Holographic diffuser design using a modified genetic algorithm

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Abstract. A modified genetic algorithm is proposed for the optimization of holographic diffusers for diffuse IR wireless home networking. The novel algorithm combines the conventional genetic algorithm and the simulated annealing algorithm, in which the simulated annealing algorithm is used to maintain a better diversity of chromosomes for the genetic algorithm. A better performance in locating the global minimum is demonstrated.
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Subject terms: computer-generated holograms; diffusers; holographic optical elements; infrared; kinoforms; genetic algorithm; simulated annealing.

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1 Introduction

Wireless home networking has recently been a hot area for both academia and industry. Compared with rf-based wireless indoor communications, IR wireless home networking provides many advantages such as broad and unregulated bandwidth, possible spatial reuse of the available bandwidth, absence of electromagnetic interference, and no multipath fading. A major issue in IR wireless networking that must be considered is the eye safety problem. Eye safety limits the amount of the power to be transmitted, and thus limits the coverage of an optical wireless home networking system. Holographic diffusers can be used to extend a collimated laser beam to cover a broad range. Holographic diffusers are usually designed using the computer-generated hologram (CGH) technique that was proposed by Brown and Lohmann[1] in 1966. Different algorithms such as error reduction, input-output, and simulated annealing have been studied for CGH optimization. It was reported recently that holographic diffusers generated based on the simulated annealing were found to have the best output compared to the error reduction and the input-output techniques.[2]

For holographic diffuser design, a phase-only encoding scheme would be used to increase the light efficiency. Phase-only CGH has the unity transmittance that provides nearly 100% light efficiency.[3] Phase-only CGHs can be implemented using kinoforms,[3] a type of surface relief micro-optical element. Because of its high diffraction efficiency and its flexibility of design, the kinoform can be used in many applications, such as phase-only filters in optical information processing, optical pattern recognition, and optical interconnection. Since it is a phase-only optical element generated by a computer, the amplitude of the transfer function is assumed to be unity. The phase information, consisting of ordinary quantized values, is usually represented by a relief profile on a recording material. Therefore, the kinoform can include the reconstruction noise caused by the unitized amplitude and phase quantization. Because reconstruction noise or error is a serious problem in many applications, it is necessary that the phase distribution of the kinoform be optimized to decrease the noise.[4]

In the design of a holographic diffuser, the system to be optimized consists of variables and a cost function representing the system configuration. Using the probability process with appropriately controlled parameters, we can find the nearly global minimum of the cost function that corresponds to the optimum condition of the system. For the phase optimization of the kinoform it is assumed that the variable is the phase of the pixels and that the cost function is the mean square error between the reconstructed image and the desired image.[2]

Figure 1 shows the relationship between the image and the hologram, where $F(m,n)$ is the hologram and $f(k,l)$ is the reconstructed image. Assume that the hologram has a size of $N\times N$. The Fourier-transformed kinoform reconstructs the image in the far field. The reconstructed image in the image plane is given by[2]

$$f(k,l)=\frac{1}{N^2}\sum_{m=1}^{N}\sum_{n=1}^{N}F(m,n)\exp\left(2\pi i\frac{mk+nl}{N}\right). \tag{1}$$

In a phase-only hologram, with P equally spaced phase levels, the $F(m,n)$ takes the value of $\exp[2(p-1)\pi i/P](p=1,\ldots,P)$. For example, in the binary and four-phase holograms, values of P are 2 and 4, respectively, then $F(m,n)$ takes the values binary, ±1, and four-phase, ±1 and $\pm i$.

The cost function E can be expressed as

$$E=\sum_{k}\sum_{l}(|\alpha f(k,l)|^2-|\mathrm{ref}(k,l)|^2)^2, \tag{2}$$

where α is the normalization factor given by

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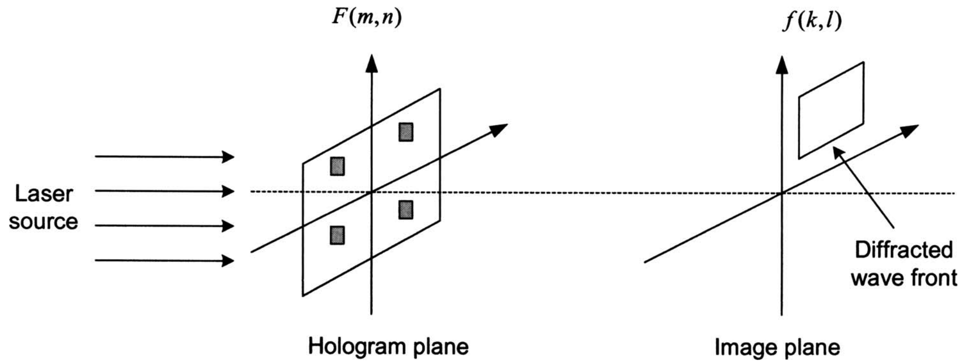


Fig. 1 Hologram and image planes.

$$\alpha = (N_{\mathrm{ref}}/\eta_t N_f)^{1/2}, \tag{3}$$

$$N_f = \sum_{k=1}^{N} \sum_{l=1}^{N} |f(k,l)|^2, \tag{4}$$

$$N_{\mathrm{ref}} = \sum_{k=1}^{N} \sum_{l=1}^{N} |\mathrm{ref}(k,l)|^2, \tag{5}$$

where η_t is the desired diffraction efficiency of the hologram; ref (k,l) refers to the desired image; and N_{ref} and N_f measure the total power within the first period of ideal diffracted amplitude and the diffracted amplitude obtained from the hologram, respectively.[2]

The optimization procedure is to find a hologram where the cost function is minimized, therefore the difference between the desired and reconstructed image is minimized.

2 Modified Genetic Algorithm

Several methods have been adopted for the optimization of a kinoform.[2–6] In this paper, the optimization of the phase distribution of a kinoform by a modified genetic algorithm (GA) is proposed. The GA is a computational optimizing method that is analogous to the evolution of life.[7,8] GAs are stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival.[8] It works on a population of encoded solutions called chromosomes and the chromosome is composed of a unique string of genes.[8] There are basically two types of representation methods for the GA: binary encoding and floating point encoding. The binary encoding is normally used for discrete model parameter values, while the floating point encoding is for continuous model parameter values. In our problem, since diffuser design is discrete, we adopt the binary encoding. A chromosome is a vector $\mathbf{w}$ of n bits:

$$\mathbf{w} = [w_1, w_2, \ldots, w_n] \in G, \tag{6}$$

where the genes w_i with $i=1,2,\ldots,n$ have binary values (0 or 1), n is the number of genes, and G is the genotypic ensemble of the 2^n possible chromosomes. Each chromosome $\mathbf{w}$ corresponds to a unique noncoded solution of the optimization problem.[8] The chromosome is characterized by performance with respect to objective function (fitness), which is the minimum cost function between the reference image and the hologram-generated image for our problem. The population of the next generation is formed by genetic operators such as selection, cross-over, and mutation to their parent population. Chromosomes with high fitness have a higher probability to survive in the next generation. In this way, the GA can locate a relatively global optimum chromosome after certain iterations.

Simulated annealing (SA) was introduced by Kirkpatrick and Vecchi in 1983, and was proposed based on an analogy with the annealing of solids: the object function to be minimized is analogous to the energy of solids and the control parameter is analogous to the temperature of solids.[9] SA can start from a random initial state. Random change is generated for the state. The change is accepted if it results in better performance of the object function. If the change results in worse performance, it is accepted with certain probability that is a function of the temperature.[9,10] The temperature is initially high and decreases over time. This probability function is usually given by the Boltzmann distribution:

$$B = \exp(-\Delta E/T), \tag{7}$$

where ΔE is the change in the object function, and T is the temperature. In the diffuser design, ΔE is the cost function between the reference image and the hologram-generated image.

In fact, SA can be viewed as a special type of the GA with the population size equal to 1. Although the GA and SA are similar in many ways, there are some important differences between them. The leading process in an SA is mutation, while selection is the leading process in a GA. The advantage of the GA is that it maintains more solutions than SA and can search in a broader range. Furthermore, GA is parallel in nature. However, the GA has one critical shortcoming. The GA does not possess a formal proof of convergence to the global optima, while SA processes as long as the cooling schedule is slow enough,[11] although in practice there must be a trade-off between the cooling schedule and the speed of the program. For the GA, when a chromosome $\mathbf{w}=[w_1, w_2, \ldots, w_n]$ has a large number of gene n, the performance is usually poor. The reason is that the GA cannot maintain population diversity itself. Some important genes may be lost during the search for a global optimum. Holographic diffuser design is such a case that has the characteristic of large genes. Although large population size may result in better performance, we must select proper population size to reduce the computation complexity. For an image with size of 64×64 and with the representation of quantization level 4, the size of the ensemble of solutions is 2^{8192}. In this paper, we propose a modified GA that combines SA and the GA to solve such a problem.

3 Description of the algorithm

The optimization procedure using the modified GA consists of the following six steps:

3.1 *Step 1: Initialization*

The phase-distribution of a kinoform with a size of $N \times N$ pixels is encoded as an individual chromosome, which is represented by a $N \times N$ matrix. Each gene of the chromosome is ranged within the maximum quantization level. At the beginning, all the chromosomes are generated at random. In our simulations, we use a quantization level of 4 to represent the kinoform. The quantization level must be greater than 2 to avoid the problem of conjugate-image generated by the CGH.[2] The higher the quantization level, the better the image quality. But holographic diffusers with higher quantization levels are more difficult to fabricate. A good trade-off in the diffuser design is to use a quantization level of 4. The population size in the proposed modified GA is 100, a value that is commonly used[12] in GAs.

3.2 *Step 2: Selection*

Selection is based on the fitness of object function and it is used to cause those individuals with higher fitness to be selected with higher probability. One method of selection is based on a roulette game.[8] The fitness Q of each chromosome c_i is ranked in an ascending order: $Q(c_1), Q(c_2), \ldots, Q(c_p)$. The chromosome c_i is selected for reproduction if

$$Q(c_{i-1}) < r = Q(c_i), \quad (8)$$

where r is a uniform random number ranged from 0 to 1. Note that $Q(c_i)$ is the cumulative selection probability, which depends on the chromosome fitness. In this process, the fitness depends on the cost function E and we can set the fitness to $1/E$ since the cost function is inverse to the fitness. The simulation results of the roulette game show that it results in the search to converge quickly and to be trapped to a local minimum even if the mutation probability is set large. A different approach[4] is also investigated here. For each generation $n(n \geqslant 2)$, select $(1-s)$ and s of all the individuals with the best fitness from the parents respectively to form the offspring. Therefore, s best individuals are selected twice and s worst individuals are replaced in the new generation. Here s is the selection probability, which in our design is 18%. It is different from the roulette game in that this approach is based on the rank of the fitness in a population pool instead of the relative fitness to other population. The advantage of this approach is that it is independent of the fitness distribution and the excellent individuals are treated more fairly, therefore the pressure for the best genes to propagate is reduced and the population diversity can be maintained better. In the selection process, the elitism principle is adopted.[13] For the k'th generation, select the chromosomes with the best fitness from the $(k-1)$'th generation if the best fitness of the k'th generation is worse than the $(k-1)$'th generation. The elitism can reduce the genetic drift, which resulted from mutation and cross-over. It increases the selection pressure by ensuring the best chromosome to copy its traits to the next generation.[13,14]

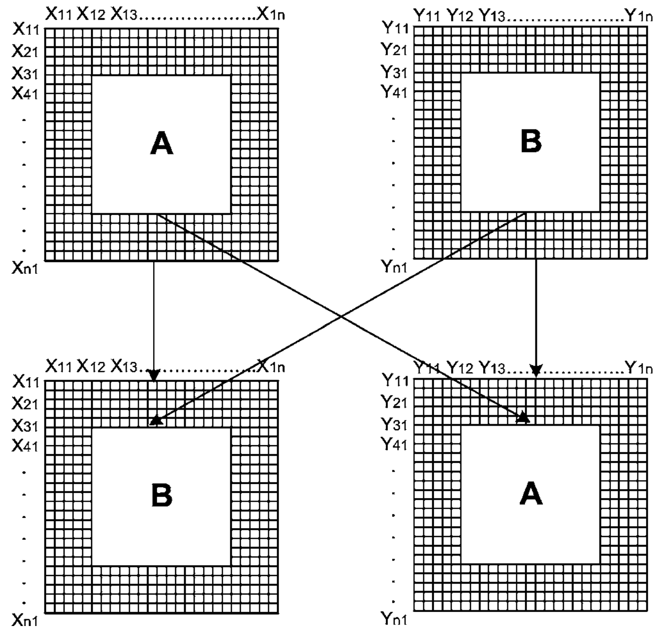


Fig. 2 Double-point cross-over between two chromosomes.

3.3 *Step 3: Cross-Over*

Two individuals are selected randomly with the probability

$$r < P_c, \quad (9)$$

where P_c is the cross-over probability, and r is a uniform random variable[8] ranging from 0 to 1. Cross-over generates new individuals by combining genes from their parents. The methods of cross-over include single-point cross-over and double-point cross-over. The single-point cross-over divides each of the parents into two parts and exchanges the two parts between the two individuals; double-point cross-over divides each of the parents into three parts and exchanges the middle parts between the two individuals. Double-point cross-over is reported to have better performance[15] and is used in our diffuser design.

In our design, the cross-over probability P_c is 0.8, which means that the P_c of all individuals are crossed over.[12] It is accepted that P_c cannot be too low and a value below 0.6 is rarely used.[11] Note that a kinoform is a 2-dimensional optical element; therefore, four random variables are generated to divide the kinoform, as can be seen in Fig. 2.

3.4 *Step 4: Mutation*

To maintain a good genetic diversity of the genes in a population, the genes are mutated with the mutation probability P_m. The mutation probability is a very important parameter that should be chosen carefully. A premature

Table 1 Normalized cost functions of different mutation methods.

	Maximum Cost Function	Minimum Cost Function	Average Cost Function
Tuned optimal P_m	1	0.7449	0.8153
Exponentially decreasing P_m	0.9354	0.7305	0.7769
1/5 success rule of P_m	0.9453	0.7240	0.7772

convergence can be resulted from a too-low mutation probability, whereas a slow and poor convergence can be resulted from a high mutation probability.[8] A random variable is generated and each gene is mutated if the random variable is less than P_m. In our design, three mutation methods are investigated.

A widely used method to control P_m is to use the "optimally tuned" value, which means that P_m is set to an optimal value by experiments.[8,12] The commonly used[12] value of P_m is between 0.001 and 0.01. In our simulations, we assign different values to P_m and compare the performance of the algorithm while keeping other parameters (population size, cross-over probability, etc.) the same. For the design problem here, a P_m of 0.002 is found to be the optimal value. The "tuned optimal" method is the simplest approach, but it lacks of adaptability; since during the evolutionary process, P_m should be higher at first to achieve a wider search range but lower and lower afterward to mitigate the deterioration of good genes. Furthermore, the effort to find the optimal value is time consuming and other parameters (cross-over probability etc.) have a great impact on the optimal value of P_m. Exponentially decreased P_m is a modification to the "tuned optimal" P_m in which P_m is not a fixed value but decreases over generations. The value of P_m can be expressed as

$$P_m(i+1) = \alpha P_m(i), \tag{10}$$

where i represents the i'th generation. The initial P_m is set to 0.01 and $\alpha = 0.985$.

The "1/5 success rule" can also be used[8] to find the optimum value of P_m. The 1/5 success rule states that the ratio of successful mutations to all mutations should be 1/5. The process to adjust P_m is actually an evolutionary process. After each k generation, the cost functions of parents and descendents are compared. The P_m is increased by a factor of α if more than 1/5 descendents have better cost functions than their parents and decreases otherwise. This can be expressed as

$$P_m = \begin{cases} \alpha P_m & \text{if } \varphi(k) < 1/5 \\ P_m/\alpha & \text{if } \varphi(k) > 1/5 \\ P_m & \text{otherwise}, \end{cases} \tag{11}$$

where $\varphi(k)$ is the success ratio of mutation.

For each of the above methods we use the 16×16 image to simulate for 20 times and the results are shown in Table 1. From Table 1, we can see that the exponentially decreased P_m and the 1/5 success rule P_m perform better than the tuned optimal method. The performance difference between the exponentially decreased P_m and the 1/5 success rule P_m is not apparent. However, the disadvantage of the 1/5 success rule is that it is more computationally intensive since there is a monitoring process during the search. Therefore, as far as speed and performance are concerned, the approach using exponentially decreased P_m provides the optimal trade-off.

3.5 *Step 5: Mutation by SA*

Although we choose P_m carefully, there is still a high probability that the search for best cost function will converge to a premature optimum. The reason is as already mentioned: we have a large ensemble of genes but a low population size. After certain iterations, the cost functions of almost all the chromosomes will be the same. Increasing P_m can delay the speed of convergence and diversify the population, but the random mutation may destroy excellent genes when the chromosomes converge to nearly optimal. To maintain better diversity without destroying excellent genes, we incorporate SA as a supplement mutation algorithm into the GA.

As discussed, selection is the leading evolutionist process in the classical GA, whereas mutation is the leading evolutionist process in SA. In the GA, new genes can only be introduced in a population by occasionally random mutations, which will lead to better or worse individuals with the same possibilities, whereas mutation in SA will only occasionally lead to worse individuals. In our algorithm, SA acts not only as a way to maintain diversity of the chromosomes, but also as a local search for better genes.[16]

To measure the diversity of chromosomes, we introduce a parameter called variance of fitness (VOF). VOF is derived from the cost function in our design. If VOF is 0, that means all the chromosomes are the same. The process of using SA is that after every n iterations from steps 2 to 4, we check the VOF. If the VOF is less than 1, we randomly select k chromosomes and use SA to mutate these chromosomes. Therefore, better diversity of chromosomes can be maintained without destroying the excellent genes.

3.6 *Step 6: Output the Result*

Steps 2 to 5 are performed repeatedly until the change of the total fitness of all the chromosomes in certain iterations is less than a minimum value we define. The chromosome with the best cost function is then what we need. The process is shown in Fig. 3.

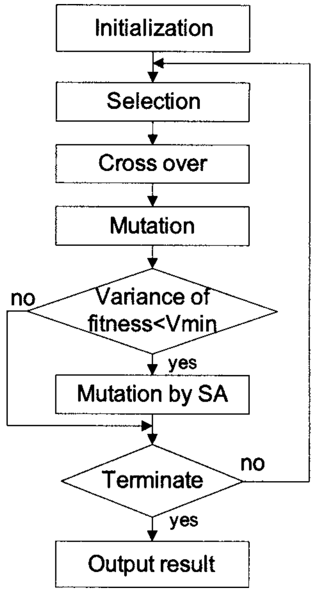


Fig. 3 Flow chart of the modified GA for CGH design.

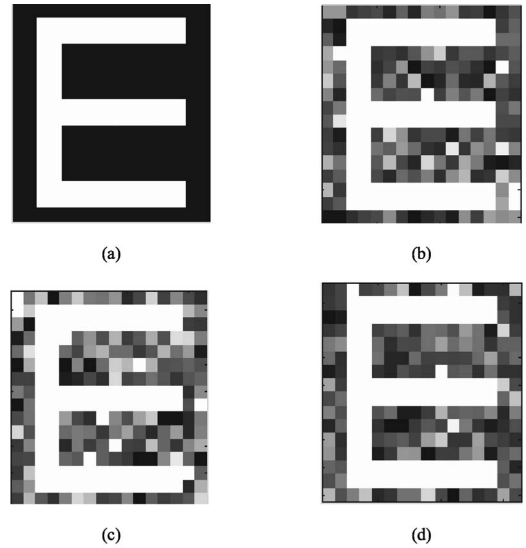


Fig. 4 Reconstructed 16-×16-pixel image of the kinoform : (a) original image, (b) image reconstructed by the classical GA, (c) image reconstructed by SA, and (d) image reconstructed by the modified GA.

4 Results and Discussions

In the simulations, we compare the classical GA, SA, and modified GA under different circumstances. Two images with image sizes of 16×16 and 64×64 are used in the simulations.

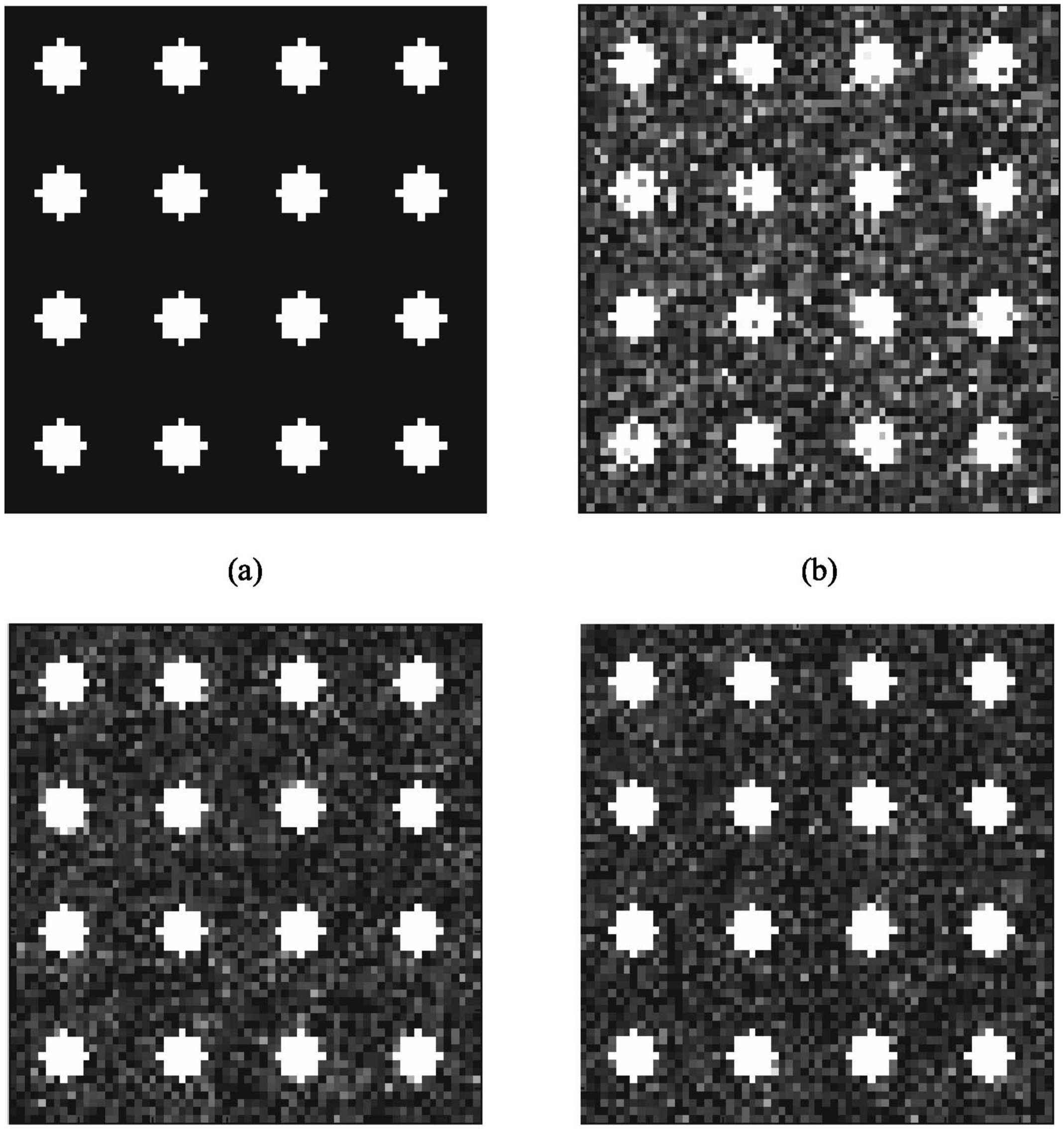
First, for the 16-×16-pixel image, we run simulations to generate holograms with the GA, SA, and the modified GA 20 times, respectively. Table 2 summarizes the cost functions of the three algorithms and Fig. 4 shows the original and reconstructed images. The table demonstrates that the performance among the algorithms is the modified GA> the SA> the GA. The smaller variance of SA compared to the other two algorithms demonstrates that SA has the most stable output, while the GA has the least stable output. The better variance of the modified GA than the GA shows that after the introduction of SA as a mutation algorithm, the GA can maintain much better population diversity, and therefore, we can greatly reduce the convergence to a local minimum. In addition, we also find that the performance of the best individual of the modified GA is better than the SA. The reason is that the modified GA has a larger population size than the SA (population size is 1 for the SA) and can search the chromosomes in a broader range.

Next, for the 64×64 pixel image, Fig. 5 shows a 64×64 spot pattern to be used for the diffuser design. The diffuser designed based on this pattern will diffract the incoming single laser beam to 4×4 beams. In IR wireless home networking systems, the diffracted beams are usually further diffused by the ceiling of the office or home, which would finally provide a uniform diffuse IR distribution to cover the entire space. For the 64×64 image, the same procedure is employed to design the diffuser. We find that in this case, the classical GA performs much poorer than the other two. If we take average of the cost functions and normalized them, we find that the cost functions of the classical GA, SA, and the modified GA are 1, 0.8473, and 0.8461, respectively. This shows that the modified GA and SA perform much better than the classical GA, and the modified GA provides the best performance.

The reason is that the solution ensemble of an image with 64×64 pixels is 2^{16} times larger than an image with 16×16 pixels. With the population size the same and only the random mutation to search for a better gene, it is very difficult for the classical GA to find a global optimum in such a large solution ensemble. Therefore one normal method for the classical GA to guarantee the performance as the solution ensemble increases is to enlarge the population size. The introduction of SA as a complementary mutation method can better diversify the population to re-

Table 2 Normalized cost functions of the classical GA, SA, and the modified GA.

Algorithms	Maximum Cost Function	Minimum Cost Function	Average Cost Function	Variance of Cost Function
GA	1	0.7449	0.8153	1
SA	0.8286	0.7325	0.7704	0.1776
Modified GA	0.8827	0.7197	0.7665	0.2639



(a) (b) (c) (d)

Fig. 5 Reconstructed 64- ×64-pixel image of the kinoform : (a) original image, (b) image reconstructed by the classical GA, (c) image reconstructed by the SA, and (d) image reconstructed by the modified GA.

duce the population size needed. Furthermore, our simulation shows that when the GA approaches an optimal area, SA can quickly locate the exact place by its internal search process, but the cross-over and other operators of the GA may cause the search to drift out of that area, which means that SA can act as a local search tool.

Figure 6 shows the convergence process of the cost functions of the classical GA and the modified GA. For the classical GA, it converges more sharply than the modified GA at the beginning. But because its internal mutation algorithm cannot maintain good population diversity, it is trapped at a premature minimum after about 1500 iterations. As we can see from Fig. 6, after 1500 iterations, the cost functions does not improve much. We investigated the VOF of the classical GA and the modified GA, and found that the VOF of the classical GA decreases quickly, and after 1500 iterations it is almost 0. On the contrary, the VOF of the modified GA can always remain at a relatively higher value. Therefore, the better population diversity makes it possible for the modified GA to search through a much wider area and get a better result.

However, the modified GA will take a longer computation time than the conventional GA since the mutation process of the modified GA combines with SA. The computation times of different algorithms depends much on the inverse Fourier construction of a hologram because of its computation intensity. As our simulation shows, the inverse Fourier transform occupies around 70% of the computation

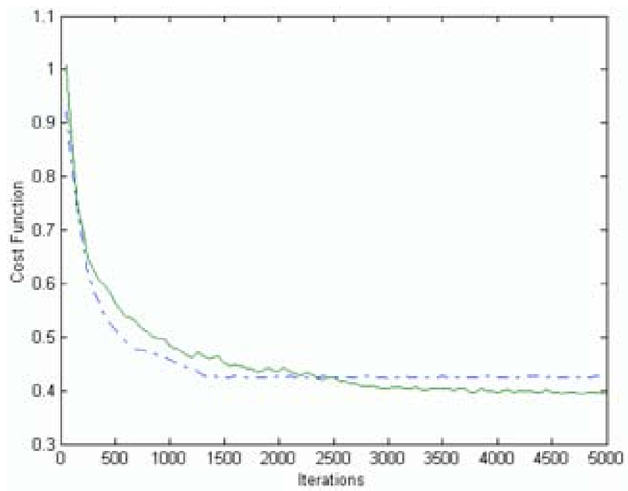


Fig. 6 Cost functions of the classical GA (dotted curve) and the modified GA (solid curve).

time in the GA and 95% of computation time in SA. The modified GA requires about 10% more inverse Fourier transform computation than the normal GA. For a GA process with 100 populations and 2000 iterations and a SA process with 100,000 iterations, the ratio of the computation times of the modified GA, the conventional GA, and the SA is around 3:2.6:1.

The hologram designed by the modified GA has an improved performance. A four-level phase hologram, as shown in Fig. 7(a), is calculated by the modified GA and fabricated at a pixel resolution of 2 μm on a quartz substrate, with a phase difference of 0, $\pi/2$, π, $3\pi/4$ rad at each pixel. To make full use of the 0.81-mm source laser beam width, the 64-$\times$64-pixel basic cell was stepped in a 16 $\times$16 array to create a total hologram size of 1024 $\times$1024 pixels, with a total physical size of 2.048 $\times$2.048 mm. The fabricated hologram mask was illuminated using a 7-mW, 633-nm laser source normally incident on the mask, and the obtained reconstructed hologram is shown in Fig. 7(b). The reconstructed image was obtained by projecting the image onto a planar surface, such as a wall, in an enclosed dark room environment with no other sources of light besides the hologram. We can observe that the obtained results are similar to the theoretically determined reconstruction pattern from Fig. 5(a). However, a large central spot can be seen in the reconstructed pattern and this is attributed to fabrication limitations,[17] containing almost 20% of the input laser power. By optimizing the fabrication techniques, the central spot power could be reduced to about 0.1%.

5 Conclusion

The GA was proposed to imitate the principles of natural evolution as a method to solve parameter optimization problems. How to control the values of various parameters and how to maintain the population diversity are two of the most important issues to be solved in the GA. Although the GA works well for a wide variety of applications in engineering and science, when facing those problems with a large ensemble of solutions such as CGH design, the GA works poorly and may converge with a high probability to a local optimum. The modified GA was proposed in this paper to solve this problem. In the modified GA, we used a selection process base on the rank of fitness, the exponentially decreased mutation probability, and incorporated SA as the mutation algorithm into the GA to maintain good population diversity. We compared the modified GA with the classical GA and SA. The simulation result showed that for images with small and large sizes, even with a small population size, the modified GA could search the nearly global optimum with a high probability.

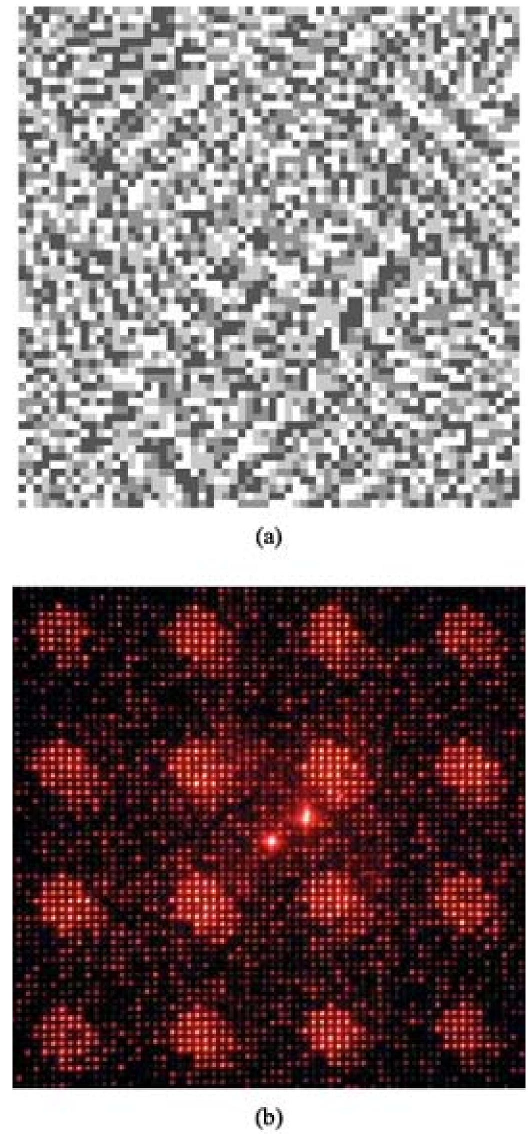


Fig. 7 Holographic diffuser fabricated on a quartz substrate: (a) 64-$\times$64-pixel basic cell hologram mask obtained using modified GA and (b) pattern reconstructed using a fabricated hologram mask of a 16$\times$16 array of the basic cell.

References

1. J. R. Brown and A. W. Lohmann, "Complex spatial filtering with binary masks," *Appl. Opt.* **5**(6), 967–969 (1966).
2. J. P. Yao, G. C. K. Chen, and T. K. Lim, "Holographic diffuser for diffuse infrared wireless home networking," *Opt. Eng.* **42**(2), 317–

324 (2003).
3. T. Yatagai, "Phase only computer generated hologram produced by an ion-exchange technique," *Opt. Lett.* **13**(11), 952–954 (1988).
4. N. Yoshikawa, M. Itoh, and T. Yatagai, "Quantized phase optimization of two-dimensional Fourier kinoforms by a genetic algorithm," *Opt. Lett.* **20**(7), 752–754 (1995).
5. J. R. Fienup, "Iterative method applied to image reconstruction and to computer-generated holograms," *Opt. Eng.* **19**(3), 297–305 (1980).
6. M. A. Seldowitz, J. P. Allebach, and D. W. Sweeney, "Synthesis of digital holograms by direct binary search," *Appl. Opt.* **26**(14), 2788–2798 (1987).
7. R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, Wiley, New York (1998).
8. Z. Michalewicz, *Genetic Algorithms+Data Structures=Evolution Programs*, 2nd ed., Springer-Verlag, Berlin (1994).
9. S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," *Science* **220**(4598), 671–680 (1983).
10. N. Yoshikawa and T. Yatazai, "Phase optimization of a kinoform using simulated annealing," *Appl. Opt.* **33**(5), 863–868 (1994).
11. G. Rudolf, "Convergence properties of canonical genetic algorithms," *IEEE Trans. Neural Netw.* **5**(1), 96–101 (1994).
12. A. E. Eiben, R. Hinterding, and Z. Michalewicz, "Parameter control in evolutionary algorithms evolutionary computation," *IEEE Trans. Evol. Comput.* **3**(2), 124–141 (1999).
13. J. A. Vasconcelos, J. A. Ramirez, R. H. C. Takahashi, and R. R. Saldanha, "Improvements in genetic algorithms," *IEEE Trans. Magn.* **37**(5), 3414–3417 (2001).
14. J. N. Gillet and Y. L. Sheng, "Multiplexed computer-generated holograms with polygonal-aperture layouts optimized by genetic algorithm," *Appl. Opt.* **42**(20), 4156–4165 (2003).
15. K. P. Wong and Y. W. Wong "Genetic and genetic/simulated-annealing approaches to economic dispatch," *IEE Proc.: Gener. Transm. Distrib.* **141**(5), 507–513 (1994).
16. G. Zhou, Y. Chen, Z. Wang, and H. Song, "Genetic local search algorithm for optimization design of diffractive optical elements," *Appl. Opt.* **38**(20), 4281–4290 (1999)
17. P. L. Eardley, D. R. Wisely, D. Wood and P. McKee, "Holograms for optical wireless LANs," *IEE Proc.: Optoelectron.* **143**(6), 365–369 (1996).

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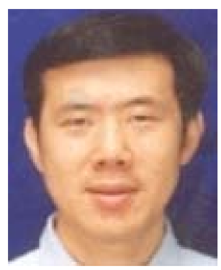

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