Enhanced Performance for Multi-variable Optimization Problems by Use of GAs with Recessive Gene Structure

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Abstract

In this paper we propose a dual gene system using the recessive gene model, RGM, to solve difficult multi-variable optimization problems. Genetic algorithms (GAs) are widely applied to many optimization problems and usually suffer loss of diversity, leading to evolutionary stagnation. The dual gene system is exploited to maintain diversity, significantly boost evolutionary computation precision and avoid stagnation. We show by computer simulations that RGM has a higher search efficiency in multi-variable optimization functions. Further, RGM performs better on small populations than the single, dominant gene approach for the same computational cost.

Keywords: Recessive gene, Multi-modal function, Multi-variable optimization, Computational cost.

1 Introduction

Evolutionary computation in optimization relies on processes loosely based on natural selection, cross-over and mutation, that are repeatedly applied to a population of binary strings which represent potential solutions. Most GAs experience problems of convergence due to loss in diversity [1]. There is need to devise ways of avoiding the mechanism of evolutionary stagnation.

We used the basic information on Mendelian genetics to illustrate that a recessive characteristic might significantly affect a closed population [2]. In observing living organisms, characteristics of the offspring do not always resemble those of parents. A dual gene system exists whereby some alleles are dominant hence always expressed, while some are recessive, that is, only expressed under certain conditions. However, the individual preserves the recessive gene, which is sent to the next generation, thus maintaining the diversity of the characteristics of the living organism. RGM utilizes both dominant and recessive genes in the cross-over and mutation operations in the mating phase of the GA. To confirm the efficiency of the scheme we applied RGM to two multi-variable optimization problems.

The structure of this paper is as follows: in Section 2 we present the RGM and in Section 3 we describe the test functions. Simulation results are detailed in Section 4 and a discussion makes up section 5. Finally, we draw some general conclusions in Section 6.
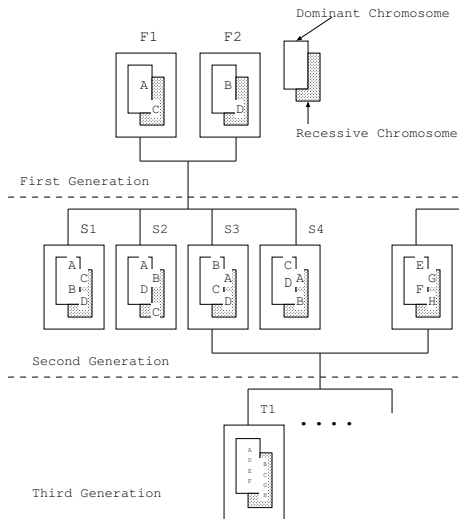
2 Recessive Gene Model, RGM

Figure 1: Schematic of the Recessive Gene Model

Figure 1 shows the structure of the double gene system. In usual GA systems only the dominant genes appear, hence in the first generation of two individuals F_1 and F_2, only the dominant characteristics A

and B appear, respectively. In the second generation, each of the individuals S_1, S_2, S_3 and S_4 will display two chromosomes: 1 dominant and 1 recessive. As an example, F_1 and F_2 will produce two offspring, $S3$ and its complement, $S3'$, in the second filial generation simultaneously. Offspring $S3$ will have the chromosomes BC (dominant) and AD (recessive), while $S3'$, has CB and DA as dominant and recessive, respectively.

P is the probability that a recessive chromosome is selected to be a dominant chromosome in the next generation. In the special cases of $P = 0\%$ and $P = 100\%$ then the offspring will be S_1 and S_4 respectively. The essence of the dual gene system is to provide a larger variety of offspring for the search.

3   Problem Formulation

Our two test functions were Easom's and Schaffer's F6, from the classical benchmark similar to those defined by Kenneth De Jong [3], [4], [5].

3.1   The Easom Unimodal Function

For this function the global minimum has a small area relative to the search space; the function was inverted for minimization, and takes the form:

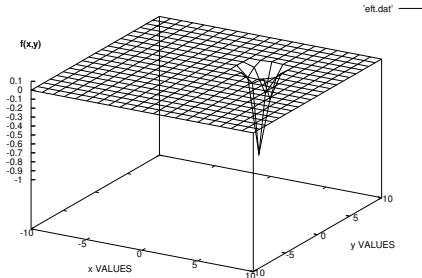$$f(x, y) = -\cos(x)\cos(y)e^{-((x-\pi)+(y-\pi))}$$

Figure 2: Easom function in 3-D

Figure 2 shows a 3-D depiction of the Easom function. The analytical global minimum of the Easom function is -1 when $(x, y) = (\pi, \pi)$.

3.2   Schaffer's F6 Multi-modal Function

This parametric optimization problem is multimodal, represented by the equation:

$$f(x, y) = 0.5 + \frac{\sin^2(\sqrt{x^2+y^2})-0.5}{1+0.001(x^2+y^2)^2}.$$

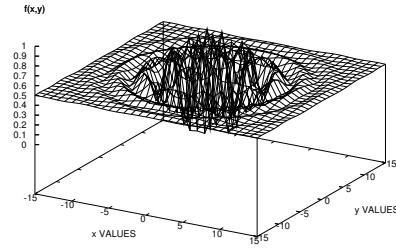The function is a two-parameter "ripple", like the waves in a pond caused by a pebble.

Figure 3: Schaffer's F6 function in 3-D

Figure 3 shows Schaffer's F6 function; the centermost ring represents the circular global optimum.

Table 1: Analytical results for Schaffer's F6

Optima	r	$f(x, y)$
Global	$\frac{\pi}{2}$	0.996989
1st local	$\frac{3\pi}{2}$	0.838081
2nd local	$\frac{5\pi}{2}$	0.606185
3rd local	$\frac{7\pi}{2}$	0.532483

Table 1 gives the analytical values for the various maxima. For each set of values at the various optima, the relation $r = \sqrt{x^2 + y^2}$ exists.

4   Simulation Results

4.1   GA Parameters

A random generation of (x, y) values in Euclidean space was used in the GA search for both functions.

Table 2: Constant parameters

Binary bit length, B	16
Selection pressure, parents P_p	0.5
Selection pressure, children P_c	0.6
Selection method	Roulette wheel
Crossover	2-point

Table 2 shows the constant parameters in the GA search. The sample size, N, was kept at 50 for most of the simulations.

Table 3: Variables

Percentage of recessive gene, $P\%$	$0 < P < 100$
Rate of mutation, $M\%$	$0 < M < 100$
No. of generations, G	$0 < G < 100$
Sampling population, N	$20 < N < 100$

Table 3 shows the variables utilized in the GA search.

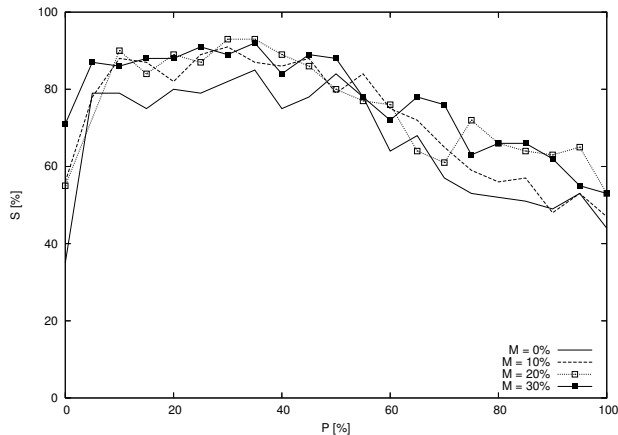## 4.2 Searching performance results for the Easom function

Figure 4: Recessive gene performance for the Easom function.

Figure 4 shows the searching performance for the Easom function. In the case of $P = 0\%$, only using dominant chromosomes, success rate is lower than for for the case of the recessive gene, when $P \neq 0\%$; however, when P is too large the search is not very efficient. Mutation plays a significant role in the search. It is seen that in the absence of mutation, for the case $M = 0\%$, then the search improves with P. Search space was in the whole region, $(x, y) = [-10,10]$.
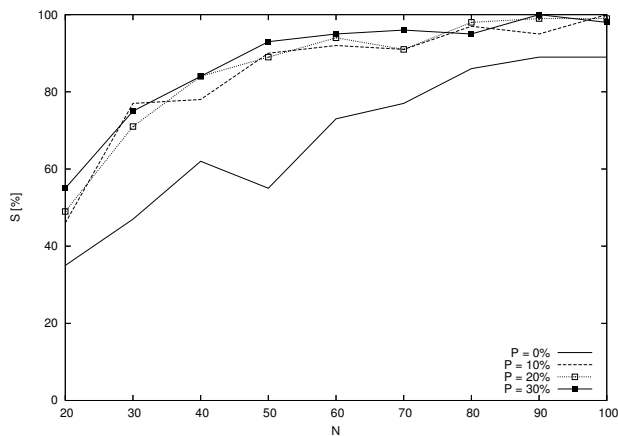

Figure 5: Effect of varying sampling population on performance for the Easom function. $(M = 20\%)$.

From Figure 5 we can observe that though the search performance improves with increase in the population size, the recessive gene performs better at low populations than for the case where $P = 0\%$.
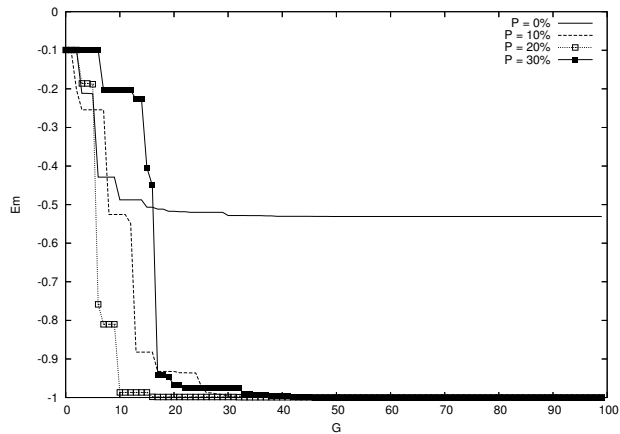

Figure 6: Effect of generations and recessive gene on efficiency for the Easom function. $(M = 20\%)$.

Figure 6 shows the mean of the best values of the function on 100 trials per generation. It gives a strong indication of the advantage of the recessive gene in this unimodal search, where the attainment of the best mean value, E_m, of the function is faster when $P \neq 0\%$ and there is stagnation when $P = 0\%$. For the Easom function, rate of convergence to solution is fastest when $P = 20\%$.

4.3 Searching performance results for Schaffer's F6 function

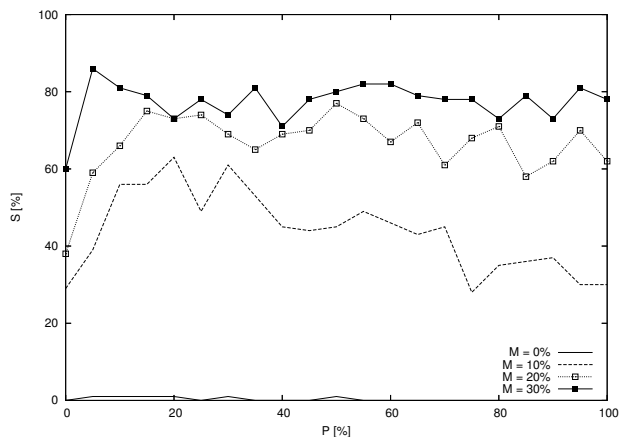

Figure 7: Recessive gene performance, Schaffer's F6.

Figure 7 shows that success in search for the global optimum is best when $P \neq 0\%$. Mutation is essential in this multimodal search, as there is practically no search when $M = 0\%$. Mutation enhances the search by offering diversity among the population. Search for the global optimum was investigated from an initial sampling in the range [11,13] of the global search space [-15,15] for (x, y) values.
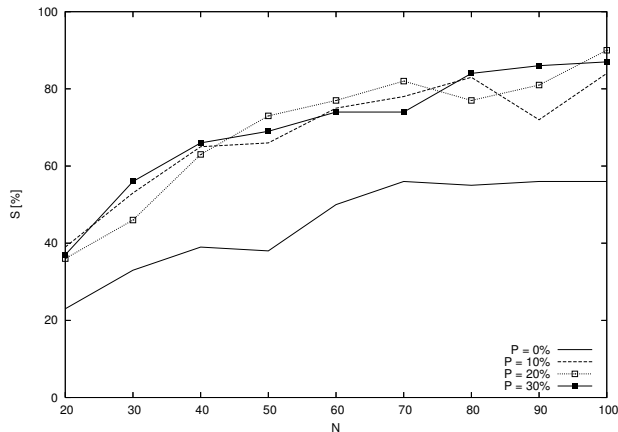
Figure 8: Effect of varying sampling population on performance for Schaffer's F6 function. ($M = 20\%$).

Figure 8 shows that though increasing N greatly improves the search, RGM performs relatively well with small population when $P \neq 0\%$ and it is inadequate when $P = 0\%$.
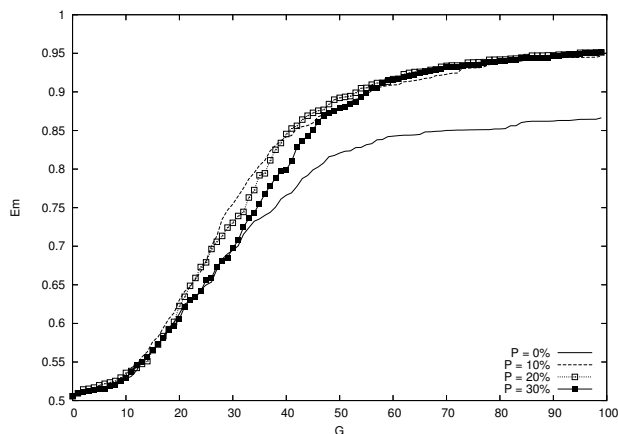

Figure 9: Effect of generations and recessive gene on efficiency for Schaffer's F6 function. ($M = 20\%$).

Figure 9 indicates the advantage of using the recessive gene as convergence is influenced by P; for $P = 0\%$ there is stagnation at some local optima.

5 Discussion

Using RGM, we compared the performance of the GA driven by a gradually increasing recessive gene to the dominant case. Figures 4 and 7 are the basis of our research; for the Easom function the success rate is lower when using only dominant chromosomes than for $P \neq 0\%$. However the search performance is degraded when P is too large. It can be inferred that for

the unimodal search the recessive gene performs the function of mutation. For the Schaffer's F6, search improves with P; mutation is integral to the evolution as there is practically no success for $M = 0\%$.

Figures 5 and 8 show that for the respective functions, though N greatly influences the search, there is inferior evolutionary success for $P = 0\%$. GA efficiency is enhanced by a large N, though this requires more memory and takes longer to converge. Since computational cost, C_c, in terms of time and memory, is in direct proportion to N, then C_c for $N = 100$ should be twice the C_c for $N = 50$. It can be seen from Figures 5 and 8 that performance is superior for the case $P \neq 0\%$, $N = 50$ than for $P = 0\%$, $N = 100$.

Figures 6 and 9, for Easom and Schaffer's F6 respectively, show that the rate of convergence is high for $P \neq 0\%$ and that there is stagnation when $P = 0\%$.

Maintaining diversity in the GA search ensures high efficiency yet avoids quick convergence and stagnation. RGM ensures accurate convergence at low N and this is desirable for memory storage during computations. However, RGM may be computationally expensive.

6 Conclusions

In this paper, we have shown that RGM avoids stagnation due to diversity, works very well at low sampling populations and that the recessive gene performs the function of mutation. Further, performance with recessive chromosomes is superior to the purely dominant chromosomes case. We believe the management of the computational cost could be further improved.

References

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