Tuning Genetic Algorithms for Problems Including Neutral Networks - A More Complex Case: The Terraced NK Problem -

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Abstract

Neutral networks, which occur in fitness landscapes containing neighboring points of equal fitness, have attracted much research interest in recent years. In a recent paper [12], we have shown that, in the case of a very simple test function, the mutation rate of a genetic algorithm is an important factor for improving the speed at which a population moves along a neutral network. Our results also suggested that a variable mutation rate strategy is beneficial for fast and stable genetic search. In this work, we conduct a series of computer simulations with a more complex test function, the terraced NK landscape, in order to investigate whether our previous results generalize to this more complex case. Two types of GA were used. One is the standard GA, where the mutation rate is constant, and the other is the operon-GA, whose effective mutation rate at each locus changes independently according to the history of the genetic search. It is found that the variable mutation rate strategy is also beneficial with this more complex test function, and that these benefits increase as the fitness landscape becomes more rugged.

1 Introduction

Selective neutrality has been found in many real-world applications of artificial evolution, such as the evolution of neural network controllers in robotics [1], and on-chip electronic circuit evolution [2]. This characteristic, caused by highly redundant mappings from genotype to phenotype, is also found in natural systems, and has been of particular interest to evolutionary theorists and molecular biologists [3]. Landscapes which include neutrality have been conceptualized as containing *neutral networks* [4][5][6].

It has been shown that there is a clear transition in evolutionary dynamics for populations on neutral networks over the mutation rate range. At a low mutation rate, the population is maintained in a cluster on the neutral network. As the mutation rate increases, the population gradually loses the current network. That is, some individuals fall to lower neutral networks. At a certain critical mutation rate, the whole population will have fallen to lower neutral networks. This mutation rate is called the *phenotypic error threshold*[1] [8][9][10]. This implies that if we adopt a constant mutation rate strategy, we should set a low mutation rate so as to avoid any error threshold effects during the process of evolution. However, from a practical point of view, it would be efficient to minimize the duration of equilibrium periods; that is, periods during which the mean fitness of the population does not change [11].

Recently, we have investigated the effect of selection pressure and mutation rate on the speed of population movement on very simple neutral networks, using the Balance Beam Function (BBF) [12]. BBF landscapes have no ruggedness. Our results can be summarized as follows:

(1) For a given population size, plotting the speed of population movement against its mutation rate resulted in a concave curve, demonstrating the existence of an optimal mutation rate and an error threshold for speed .

(2) Without *elitism*, the optimal mutation rate was just below the error threshold.

(3) High selection pressure improved the speed at which a population moved on a neutral network.

(4) A variable mutation rate strategy [13] improved the efficiency of the search when the constant mutation rate was less than the optimal constant mutation rate.

[1] These concepts originate from molecular evolution [7].

We are interested in whether these observations are consistent with more complex problems including not only neutrality but also ruggedness. This is because we want to solve complex real-world problems. However, because of their complexity, investigating such problems is unlikely to lead to generalizable conclusions. Therefore, in this paper, we investigate the effect of ruggedness by employing a more complex test function. Tunably neutral NK landscapes [8][9] incorporate both neutrality and ruggedness. It has been demonstrated that increasing neutrality does not affect the ruggedness of a tunably neutral NK landscape, although it does reduce the number of local optima [5][8][9]. Thus, we cannot neglect the effect of ruggedness. In this kind of landscape, individuals can easily get trapped on local optima if there is a low mutation rate and high selection pressure. However, using a low selection pressure may require setting a much lower mutation rate in order to avoid the effect of an error threshold [12], and as a result evolution would proceed more slowly. One approach to overcoming this problem would be to adopt *variable mutation rate strategies.*

In this paper, we employ a standard GA, which employs a constant mutation rate, and the operon-GA [13], which can change its mutation rate strategy. We investigate the performance of both GAs with different selection pressures. Section 2.1 describes the terraced NK landscape, which is used as a test problem in this work. Section 2.2 describes the simulation conditions. Section 2.3 gives the results of our computer simulations. Section 3 discusses the effect of the error threshold and the variable mutation rate strategy on smooth and the rugged landscapes. Conclusions are given in the last section.

2 Computer Simulations

2.1 Test Functions

A terraced NK landscape was employed as the test function in our computer simulations. This is the tunably neutral landscape proposed by Newman *et al.* [9]. A terraced NK landscape has three parameters: N, the length of the genotype; K, the number of epistatic linkages between genes; and w, the contribution of a locus to the fitness of the entire genotype.

The fitness value is calculated as follows: The fitness contribution of the i-th locus, w_i, is an integer, generated randomly in the range $0 \leq w_i < F$, $i = 1, \cdots, N$. To calculate the fitness, W, of a genotype, the fitness contribution of each locus is averaged, and then divided by $F-1$, normalizing W to the range 0.0 to 1.0. More formally:

$$W = \frac{1}{N(F-1)} \sum_{i=1}^{N} w_i. \qquad (1)$$

The neutrality of the landscape can be tuned by varying the value of F. The neutrality of the landscape is maximized when $F = 2$, and is effectively non-existent as $F \to \infty$.

2.2 Simulation Conditions

Computer simulations were conducted using a population size of 50. The operon-GA [13] uses standard bit mutation and five additional genetic operators: *connection*, *division*, *duplication*, *deletion* and *inversion*. The probabilities for genetic operations were set at 0.3 for *connection* and *division*, 0.2 for *duplication* and 0.05 for *deletion* and *inversion*, as recommended by Ohkura and Ueda [13]. The length of the value list in a locus was 6. The genetic operation for the standard GA (SGA) was standard bit mutation. For both GAs, the per-bit mutation rate, q, was set at 0.01, based on Mühlenbein's suggestion [16]. Crossover was not used with either GA. Tournament selection was adopted. *Elitism*[2] was optionally applied. The tournament size s was set at $\{2, 6\}$ because low selection pressure is generally preferable with the SGA, whereas high selection pressure is preferable with the OGA. A generational GA was used. We conducted 50 independent runs for each problem under the landscape parameters, $N = 100$, $K = \{0, 5, 25, 50\}$, $F = 2$. Each run lasted 3,000 generations ($K = \{0, 5, 25\}$) and 10,000 generations ($K = 50$). All results were averaged over 50 runs.

2.3 Simulation Results

Fig. 1 shows the maximum fitness at each generation for the SGA and OGA, with and without elitism, and for different values of K and s.

For $K = 0$, there is no ruggedness, and the landscape is similar to simple neutral networks of the BBF. Figs. 1(a) and 1(b) show the results for the four GA conditions for $s = 2$ and 6 respectively. No significant differences in performance were observed. This is consistent with the results obtained with simple neutral networks using the BBF [12].

For $K = 5$, both GAs performed better with elitism than without it for $s = 2$. However, for $s = 6$ there was no significant difference between the four GA conditions. Fitness increased faster for $s = 6$ than for $s = 2$.

For $K = 25$ and $K = 50$, differences between the SGA and the OGA were much more pronounced than at $K = 0$ and $K = 5$. As with $K = 5$, both GAs performed better with elitism than without it for $s = 2$. The OGA was outperformed by the SGA for $s = 2$, however, the OGA outperformed the SGA for $s = 6$. A closer examination reveals that the OGA performed better for $s = 6$ than the SGA did for $s = 2$ with *elitism.*

[2]An individual, randomly selected from those individuals with the highest fitness value, is passed unmutated to the next generation.

3 Discussion

The evolutionary dynamics of the obtained results in the previous section can be explained as follows:

- *the effect of the error threshold*

  When weak selection pressure is used, the SGA and OGA both show poor performance. The OGA performs slightly worse than the SGA, as shown in Figs. 1(c), 1(e) and 1(g). This is due to the fact that the effective mutation rate is more likely to exceed the error threshold when selection pressure is weak [10] (Fig. 2(a), 2(b)). This is consistent with the results obtained using the BBF [12].

- *the variable mutation rate strategy*

  The variable mutation rate strategy of the OGA is a better approach on highly rugged landscapes when selection pressure is high. For $s = 6$ and, with elitism, for $s = 2$, the SGA is easily trapped on local optima when the landscape is highly rugged ($K = 25$ and $K = 50$); in contrast, on the same landscapes, for $s = 6$, the OGA continues to find better regions. This improvement is due to the online adaptation of mutation rates during process of evolution, as shown in Figs. 2(c) and 2(d).

4 Conclusions

In this work, we applied the standard GA and the operon-GA to terraced NK landscapes, and investigated their performance using different levels of ruggedness and different selection pressures. Our results can be summarized as follows:

- The standard GA and the operon-GA show very similar performance on landscapes with no ruggedness. This is consistent with results of our previous experiments using the BBF.
- Without elitism, both types of GA search inefficiently when landscapes are rugged and selection pressure is low.
- The benefits of the variable mutation rate strategy used by the operon-GA become increasingly clear as the ruggedness of the landscapes increases.

These results suggest some guidelines for tuning the performance of GAs. Future work will investigate how well these tuning guidelines apply to real-world problems, such as the evolution of artificial neural networks for robot control.

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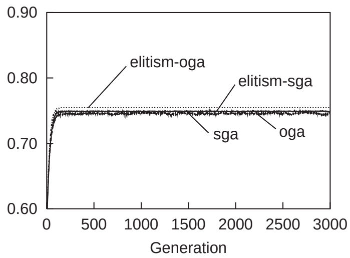
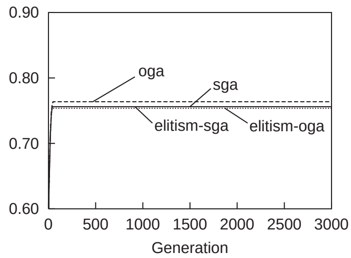
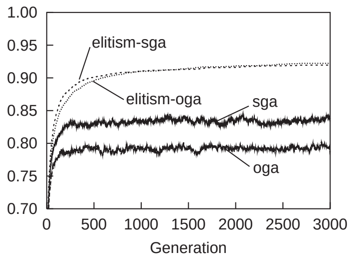


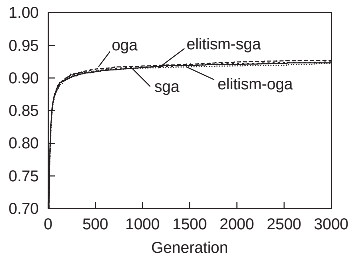
(a) $(K, s) = (0, 2)$



(b) $(K, s) = (0, 6)$



(c) $(K, s) = (5, 2)$



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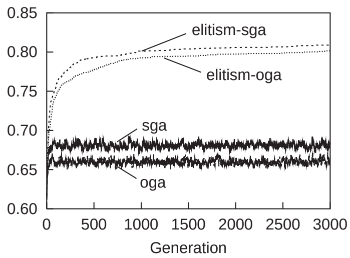
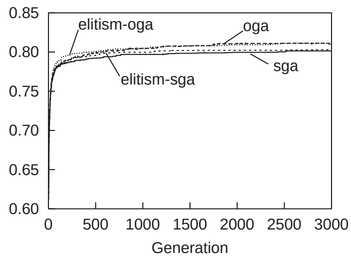
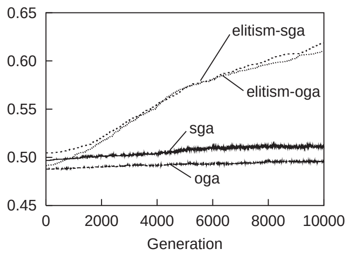


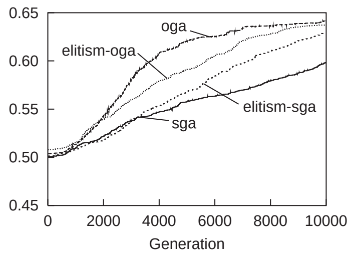
(e) $(K, s) = (25, 2)$



(f) $(K, s) = (25, 6)$

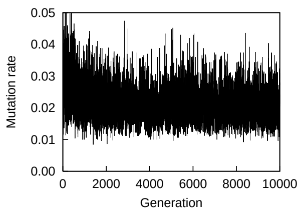


(g) $(K, s) = (50, 2)$

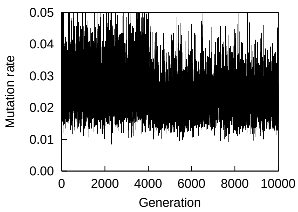


(h) $(K, s) = (50, 6)$

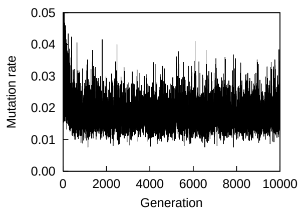
Figure 1: The maximum fitness



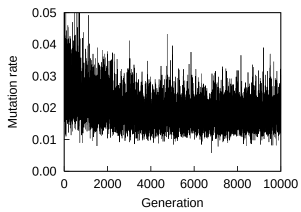
(a) $s = 2$, elitism



(b) $s = 2$, without elitism



(c) $s = 6$, elitism



(d) $s = 6$, without elitism

Figure 2: Average effective mutation rate by Operon-GA for $K = 50$ in a typical run