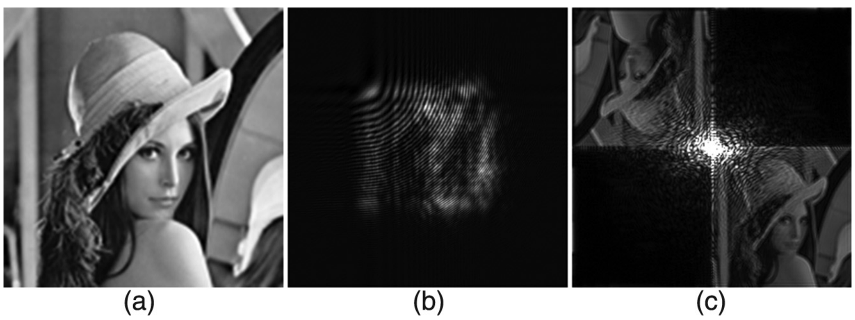

Fig. 2 CGH of 256 gray-scale Lena image and corresponding reconstructed image: (a) original Lena image (128×128 pixels), (b) CGH of (a) (256×256 pixels), and (c) reconstructed image of (b) (256×256 pixels).

$$x_l = f(I_l). \tag{8}$$

The processing of the QBPNN in the hidden layer and output layer can be described using Eqs. (4)–(6).

In the quantum neuron model, the quantum state $|1\rangle$ represents the firing neuron state, while the quantum state $|0\rangle$ represents the nonfiring neuron state, and an arbitrary neuron state can be described as a coherent superposition state of the two. In a QBPNN, the final output value [i.e., $\text{output}_n (n = 1,2,\ldots,N)$] of the n'th output layer neuron is described as the probability of the firing neuron state, which is the probability when the quantum state $|1\rangle$ appears. That is

$$\text{output}_n = |\text{Im}(O_n)|^2. \tag{9}$$

3.3 *Training Algorithm of Quantum Back-Propagation Neural Network*

The steepest descent method, which is adopted in the BPNN algorithm, is also applied in the QBPNN algorithm. The learning rule of the QBPNN can be expressed as[13]

$$\theta^{\text{new}} = \theta^{\text{old}} - \eta \frac{\partial E_{\text{total}}}{\partial \theta^{\text{old}}}, \tag{10}$$

$$\lambda^{\text{new}} = \lambda^{\text{old}} - \eta \frac{\partial E_{\text{total}}}{\partial \lambda^{\text{old}}}, \tag{11}$$

$$\delta^{\text{new}} = \delta^{\text{old}} - \eta \frac{\partial E_{\text{total}}}{\partial \delta^{\text{old}}}, \tag{12}$$

where η is the learning coefficient and E_{total} is the square error function, which is described as follows:

$$E_{\text{total}} = \frac{1}{2} \sum_{b=1}^{B} \sum_{n=1}^{N} (\text{target}_{n,b} - \text{output}_{n,b})^2, \tag{13}$$

where B is the block number of learning patterns, and $\text{target}_{n,b}$ and $\text{output}_{n,b}$ are the target output value and actual output value for the n'th output layer neuron when the b'th training sample is used in the network, respectively.

4 Computer-Generated Hologram Compressed using Quantum Back-Propagation Neural Network

During compression, a normalized CGH ($X \times Y$ pixels) is partitioned into pattern blocks ($x_p \times y_p$ pixels). Each pattern block is converted into a dimensional vector $L \times 1$ (i.e., $L = x_p \times y_p$) as a training sample for the QBPNN.

The compression structure of the QBPNN consists of fewer hidden layer neurons than input layer and output layer neurons. The image data are input in the input layer, which is forced through the small opening of the hidden layer to enable image encoding and decoding from the hidden layer to the output layer. The number of hidden layer neurons is K, where $K < L = N$, and the value of K is determined by the different compression ratios.[15]

The training of the QBPNN is complete when the number of learning iterations is greater than our set value or the error value Err between the input and output CGH is less than our set value Err_{max}. The error measurement is described as

$$\text{Err} = \frac{1}{X \times Y} \sum_{b=1}^{B} \sum_{m=1}^{L} [g(b,l) - \bar{g}(b,l)]^2, \tag{14}$$

where $g(b,l)$ is the normalized gray-scale value of the original CGH and $\bar{g}(b,l)$ is the corresponding normalized value of the processed CGH.[13]

5 Experimental Results and Analysis

5.1 *Quality Evaluation of Reconstructed Image*

To estimate the efficiency and distortion of the processed CGH, we used the compression ratio (R), mean-squared error (MSE), and peak signal-to-noise ratio (PSNR) as quality evaluation parameters[10]

$$R = \frac{S_c}{S_o} = \frac{K}{L}, \tag{15}$$

$$\text{MSE} = \frac{1}{X \times Y} \sum_{x=1}^{X} \sum_{y=1}^{Y} |f(x,y) - \bar{f}(x,y)|^2, \tag{16}$$

$$\text{PSNR} = 10 \log_{10} \frac{x_{\text{peak}}^2}{\text{MSE}} (dB), \tag{17}$$

where S_c is the size of a compressed CGH, and S_o is the size of an original CGH ($X \times Y = 256 \times 256$ pixels). $f(x,y)$ is the reconstructed image function of an original CGH, while $\bar{f}(x,y)$ is the reconstructed image function of a processed CGH. x_{peak} is the peak-to-peak value of the image data.

5.2 *Comparing Processed Image of QBPNN and BPNN*

Based on the flowchart in Fig. 1, the CGH compression, transmission, and reconstruction experiments were implemented using the QBPNN and BPNN, respectively.

A CGH of a 256 gray-scale Lena image (128×128 pixels) was first normalized using values in the range of 0 to 1. In addition, we set $x_p = y_p = 8$ for the QBPNN and BPNN. Thus, the CGH was partitioned into 1024 pattern blocks. In the QBPNN and BPNN, the neuron numbers of the input and output layers were set to $L = N = 64$. Only the neuron number of the hidden layer K was varied, with values of 32, 16, 8, and 4 for compression ratios of 0.5000, 0.2500, 0.1250, and 0.0625, respectively.

We compared the learning iterations of the QBPNN and BPNN algorithms for a CGH compressed and transmitted under four different compression ratios. The maximum number of learning iterations was set at 5000, and the maximum error Err_{max} for the training was set for the different compression ratios. Under each compression ratio, the learning coefficient η was varied from 0.05 to 0.70 in increments of 0.05 to determine the minimum average number of learning iterations. In addition, to obtain stable averages, 10 learning trials were performed for each learning coefficient. The experimental learning iteration results for the BPNN- and QBPNN-based compressions are shown in Fig. 3.

As shown in Fig. 3(a), when the compression ratio is 0.5000, the QBPNN can complete the convergence in ∼2127 learning iterations; however, even if the learning iterations of the BPNN reach 5000, it cannot converge. Through experimental analyses, we determined that the ideal learning coefficient η_{QBP} for a QBPNN is 0.40, while η_{BP} is 0.20 for the minimum average number of learning iterations.

As shown in Fig. 3(b), when the compression ratio is 0.2500, the QBPNN can complete the convergence in ∼1180 learning iterations, whereas the BPNN needs 1646 learning iterations. In addition, the optimal learning coefficient η_{QBP} is 0.35, while η_{BP} is 0.20 for the minimum average number of learning iterations.

Figures 3(c) and 3(d) show the results when the compression ratios are 0.1250 and 0.0625, respectively. The QBPNN can complete the convergence in ∼1138 and 1144 learning iterations, whereas the BPNN needs 4822 and 1606 learning iterations. In addition, the values for the optimal learning coefficient η_{QBP} are 0.35 and 0.25, respectively, whereas the η_{BP} values are 0.15 and 0.15, respectively, for the minimum average number of learning iterations.

Based on an experimental analysis, we found that the QBPNN always required fewer learning iterations than the BPNN at their optimal leaning coefficients under the compression ratios for different neuron numbers of the hidden layer. This means that the QBPNN has a higher learning convergence speed than the BPNN. The comparison data are listed in Table 2.

We compared the MSE and PSNR averages of the reconstructed images for a CGH compressed and transmitted by the QBPNN and BPNN. For example, when the compression ratio was 0.5000, at the optimal learning coefficients $\eta_{\mathrm{QBP}} = 0.40$ and $\eta_{\mathrm{BP}} = 0.20$, the MSE averages for the QBPNN and BPNN were 204.4667 and 246.3755 dB, respectively. The PSNR averages for the QBPNN and BPNN were 25.0246 and 24.2148 dB, respectively. For the other compression ratios, the experimental results are shown in Table 3.

For example, when the compression ratio was 0.5000, the experimental results of simulation are shown in Fig. 4. We observed some differences between Figs. 4(b) and 4(d) because the QBPNN training was stopped based on the value of $\mathrm{Err}_{\max}$, whereas the BPNN training was stopped

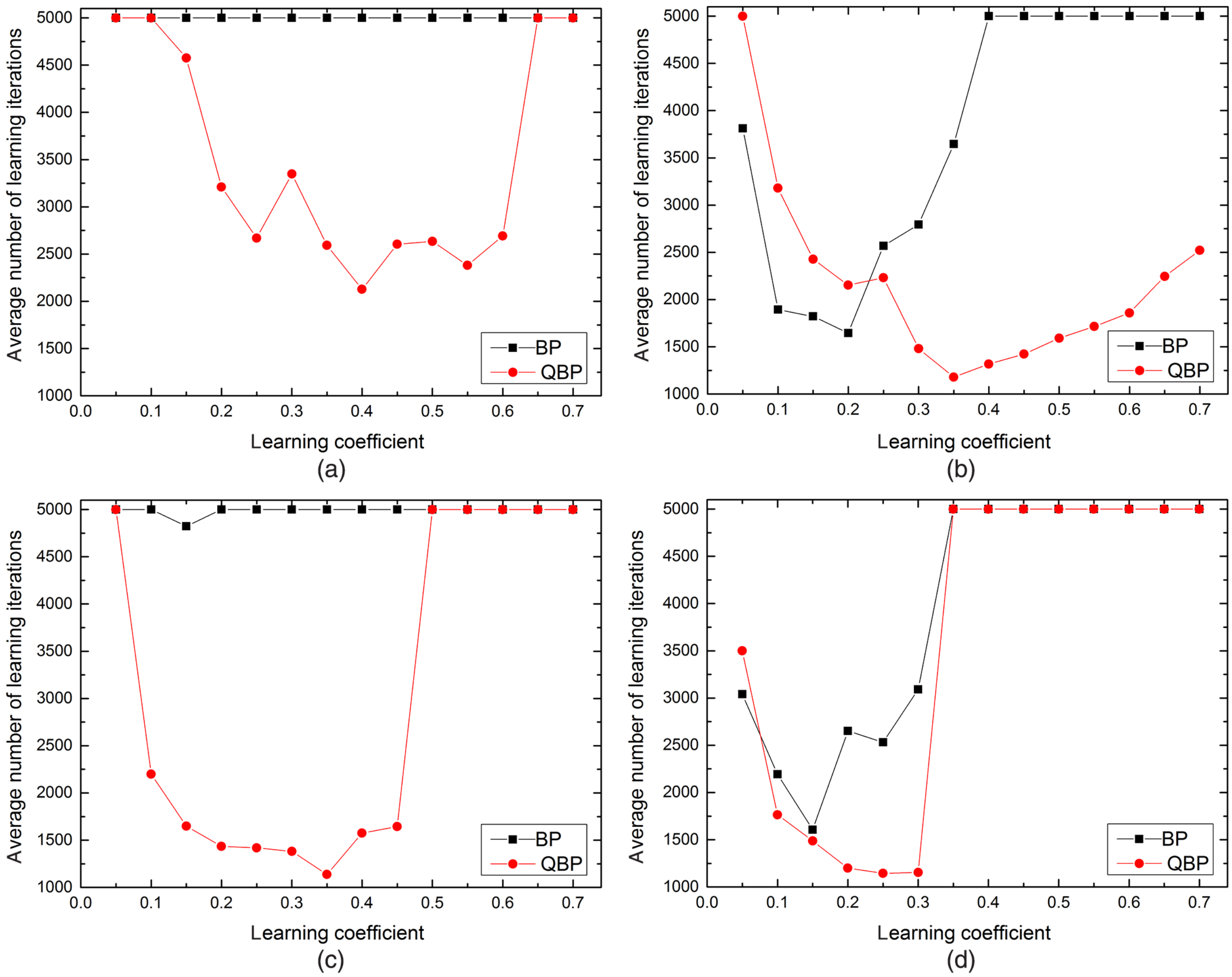

Fig. 3 Learning iteration results for QBPNN and BPNN algorithms. (a) $R = 0.5000$, $\mathrm{Err}_{\max} = 0.0005$, (b) $R = 0.2500$, $\mathrm{Err}_{\max} = 0.0015$, (c) $R = 0.1250$, $\mathrm{Err}_{\max} = 0.0023$, and (d) $R = 0.0625$, $\mathrm{Err}_{\max} = 0.0030$.

Table 2 Comparison of QBPNN and BPNN.

Compression parameters		QBPNN		BPNN	
R	Err_{max}	Iterations	η_{QBP}	Iterations	η_{BP}
0.5000	0.0005	2127	0.40	5000	0.20
0.2500	0.0015	1180	0.35	1646	0.20
0.1250	0.0023	1138	0.35	4822	0.15
0.0625	0.0030	1144	0.25	1606	0.15

Table 3 Quality evaluation of reconstructed image.

Method	η	R	MSE	PSNR (dB)	Iterations
QBPNN	0.40	0.5000	204.4667	25.0246	2127
BPNN	0.20	0.5000	246.3755	24.2148	5000
QBPNN	0.35	0.2500	554.5920	20.6911	1180
BPNN	0.20	0.2500	615.9231	20.2355	1646
QBPNN	0.35	0.1250	943.9029	18.3815	1138
BPNN	0.15	0.1250	1.0359×10^3	17.9775	4822
QBPNN	0.25	0.0625	1.4327×10^3	16.5693	1144
BPNN	0.15	0.0625	1.5765×10^3	16.1539	1606

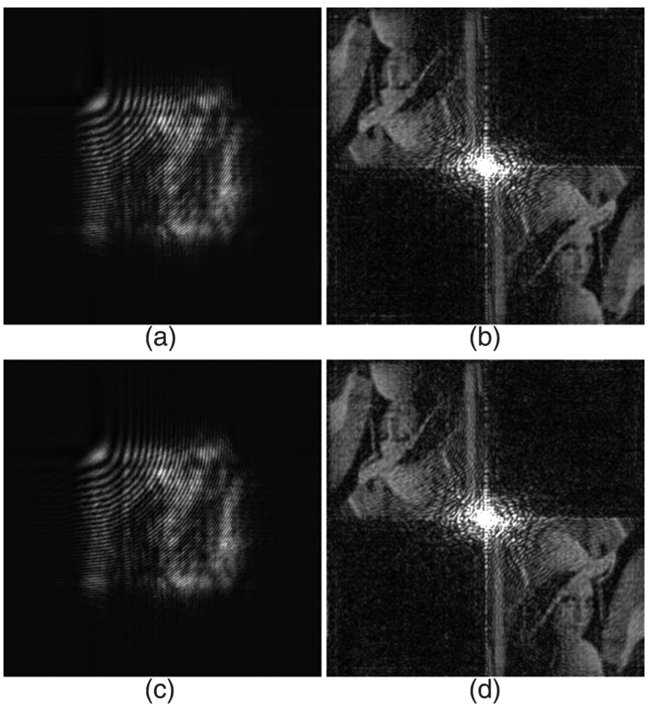

Fig. 4 Examples of CGH compressed, transmitted, and reconstructed using QBPNN and BPNN when the compression ratio was 0.5000, (a) CGH compressed and decompressed using BPNN, (b) reconstructed image of (a), (c) CGH compressed and decompressed using QBPNN, and (d) reconstructed image of (c).

based on the maximum number of learning iterations, i.e., 5000.

These results showed that the CGH compressed and transmitted by the QBPNN had a better reconstructed image quality than that compressed and transmitted by the BPNN, despite the smaller number of learning iterations, when the compression ratio was 0.0625 to 0.5000.

Moreover, this scheme can also be valid for processing other CGH, but the weight connections, threshold parameter, and reversal parameter have to be recalculated in the QBPNN. In contrast, for different compression ratios, the optimal learning coefficients are fixed or unchanged.

6 Conclusion

We propose a method for CGH compression, transmission, and reconstruction using a QBPNN and FTT, which can be used to adaptively and intelligently process the nonlinear holographic information distribution. The gray-scale Lena image could be converted into a CGH using the Fresnel holographic algorithm. The CGH could be encoded and decoded using the QBPNN. Then, the FTT was adopted to reconstruct the image of the processed CGH. The number of neurons in the hidden layer could be conveniently controlled to achieve different compression ratios. When the compression ratio was 0.0625 to 0.5000, the CGH compression and transmission using a QBPNN produced better-quality reconstructed images. At the optimal learning coefficients, the experimental results of simulation showed that the QBPNN could produce better-quality reconstructed images than the BPNN, despite the smaller number of learning iterations at the same compression ratio. Thus, this method can be used to compress and transmit CGH. In the future, we will discuss the effects of this scheme for DH.

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