A Simple But Effective Evolutionary Algorithm for Complicated Optimization Problems

Y. G. Xu, G. R. Liu

Abstract -- **A simple but effective evolutionary algorithm is proposed in this paper for solving complicated optimization problems. The new algorithm presents two hybridization operations incorporated with the conventional genetic algorithm. It takes only 4.1% ~ 4.7% number of function evaluations required by the conventional genetic algorithm to obtain global optima for the benchmark functions tested. Application example is also provided to demonstrate its effectiveness.**

Keywords -- **Evolutionary algorithm, optimization.**

I. Introduction

Evolutionary algorithms have been known as the effective technique for solving complicated optimization problems such as those with multi-modal, non-differentiable and non-continuous objective functions [1, 2]. Of the present evolutionary algorithms, hybrid genetic algorithms (GAs) have received the increasing attention and investigation in recent years [3]. This is because the hybrid GAs combine the globe explorative power of conventional GAs with the local exploitation behaviors of deterministic optimization methods, they usually outperform the conventional GAs or deterministic optimization methods to be individually used in engineering practice.

In this study, a new hybrid GA (called nhGA) is proposed. It presents two hybridization operations incorporated with the conventional GA. The first one is to use a simple interpolation method to move the best individual produced by the conventional genetic operations to an even better neighboring point in each of generations. The second one is to use a hill-climbing search to move a randomly selected individual to its local optimum. This is may be done only when the first hybrid operation fails to improve the best individual consecutively in several generations. Compared with the other hybrid GAs, the nhGA is not only excellent in the convergence performance, but also very simple and easy to be implemented in engineering practice.

II. Evolutionary Algorithm - nhGA

Basically, the newly proposed evolutionary algorithm nhGA is the further development for the hybrid GA called hGA [4].

G. R. Liu is a Fellow with Singapore-MIT Alliance (HPCES), Associate Professor with Department of Mechanical Engineering, The National University of Singapore. E-mail: mpeliugr@nus.edu.sg.

Y. G. Xu is a Research Fellow with Singapore-MIT (HPCES). E-mail: smaxuyg@nus.edu.sg.

As the hGA has been discussed in detail in Ref. [4], which may be used as a reference to explain the mechanism of nhGA, it is decided herein to only give a brief description for the implementation process of nhGA as follows:

(1) j=0, start up the evolutionary process.

  (a) Select the operation parameters including population size N, crossover possibility p_c, mutation possibility p_m, random seed i_d, control parameter α and β [4], etc.

  (b) Initialize N individuals, $\boldsymbol{P}(j)=(p_{j1}, p_{j2},\ldots,p_{jN})$, using a random method. Every individual p_{ji} (i=1,…,N) is a candidate solution.

  (c) Evaluate the fitness values of $\boldsymbol{P}(j)$.

(2) Check the termination condition. If “yes”, the evolutionary process ends. Otherwise, $j=j+1$ and proceed to next step.

(3) Carry out the conventional genetic operations in order to generate the offspring, i.e. the next generation of solutions, $\boldsymbol{C}(j)=(c_{j1}, c_{j2},\ldots,c_{jN})$. These operations to be used include niching [5], selection [1], crossover [1], elitism [5], etc.

(4) Implement the first hybridization operation.

  (a) Construct the move direction $\bar{d}$ of best individual.

$$\bar{d} = (c_j^b - c) \tag{1}$$

$$c = \begin{cases} c_{j-1}^b & c_j^b \neq c_{j-1}^b \\ c_j^s & c_j^b = c_{j-1}^b \end{cases} \tag{2}$$

  Where c_{j-1}^b is the best individual in $C(j$-1) at the j-1-th generation, c_j^b and c_j^s are the best and second best individuals in $C(j)$ at the j-th generation, respectively.

  (b) Generate two new individuals c_1, c_2, and evaluate their fitness values;

$$c_1 = c_j^b + \alpha \bar{d} \tag{3}$$

$$c_2 = c_{j-1}^b + \beta \bar{d} \tag{4}$$

  where α and β are control parameters. They are recommended to be within 0.1 ~ 05 and 0.3 ~ 0.7, respectively [4].

  (c) Select a better individual c_m,

$$f(c_m) = \max\{f(c_1), f(c_2)\} \quad c_m \in \{c_1, c_2\} \qquad (5)$$

$f(.)$ is the fitness function.

(d) Replace the individual c_j^b in $\boldsymbol{C}(j)$ with the individual c_m. This results in a upgraded offspring $\boldsymbol{C}_u(j)=(c_{j1}, c_{j2},\ldots,c_m,\ldots,c_{jN-1})$.

(e) Check if there occurs population convergence in $\boldsymbol{C}_u(j)$. If "yes", implement restarting strategy [4] to generate the new $\boldsymbol{C}(j)$.

(5) Check if the best individual keeps unimproved consecutively in the M generations (M=3~5). If "yes', implement the second hybrid operation.

(a) Randomly select a individual c_{ji} in $\boldsymbol{C}_u(j)$.

(b) Take c_{ji} as an initial point to start the hill-climbing search.

(c) Replace individual c_{ji} with the local optimum c_{jL} obtained by the hill-climbing search.

(6) Go back to step (2).

It is clear from the above description that the newly proposed nhGA, compared with the previous hGA, does not incur any deterioration of population diversity when incorporated with the hybridization operations.

III. Performance Test

A. Benchmark functions

Three benchmark functions are used to test the proposed nhGA. Each of benchmark functions has lots of local optima and one or more global optima. Figure 1 shows the search space of function *F1*.

F1: $$f(x_1, x_2) = \prod_{i=1}^{2} \sin(5.1\pi x_i + 0.5)^{80} e^{-4\log 2(x_i - 0.0667)^2 / 0.64}$$

$$\pi = 3.14159,\ 0 < x_i < 1.0,\ i=1,2$$

F2: $$f(x_1, x_2, x_3) = \sum_{i=1}^{10} \{e^{-ix_1/10} - e^{-ix_2/10} - [e^{-i/10} - e^{-i}]x_3\}^2$$

$$-5 < x_i < 15,\ i=1,2,3$$

F3: $$f(x_1, ..., x_5) = \pi\{10\sin(\pi x_1)^2 + \sum_{i=1}^{4}[(x_i - 1)^2(1 + 10\sin(\pi x_{i+1})^2]\}/5 + (x_5 - 1)^2$$

$$\pi = 3.14159,\ -10 < x_i < 10,\ i=1,\ldots,5$$

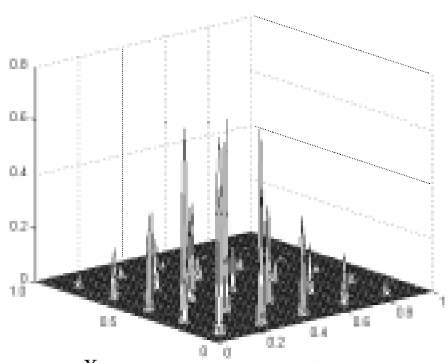
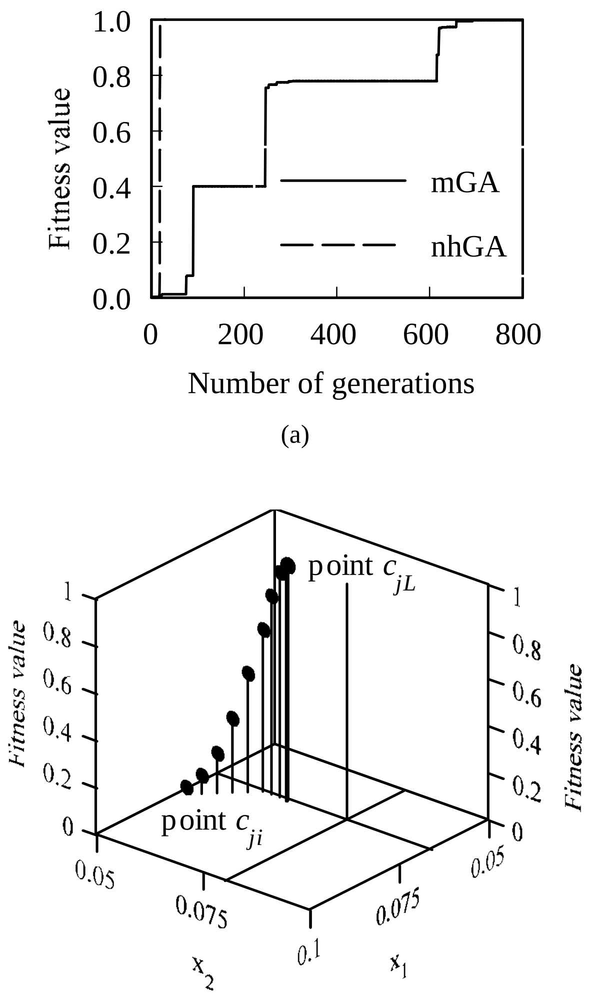


Fig. 1. Search space of benchmark function *F1*.

TABE I

MEAN NUMBERS OF FUNCTION EVALUATIONS TO CONVERGENCE

No.	Global Optimum	Func. Value	$\bar{n}$	$\bar{n}_m$	$\bar{n}/\bar{n}_m$ (%)
F1	(0.0669, 0.0669)	1.0	141	3365	4.2
F2	(1, 10, 1)	0.0	237	5745	4.1
F3	(1, 1, 1, 1, 1)	0.0	6637	139915	4.7



(b)

Fig. 2. (a) Convergence process in view of generations. (b) Hill-climbing process in hybridization operation.

For each of benchmark functions, the nhGA runs 10 times with the different random seed i_d. The 10 random seeds are -

1×10^2, -5×10^2, -1×10^4, -1.5×10^4, -2×10^4, -3×10^4, -3.5×10^4, -4×10^4, -4.5×10^4, -5×10^4, respectively. The other operation parameters are N=5, p_c=0.5, p_m=0.02, α=0.2, β = 0.5 and M=3. Tournament selection, one child, niching, elitism are chosen to use. Table 1 shows the mean numbers of function evaluations, $\bar{n}$ and $\bar{n}_m$, that are taken to reach the global optima using the nhGA and conventional mGA [5], respectively. It can be found that the nhGA demonstrates a much faster convergence than the conventional mGA.

Figure 2 shows the convergence processes of benchmark function *F1* using the nhGA against the mGA, from which comparison of the convergence processes between nhGA and mGA can be seen more clearly.

B. *Application example*

Figure 3 schematically shows a valve-less micropump. The pressure-loss coefficients, ζ_p and ζ_n, in the flow channels can be optimally solved from the following objective function [6]:

$$\min E(\zeta_p, \zeta_n) = \left(\sum_{i=1}^{n} \left| Q_i(\zeta_p, \zeta_n) - Q_i^m \right|^2 \right)^{\frac{1}{2}} \qquad i=1,\ldots,K \quad (6)$$

$$\zeta_{pmax} \le \zeta_p \le \zeta_{pmin}, \quad \zeta_{nmax} \le \zeta_n \le \zeta_{nmin}$$

$Q_i(\zeta_p, \zeta_n)$ is the mean flux calculated from a complicated model [5] using the trial ζ_p and ζ_n, Q_m^i is the measured mean flux at the i-th trial. K is the number of trials.

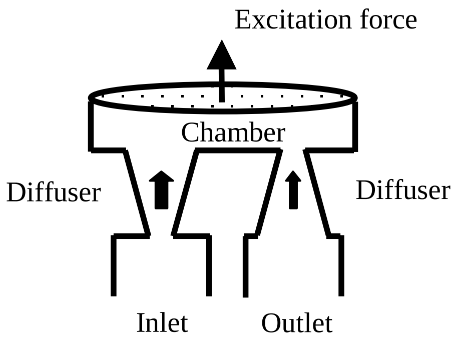


Fig. 3. Cross-sectional view of a micropump.

TABLE II
SOLUTIONS FOR 3 SIMULATED CASES

	n	ζ_p	ζ_n	$e(\zeta_p)$ (%)	$e(\zeta_n)$ (%)
Case I	790	1.389	0.918	-4.9	-3.4
Case II	767	1.307	0.894	2.1	2.8
Case III	525	1.112	0.443	5.9	5.5

The nhGA is used for solving this problem. Table 2 shows the corresponding solutions for 3 simulated cases. In Table 2, n is the number of function evaluations taken by the nhGA, ζ_p and ζ_n are the solved pressure-loss coefficients, $e(\zeta_p)$ and $e(\zeta_n)$ are the errors with respect to their true values, respectively. It can be seen that nhGA converges to the satisfactory results very fast. The maximal error of solved ζ_p and ζ_n are only -4.9%, 2.8% and 5.9% for 3 simulated cases, respectively.

IV. CONCLUSION

In this study, a simple but effective evolutionary algorithm nhGA is proposed. Numerical examples have demonstrated its effectiveness and efficiency. This provides a new choice for solving the complicated optimization problems in engineering practice.

REFERENCES

[1] T. Back, U. Hammel and H. P. Schwefel, "Evolutionary computation: comments on the history and current state," *IEEE Trans. Evol. Comput.*, vol. 1, pp. 3-17, 1997.

[2] D. E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley publishing company, USA, 1989.

[3] M. Gen and R. W. Chen, *Genetic Algorithms and Engineering Design*, John Wiley & Sons, New York, 1997.

[4] Y. G. Xu, G. R. Liu and Z. P. Wu, "A novel hybrid genetic algorithm using local optimizer based on heuristic pattern move," *Appl. Artif. Intell. – An Int. J.* vol. 15, pp. 601-631, 2001.

[5] D. L. Carroll, "Genetic algorithms and optimizing chemical oxygen-iodine lasers," *Developments in Theor. and Appl. Mech.* Uni. of Alabama, vol. 10, pp. 411-424, 1996.

[6] Y. G. Xu, G. R. Liu, L. S. Pan and N. Y. Ng, "Parameter Identification of Dynamic Flow-Pressure Characteristics in Valve-less Micropumps," *J. of Micromech. Microeng.*, Submitted for publication, July 2001.

Y. G. Xu is currently a research fellow with Singapore-MIT Alliance. He received the Ph. D from Huazhong University of Science and Technology, China, in 1996. His research interests cover (a) simulation and optimization: large-scale structures, smart structures and MEMS, (b) structural damage detection and health monitoring: modal analysis methods, elasticwave propagation methods and PZT actuator-sensor impedance methods, (c) inverse problem algorithms: adaptive neural networks techniques and hybrid genetic algorithms, and (d) Vibration & noise control, probability fracture mechanics and reliability analysis, wavelet analysis.