Chaotic Crossover Operator on Genetic Algorithm

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***Abstract*—In this paper, chaos based a new arithmetic crossover operator on the genetic algorithm has been proposed. The most frequent issue for the optimization algorithms is stuck on problem's defined local minimum points and it needs excessive amount of time to escape from them; therefore, these algorithms may never find global minimum points. To avoid and escape from local minimums, a chaotic arithmetic crossover operator has been employed on a genetic algorithm. Unimodal and multi modal benchmark functions have been used for comparing and test procedures. The genetic algorithm with this new arithmetic crossover operator has yielded better results than original arithmetic crossover operator does. With this new chaos based arithmetic crossover operator diversity and uniqueness of the genetic algorithm's late population are increased. Therefore, even in the late stages of the optimization process, the genetic algorithm tried to search the entire search space and improved the best solution.**

***Index Terms*—genetic algorithm, chaos, crossover operator**

I. Introduction

Optimization process is to find the desired solution for a predefined problem. The easiest and fastest way to solve the optimization problem is to employ fast computers and proper algorithms. Besides, in some cases, finding the exact solution can introduce unacceptable amount of time. To overcome such difficulties, heuristic search algorithms have been developed such as Genetic Algorithms (GA), Differential Evolution Algorithms (DEA), Particle Swarm Optimizations (PSO), and Ant Colony Optimizations (ACO). GA is the most popular population based heuristic algorithm since it was developed by Holland in 1975 [1]. This algorithm runs faster and requires less memory. GA individuals have limited shared memories. They can only remember the best individual's variables and result. GA uses this information on the calculation of new individuals. With this feature, GA consumes less memory than other optimization algorithms do and works efficiently. Sometimes, GA may stuck on the local minimums like other algorithms. To solve this downside, some steps of GA can be modified.

In this paper, we have presented a chaos based Chaotic Arithmetic Crossover operator (CAC) to improve the population diversity of GAs. CAC utilizes unpredictability and randomness of the chaos theory. By the help of the chaos theory, GA does not stuck on local minimums and finds near exact solution all the time.

II. Background and Related Work

A. Genetic Algorithm

GA is a population-based algorithm that inspired from biological reproduction on cellular level [1]. In this algorithm, population is acquired from individual genes. GA has five critical steps, which affect the performance of the algorithm, as seen in pseudo code of GA given below.

Algorithm 1	Genetic Algorithm
1:	Create initial population.
2:	Repeat
3:	Evaluate fitness value for each individual.
4:	Select parents according to selection scheme.
5:	Create new children by crossover.
6:	Mutate children.
7:	Until Stopping criteria

In genetic operator part of GA, two important steps affect the performance of the algorithm directly. The first one is crossover step that selects two combined parents regarding to selection scheme to generate a new child, which eliminates poor individuals and helps GA to convergence. The latter one is the mutation step that updates new child's random part.

The steps of GA has have been improved by several studies recently. New crossover operators [2, 3, 4],

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selection mechanism [5] and mutation operator [6] have been introduced and reviewed [7, 8, 9, 10].

B. Chaotic Systems

Chaotic systems have been developed from chaos theory, which is a study field in math. The idea is based on the unpredictability aspect of nature. In chaotic systems, even a small change in the inputs can cause a considerable change in the outputs. This situation is called butterfly effect and it has been first proposed in 1880s by Henri Poincaré [11].

In recent studies, chaotic number generators developed from chaotic systems have been used for generating random numbers and they have yielded better results. Chaotic sequences in evolutionary algorithms were proposed in [12] and studies on chaotic sequences were introduced in [13].

III. Proposed Work

In related works, GA algorithm works fast and efficiently, however, like other optimization algorithms, GA stucks on local minimums. The efficiency of GA depends on population diversity and to achieve better diversity, the crossover part of GA must produce unique individuals.

The number generators in almost all compilers are based on seeded structures. Number generators generate identical set of numbers unless varied seeds are used. At the end of GA procedure, gene pool is filled by near solutions. Due to the seed structure of the compiler, selection from these solutions can make new individuals as similar as before and this drawback can eventually leads to stuck on local minimums.

In cellular level, crossover with obtained gene from the parents produces unique individuals even if the parents are always the same. To maintain the uniqueness, one of the parent's gene must be dominant and the other must be recessive. In order to simulate this situation, we used chaos based CAC operators. Mathematical expression of the CAC operator is given in (1).

$$c(x_i) = m * p_1(x_i) + (1-m) * p_2(x_i) \quad (1)$$

where x_i is the new generated child's position in dimension (i), m is the random number generated by chaotic random number generator, $p_1(x_i)$ and $p_2(x_i)$ are the positions of the parent 1 and parent 2 in dimension (i).

We have used logistic map in chaotic number generator because of the map's simplicity. Mathematical expression of the chaotic number generator is given in (2)

$$\begin{aligned} map &= 4 * z * (1-z) \\ m &= (0.5 * r) + (0.5 * map) \end{aligned} \quad (2)$$

In equation (2), z and r are the different random numbers generated from compiler's random number generator and m is the generated random number from chaotic number generator and used in (1).

GA with this new crossover operator has been tested on multi modal and unimodal benchmark functions. We have set population size to 100 and have used Gaussian mutation operator along with roulette-wheel selection scheme. All parameters used are given in Table I.

TABLE I. Parameters of Genetic Algorithm

Parameter	Value
Population Size	100
Selection Scheme	Roulette Wheel
Crossover Rate	0.75
Mutation Operator	Gaussian
Mutation Rate	0.1
Mutation Variance	1.0 decreasing to 0.1

IV. Results

A. Test Problems

In this study, we have employed a unimodal and two multi-modal benchmark functions that are popular and used in several studies [2], [3].

The first one is unimodal and it is called Ellipsoidal function that is given in (3).

$$f_1(x) = \sum_{i=1}^{n} i * x_i \quad (3)$$

The second function is multi modal and called Rastrigin function that is given in (4).

$$f_2(x) = x_i^2 - 10 * \cos(2 * \pi * x_i) + 10 \quad (4)$$

The last multi modal function is Ackley function, which is given in (5).

$$\begin{aligned} f_3(x) = 20 + \exp(1) - 20 * \exp\left(-0.2 * \sqrt{\frac{1}{n} * \sum_{i=1}^{n} x_i^2}\right) \\ - \exp\left(\frac{1}{n}\sum_{i=1}^{n} \cos(2 * \pi * x_i)\right) \end{aligned} \quad (5)$$

In all functions, n stands for dimension and i denotes the current dimension. Initialization range of the functions is shown in Table II.

TABLE II. Initialization Range of Benchmark Functions

Function	Initialization Range
Ellipsoidal Function	(-100, 100)
Rastrigin Function	(-5.12, 5.12)
Ackley Function	(-32.768, 32.768)

All test runs for 10, 20 and 30 dimensions for each function. GA runs for 1000, 1500 and 2000 iteration in 10, 20 and 30 dimensions respectively. Each function runs for 15 times.

B. Results

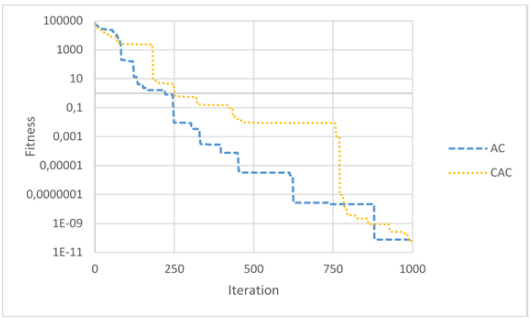
Comparative results of arithmetic crossover and CAC on benchmark functions are given in Table III. GA with AC stucks on local minimums in most cases especially in

higher dimensions. However, GA with CAC never stucks on the local minimums and reached the near global minimum point in every test cases even in higher dimensions.

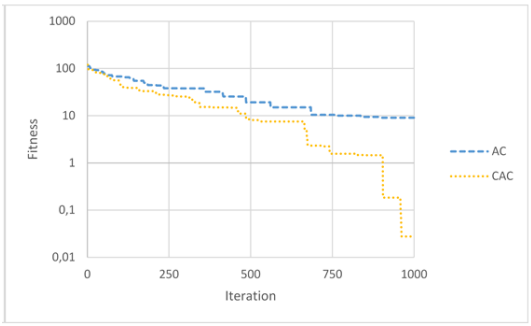
Table III shows that especially in Rastrigin function, GA with CAC algorithm has yielded clearly better results than GA with AC algorithm and only in Ackley function in 30 dimensions; GA with AC yielded slightly better results. Besides, our approach has always outperformed the original GA algorithm. Fig. 1, Fig. 2, and Fig. 3 illustrates the relationship between fitness and iteration when Ellipsoidal, Rastrigin, and Ackley functions used in three varied dimension size i.e. 10, 20, and 30.

TABLE III. TEST RESULTS OF GENETIC ALGORITHM WITH AC AND CAC

Function	Dimension	GA with AC Mean (Std-dev)	GA with CAC Mean (Std-dev)
Ellipsoidal Function	10	7.77683E-11	5.42E-11
		(2.76868E-10)	(1.03E-10)
	20	2.34379E-29	4.1598E-48
		(7.81952E-29)	(1.55646E-47)
	30	1.14441E-44	4.95971E-94
		(3.02353E-44)	(1.802E-93)
Rastrigin Function	10	9.053261337	0.027726909
		(13.78879335)	(0.101600676)
	20	8.970391741	0.045290179
		(21.95426934)	(0.123722335)
	30	20.05002924	6.68703E-05
		(39.8305619)	(0.000250206)
Ackley Function	10	7.28519E-10	1.44773E-14
		(2.53808E-09)	(5.39451E-14)
	20	4.53021E-12	9.35578E-13
		(1.69474E-11)	(3.50227E-12)
	30	2.16123E-15	2.87178E-15
		(1.57107E-15)	(1.24068E-14)



(a)



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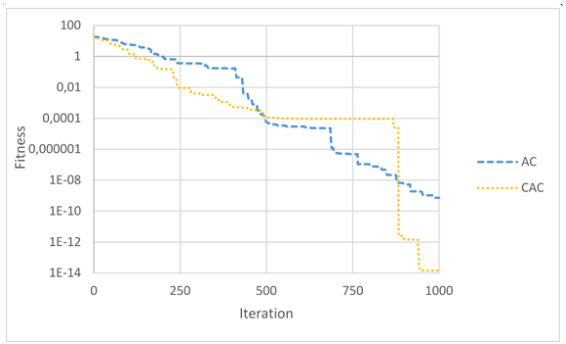
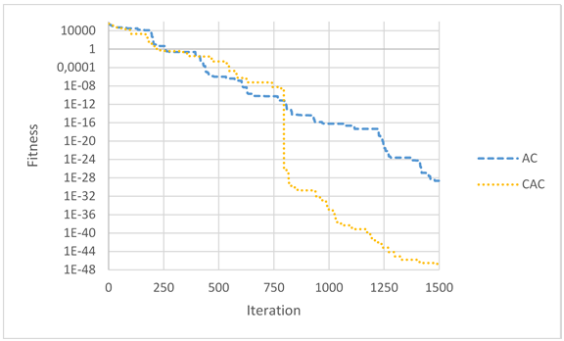
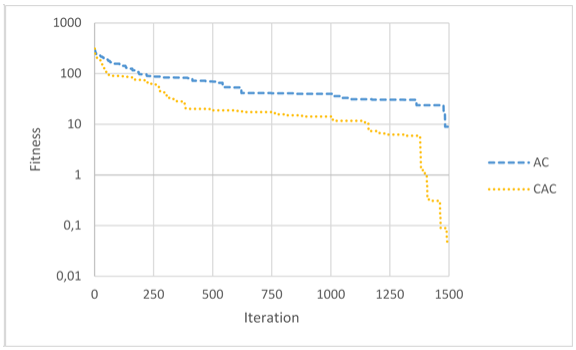


(c)

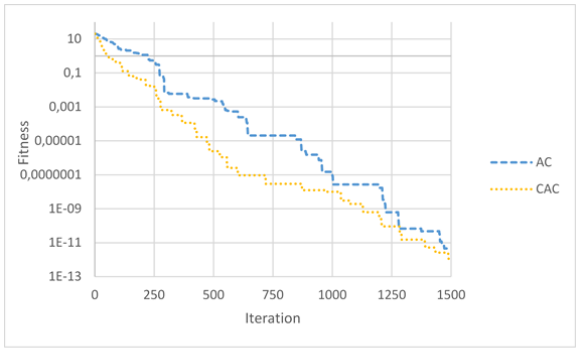
Figure 1. (a) Ellipsoidal Function, (b) Rastrigin Function, (c) Ackley Function at 10 Dimension.



(a)



(b)



(c)

Figure 2. (a) Ellipsoidal Function, (b) Rastrigin Function, (c) Ackley Function at 20 Dimension

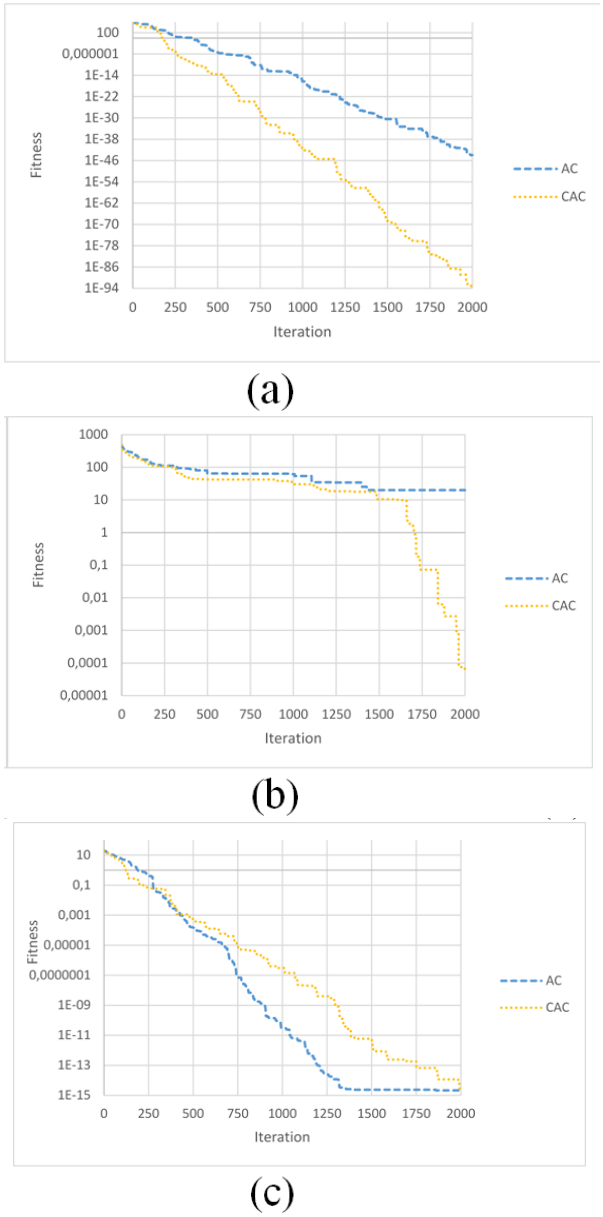


Figure 3. (a) Ellipsoidal Function, (b) Rastrigin Function, (c) Ackley Function at 30 Dimension

V. CONCLUSIONS

GA with CAC algorithm has outperformed GA with AC algorithm. The effect of chaotic systems on the crossover operation leads improved population diversity and uniqueness in the late stages of GA crossover step. Therefore, GA does not stuck on local minimums and probability of the finding near approximate solution has been increased.

For future research, the rest of steps of GA such as mutation can be united with chaotic systems. The effect of the other maps for chaos can be investigated and hybrid stages for GA can be studied.

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