

決定論的・自己適応的 GA における並列可変突然変異に関する 0/1 複数ナップサック問題を用いた検討

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本稿では、世代交代型の決定論的・自己適応的 GA における交叉に並列適用する可変突然変異について、0/1 複数ナップサック問題を用いた検討を行い、交叉にシリアル適用する従来の可変突然変異モデルとの比較を行う。交叉に並列適用する可変突然変異は、決定論的・自己適応的 GA においてより高速で信頼性の高い収束を達成する、より効果的かつ効率のよい構成となり得ることがわかった。また、従来の可変突然変異モデルは、自己適応的な突然変異率制御にネガティブに作用することもわかった。

A Study on Parallel Varying Mutation in Deterministic and Self-Adaptive GAs with 0/1 Multiple Knapsack Problems

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In this work we study varying mutations applied parallel to crossover in generational deterministic and self-adaptive varying mutation GAs with 0/1 multiple knapsack problems, and compare them with the conventional generational model of varying mutations that apply mutation mostly serial to crossover. We found that varying mutation parallel to crossover can be a more effective and efficient framework in both deterministic and self-adaptive GAs to achieve faster convergence velocity and higher convergence reliability. We also found that the conventional model of varying mutations affects negatively the self-adaptive mutation rate control.

1. Introduction

One of the approaches for parameter control in genetic algorithms (GAs) seeks to combine crossover with (higher) varying mutation rates during the course of a run[1]. It has been shown that deterministically varying mutation rates over the generations and/or across the representation can improve the performance of GAs[2]. Self-adaptive mutation rate schedules have also been proposed to control the mutation rate of generational and steady state GAs[3]. From the application of operators standpoint, varying mutation GAs have been mostly designed similar to a canonical GA. Under these conventional varying mutation approaches, higher mutations are mostly applied serial to crossover. This rises questions regarding the interference that one operator could cause to the other and its possible impact on the performance and robustness of conventional varying mutation algorithms in general and self-adaptive mutation GAs in particular.

We continue to explore a model of generational GA (GA-SRM) that applies varying mutations (SRM) parallel to crossover and “background” mutation (CM), putting the operators in a cooperative-competitive stand with each other by subjecting their offspring to

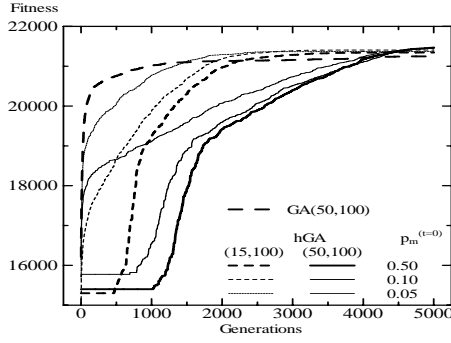
extinctive selection. The GA-SRM model was proposed in previous reports and its internal structure was studied in depth using an adaptive schedule for varying mutation[4]. In this work, the GA-SRM model of parallel varying mutations is applied to other subclasses of varying mutation GAs (deterministic and self-adaptive varying mutation GAs) and compare it with the conventional generational model of varying mutations GAs across a broad range of difficult, large, and highly constrained 0/1 multiple knapsack problems[5].

2. A Conventional Varying Mutation GA

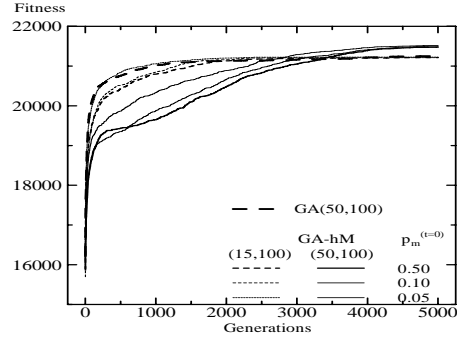
A conventional varying mutation GA, similar to canonical GAs, applies crossover with probability p_c followed by mutation with probability p_m per bit. In the absence of crossover ($1 - p_c$), mutation is applied alone. From the application of operators standpoint, it can be said that the probability of crossover p_c enables an implicit parallel application of two operators. One of the operators is crossover followed by mutation (CM) and the other one is mutation alone (M). It should be noted that mutation in both CM and M is governed by the same mutation probability p_m and applies the same “bit by bit” mutation strategy. Since p_c is usually set to 0.6, and higher values are often

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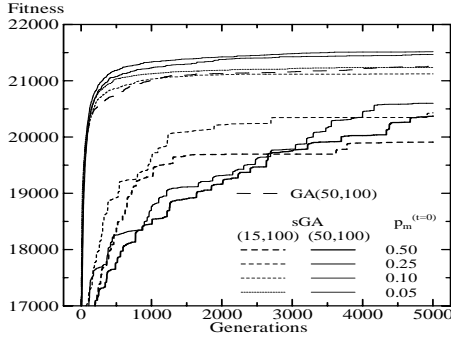


(a) Serial to Crossover

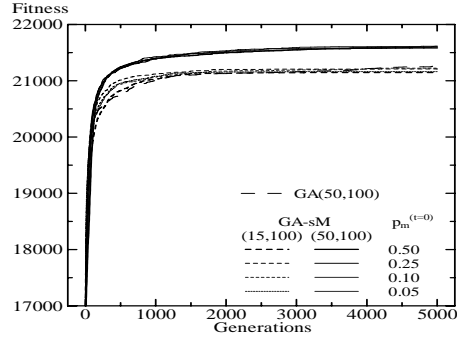


(b) Parallel to Crossover

Figure 2: Deterministic Varying Mutation ($m = 30, n = 100, \phi = 0.25$)



(a) Serial to Crossover



(b) Parallel to Crossover

Figure 3: Self-Adaptive Varying Mutation $p_m^{(t=0)}(i) = p_m^{max}$ ($m = 30, n = 100, \phi = 0.25$)

In our study we use difficult, large and highly constrained, 0/1 multiple knapsack problems³[5]. A 0/1 multiple knapsack problem consists of m knapsacks (constraints) and n objects (size of the search space: 2^n). Each knapsack is of different capacity and each object has associated a profit. Also, there is a set of weights for each object, one per knapsack. The objective of the problem is to find the combination of objects such that profit is maximized but no knapsack is overfilled with objects' weights. Besides m and n , other parameter of the problem is the tightness ratio ϕ between knapsack capacities and object weights (which implies a ratio between the feasible region and the whole search space).

5. Deterministic Varying Mutation

Deterministic mutation varies mutation rates with exactly the same schedule whether it is applied serial (hGA) or parallel to crossover (GA-hM) and therefore is an ideal candidate to isolate and observe the impact of higher mutations in both models of GAs. **Figure 2** plots the average fitness of the best-so-far individual over the generations by hGA and GA-hM using various populations (μ, λ) and initial mutation probabilities $p_m^{(t=0)}$. From these figures it become apparent

that varying mutation parallel to crossover is less disruptive than conventional varying mutation. Note in the case of hGA the initial *flat* periods in which the fitness of the best-so-far individual did not improve. This is a clear indication of the disruption caused by high mutation after crossover. Contrary to hGA, in the case of GA-hM there are no initial *flat* periods and in all cases GA-hM converges faster than hGA for similar values of (μ, λ) and $p_m^{(t=0)}$. In GA-hM, similar to hGA, a $(\mu, \lambda) = (50, 100)$ extinctive ratio gives better final results than $(\mu, \lambda) = (15, 100)$.

6. Self-Adaptive Varying Mutation

A self-adaptive scheme uses one mutation rate per individual. Two important ingredients of self-adaptation are the diversity of parameter settings and the capability of the method to adapt the parameters. To observe the influence that the conventional/parallel application of varying mutations could have on the self-adaptive capability itself we avoid initial diversity of parameters. **Figure 3** plots the average fitness of the best-so-far individual over the generations by sGA and GA-sM using populations $(\mu, \lambda) = \{(15, 100), (50, 100)\}$ and mutation ranges of $p_m = [p_m^{min}, p_m^{max}] = [1/n, \{0.50, 0.25, 0.10, 0.05\}]$. In all cases initial mutation for each individual is set to the maximum value allowed for the

³<http://mscmga.ms.ic.ac.uk/jeb/orlib/info.html>

range, $p_m^{(t=0)} = p_m^{max}$.

From **Figure 2** and **Figure 3** it is worth noting the following. (i) Self-adaptive mutation increases convergence speed compared to deterministic mutation either serial or parallel to crossover. Between sGA and GA-sM, however, looking at **Figure 3 (a)** and **(b)** note that sGA can match GA-sM's convergence velocity only for small values of $p_m^{(t=0)}$. This is an indication that even in the presence of adaptation the convergence velocity of a conventional varying mutation GA would depend heavily on initial mutation rates, which is not an issue if adaptive mutation is applied parallel to crossover. (ii) Contrary to deterministic varying mutation, convergence reliability of self-adaptive mutation serial to crossover could be severely affected, which becomes quite notorious if no initial diversity of parameters is allowed. On the other hand, the initial lack of diversity of parameters does not affect convergence reliability of GA-sM. Note in **Figure 3 (b)** that for the same selection pressure convergence reliability of GA-sM is similar for all values of $p_m^{(t=0)}$. (iii) Similar to deterministic varying mutation, better results are achieved by $(\mu, \lambda) = (50, 100)$ rather than by $(\mu, \lambda) = (15, 100)$.

Next, we allow for initial diversity of parameters setting $p_m^{(t=0)}$ to a random value between the minimum and maximum value allowed for mutation. In this case, the disruption that higher serial mutation causes to crossover becomes less apparent due to the initial diversity of parameters and convergence speed is similar for both sGA and GA-sM. Convergence reliability of sGA also improves. However, the negative impact on reliability remains quite significant for sGA (see 7.). In sGA an appropriate mutation parameter implies parameters that would not affect greatly crossover, which can mislead the mutation rate control negatively affecting performance. In sGA there is a selective bias towards smaller mutation rates.

7. Convergence Reliability

To obtain a broader perspective on the performance of the GAs we apply them to several knapsacks problems varying ϕ , m , and n . Each combination of ϕ , m , and n defines a subclass of problem. Here we use totally 7 subclasses of problems, defined by $(m = 30, n = 100, \text{ and } \phi = \{0.75, 0.50, 0.25\}; n = 100, \phi = 0.25, \text{ and } m = \{5, 10\}; m = 30, \phi = 0.25, \text{ and } n = \{250, 500\})$. Ten random problems are used for each subclass. We test the statistical significance of the results achieved by hGA, GA-hM and sGA, GA-sM. **Table 1** shows results of the 6 corresponding two-factor factorial ANOVA, where $Pval$ is the p value (the smallest significant level α that would allow rejection of the null hypothesis). Inspection of the

Table 1: Convergence Reliability: Factorial ANOVA

Source	df	hGA, GA-hM		sGA, GA-sM	
		F	Pval	F	Pval
GA	1	3.260	0.0766	9.731	0.0029
ϕ	2	1175.553	0.0000	570.167	0.0000
GA- ϕ	2	0.454	0.6373	4.078	0.0224
GA	1	6.219	0.0157	12.418	0.0009
m	2	549.927	0.0000	519.263	0.0000
GA- m	2	0.051	0.9505	4.867	0.0114
GA	1	8.685	0.0047	42.053	0.0000
n	2	94.062	0.0000	58.371	0.0000
GA- n	2	0.010	0.9903	0.506	0.6055
MSError	54				

p values under hGA,GA-hM reveals that there is some indication of an effect due to the conventional/parallel application of deterministic varying mutation, since $Pval = 0.066$ and $Pval = 0.061$ for ϕ and m are not much greater than $\alpha = 0.05$. However, looking under sGA,GA-sM, there is indication of an strong main effect of applying self-adaptive varying mutation conventional/parallel to crossover.

8. Conclusions

We have studied the application of varying mutation either serial or parallel to crossover and discussed its effect on the performance of deterministic and self-adaptive varying mutation GAs. Experiments were conducted with several 0/1 multiple knapsacks problems. We found that varying mutation parallel to crossover can be a more effective and efficient framework in both deterministic and self-adaptive GAs to achieve faster convergence velocity and higher convergence reliability. We also found that the conventional model of varying mutations affects negatively the self-adaptive mutation rate control.

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