A Hybrid Spiral-Genetic Algorithm for Global Optimization

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***Abstract*—Genetic algorithm (GA) is a well-known population-based optimization algorithm. GA utilizes a random approach in its strategy which inspired from a biological process of a chromosome alteration. Chromosomes which consists of several genes are randomly self-altered their own structure and also randomly combined their structure with other chromosomes. The unique biological process has inspired many researchers to develop an optimization algorithm. Yet, the algorithm still popular and is adopted as a tool to solve many complex problems. On the other hand, Spiral Dynamic Algorithm (SDA) is a relatively new population-based algorithm inspired by a natural spiral phenomenon. It utilizes a deterministic approach in its strategy. Movement of a search point from one location to another in a form of a spiral trajectory and relies on pre-defined parameters. However, both algorithms suffer a pre-matured convergence and tend to trap into a local optima solution. This paper presents an improved algorithm called a Hybrid Spiral-Genetic Algorithm. The algorithm is developed based on a combination of the well-known GA and the SDA. The spiral equation of the SDA is adopted into the GA to enhance both exploration and exploitation of the original GA. The algorithm is tested with several benchmark functions of a single-objective algorithm and compared with the original SDA and GA. The result of the test shows that the proposed algorithm outperformed its predecessor algorithms significantly.**

***Index Terms*—Spiral Dynamic Algorithm; Genetic Algorithm.**

I. INTRODUCTION

Nowadays, an optimization algorithm plays an important role in solving many complex problems in real world. It has been widely applied in various fields including science and non-science as a tool to get many optimal parameters. With the application of the algorithm, an optimum result or decision can be easily achieved. Moreover, with the growth of fast computing technologies, the adoption of the optimization algorithm is increasing. Yet, fast computing machines with affordable price can be easily found in the current world market.

Research on developing and improving optimization algorithms has started since many years back. Most of the developed algorithms are inspired by biological or natural phenomena. Algorithms inspired by living creature are known as biological-inspired algorithms while algorithms inspired by other than living creature are known as natural-inspired algorithms. Some of the well-known biological-based optimization algorithms include Particle swarm optimization [1], the Genetic algorithm (GA) [2] and Firefly algorithm [3]. Examples of natural-inspired optimization algorithms include Harmony search algorithm [4], Chemical reaction algorithm [5] and Spiral dynamic algorithm (SDA) [6]. All these algorithms free from the derivative operation and thus suitable for solving simple and complex problems.

GA is one of the earliest introduced optimization algorithms among the population-based category. Research on GA has reached a matured-phase. Various adaptive and hybrid types GA-based algorithms have been developed since the introduction of the original GA. Adaptive types GA include formulation to adjust mutation and crossover operators [7], [8] and operators selection [9]. Several types of selection have been applied in GA. Some of the commonly found in the literature are roulette wheel, elitism, rank and tournament selections. There are also different types of crossover and mutations have been proposed by researchers [10]. These variants of adaptive types GA open new perspectives to researchers on the strategy to improve the algorithm performance.

Hybrid type GA can also be extensively found in the literature. Eroglu and Kilic [11] proposed a Hybrid GA-Local search method. Random selection, single-point mutation and crossover were applied to the basic GA operations. Local search method was adopted as a further step to include additional mutation operation based on feature selection. Rahmani and Mirhassani [12] proposed GA-Firefly algorithm. Crossover operation of GA was applied to the first two best fitness of ranked fireflies. It was followed by a mutation operation on a randomly selected firefly to increase the diversity of the algorithm. Alsaeedan et al. proposed a GA-Ant colony algorithm [13]. Single-point crossover and mutation or uniform crossover and mutation operations were adopted into Ant colony algorithm based on crossover rate or mutation rate respectively. Value of the mutation and crossover rates in the proposed algorithm was adaptively varied with respect to fitness of the ant agent. Garai and Chaudhurii proposed a GA- Tabu algorithm [14]. Local tabu search method was applied to GA to avoid the GA from being trapped in local optima solution. Tabu search was invoked whenever the best fitness of GA was not changed after several GA iterations. The rest of GA operations will continue once the Tabu algorithm has completed its cycle.

SDA is a relatively new population-based algorithm. Various adaptive and hybrid type SDA have been introduced. The adaptive type SDA includes ASDA where a linear-based equation was adopted into the spiral equation of SDA [15]. Unlike the original SDA, the equation defined spiral radius and angle within a specified range for each search point. Throughout the search process, different search points can have different motion trajectories. Examples of hybrid SDA include hybrid spiral-bacterial foraging algorithm [16] and hybrid spiral dynamic-bacteria chemotaxis algorithm [17]. In both algorithms, chemotaxis strategy of a bacterial foraging algorithm (BFA) was combined with the spiral equation of

SDA. The strategy combined random approach of a bacterium with a deterministic approach of SDA. The proposed algorithm improved the accuracy of both original BFA and SDA algorithms. Most recent work of SDA development was an enhanced chaotic SDA [18]. SDA was combined with biological inspired artificial bee colony (ABC) algorithm and chaos function. A logistic chaotic map was applied to the spiral equation to replace a constant radius of SDA. Meanwhile, the local search strategy of ABC was adopted as an additional step into SDA to tackle exploitation strategy in a local region. In another work, the authors adopted greedy selection strategy into SDA to determine the best search point in every iteration [19].

This paper proposes a new hybrid GA type named Hybrid Spiral-Genetic algorithm (HSGA). The strategy integrates a spiral equation of the SDA into the original GA. It improves the accuracy of both SDA and GA algorithms. The rest of this paper is organized as follow. Sections 2 and 3 present a brief introduction to the GA and SDA. A detailed explanation of the proposed HSGA is presented in Section 4. Section 5 explains about benchmark functions used in the work. Section 6 presents the performance test set-up while Section 7 discusses the result of the performed test. Finally, the conclusion of the paper is presented in Section 8.

II. Genetic Algorithm

GA strategy was inspired by a biological process of a genetic and natural selection. It consists of three main processes such as selection, crossover and mutation. Selection refers to a strategy to select two genes from a genetic population prior to crossover and mutation operations. A random selection is the simplest type of selection. In this case, two chromosomes are randomly selected as the parent chromosomes to create two new chromosomes that inherit some genetics of the parent chromosomes. This process is called a crossover operation. Genes from those two parent chromosomes are randomly selected and exchanged their genes. Mutation is a genetic operation after the crossover. It is an operation to reproduce a single chromosome. The fittest chromosome is normally selected as the target chromosome for mutation. A selected chromosome is mutated in which its genetic structure is randomly changed. All the parents, cross-over and mutated chromosomes generated based on the mentioned operations are ranked according to their fitness level. Some of the fittest chromosomes are retained in the chromosome population. The evolution process of chromosomes is repeated continuously.

III. Spiral Dynamics Algorithm

SDA strategy is formulated inspired by natural spiral phenomena. It is a relatively simple algorithm when compared with other population-based algorithms. In SDA, prior to a search operation, the fitness of each agent is evaluated. Then, each search agent moves in a spiral trajectory towards the fittest agent in the population. The fittest agent in the population is formulated such that it is the spiral centre of the spiral trajectory. The processes are continuously repeated. The motion trajectory for the mentioned process is determined by two parameters called spiral angle and spiral radius. Those two parameters are constant and the same for all search agents. The SDA strategy relies on a spiral equation that generates a spiral form of the agents' motion as shown in Equation (1). x^* is the location the fittest chromosome in the population, I_n is the identity matrix with $n \times n$ dimensions, r and θ are the spiral radius and angle respectively, $x_{i\,current}$ is the i^{th} chromosome location in current iteration, $S(r,\theta)$ is the n x n rotational matrix with respect to spiral radius and angle and $x_{i\,new}$ is the i^{th} chromosome location in the new or next iteration.

$$x(k+1) = S(r,\theta)x(k) - (S(r,\theta) - I)x^* \qquad (1)$$

In SDA, as the iteration increases, the step size of search agents moving from one location to another is reduced. This is due to the motion of the agents towards a centre of the spiral form.

IV. Hybrid Spiral-Genetic Algorithm

In HSGA, a deterministic spiral motion of SDA and a random approach of GA is synergized. GA is viewed as a good algorithm in terms of its diversity and thus able to search a feasible search space thoroughly. On the contrary, the spiral trajectory of SDA is considered as a good algorithm to search at a more confined space. The concept of elitism of SDA is also adopted into GA. All of the agents in SDA are formulated such that they move towards the best agent in the population. Moreover, movement of the agents from the outer layer of the spiral form towards the centre of the spiral form creates dynamic step size. A step-by-step HSGA algorithm is explained as follows.

A. A step-by-step HSGA algorithm.

1. **Initialize chromosome populations**.
   a) Randomly generate chromosome population.
   b) Evaluate fitness value of each chromosome.

2. **Apply crossover operation**.
   a) Randomly select two parent chromosomes.
   b) Apply a random-based crossover.
   c) Evaluate fitness value of the crossover chromosome offsprings.

3. **Apply mutation operation**.
   a) Randomly select two parent chromosomes.
   b) Apply a random-based mutation.
   c) Evaluate fitness value of the mutated chromosome off springs.

4. **Apply SDA**.
   a) Move chromosomes spirally by applying the spiral equation as shown in Equation (1).
   b) Evaluate fitness value of the newly generated chromosomes.

5. **Rank** the chromosomes and retain some of the fittest chromosomes in the population.

6. **Repeat** the process until a termination criterion is reached.

In HSGA, the selection, crossover and mutation operations for GA as shown in steps 2 and 3 utilize a random approach. The operations are the same as other basic GAs found in the literature. The integration of SDA strategy into GA is shown in step 4. A spiral equation of SDA is adopted and thus moves all the chromosomes in a spiral form. This ensures the combination of random and deterministic spiral strategies are applied.

V. BENCHMARK FUNCTION

Numerous benchmark functions to test a newly developed single-objective type algorithm. Some of the well-known features of the test functions include uni-modal or multimodal. Uni-modal refers to a test function that has only a single optimal solution in its search region. On the other hand, a test function with more than one optimal solution is referred to as a multimodal test function. Solving a multimodal test function is more challenging due to its environmental landscape and multiple locations of the optimal solution. 6 test functions are considered in this work and they are summarized in Table 1. All test functions contain continuous, scalable and differentiable features of the fitness landscape. All the test functions were set up to have 60 dimensions only. Mathematical formulations of the test functions are shown in Equations (2) – (7).

Table 1
Benchmark Test Functions

Function No.	Function name	Landscape	Search range
1	Sphere	Unimodal, separable	[-5.12, 5.12]
2	Rosenbrock	Unimodal, non- separable	[-5, 10]
3	Dixon & Price	Unimodal, non-separable	[-10, 10]
4	Ackley	Multimodal, non-separable	[-15, 30]
5	Rastrigin	Multimodal, separable	[-5.12, 5.12]
6	Griewank	Multimodal, non-separable	[-600, 600]

Test function 1, Sphere:

$$f_1(x) = \sum_{i=1}^{n} x_i^2 \tag{2}$$

Test function 2, Rosenbrock:

$$f_2(x) = \sum_{i=1}^{n} (100 \times (x_{i+1} - x_i^2)^2 + (1 - x^i)^2) \tag{3}$$

Test function 3, Dixon & Price:

$$f_3(x) = (x_1 - 1)^2 + \sum_{i=2}^{n} i(2x_i^2 - x_{i-1})^2 \tag{4}$$

Test function 4, Ackley:

$$f_4(x) = -20\exp(-0.2\sqrt{\left(\frac{1}{n}\sum_{i=1}^{n} x_i^2\right)} - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e \tag{5}$$

Test function 5, Rastrigin:

$$f_5(x) = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10] \tag{6}$$

Test function 6, Griewank:

$$f_6(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \tag{7}$$

VI. PERFORMANCE TEST

Parameter set-up for the performance test is explained in this section. In general, HSGA adopted all parameters of the original GA. The values of these parameters were set the same for both GA and HSGA. However, 2 more additional parameters i.e spiral angle and radius were assigned for the HSGA. The values of all parameters for both algorithms are shown in Table-2.

Table 2
Parameter Setup for The Performance Test.

Parameter	GA	HSGA
Spiral angle, θ	-	$\frac{\pi}{4}$
Spiral radius, r	-	0.96
No. of iteration	1000	
No. of population	100	
Crossover percentage, P_c	0.7	
Mutation percentage, P_m	0.3	
Crossover rate, λ	0.4	
Mutation rate, mu	0.1	

VII. RESULT AND DISCUSSION

Results of the performance test are presented in terms of both graphical and numerical representations. The graphical result shows convergence trend while numerical result presents the accuracy achieved by both GA and HSGA. Figures 1- 6 show graphical results of both GA and HSGA convergence to a near-optimal accuracy. The red dotted-line and the blue smoothed-line represent GA and HSGA graphs respectively. The x-axis represents a number of iteration while the y-axis represents cost function result.

Notice that, for function 1, the GA trapped into local optima solution starting at about the first 100 iterations until the rest of iterations. Graph 2 shows both GA and HSGA present almost the same performance. HSGA presents a little bit better performance starting from iteration 500 towards the end. In graph 3, HSGA performed slightly better than GA in terms of speed and accuracy. HSGA presents a little bit better performance starting from iteration 600 towards the end. Graph 4 shows that HSGA trapped into a local optima. It unable to converge further starting from iteration 100. GA performed significantly better than HSGA. In terms of convergence speed, HSGA shows a faster convergence speed for the 100 iterations. Graph 5 shows both algorithms have reached almost the same accuracy at iteration 800. However, GA was not able to further converge and trapped into a local optima for the last 200 iterations. Graph 6 shows that HSGA significantly outperformed GA in term of searching for an optimal solution and thus has a better accuracy. It also presents slightly faster convergence speed.

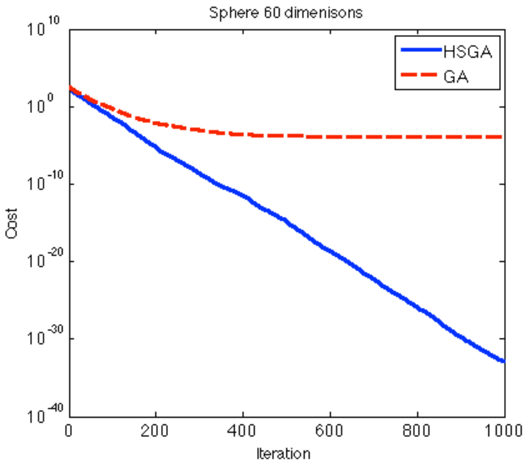

Figure 1: 60 dim. of a Sphere function.

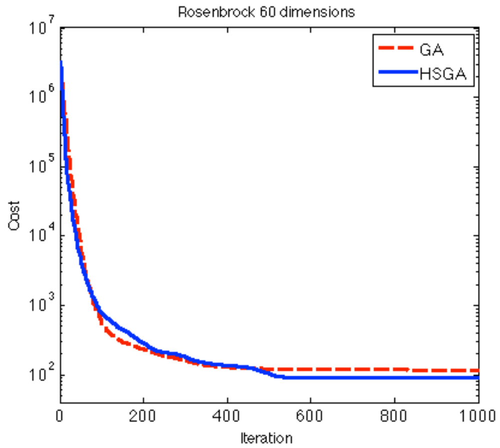

Figure 2: 60 dim. of a Rosenbrock function.

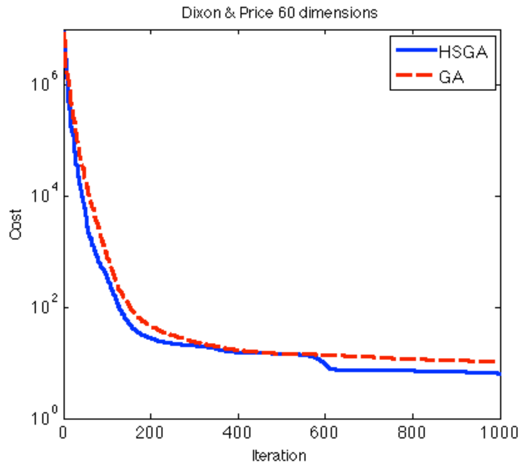

Figure 3: 60 dim. of a Dixon & Price function.

The numerical result of the acquired optimal solutions for the benchmark functions optimized by GA and HSGA is shown in Table-3. The best result is highlighted in bold font. Notice that out of 6 functions, GA outperformed the HSGA only for function 4, Ackley. Table 4 shows numerical result of the total computation time in second for both GA and HSGA. Since the proposed approach has additional steps in its strategy, therefore it has a higher computational time for all test functions. HSGA has about double total computation time of the original GA.

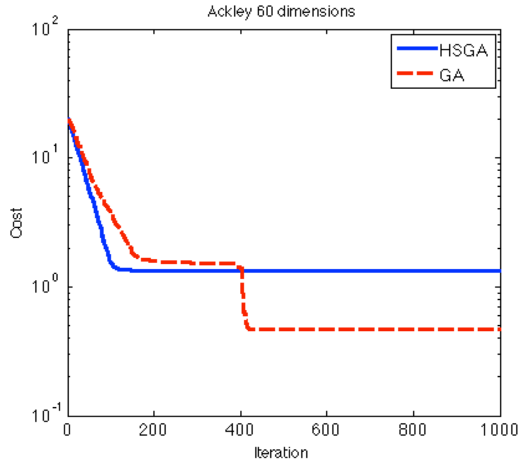

Figure 4: 60 dim. of an Ackley function.

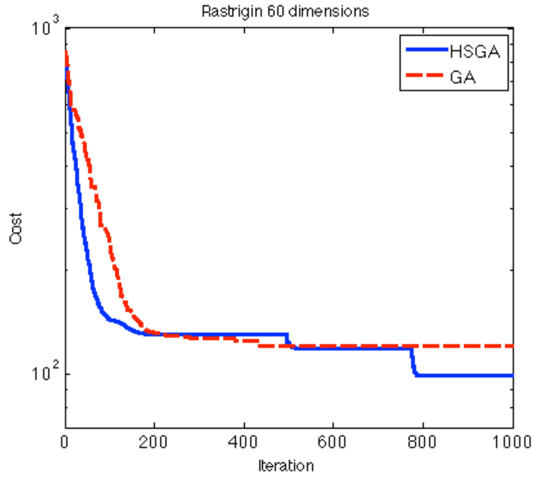

Figure 5: 60 dim. of a Rastrigin function.

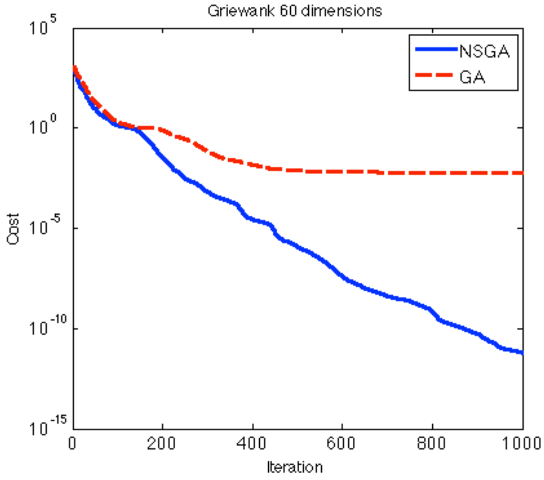

Figure-6: 60 dim. of a Griewank function.

Table 3
Acquired Optimal Solution for The Test Functions.

Func. No.	Function name	GA	HSGA
1	Sphere	1.23×10^{-4}	1.75×10^{-33}
2	Rosenbrock	116.50	89.88
3	Dixon & Price	10.67	6.43
4	Ackley	4.65×10^{-1}	1.34
5	Rastrigin	120.40	98.59
6	Griewank	5.80×10^{-3}	6.60×10^{-12}

Table 4
Total Computation Time in Seconds.

Func. No.	Function name	GA	HSGA
1	Sphere	14.61	31.34
2	Rosenbrock	15.59	31.29
3	Dixon & Price	15.63	33.30
4	Ackley	16.95	34.12
5	Rastrigin	15.58	32.25
6	Griewank	17.73	31.54

VIII. Conclusion

A new algorithm namely a Hybrid Spiral-Genetic Algorithm (HSGA) has been presented. It has been developed based on mainly on a Genetic algorithm (GA) and partly from a Spiral dynamic algorithm (SDA). A spiral equation of SDA has been adopted into GA. It introduces a deterministic approach to the GA strategy. A concept of an elitism and a dynamic step size have been incorporated into GA. The result has shown that the proposed HSGA significantly improves the accuracy of GA in most of the benchmark functions. It also has shown that including the spiral equation into GA has introduced a little bit faster response. However, the equation has introduced an additional step into GA strategy. Therefore, it increases a total computation time for the proposed algorithm to complete a full cycle. The proposed algorithm will be further tested with other state-of-the-art benchmark functions with various dimensions and parameter setting. The algorithm is seen as a good algorithm to be applied to solve various real-world problems.

Acknowledgment

The authors would like to thank Universiti Malaysia Pahang, Malaysia and Ministry of Higher Education Malaysia for sponsoring this project under research grant no. RDU1603138.

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