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2019

Mehdi, H. H. V., Mozaffarzadeh, M., Upputuri, P. K., & Pramanik, M. (2019). Genetic algorithm for feedback-based wavefront shaping in optical imaging. Proceedings of SPIE - Photons Plus Ultrasound: Imaging and Sensing 2019. doi:10.1117/12.2509520

https://hdl.handle.net/10356/102644

https://doi.org/10.1117/12.2509520

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SPIE.

Event: SPIE BiOS, 2019, San Francisco, California, United States

Genetic Algorithm for Feedback-Based Wavefront Shaping in Optical Imaging

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ABSTRACT

Traditional optical devices rely on light propagation along a straight path. However, when the light propagates through a blurred medium, its direction get scattered by microscopic particles. This inhomogeneous distortion results in a diffused focus point. Light scattering is one of the main limitations for the optical imaging. This limitation decreases the resolution in depth. Therefore, the ability of focusing light at a desired position has a huge worthwhile for applications of optical imaging. Over the past few years, it was shown that light can be focused inside an object even with strong scattering particles, just by shaping the wavefront of the incident beam. The most successful approaches for light focusing at the presence of scattering objects are feedback-based optical wavefront shaping. In this paper, an iterative feedback-based wavefront shaping is proposed. It uses the genetic algorithm. In summary, we aim to obtain a high intensity in the focus point with fewer steps in iteration while increase the signal-to-noise. The simulations results show that both the above mentioned goals are achieved using the proposed method.

Keywords: Genetic algorithm, Wavefront shaping, Scattering, Focusing, Feedback-based methods

1. INTRODUCTION

Even though, a corrected incident wavefront can focus light anywhere at the target, finding this appropriate wavefront is complex. This goal can be obtained when we place a detector in the focus position and use a feedback scheme [1-3]. The resulting waves could produce a focal spot albeit propagation through the scattering media [2-4].

The basic of wave front shaping methods for focusing light is subdividing the spatial light modulator into L segments and finding suitable phase for each segment between 0 and 2pi, in order to maximize the intensity of a spot in the output plane. In the last couple of years, some iterative methods for focusing light at the presence of scattering objects have been demonstrated [5–7]. The most challenging characters for these methods are Signal-to-noise and decreasing the steps of finding correct wavefront. Two basic algorithms which optimize each input mode independently and separately are the stepwise sequential (in articles named as transmission matrix (TM)) and the continuous sequential (CSA) algorithms [5]. Furthermore, the performance of algorithms which modulate just a single mode decreases in the low SNR condition since the effect of interference signal detected at the output plane is nominal. The partitioning algorithm (PA), at each iteration, randomly select a constant numbers of the input modes and modulates them [5], which causes a faster initial enhancement of the focal spot intensity even in low SNR state [2], [4]. However, the PA progresses more slowly than the TM and CSA [5], [8]. Recently, using genetic algorithm (GA) in the feedback-based wavefront shaping is introduced as a robust method which could approach adaptively to the optimize phase mask. The GA technique is faster than the CSA or PA while it is very persistent to noise errors [4].

It can be a really helpful success for applications to achieve the ability of focus light at any desired position. The field of wavefront shaping is a new high profile under rapid development concept where it's potential have been demonstrated in many medical [9–16], physical [17-23], industrial [21–23] instrument and application.

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Photons Plus Ultrasound: Imaging and Sensing 2019, edited by Alexander A. Oraevsky, Lihong V. Wang, Proc. of SPIE Vol. 10878, 108786G · © 2019 SPIE · CCC code: 1605-7422/19/$18 · doi: 10.1117/12.2509520

In terms of Focusing light through turbid material, the importance of faster and more robust algorithms are more dramatic in dynamic environments such as tissue biological which are constantly fluctuating. In this paper we introduce a new genetic algorithm (NGA) method to accelerate focusing process through turbid biological. The NGA technique increases the focal spot intensity best and even faster than traditional GA.

2. METHODS

2.1 Appling new genetic algorithm (NGA) to phase mask optimization

The Genetic feed-back based wavefront shaping algorithm is based on principle of evolution inspired in nature to achieve the best solution. Generally, GA is well-suited for optimization problems where the volume of optimization is enormous and there is a fairly ample time [4], [24], [25]. Therefore, it cannot always be suitable to optimize the phase of the large N input modes in the focusing dynamic target where time limit is very important [26], [27].

In order to focus light through turbid media the GA starts by generating an initial population of phase masks. Each phase mask is created by selecting each input mode value from a discrete set random of phase values, $[0,\ \pi/D,\ 2\pi/D,\ ...,\ (\mathrm{D}-1)\pi/D]$ (which in this study D is set 10). Each created phase masks of population is ranked by the cost function. Here, cost function is defined the intensity of a desire spot in the output plane; and so cost function ranking is according to a phase mask with higher output intensity receives a higher rank. In the traditional GA two masks as parent masks from the population are randomly chose for reproduction, while, the NGA instead of selecting only two masks, it chose *num* number. Actually, the NGA is exactly the same as GA is that the *num* value in GA is 2 while in NGA is optional. Here in this parent selection mode, a higher probability of selection is given to higher ranked phase masks. The elements of new offspring are created by selection randomly related elements of the elected parent masks. In order to prevent premature convergence of the optimized phase offspring, R percentage of modes are choose randomly and then mutated. The amount of R decreases as the algorithm runs and nears the optimal phase mask in order to prevent algorithm from mutating too many optimized phase modes. Here, R is determined as:

$$R = (R_0 - R_{end})\,\mathrm{e}^{-\frac{i}{\lambda}}, \tag{1}$$

where, R_0 and R_{end} are the primary and ultimate mutation rate, respectively, i is measurement number, and λ is the decay factor. The cost function of the new offspring is measured and used to rank within the existing population through a generational method. For each generation, after acquire G number of masks (in this case half of the population size), the lower ranked masks of the previous generation are replaced by the G number of new offspring's according of their rank. Subsequently, the masks in new population are sorted based rank again. The algorithm iteratively optimizes the phase masks. Fig. 1 shows the iterative NGA in achieving a optimization phase plan shaping to focus at spot through scattering target [5].

2.2 Modeling of GA-enabled focusing through scattering

The output complex field is an M-mode plan, $\mathbf{E} = [E_1, E_2, ..., E_M]$, which each mode m, could be modeled as a linear relation between the input complex fields which is an L-mode plan. The optical path through the scattering material is represented by an $M \times L$ transmission matrix where each element of it, t_{ml}, relates the field at input mode l to the output mode m. Assuming $A_l e^{i\phi_l}$ is the ϕ_l phase delayed input mode l with amplitude contribution A_l. The output complex field can be written as:

$$E_m = \sum_{l=1}^{L} t_{ml} A_l e^{i\phi_l}. \tag{2}$$

Here, the transmission matrix is generated from a circular Gaussian distribution, the amplitude contribution A_l is assumed to be $A_l = 1/L$, and ϕ_l for a strong scattering media is distributed randomly [5]. The intensity of the scattering target output mode, m, obtained as:

$$I_m = \left|E_m\right|^2 = \frac{1}{L}\left|\sum_{l=1}^{L} t_{ml} e^{i\phi_l}\right|^2 . \tag{3}$$

The simulation uses the GA phase optimization algorithm to increase the cost function or in another word to maximize the intensity of a specified output mode. All of simulation a Gaussian noise added to the transmission matrix in order to provide experimental conditions [5].

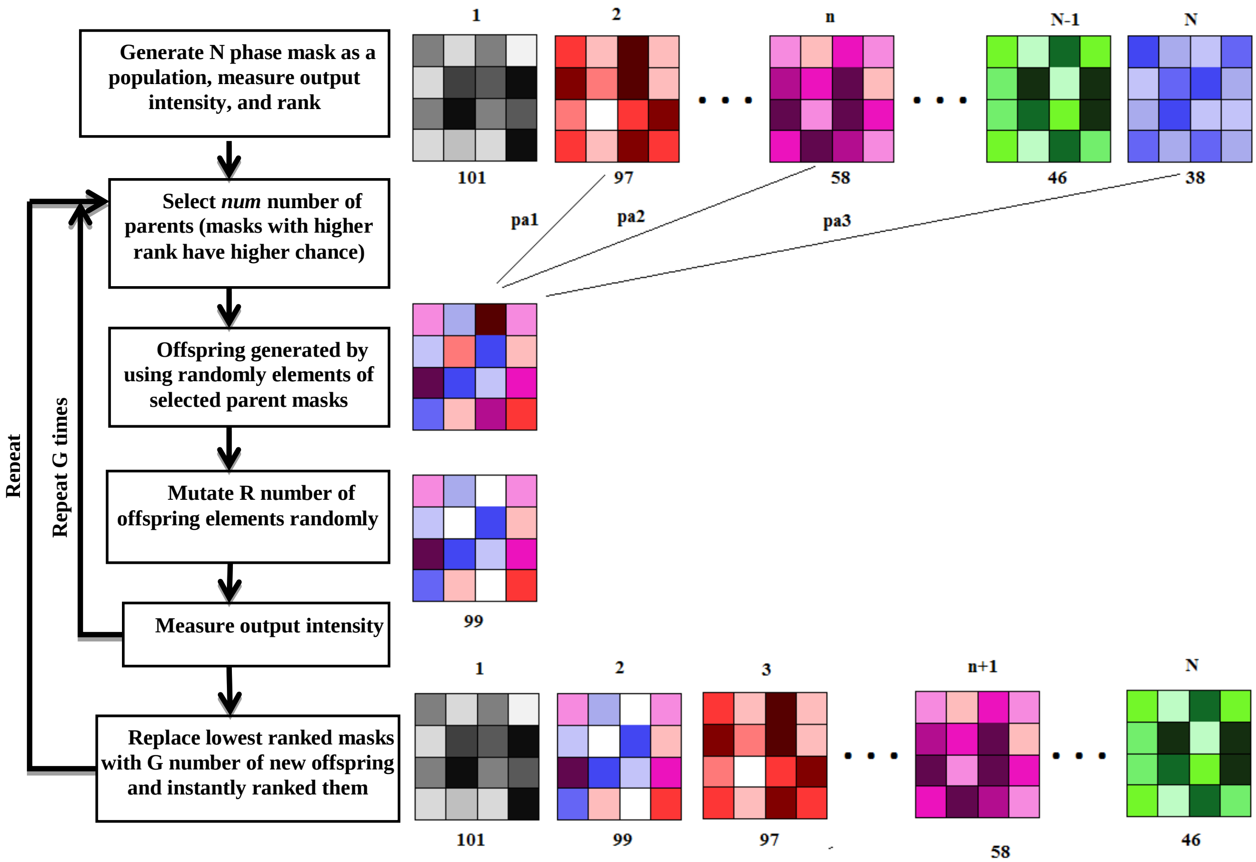

Figure 1. The steps of the new genetic algorithm are showing at block diagram, (1) generation a population of phase masks is created. Each mask is shown in different colors, and their phase proportions are portrayed by its color intensity. Subsequently, the masks are ranked according to their cost function measuring (2) num numbers of phase masks of population are Selected as parents based on their election probability. The new offspring mask is created by combining randomly elected parents. (3) R number of input modes of the new offspring are muted; and subsequently, it's cost function of this new offspring mask is measured. (5) After generating G number of new offspring, they are used to place within the population. (5) The process repeat until a certain of iterations number or a optimize solution.

3. RESULTS

In Figure 2(a) the performance of progress of GA algorithm with various *num* is investigated along the number of measurements. A measurement being is defined as the process of generating a new offspring. The NGA with 10 phase samples is simulated through $5L$ measurements for *num*, 2 to 6. Here used $L = 1024$ input modes with an infinite persistence time. It means the GA parameters selected for the simulation are indicated in Table 1. In the following the effect of parameters like population size, the number of new offspring per generation (G), and R_{end} are explored on traditional GA and NGA with elected *num*. In all of simulation each algorithm was simulated 100 times, each time with a new transmission matrix and with noise at 30% of initial intensity, then averaged for comparison.

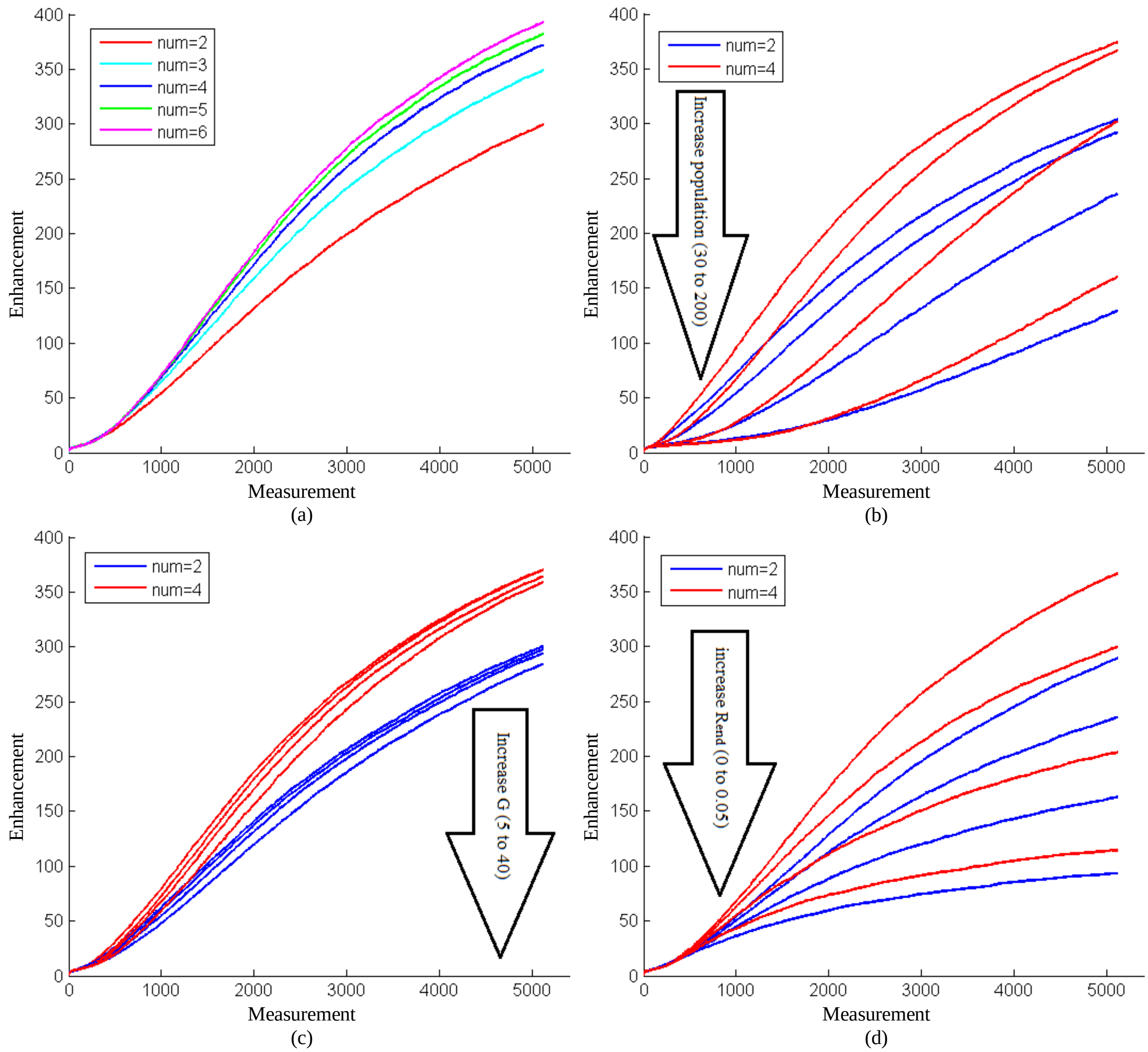

Figure 2. (a) the average of 100 times simulations of the new genetic algorithm with different amount of num (2 to 6) in order to compare the enhancement of the focus intensity along the measurements. comparasion the performance of NGA with num-value of 2 (traditional GA) and 4 in diferent amount of (b) populations among [30, 50, 100, and 200]. (c) Gs among [5,15, 25, and 40], and (d) R_{end} s among [0.012,0.025,0.050, and 0.100].

The simulation results indicate that the increasing amount of num from 2 to 6, enhances the intensity of the output mode higher and even more quickly. So that GA in the state of $num = 6$ after about $3{\cdot}N$ measurements could acquire the maximum enhancement of traditional GA (NGA with $num = 2$) through $5L$ measurements. However the result of NGA for num, upper and equal 4 are almost the same.

Further simulations, results show at Figure 2.(b) –(d), were run to explore the effect of population size, the number of new offspring per generation (G), and R_{end}, respectively, on the progress of enhancement with the general parameters set as listed in Table 1. The results show, a smaller population for both GA and NGA could achieve enhancement more quickly and even higher. Different number of new offspring per generation (G), does not significant effect on both GA and NGA algorithm. As the Figure 2(d) shows, in both of GAs algorithm, the small amount of R_{end} could be more impressive brilliantly.

Table 1. General GA parameters used in various simulations reported in this paper.

Parameter	Value
Input modes (N)	1024
Population size (Pop)	50
New offspring per generation (G)	0.5 Population
Mutation rate begin (R0)	0.1
Mutation rate end (Rend)	0.012
Mutation rate decay factor (λ)	600
Additive Gaussian noise	30 % of <I0>

4. DISCUSSION AND CONCLUSION

The NGA optimizes modes in parallel by using maximum possible variety of available masks which results showed a faster enhancement of the focus intensity and achieved a higher overall enhancement than traditional GA. The high noise robustness of the NGA could be useful as the need for higher speed algorithms increases. Higher speed algorithms would allow for focusing through more temporally dynamic samples such as biology tissue.

The simulations results show that the performance of new genetic algorithm phase mask optimization algorithm in comparison of traditional has a similar behavior to its parameters like population size, the number of new offspring per generation (G), and R_{end} .

It is worth noting that the simulation results presented in this paper are based on stable scattering media. It would be more efficient to implement the NGA in dynamic biology target experimentally and numerically. This could be an interesting topic for the future study.

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