An Improvement of Genetic Algorithm with Rao Algorithm for Optimization Problems

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***Abstract*— This paper proposes an improvement of genetic algorithm for optimization problems. In this study, the Rao algorithm was applied in crossover and mutation operators instead of traditional crossover and mutation. The algorithm was tested on six benchmark problems and compared with differential evolution (DE), JDE self-adaptive algorithm, and intersection mutation differential evolution (IMDE) algorithm. The computation results illustrated that the proposed algorithm can produce optimal solutions for three of six functions. Comparing to the other three algorithms, the proposed algorithm has provided the best results. The findings prove that the algorithm should be improved in this direction and show that the algorithm produces several solutions obtained by the previously published methods, especially for the continuous step function, the multimodal function and the discontinuous step function.**

Keywords*— *optimization function, genetic algorithm, Rao algorithm, crossover operator; mutation operator

I. Introduction

Optimization is an attempt to achieve an optimal solution under the given situation. The main purpose of optimization is to reduce time or increase the desired benefits. An optimization method can be defined as the process of achieving an optimal solution that responds to the given objective function. Recently, many algorithms have been brought to solve the optimization problems. The natural evolution or the behavior of the natural entities inspired researchers to study and develop an algorithm that performs such behavioral learning and it's called the natural inspiring algorithm. The algorithm has been applied to solve many problems such as classification problems, prediction, forecasting, optimization problems, and much more. These algorithms are widely used to find optimal solutions in the optimization problems, it produces best solutions. Bee colony Optimization [1], Particle Swarm Optimization (PSO) [2], Differential Evolution (DE) [3], Simulated Annealing (SA) [4] and Ant Colony Optimization [5], Self-adaptive differential evolution algorithm (Evo-DE) [6], and Genetic Algorithm (GA) [7] are some examples of such algorithms.

Rao algorithm was developed by Rao [8] in 2020. The main idea is the adoption of the three-simple metaphor-less optimization algorithms for solving the optimization problems. The equation of the three-simple metaphor-less show by Equation 1, 2, and 3.

$$x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}(x_{j,best,i} - x_{j,worst,i}) \quad (1)$$

$$x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}(x_{best,i} - x_{worst,i}) + r_{2,j,i}(|x_{j,k,i}\ or\ x_{j,l,i}| - |x_{j,l,i}\ or\ x_{j,k,i}|) \quad (2)$$

$$x'_{j,k,i} = x_{j,k,i} + r_{1,j,i}(x_{best,i} - x_{worst,i}) + r_{2,j,i}\left(|x_{j,k,i}\ or\ x_{j,l,i}| - (x_{j,l,i}\ or\ x_{j,k,i})\right) \quad (3)$$

where $x_{best,i}$: is the best population in the i^th iteration.

$x_{worst,i}$: is the worst population in the i^th iteration.

$x'_{j,k,i}$: is the update value of $x_{j,k,i}$.

$r_{1,j,i}$ and $r_{2,j,i}$: are the random value in the range [0,1].

$x_{j,k,i}$: is the solution k.

$x_{j,l,i}$: is the randomly solution l.

In Equation (2) and (3), in term $x_{j,k,i}$ or $x_{j,l,i}$ if the fitness value of $x_{j,k,i}$ is better than $x_{j,l,i}$, $x_{j,k,i}$ can be used, or use $x_{j,l,i}$; and in term $x_{j,l,i}$ or $x_{j,k,i}$ if the fitness value of $x_{j,l,i}$ is better than $x_{j,k,i}$, $x_{j,k,i}$ is used, or use $x_{j,l,i}$. The performance of Rao algorithm is good and quite competitive.

This paper presents a hybrid genetic algorithm with Rao algorithm to solve optimization problems. The performance of the proposed algorithm was compared with differential evolution (DE), JDE self-adaptive algorithm, and intersection mutation differential evolution (IMDE) algorithm.

Following this introduction, Section 2 explains the original genetic algorithm. Section 3 presents a proposed algorithm. In Section 4, the experimental results are presented and discussed. Finally, Section 5 is the conclusion of the study.

II. The Genetic Algorithm

Genetic algorithm (GA) is a natural evolution algorithm. The main idea is derived from the behavior of reproduction of animal, consisting of selection, crossover and mutation. Many researchers have been applying genetic algorithm to solve problems in various fields, including the optimization problems. The original genetic algorithm consists of the following components:

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Step 1: Generate an initialize of the populations (NP vector solutions) randomly.

Step 2: Evaluate the fitness function/objective function of the populations.

Step 3: Produce the next generation by the following steps:
(a) select two current populations, P1 and P2 (roulette wheel).
(b) apply one-point crossover operator to P1 and P2 with crossover rate (Pc) to obtain a child chromosome C1 and C2.
(c) apply mutation operators to C1 and C2 with mutation rate (Pm) to produce C1' and C2'.

(d) select the new generations by their fitness ranking.

Step 4: Replace the source population with the new generations.

Step 5: Return to Step 2 if stopping criteria is not met.

III. The Proposed Algorithm

This paper aims to improve the crossover and mutation operators of genetic algorithm for continuous optimization problems. After initial populations and evaluation of their fitness values, the Rao algorithm is applied to improve procedures of crossover and mutation. The processes are explained in details as follows:

(i) After initial population and evaluation of fitness all of population, selection best and worst solution in the populations.

(ii) The selection step uses the roulette wheel to randomly select current individual P2.

(iii) The crossover operation is performed in this step. The Rao algorithm, Equation (4), Equation (5), and Equation (6) are applied to calculate the value in the genes of the parents.

$$P^{1\prime}_{j,k,i} = P_{j,k,i} + r_{1,j,i}\left(P_{j,best,i} - P_{j,worst,i}\right) \tag{4}$$

$$P^{2\prime}_{j,k,i} = P_{j,k,i} + r_{1,j,i}\left(P_{j,best,i} - P_{j,worst,i}\right) + r_{2,j,i}\left(\left|P_{j,k,i}\ or\ P_2\right| - \left|P_{j,k,i}\ or\ P_2\right|\right) \tag{5}$$

$$P^{3\prime}_{j,k,i} = P_{j,k,i} + r_{1,j,i}\left(P_{j,best,i} - P_{j,worst,i}\right) + r_{2,j,i}\left(\left|P_{j,k,i}\ or\ P_2\right| - \left(P_{j,k,i}\ or\ P_2\right)\right) \tag{6}$$

where $P_{j,best,i}$: is the best population in the i^th^ iteration.

$P_{j,worst,i}$: is the worst population in the i^th^ iteration.

$P^{1\prime}_{j,k,i}, P^{2\prime}_{j,k,i}, and\ P^{3\prime}_{j,k,i}$: is the update value of $P_{j,k,i}$.

P_2: population from the selection step.

$r_{1,j,i}\ and\ r_{2,j,i}$: the sigmoid function is applied to calculate the value by Equation (7).

$$r_{1,j,i}\ and\ r_{2,j,i} = 1 - \left(\frac{-e^{\frac{best_{fit}}{\mathrm{worst_{fit}}}}}{1+\left(-e^{\frac{best_{fit}}{\mathrm{worst_{fit}}}}\right)}\right) \tag{7}$$

where $best_{fit}$: the best fitness of all solutions.

$worst_{fit}$: the worst fitness of all solutions.

From Equation (5) and (6), in term $P_{j,k,i}\ or\ P_2$ if the fitness value of P_{j,k,i_1} is better than P_2, then $P_{j,k,i}$ is used, or use P_2; and in term $P_{j,k,i}\ or\ P_2$ if the fitness value of $P_{j,k,i}$ is better than P_2, then P_2 is used, or use $P_{j,k,i}$.

(iv) Mutation operation is working on parent solution and child from crossover operation shown in Fig.1 and the created new children shown in Fig.2.

$$x_q^m = \min\begin{cases} f\left(x_q^{P1\prime}\right): q = 1,2,3,\cdots,ND \\ f\left(x_q^{P2\prime}\right): q = 1,2,3,\cdots,ND \\ f\left(x_q^{P3\prime}\right): q = 1,2,3,\cdots,ND \\ f\left(x_q^{P1m\prime}\right): q = 1,2,3,\cdots,ND \\ f\left(x_q^{P2m\prime}\right): q = 1,2,3,\cdots,ND \\ f\left(x_q^{P3m\prime}\right): q = 1,2,3,\cdots,ND \end{cases} \tag{8}$$

where

x_q^m : the best fitness value from Equation (8).

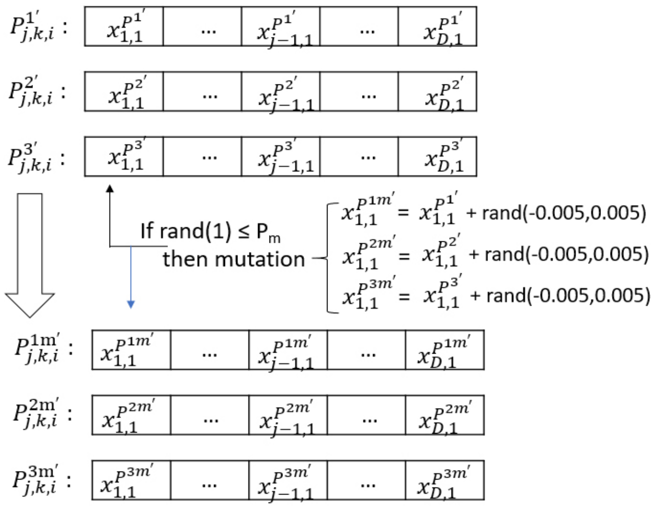

Fig. 1. Mutation Operation (permutation rate 0.8)

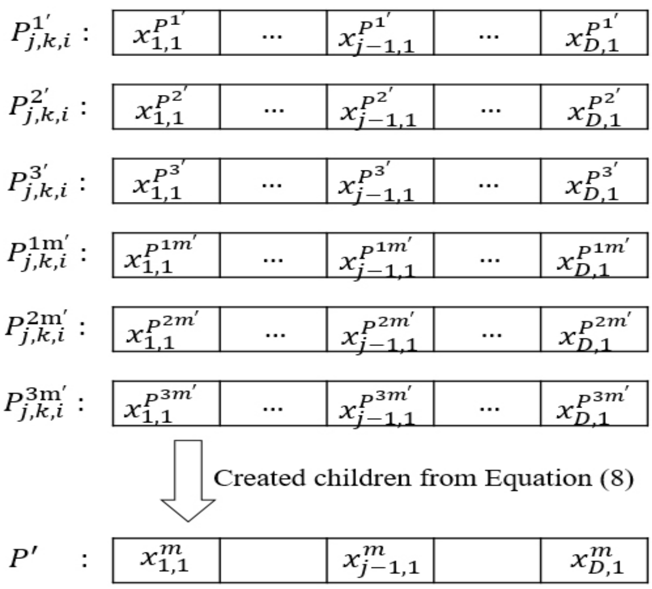

Fig. 2. New children from the mutation step

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After mutation step, P' is the children from the procedure (iv).

(v) Selection operator selects initial population and children from the two operators are evaluated for their fitness value. Then, the new generations are selected by their ranking value.

The new population is then improved all processes until the stopping condition is met.

TABLE I. THE PARAMETERS USED IN THE EXPERIMENTS

Parameters	Values
Population size, NB	50
Dimension, (ND)	30
Mutation parameters, Pm	0.8
Crossover parameter, Pc	1

IV. THE EXPERIMENTAL RESULTS

The proposed algorithm was tested on 6 different benchmark functions from Yao et al. [9]. The tested functions are presented in Table 2, including Sphere function, Schwefel function, Rosenbrock function, Step function, Quartic function, and Ackleg function.

The computational results shown in Table 3 present a comparison of the proposed algorithm with differential evolution (DE), JDE self-adaptive algorithm, and intersection mutation differential evolution (IMDE) algorithm. It indicates that the proposed algorithm has offered better results than the other four algorithms, namely Sphere function, Quartic function, and Ackleg function. Regarding Schwefel function, JDE algorithm has produced better results than the proposed algorithm. In addition, JDE algorithm, IMDE 1st process, and IMDE 2nd process give the results of the Rosenbrock function better than the proposed algorithm.

V. CONCLUSIONS

This paper has proposed an improvement of genetic algorithm for optimization function. In order to improve the performance of genetic algorithm, the Rao algorithm was applied to calculate values in crossover and mutation operators. The testing on six various functions has demonstrated that the proposed algorithm provides the optimal value for three of six functions. The experimental results has confirmed that the proposed algorithm can solve the continuous functions, the discontinuous functions, and the multimodal function efficiently.

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TABLE II. THE BENCHMARK FUNCTIONS

Function	Iteration	Dimension (D)	Search space	fmin
$f_1(x) = \sum_{i=1}^{D} x_i^2$	1,500	30	[-100, 100]	0
$f_2(x) = max_i\{\lvert x_i \rvert, 1 \le i \le D\}$	5,000	30	[-100, 100]	0
$f_3(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2) + (x_i - 1)^2]$	20,000	30	[-30, 30]	0
$f_4(x) = \sum_{i=1}^{D} (\lfloor x_i + 0.5 \rfloor)^2$	1,500	30	[-100, 100]	0
$f_5(x) = \sum_{i=1}^{D} i x_i^4 + rand[0,1)$	3,000	30	[-1.28, 1.28]	0
$f_6(x) = -20\, exp\left(-0.2\sqrt{\frac{1}{30}\sum_{i=1}^{D} x_i^2}\right) - exp\left(\frac{1}{30}\sum_{i=1}^{D} cos\, 2\pi x_i\right) + 20 + e$	1,500	30	[-32, 32]	0

TABLE III. THE EXPERIMENTAL REUSLTS

Functions	DE	JDE	IMDE 1st process	IMDE 2nd process	Proposed algorithm
F1	1.58E - 3	1.1E - 28	2.5E - 32	2.1E - 35	**3.02E - 110**
F2	1.9E-3	**0**	0.2E-3	3.4E-24	5.85E - 57
F3	8.35E-27	**0**	**0**	**0**	1.06E - 12
F4	**0**	**0**	**0**	**0**	**0**
F5	2.63E-3	3.15E-3	2.4E-4	3.4E-4	**0**
F6	1.5017	7.7E-15	4.9E-15	4.6E-15	**0**

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