Gene Silencing Genetic Algorithm for 0/1 Knapsack with Object Preferences

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Abstract

Genetic Algorithms are efficient search and optimization techniques inspired by natural evolution. To show the difficulties in solving constrained optimization problems through GA, the 0/1 knapsack problem with user specific object preferences has been taken up. A new genetic operator, namely, 'gene silencing' inspired from biology is used along with standard GA. The experimental results for varying number of objects and user preferences show that genetic algorithm with gene silencing produces better results when compared to standard GA.

Keywords: Genetic algorithm, 0/1 knapsack, constraint satisfaction, gene silencing operator

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1. Introduction

Genetic Algorithms[1,2] are generally considered to be good at solving optimization problems. But, constrained optimization through GA is considered to be a challenging task because, GAs are not considered to be directly suitable to solve such problems. To illustrate the fact, the problem of 0/1 knapsack with multiple user specific object preferences has been taken up in this paper. This is a slight variant of the standard 0/1 knapsack problem wherein, the user is free to select some objects of his choice that should be compulsorily included in the knapsack also satisfying the problem constraints. This can be stated as an instance specific constraint as it can be varied with each execution of the problem. As standard GA was not able to produce the required solutions in the expected time period, we attempted for GA with population sizing and fitness function variation, [3,4] which incorporates the reward score for expected object preferences.[5] But still, the results were not very satisfactory. Hence, we have incorporated a new operator called gene silencing inspired from biology to meet out the required object preferences in this paper.

The organization of the paper is as follows: Section-2 gives the related work; section-3 explains the proposed system which includes a description of the new operator namely gene silencing and how it is used along with GA. Section-4 gives the experimental results and section-5 concludes the paper.

2. Related Work

A number of Genetic Algorithms have been used to solve constraint optimization problem and [6,7] are some of them that are used for solving knapsack with multiple constraints.

Methodologies in literature include different forms of penalty functions [8,9] that vary with the problem. Since the penalty factors have to be assigned based on the degree of violation of the constraints, it seemed to be a difficult task. Also, the issue of diversity maintenance along with constrained optimization has to be taken care as explained in[10] to get a globally optimum solution. This paved the way for identifying a new biologically inspired operator for solving the constrained optimization problems. Other biologically inspired operators like transposons [11], transformation [12], etc, have also been applied to genetic algorithms in the past for various reasons and they were found to yield promising results. With respect to the gene silencing operator, some related operators have been found in literature. For instance, the mask operator [13] is a type of operator that works at the gene level. This is used along with crossover operator to set some preferences in the selection of genes during crossover, but the problem with mask is the selection of a suitable mask that varies with problem. . Moreover, it is not heritable over the successive generations. This will result in the disruption of the good building block by the crossover and mutation operators.

Similarly, some repair functions [14] have also been used at the gene level, even for solving the 0/1 knapsack problem. Some knowledge based operators [15] are also used in other type of problems like course timetabling problem to set some user specific preferences. Also, standard GA would set different penalty values[16] based on the requirement. A variety of repair functions and crossover operators have also been applied to the above said problem. Alternatively, it has been shown that based on biased genetic operators[17], one could achieve the required preference settings. But all the above stated techniques have got some limitations like the following.

- One may not get the exact solution that is required.
- If there are one or more preferences you may not get the correct choice of preference on convergence.
- Choosing the right penalty values for instance specific constraint is difficult and the success of the GA relies on the efficient determination of these penalty values.
- When instance specific constraints are satisfied, there may be a few violations of high penalty constraints or a sacrifice in the maximum fitness value that could be achieved.
- The number of generations taken for convergence increases drastically with the number of preferences, and sometimes, the GA may not converge at all if 100% preference settings are expected.

Thus, this paper presents a different type of knapsack problem with user specific object preferences, for which no specific work is reported in literature.

3. Gene Silencing Genetic Algorithm for the 0/1 Knapsack Problem (with object preferences)

This section explains about the new operator namely gene silencing, its usage in genetic algorithm and its applicability to the 0/1 knapsack problem.

3.1. *Gene Silencing*

Genes are considered to be small segments of DNA housed in chromosomes and each gene is responsible for a specific function. [18,19,20] Among the several thousand functional genes present in the human body , not all the genes are active at a given instance. Most of the genes are turned off or silenced appropriately preventing from doing their work of protein synthesis. For example, thousand of genes are active only during embryo development, but remain silent in healthy adults. Similarly, certain genes have to be activated in certain parts of the body and silenced in others where its functionality is not required. Example, some genes have to be activated in skin and silenced in the heart, liver and other organs.

The most important observation made is that, the phenomenon of gene silencing is heritable, i.e., when a cell divides, its daughter cells maintain not only copies of its DNA, but also the silencing of these genes. Lot of research is now being carried out in this field of genetics and sufficient knowledge of this mechanism could be exploited to evolve new cancer therapies aimed at re-silencing inappropriately activated genes. Gene silencing could also be used for determining gene function.

3.2. *GA with Gene Silencing*

The principles of genetic algorithm mimic the process of natural evolution. The concept of gene silencing discussed in the previous section could be adopted in genetic algorithm as an operator where other natural operators like crossover and mutation are already being applied for any standard GA. The population in GA comprises of the chromosomes or individuals. Each chromosome is again composed of genes, which are the target of the gene silencing operator. This property is particularly useful to set certain user specific constraints or preferences that are present in some problem apart from their optimization criterion. Hence this operator works at the gene level. This operators functions as follows: Whenever a chromosome is encountered with the required gene position set according to the user preference, they are marked as silenced. This helps is the preservation of the required building blocks to obtain an optimal solution. Once silenced, the crossover and mutation operators do not affect the particular genes. As this property of gene is heritable in nature, they are preserved over successive generations. Normally, crossover operator disrupts the good building blocks or genes, even though they are considered to be useful to evolve good solutions. But through gene silencing, the required genes are preserved from the disruptions of crossover or mutation, allowing crossover and mutation to evolve an optimal solution with the other parts of the chromosome. Since the other parts of the chromosome undergo normal crossover and mutation the application of gene silencing to the required genes in the chromosome will not necessarily lead the Genetic algorithm towards a biased solution tending to produce local optima. To evolve the optimal solution the following steps are to be followed.

(i) Generate the initial population.
(ii) Evaluate the fitness as per general 0/1 knapsack problem.
(iii) Apply gene silencing operator to the individuals who satisfy the object preferences.
(iv) (The operator will silence the required gene positions corresponding to the user specified object positions)
(v) Apply the other genetic operators (selection, crossover and mutation) to the individuals in the current generation.
(vi) Pass the generated offspring to the next generation.
(vii) Go to step-(ii)

Gene silencing could be mathematically represented as follows: Let Ci $= \{g_{i1}, g_{i2}, \ldots g_{in}\}$ be the set of all genes in chromosome-i and Cj= $\{g_{j1}, g_{j2}, \ldots g_{jn}\}$ be the set of all genes in chromosome-j.

The consequence of silencing is very much evident during the process of crossover and mutation over successive generations. Because the property of gene silencing is heritable in nature, the silenced gene does not take part in the process of crossover or mutation. This is shown in the figure below. Assume a single point crossover and the cut point is chosen to be some k in a single point crossover. This implies that the genetic materials of chromosomes Ci and Cj get exchanged after this cut point k. Assume that the (k+1) th gene in both the chromosome-i and chromosome-j are the instance preferences and they are to be silenced. The crossover operation between chromosome-i and chromosome-j is represented as follows. The below figure shows that though the crossover point is at position k, and the genetic materials are exchanged from the kth position, the genes g_{ik+1}, and g_{jk+1}, remains unaffected due to crossover. As gene silencing is heritable, this setup remains unaffected over successive generations, thus preserving the individual preferences. Similar arguments can be had with mutation operator also.

4. Experimental Results

To examine the performance of our approach for problems with instance specific constraints, the 0/1 knapsack problem[21], a special kind of knapsack problem belonging to the class of NP hard problems has been chosen. Here, the 0/1 knapsack problem with varying percentage of user specific object preferences has been taken up. The modified 0/1 knapsack problem can be stated as follows:

Let n be the number of given objects and w_i be the weight of the ith item, p_i be the profit accrued when the ith item is carried in the knapsack, and C be the capacity of the knapsack. Let x_i be a variable, the value of which is either zero or one. The variable x_i has the value one when the ith item is carried in the knapsack and zero otherwise.

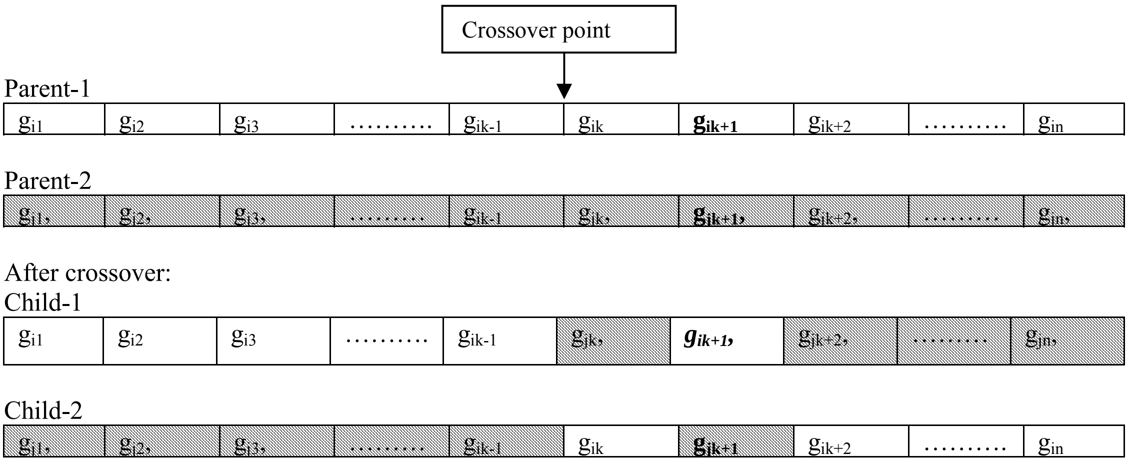

Figure 1- Effects of gene silencing after crossover

Given $\{w_1, w_2, \ldots. w_n\}$ and $\{p_1, p_2, \ldots. p_n\}$, our objective is to

$$\text{maximize } f(x_1, \ldots\ldots\ldots, x_n) = \sum_{j=1}^{n} p_j x_j$$

subject to the constraint ,

$$\sum_{j=1}^{n} w_j x_j \le c, \quad x_j = 0 \; or \; 1, \quad j = 1, \ldots\ldots, n$$

The above constraints are specific to the 0/1 knapsack problem. In addition to these constraints, consider an instance specific constraint. Denote by S, the set of above said variables x_i. Let A denote the set of user preference objects, A= {User preference objects}. Then A∈S and let some x_j ∈ A, we have to consider the following constraint.

$f(x_1, x_2, \ldots\ldots x_n)$ attains the maximum value subject to

$$\sum_{j=1}^{n} w_j x_j \le c, \quad x_j = 0 \; or \; 1, \quad j = 1, \ldots\ldots, n$$

and $x_j = 1$ for such of those x_j ∈ A

this modified form of 0/1 knapsack consists of user specific object preferences that vary with every instance of GA execution, it has been used to test the effectiveness of the gene silencing GA.

The chromosome representation that is used for the 0/1 knapsack problem is a bit vector consisting of zeroes and ones. Each gene here refers to an object i that is either 1 or 0 depending on the inclusion or non-inclusion of an object i into the knapsack respectively.

This being the general 0/1 knapsack problem, which can be solved by any standard GA, this paper assumes some object preferences. Hence some percentage of xi, are strictly required to be 1, which means the strict inclusion of certain objects in the knapsack as specified by the user. This varies for each problem instance and hence cannot be easily achieved by standard GA through random iteration and standard genetic operators.

The input data was generated randomly with the following parameter settings. The problem size was varied with the number of objects being 100, 200, 300, 400,etc. The values of Wi and Pi was randomly chosen within the range (1..100). The knapsack capacity C was each time chosen to be less than or half of the total weight of all the n objects. This was to ensure that there are few objects in the knapsack with more number of possible combinations. Thus the capability of GA with gene silencing could be thoroughly explored rather than an incidental occurrence of 1s in the preferred genes. The percentage of object preferences is obtained from the user for each GA execution. Results were obtained for varying percentages of object preferences. A set of experiments were carried out to evaluate the performance of our approach with the standard GA with and without the gene silencing operator. Each experiment comprises of about 50 runs.

The results of only four experiments, each with five runs is given in the subsequent pages due to space limitations.The experiments were carried out for a fixed number of generations and the settings of the GA parameters are as follows:

Population size : 100;
Selection : Roulette Wheel
Elitism : 0.10
Crossover percentage P_c : 0.85 ,
Crossover type : single point
Mutation Probability P_m : 0.05,
Mutationtype : Swap Mutation.
No. of generations : 100

Table 1. Experiment-1 with 100 Objects and Preference of 5 % and 10%

Problem Instance	**Standard GA without gene silencing**		**GA with Gene silencing**	
100 objects	Max. profit	% user preference achieved	Max. profit	% user preference achieved
Preference 5%	2346	60	2913	100
	2406	60	2927	100
	2372	40	3022	100
	2331	20	3176	100
	2318	40	2946	100
Preference 10%	2385	60	2988	100
	2482	40	3024	100
	2091	60	3067	100
	2567	40	2974	100
	2062	60	3017	100

Table 2. Experiment-2 with 200 Objects and Preference of 5 % and 10%

Problem Instance	**Standard GA without gene silencing**		**GA with Gene silencing**	
200 objects	Max. profit	% user preference achieved	Max. profit	% user preference achieved
Preference 5%	4365	40	5749	100
	5025	30	5679	100
	3702	50	5437	100
	4186	30	5582	100
	4762	40	5623	100
Preference 10% `				
	4353	40	5815	100
	5264	40	5951	100
	4980	20	6023	100
	4667	70	5812	100
	4876	70	5786	100

Table 3. Experiment-3 with 300 Objects and Preference of 5 % and 10%

Problem Instance	**Standard GA without gene silencing**		**GA with Gene silencing**	
300 objects	Max. profit	% user preference achieved	Max. profit	% user preference achieved
Preference 5%	8441	60	9001	100
	8203	50	8840	100
	8161	60	9168	100
	8207	70	9015	100
	8285	60	8971	100
Preference 10%				
	9133	70	9797	100
	9288	80	9816	100
	8871	60	9648	100
	8774	70	10092	100
	9476	70	9903	100

Table 4. Experiment-4 with 400 Objects and Preference of 5 % and 10%

Problem Instance	Standard GA without gene silencing		GA with Gene silencing	
400 objects	Max. profit	% user preference achieved	Max. profit	%. User preference Achieved
Preference 5%	8945	30	11131	100
	9364	50	10084	100
	9957	40	10876	100
	9343	60	10926	100
	9412	50	10663	100
Preference 10%	9975	50	11006	100
	9777	60	11168	100
	10583	70	11316	90
	10401	60	11714	90
	9948	40	11260	100

From the experimental results it is found that SGA fails to satisfy all user specified object preferences whereas GA with gene silencing achieves 100% object preferences most of the time the GA was executed. For example, 10% object preference for 400 objects implies that there are 40 user specific object preferences that have to be included in the knapsack compulsorily in addition to satisfying the profit weight constraint of the 0/1 knapsack problem. This is very time consuming and cumbersome with the standard GA if it was allowed to run till convergence. Most of the time, it did not converge with the required preference setting. Hence, the number of generations was fixed up uniformly and the results compared for both the methods.

5. Conclusion and Future Enhancements

It has been concluded that for problems like 0/1 knapsack (with object preferences), standard GA fails to converge with the required preference settings. If standard GA is allowed to run for a fixed number of generations, the user specified object preferences are not satisfied completely (100%). Hence a new gene silencing operator that is heritable over generations has been applied. The results show that it is very helpful to achieve a high percentage of user specific object preferences without sacrificing the profits gained in the knapsack. Research is under progress for the tuning of control parameters (selection, crossover, mutation methods and their percentages) to evolve best results.

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