Solution Searching for Multi-variable Optimization Problems by GA with Momentum Offspring

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Abstract

Genetic Algorithm (GA) is known as one of the most powerful solution searching mechanism for nonlinear and multi-variable optimization problems. Generally, GA takes a long time to find the solutions and sometimes it can not find the optimum solutions. In order to improve the search performance, we propose a fast algorithm of GA and a mutation method. The fast algorithm is usage of a momentum offspring (MOS). The MOS is an individual not the crossover but by the best individuals of current and past generations. The MOS is considered to have higher probability for desired solution and the effect of MOS is fast searching of the optimum solution. Furthermore, we proposed a constant range mutation (CRM) for the GA. The CRM is considered to have effect of avoiding the ineffective individual production. We apply the GA with MOS and CRM to optimization problems of two multi-variable functions and neural network training problem. Simulations show that proposed method has good performances.

Keywords: Genetic algorithm, fast algorithm, momentum offspring, constant range mutation, optimization problem, neural network training.

1 Introduction

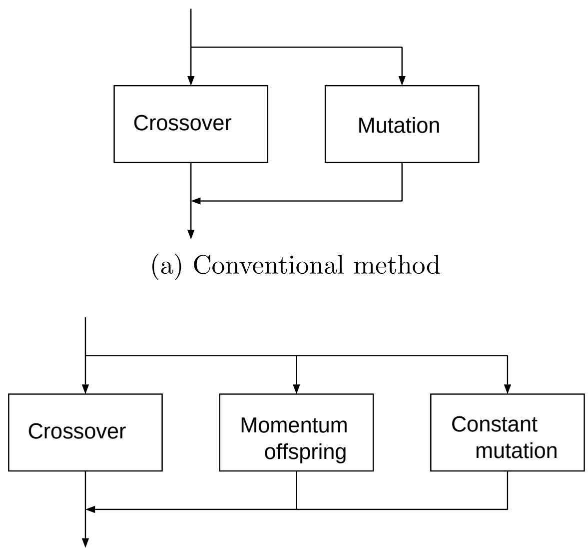
Genetic algorithms (GAs), with many precious advantages, are now widely used in various fields, especially in solving optimization problems. Generally, GAs are also time-consuming in computing, however, and sometimes it can not produce the desired results. In order to improve the search performance, we propose a fast algorithm of GA and a mutation method, i.e. momentum offspring (MOS) and constant range mutation (CRM).

In section 2, we describe a new method, then, in section 3, we investigate the search performance of the method for multi-variable functions. Finally, we apply the method for neural network training problem. We conclude this paper in section 5.

2 Fast GA

2.1 New Method of Recombination

Conventionally, GAs use the recombination, known as genetic operations or offspring production process, which typically involves crossover and mutation operators to yield offspring at each generation. The conventional recombination is shown in Figure 1 (a). To improve the performance of GA, we now propose a new recombination which includes constant range mutation (CRM) and momentum offspring (MOS) operators, as shown in Figure 1 (b). In this method, MOS and CRM are applied simultaneously but with different rates of R_{mo} and R_{mu}, respectively.



(a) Conventional method

(b) Proposed method

Fig. 1 Offspring production process

2.2 Momentum Offspring

For each generation, conventional GAs produce offspring by random process. In our proposed method, i.e. MOS, the next best individual will be determined based on the best individuals of the past and current generations. Namely, if the best individuals of the past generation $(g-1)$ and current generation (g) are x_{best}^{g-1} and x_{best}^{g}, respectively, then the best individual of next generation $(g+1)$ can be determined as:

$$x_m^{g+1} = cr\left(x_{best}^{g} - x_{best}^{g-1}\right) + x_{best}^{g} \quad (1)$$

where, c is a constant coefficient (we set c =1 here) and r is a random coefficient in the range of [0, 1]. Figure 2 shows the idea of MOS method.

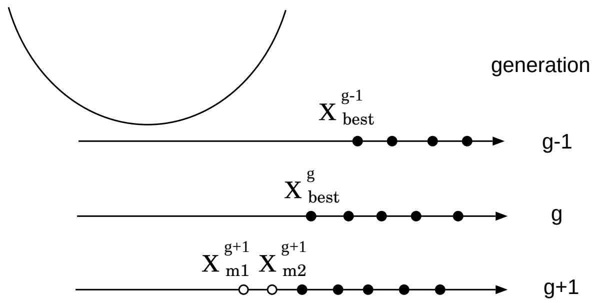


Fig. 2 Momentum offspring

2.3 Constant range mutation

Sometimes, GAs has problem when it just can produce the local optimum values. But GAs can also reduce this possibility by mutation operator. A simple way to achieve mutation would be to alter one or more genes. For reducing this problem more properly, we propose a new mutation operator that is constant range mutation (CRM). In this CRM, we will apply mutation by generating random real values in the range that widens from two parents x_{p1} and x_{p2} $(x_{p1} < x_{p2})$ a constant range of L. Namely, the applied range of mutation is $[x_{p1} - L, x_{p2} + L]$ as shown in Figure 3.

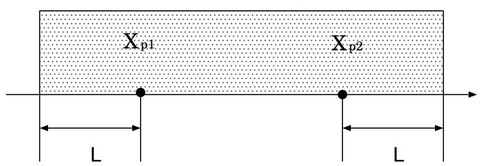


Fig. 3 Constant range mutation

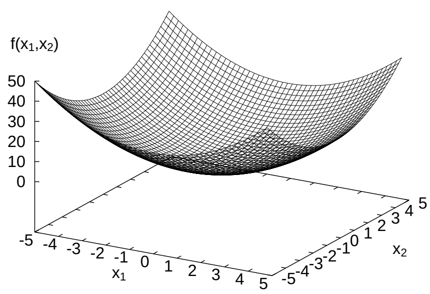
3 Optimization of multi-variable functions

We consider optimization problems of following two multi-variable functions, Sphere function and Rastrigin function,

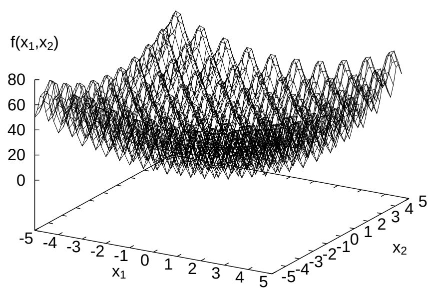
$$f(x) = \sum_{i=1}^{n} x_i^2 \quad (2)$$

$$f(x) = 10n + \sum_{i=1}^{n}\left(x_i^2 - 10\cos\left(2\pi x_i\right)\right) \quad (3)$$

where, n is number of dimensions. In this research, we will investigate the search performances of GA with MOS and CRM for above functions with n = 2. The ranges of variables are $x_i \in [-5.0, 5.0]$. $x_i = 0$. Parameters for GA are as followings: number of population is 20, number of generation is 100 and the range parameter is $L = 1.0$. The search performance is evaluated by successful evolution rates obtained from the minimum values of the function in the GA. The simulation results are shown in Figure 5, for Sphere function, and Figure 6, for Rastrigin function. Generally, it can be observed that the search performances of our proposed GA increase with R_{mo} and R_{mu} and it has better performances than the conventional GA. For Rastrigin function, it is more difficult to find the optimum value because this function is more complicated and it has some local optimum values, the performance in this case is therefore lower than the performance obtained from Sphere function.

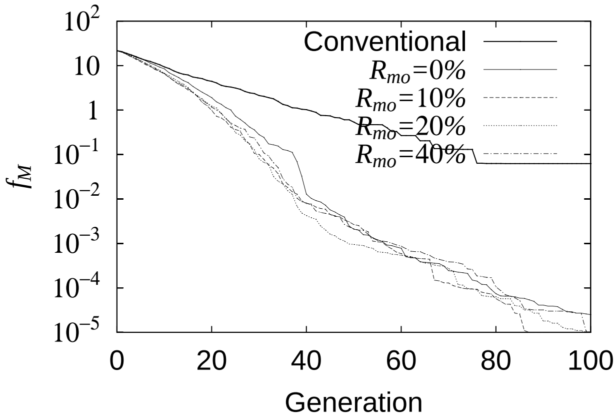


(a) Sphere fucntion

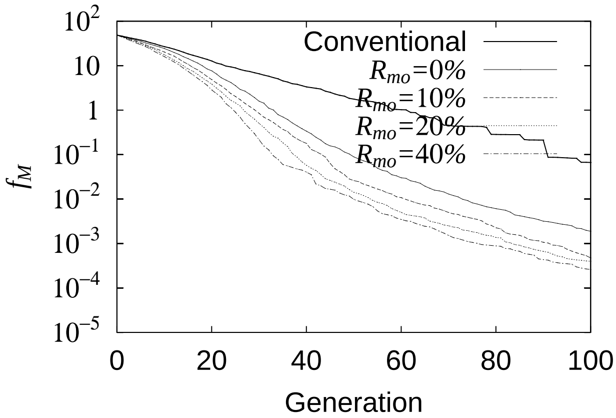


(b) Rastrigin function

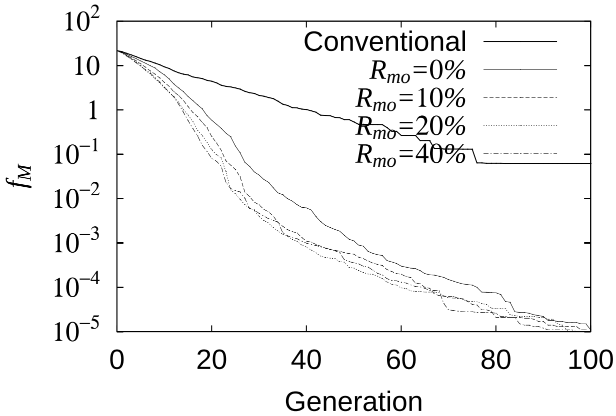
Fig. 4 Test functions



(a) $R_{mu} = 10\%$

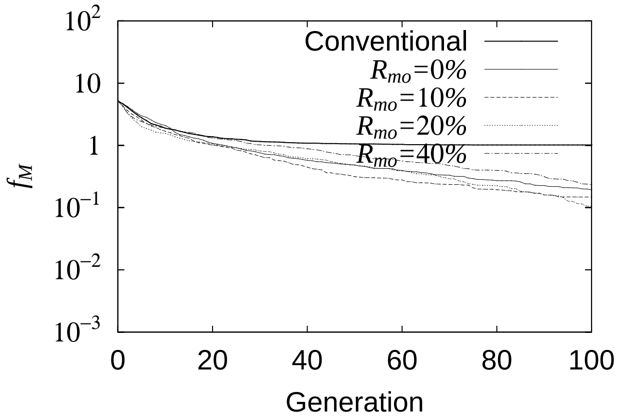


(b) $R_{mu} = 20\%$

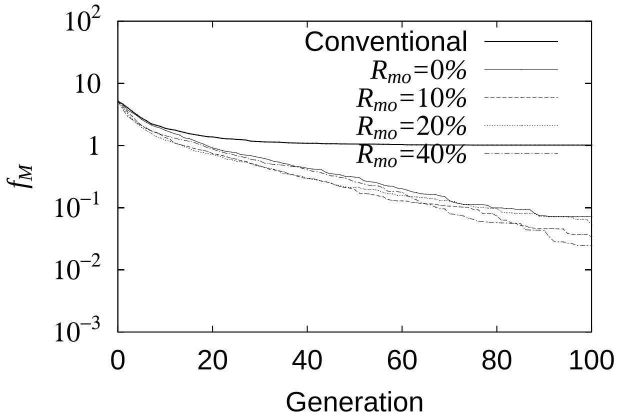


(c) $R_{mu} = 30\%$

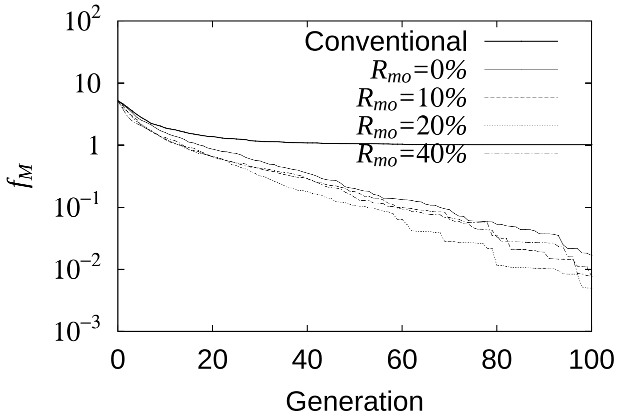
Fig. 5 Evolution results for Sphere function ($n = 2$)



(a) $R_{mu} = 10\%$

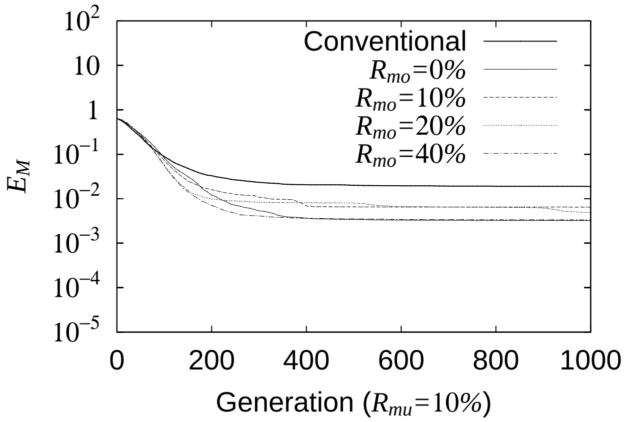


(b) $R_{mu} = 20\%$

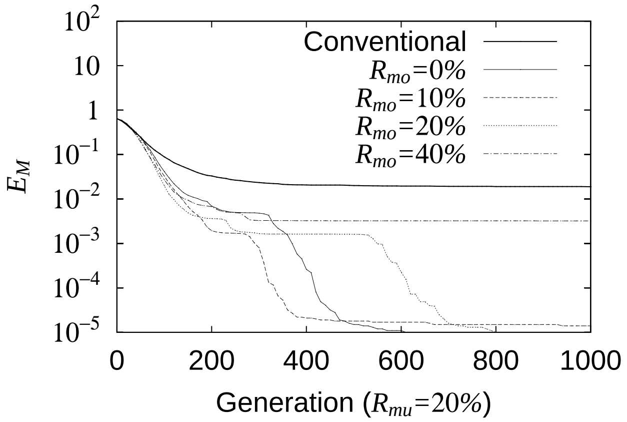


(c) $R_{mu} = 30\%$

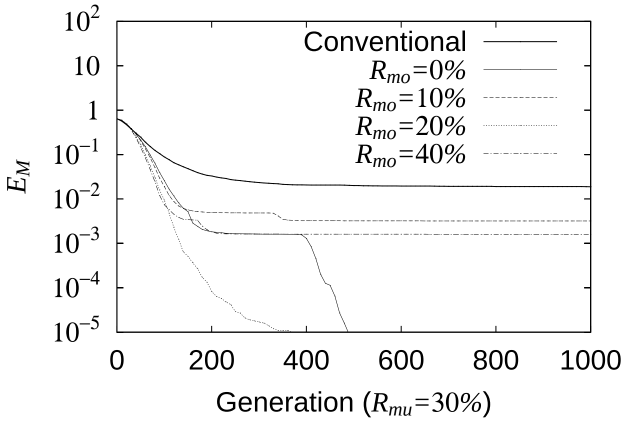
Fig. 6 Evolution results for Rastrigin function ($n = 2$)



(a) $R_{mu} = 10\%$



(b) $R_{mu} = 20\%$



(c) $R_{mu} = 30\%$

Fig. 7 Training results of NN

4 Neural network training

This section presents simulation results of neural network training problem; known as a nonlinear multi-variable optimization problem. In order to evaluate the performance of our proposed GA, we will use the well-known exclusive - or problem (XOR). Figure 7 shows the simulation results. It can be seen that the proposed method has better training performance than that of conventional method.

5 Summary

Improving GAs by design new recombination process may achieve advantages. In this research, we have presented a new method for improving the performance of GA by using a fast algorithm with momentum offspring (MOS) and constant range mutation (CRM). The simulations show that our proposed method has a good performance.

References

[1] D. E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley, 1989.

[2] L. Davis, *Hand Book of Genetic Algorithms*, Van Nostrand Reinhold, 1991.

[3] M. Gen and R. Cheng, *Genetic Algorithm and Engineering Design*, Wiley-Interscience, 1997.

[4] L. J. Eshelman and J. D. Schaffer, "Real-Coded Genetic Algorithms and Interval-Schemata" *Foundations of Genetic Algorithms 2*, Edited by L. Darrell Whitley, Morgan Kaufmann Publishers, 1993.

[5] M. Maeshiro, H. Kinjo, K. Nakazono, and T. Yamamoto, *Fast Method of Genetic Algorithm Searching and Its Application to Neural Network Training*, Technical Reprot of the IEICE NC2006-22-37, pp. 81-84, 2006. (in Japanese)

[6] H. Okamura, K. Kitasuka and T. Dohi, "Performance Evaluation of Genetic Algorithms Based on Markovian Analysis - Evaluation by Relaxation Time and Application to Real-Coded Genetic Algorithms," Transactions of the ISCIE, Vol. 16, No. 7, pp. 303-312, 2003. (in Japanese)