An Integrated Genetic Algorithm with Clone Operator

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Abstract

Genetic algorithm has got much interest and application as an optimization tool. In this paper we propose a new operator based on the concept of cloning. The proposed new operator imitates the biological cloning process. Based on a simple genetic algorithm and new operator, we propose an integrated genetic algorithm. The new algorithm is validated with standard test cases and is shown that the new operator helps in getting faster convergence and global optima.

Keywords: Optimization, Evolutionary Algorithm, Genetic Algorithm, Clone operator

1. INTRODUCTION

Genetic algorithm is a partial search algorithm designed by observing and mimicking the intelligent mechanism behind biological evolutions such as reproduction, recombination, mutation and selection, which may be used to obtain sufficiently good approximations to various classes of optimization problems. To find the optimal solution of a problem, an environment is created in which potential solutions can evolve naturally, with the parameters of the problem serving to control and shape the environment. The quality of the solutions so obtained are checked by one or more fitness functions at every stage. However, the evaluation of the fitness function often renders the problem computationally complex, and to overcome this, various approximations to fitness functions are generally used. Very complex optimization problems are sometimes solved by surprisingly simple genetic algorithms. However, the complexity of the problem has in general no direct link with the complexity of the

algorithm. A major advantage of a genetic algorithm is its generality, as it ideally does not make any assumptions about the fitness landscape. Genetic algorithms have been successfully applied in solving optimization problems of various types in fields as diverse as engineering, art, biology, economics, marketing, genetics, operations research, robotics, social sciences, physics, politics and chemistry.

The basic principles of GAs were introduced, for the first time, by John Henry Holland [1] for solving practical optimization problems and are well documented [2-10]. The aim of a GA is to achieve better results through selection, crossover and mutation. The success of any GA depends on the design of its search operators as well as their appropriate integration. There is a lot of literature to improve the effectiveness of the GA operators. There are various approaches [3,11,2,12-17] suggested to select the parent's string which may vary depending on the difficulty level of the problems. In a GA, maintaining population diversity is very important to reach to the global optimum [18]. It is necessary to select the best solution of the current generation to direct a GA to reach to the global optimum. Goldberg and Deb [19] compare four different selection schemes: proportionate selection, fitness ranking, tournament selection and steady state selection. They conclude that by suitable adjustment of parameters, all these schemes can be made to give similar performances, so there is no absolute best method. Many different crossover algorithms are devised [20,17, 21]. DeJong [22] investigated the effectiveness of multiple-point crossover. Besides, the initial population plays an important role in solving a problem by GA [23-26]. Genetic algorithms have been successfully used in numerical function optimization [22], image processing [3], combinatorial optimization [27], machine learning [28-30], data mining, information retrieval and grammar induction.

A basic genetic algorithm comprises of three genetic operators, namely, selection, crossover and mutation. Reproduction(selection) is usually the first operator applied on a population. Reproduction selects good strings in a population and forms a mating pool. There exists a number of reproduction operators in GA literature, but the essential idea in all of them is that the above average strings are picked from the current population and their multiple copies are inserted in the mating pool in a probabilistic manner.

In the crossover operator, new strings are created by exchanging information among strings of the mating pool. Many crossover operators exist in the GA literature. In most crossover operators, two strings are picked from the mating pool at random and some portions of the strings are exchanged between the strings. The two strings participating in the crossover operation are known as parent strings and the resulting strings are known as offspring strings. In practice, all parents in the mating pool are not selected for crossover operation so that some of the good strings may be preserved. This is achieved by selecting a fixed percentage of parents from the mating pool and it is known as the crossover probability.

Mutation is applied to each child individually after crossover. This operator randomly flips or alters one or more bit values at randomly selected locations in a chromosome with a small probability.

The overall GA process steps are summarized as follows:

- STEP 1 Choose coding to represent problem parameters: a selection operator, a crossover operator, and mutation operator.
- STEP 2 Choose initial population size, length of a string, probabilities of cross over and mutation, search domain of the variables, termination criteria or maximum number of iteration.
- STEP 3 Set $T = 0$. Generate initial population from the search domains randomly.
- STEP 4 Evaluate each string of the population for fitness.
- STEP 5 If termination criteria is satisfied, or $T > T_{max}$, then STOP.
- STEP 6 Perform selection on the population.
- STEP 7 Perform crossover on random pairs of strings.
- STEP 8 Perform mutation on every string.
- STEP 9 Evaluate the strings of the new population.
- STEP 10 Set $T = T + 1$, go to step 4.

In this paper, firstly, we propose a new operator based on the concept of cloning. Section 2 gives a description of the new operator and its illustration; and we propose an evolutionary algorithm which integrates the new operator with the other GA operators. In this new GA, the selection process can be absent as well. Thereafter, in section 3, we describe the proposed CGA algorithm in detail. The computational results of test problems are shown in section 4. Finally, section 5 summarizes the concluding remarks.

2. CLONE OPERATOR

We introduce a new operator called Clone Operator. Cloning of genes in the elitist set is fundamental to this approach. The elitist member(or few members) of a generation is cloned to get a member of the next generation. Cloning is carried out with a clone probability. The genes which are not cloned based on probability are mutated($0 \rightarrow 1, 1 \rightarrow 0$). It is expected that the new member will have better qualities of the parent member. As an example, consider the string

1	0	1	1	1	0	1	0	0	1

On applying the operator, each bit may undergo a cloning with a certain probability. If the cloning probability is 0.8, two genes of the string will be mutated randomly and we might get, after cloning, the string-

1	0	1	0	1	0	1	1	0	1

in which two genes, viz. the fourth and the eighth, are changed while all the others are cloned. Initial population of the GA with cloning can start either with a random population or with a population with all of its members having genes 1 or 0. One

generation to next generation, in this new proposed GA, will not contain the saplings generated by GA operators like crossover and mutation. New generation will be containing only the elitist member from the previous generation on which clone is operated.

Demonstration of cloning from generation to generation

Consider the problem,

Minimize $f(x,y) = (x-1)^2 + (y-2)^2$ where $-5 \leq x, y \leq 5$

This function has global minimum value 10 at (1,2). Let the initial population consists of 10 strings of elites

111111111111111. Let 0.75 be the cloning probability. The first two generation are given as follows;

Initial population: Elite 111111111111111

$x = 5, y = 5$, function minimum = 35.

Population after cloning	x	y	Function value
1 0 1 1 1 0 1 1 1 0 1 1 1 0 1 1	2.3333	2.3333	11.8889
0 1 1 0 1 1 1 1 0 1 1 1 0 1 1 1	-0.6471	-0.3333	18.1572
1 1 0 1 1 0 1 1 1 1 1 1 1 0 0 1	3.5882	4.7647	24.3426
1 0 1 1 0 1 0 1 1 1 0 1 1 1 1 1	2.0980	3.7451	14.2511
0 0 1 1 1 0 1 1 1 0 1 1 1 1 1 1	-2.6863	2.4902	23.8289
1 1 1 1 0 1 1 1 0 1 1 0 1 1 1 0	4.6863	-0.6863	30.8047
1 0 1 1 1 1 1 1 1 0 1 1 0 1 0 1	2.4902	2.0980	12.2303
1 1 1 0 1 1 0 1 1 1 0 0 1 1 1 1	4.2941	3.1176	22.1003
0 0 1 1 1 1 1 1 1 1 1 1 1 1 0 0	-2.5294	4.8824	30.7647
1 0 1 1 1 1 1 1 1 0 1 0 1 1 1 1	2.4902	3.4314	14.2695

Elite : 1011101110111011

$x = 2.3333, y = 2.3333$, function minimum = 11.8889.

The second generation consists of 10 strings of elites 1011101110111011.

Population after cloning	x	y	Function value
1 0 0 1 1 0 1 0 1 1 1 1 1 0 1 0	1.0392	4.8039	17.8635
0 1 1 1 1 0 1 1 1 0 1 0 1 0 1 0	-0.1765	1.6667	11.4952
1 0 1 0 1 1 1 1 1 0 1 0 1 0 1 0	1.8627	1.6667	10.8554
1 0 1 0 1 0 1 0 1 0 1 0 1 1 1 1	1.6667	1.8627	10.4633
1 0 0 1 1 0 1 0 1 0 1 0 1 1 1 1	1.0392	1.8627	10.0204
1 1 1 0 1 0 1 1 1 0 1 1 1 0 0 0	4.2157	2.2157	20.3872
1 1 0 0 1 0 1 1 1 0 1 1 0 0 1 1	2.9608	2.0196	13.8451
1 0 1 1 0 0 1 1 1 1 0 1 1 0 1 0	2.0196	3.5490	13.4391
0 0 1 1 1 0 1 1 0 0 1 0 1 1 1 1	-2.6863	-3.1569	50.1819
1 0 1 0 1 0 1 1 0 1 1 1 1 0 1 0	1.7059	-0.2157	15.4075

Elite : 1001101011001111

$x = 1.0392$, $y = 1.8627$, function minimum = 10.0204

We see that, using the new clone operator, we get closer to the global minimum just after two generations. This motivates us to develop a simple evolutionary algorithm, Cloned Evolutionary Algorithm(CEA), which is described as follows:

- STEP 1 Choose coding to represent problem parameters.
- STEP 2 Input the initial base population size, string length, probability for mutation on the initial population, search domain of the variables, termination criteria or maximum number of iteration as Tmax.
- STEP 3 Set $T = 0$. Generate initial base population.
- STEP 4 Perform cloning on the base population with specified probability.
- STEP 5 Find the best value and the best solution.
- STEP 6 Create a new population by replacing all with the best member.
- STEP 7 Evaluate each string of the population for fitness.
- STEP 8 If termination criteria is satisfied or $T > T_{max}$, then STOP.
- STEP 9 Set $T = T + 1$, go to step 5.

The flowchart for CEA is shown in Figure 1.

Figure 1: Flowchart for CEA

3. AN INTEGRATED GENETIC ALGORITHM

In order to increase the accuracy, we make some modification in CEA. After creating a new population using clone operator, apply the GA operators reproduction, crossover and mutation on the new population. This leads to an innovative and improved evolutionary algorithm: Cloned Genetic Algorithm(CGA).

The step by step procedure of CGA can be summarized as follows:

- STEP 1 Choose coding to represent problem parameters, a selection operator, a crossover operator, and mutation operator.
- STEP 2 Input the initial base population size, string length, probability for cloning, search domain of the variables, probabilities of cross over, mutation probability, termination criteria or maximum number of iteration as Tmax.
- STEP 3 Set $T = 0$. Generate initial base population.
- STEP 4 Perform cloning on the base population with specified probability.
- STEP 5 Evaluate each string of the population for fitness.
- STEP 6 Perform selection on the population.

Figure 2: Flowchart for CGA

- STEP 7 Perform crossover on random pairs of strings in the population.
 STEP 8 Perform mutation on every string in the population.
 STEP 9 Evaluate each string of the population for fitness.
 STEP 10 Find the best member and corresponding function values in the population.
 STEP 11 If Termination Criteria is satisfied, or $T > T_{max}$, THEN jump to STEP-13.
         ELSE Jump to STEP 12
 STEP 12 Set $T = T + 1$. Create new population by replacing all with the best member. AND jump to STEP 4.
 STEP 13 Store best value and corresponding solution. Then STOP.

The flowchart for CGA is shown in Fig. 2.

4. CASE STUDIES

We evaluate the performance of the proposed CGA and CEA on a set of 15 benchmark test functions (see Table 1 and Table 2) in the literature and 15 benchmark test functions in CEC05 (see Table 3) with different complexity. For CEC05 benchmark problems, the problem definition files, codes are available at the web site address: <http://www.ntu.edu.sg/home/EPNSugan>. Experiments are conducted on the 2-D problems. The results of CGA and CEA on 2-D problems on population size = 100 are compared with simple GA. Parameters used in the implementation of CGA, CEA and GA are : Population Size = 100, bit length for one variable = 16, probability of clone = random, probability of crossover = 0.80, probability of mutation = 0.05, maximum number of generations for convergence = 1000 and alternative tolerance for convergence = 0.0000000001.

We use the MATLAB to implement the algorithms. All the implementations were developed using a computer with processor Core 2 Quad processor of 64 bits that works to a frequency of 2.7GHz, 4GB of RAM Memory and Windows XP Professional Version. In table 4 and table 5, we can find the experimental results. The table 4 and table 5 provides the results with 50 Monte-Carlo simulations with the changes in the random sequence. The results are provided in terms of statistical parameters such as average, the median, the best value, the worst value and standard deviation obtained for each test functions. The number of generations for convergence of the functions taken by the three methods is shown in table 6 and table 7. The convergence maps of the algorithm on CGA, CEA and GA functions g_1 to g_5 , functions g_6 to g_{10} , functions g_{11} to g_{15} , functions f_1 to f_5 , functions f_6 to f_{10} , functions f_{11} to f_{15} are plotted in figures 3-8 respectively.

The experimental analysis shows that the algorithm converges quickly to the optimal solution and thus exhibits a superior performance in comparison to GA algorithms.

Figure 3: Convergence Graph for functions $g_1 - g_5$ using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Figure 4: Convergence Graph for functions $g_6 - g_{10}$ using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Figure 5: Convergence Graph for functions $g_{11} - g_{15}$ using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Figure 6: Convergence Graph for functions f_1 - f_5 using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Figure 7: Convergence Graph for functions f_6 - f_{10} using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Figure 8: Convergence Graph for functions f_{11} - f_{15} using CGA, CEA and GA algorithms. Left most plots are for CGA algorithm, middle plots are for CEA algorithm and right most plots are for GA algorithm.

Table 1: Test functions g_1 to g_{10}

Function	Definition
g_1	g_1 : Sphere function(De Jong's function 1) $g_1(x) = \sum_{i=1}^D x_i^2$ $-5.12 \leq x_i \leq 5.12, \quad x^* = (0, 0, \dots, 0), \quad g_1(x^*) = 0$
g_2	g_2 : Rosenbrock function (De Jong's function 2, Banana function) $g_2(x) = \sum_{i=1}^{D-1} [100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2]$ $-2.048 \leq x_i \leq 2.048, \quad x^* = (1, 1, \dots, 1), \quad g_2(x^*) = 0$
g_3	g_3 :Ackley's function $g_3(x) = 20 + e - 20 \exp\left(-0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2}\right) - \exp\left(\frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i)\right)$ $-32.768 \leq x_i \leq 32.768, \quad x^* = (0, 0, \dots, 0), \quad g_3(x^*) = 0$
g_4	g_4 : Rastrigin function $g_4(x) = 10D + \sum_{i=1}^D x_i^2 - 10 \cos(2\pi x_i)$ $-5.12 \leq x_i \leq 5.12, \quad x^* = (0, 0, \dots, 0), \quad g_4(x^*) = 0$
g_5	g_5 : : Griewank function $g_5(x) = 1 + \sum_{i=1}^D \frac{x_i^2}{4000} - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right)$ $-600 \leq x_i \leq 600, \quad x^* = (0, 0, \dots, 0), \quad g_5(x^*) = 0$
g_6	g_6 : Schwefel's Double Sum function $g_6(x) = \sum_{i=1}^D \left(\sum_{j=1}^i x_j\right)^2$ $-65.536 \leq x_i \leq 65.536, \quad x^* = (0, 0, \dots, 0), \quad g_6(x^*) = 0$
g_7	g_7 : : Schwefel's Max function $g_7(x) = \max_i (x_i : i \in \{1, 2, \dots, n\})$ $-100 \leq x_i \leq 100, \quad x^* = (0, 0, \dots, 0), \quad g_7(x^*) = 0$
g_8	g_8 : Schwefel's absolute function $g_8(x) = \sum_{i=1}^D x_i + \prod_{i=1}^D x_i $ $-10 \leq x_i \leq 10, \quad x^* = (0, 0, \dots, 0), \quad g_8(x^*) = 0$
g_9	g_9 : The Step function $g_9(x) = \sum_{i=1}^D (\text{floor}(x_i + 0.5))^2$ $-100 \leq x_i \leq 100, \quad x^* = (0, 0, \dots, 0), \quad g_9(x^*) = 0$
g_{10}	g_{10} : The Tenth Power function $g_{10}(x) = \sum_{i=1}^D x_i^{10}$ $-5.12 \leq x_i \leq 5.12, \quad x^* = (0, 0, \dots, 0), \quad g_{10}(x^*) = 0$

Table 2: Test functions g_{11} to g_{15}

Function	Definition
g_{11}	g_{11}: Easom function $g_{11}(x) = -\cos(x_1)\cos(x_2)\exp(-(x_1 - \pi)^2 - (x_2 - \pi)^2)$ $-100 \leq x_i \leq 100$, $x^* = (\pi, \pi)$, $g_{11}(x^*) = -1$
g_{12}	g_{12}: Shenkel's foxholes function $g_{12}(x) = \left[\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^2 (x_i - a_{ij})^6} \right]^{-1}$ where a_{ij} is the element in the ith row and jth column of $a = \begin{bmatrix} b_0 & \cdots & b_0 \\ b_1 & \cdots & b_1 \end{bmatrix}$ $b_0 = [-32 \quad -16 \quad 0 \quad 16 \quad 32]$ $b_i = (16(i-1) - 32) [1 \quad 1 \quad 1 \quad 1 \quad 1]$ $-65.536 \leq x_i \leq 65.536$, $x^* = (-32, -32)$, $g_{12}(x^*) = -1$
g_{13}	g_{13}: Goldstein-Price function $g_{13}(x) = [1 + (x_1 + x_2 + 1)^2(19 - 14x_1 + 3x_1^2 - 14x_2 + 6x_1x_2 + 3x_2^2)]$ $\times [30 + (2x_1 - 3x_2)^2(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)]$ $-2 \leq x_i \leq 2$, $x^* = (0, -1)$, $g_{13}(x^*) = 3$
g_{14}	g_{14}: Six hump camel back function $g_{14}(x) = [(4 - 2.1x_1^2 + x_1^{4/3})x_1^2 + x_1x_2 + (-4 + 4x_2^2)x_2^2]$ $-3 \leq x_1 \leq 3, -2 \leq x_2 \leq 2$, $x^* = (-0.0898, 0.7126), (0.0898, -0.7126)$, $g_{14}(x^*) = -1.0316$
g_{15}	g_{15}: Branin's rcos function $g_{15}(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6 \right)^2 + \left(10 - \frac{5}{4\pi} \right) \cos x_1 + 10$ $-5 \leq x_1 \leq 10, 0 \leq x_2 \leq 15$, $x^* = (-\pi, 12.275), (\pi, 2.275), (9.42478, 2.475)$ $g_{15}(x^*) = 0.397887$

Table 3: CEC 05 benchmark functions f_1 to f_{15}

Function	Definition	D	f_{min}
f_1	Shifted Sphere Function(F1)	$[-100, 100]^D$	-450
f_2	Shifted Schwefel's Problem 1.2(F2)	$[-100, 100]^D$	-450
f_3	Shifted Rotated High Conditioned Elliptic Function(F3)	$[-100, 100]^D$	-450
f_4	Shifted Schwefel's Problem 1.2 with Noise in Fitness(F4)	$[-100, 100]^D$	-450
f_5	Schwefels Problem 2.6 with Global Optimum on Bounds(F5)	$[-100, 100]^D$	-310
f_6	Shifted Rosenbrock's Function(F6)	$[-100, 100]^D$	390
f_7	Shifted Rotated Griewanks Function without Bounds(F7)	$[0, 600]^D$	-180
f_8	Shifted Rotated Ackley's Function with Global Optimum on Bounds(F8)	$[-32, 32]^D$	-140
f_9	Shifted Rastrigins Function(F9)	$[-5, 5]^D$	-330
f_{10}	Shifted Rotated Rastrigin's Function(F10)	$[-5, 5]^D$	-330
f_{11}	Shifted Rotated Weierstrass Function(F11)	$[-0.5, 0.5]^D$	90
f_{12}	Schwefels Problem 2.13(F12)	$[-\pi, \pi]^D$	-460
f_{13}	Expanded Extended Griewank's plus Rosenbrock's Function(F13)	$[-5, 5]^D$	-130
f_{14}	Shifted Rotated Expanded Scaffer's F6(F14)	$[-100, 100]^D$	-300
f_{15}	Hybrid Composition Function(F15)	$[-5, 5]^D$	120

F-Function D-Dimensionality of the function S-The ranges of variables f_{min} - Minimum value of the function

Table 4: Comparison results of the best value, the median, the worst value, average, and standard deviation of the functions g_1 to g_{15} for 50 independent runs using CGA,CEA and GA methods

Function	Method	Best	Median	Worst	Average	S.D	x_1	x_2	Convergence
g_1	CGA	1.1134e-10	9.9101e-10	4.0103e-09	1.4509e-09	1.0264e-09	-0.9543 e-05	0.4502e-05	48
	CEA	3.1897e-11	1.9406e-10	2.6118e-10	1.9574e-10	7.0675e-11	0.4807e-05	-0.2965e-05	17
	GA	4.6568e-06	4.6568e-06	2.3284e-05	1.3970e-05	9.4081e-06	0.0015	0.0015	136
g_2	CGA	4.2230e-10	4.2230e-10	4.2230e-10	4.2230e-10	3.6557e-25	1.0000	1.0000	95
	CEA	2.3516e-08	2.3516e-08	2.0979e-07	4.3060e-08	5.5168e-08	1.0000	1.0000	15
	GA	7.2552e-07	1.8174e-05	5.1102e-05	2.2489e-05	1.5667e-05	1.0008	1.0017	172
g_3	CGA	4.1684e-05	2.2875e-04	3.7598e-04	2.2850e-04	8.3228e-05	-0.0491 e-04	-0.1389e-04	111
	CEA	4.3708e-05	4.6823e-04	6.9224e-04	4.3041e-04	2.0039e-04	-0.0623 e-04	-0.1414 e-04	15
	GA	0.0020	0.0020	0.0034	0.0023	8.6401e-04	-0.4883 e-03	-0.4883 e-03	62
g_4	CGA	7.7170e-10	1.3390e-08	3.2317e-08	1.6150e-08	8.6917e-09	0.1915 e-05	0.0473e-05	57
	CEA	1.0093e-10	1.8868e-07	7.1941e-07	2.6063e-07	2.2747e-07	0.6054 e-06	-0.3771e-06	18
	GA	2.4219e-06	1.2109e-05	2.1797e-05	1.1722e-05	7.0457e-06	0.7813 e-04	-0.7813 e-04	85
g_5	CGA	0.0050	0.0050	0.0050	0.0050	1.6831e-06	0.3011 e-03	-0.6374 e-03	68
	CEA	0.0050	0.0050	0.0051	0.0050	2.2805e-05	0.1725 e-03	0.7287 e-03	18
	GA	0.0061	0.0127	0.0143	0.0121	0.0023	0.0092	0.0641	110
g_6	CGA	1.5148e-10	8.9784e-09	1.2233e-08	9.1321e-09	5.3891e-09	0.1227 e-04	-0.1322e-04	85
	CEA	5.5333e-10	3.2741e-08	9.7317e-08	5.4932e-08	4.1444e-08	0.2345 e-04	-0.2161 e-04	21
	GA	1.0000e-06	1.3000e-05	2.5001e-05	1.4360e-05	7.0735e-06	-0.0010	0.0010	89
g_7	CGA	1.7325e-05	1.5898e-04	2.6459e-04	1.6789e-04	6.6164e-05	-0.1733 e-04	-0.1180 e-04	36
	CEA	5.4528e-05	2.2733e-04	0.0010	4.5618e-04	3.1448e-04	-0.5453 e-04	0.0392 e-04	20
	GA	0.0015	0.0046	0.0076	0.0052	0.0022	-0.0015	0.0015	49
g_8	CGA	3.8332e-06	2.4977e-05	5.5813e-05	2.8145e-05	1.4871e-05	-0.3015 e-05	0.0818 e-05	77
	CEA	7.7840e-06	4.5508e-05	5.1125e-05	3.7532e-05	1.0428e-05	0.5559 e-05	-0.2225 e-05	15
	GA	3.0520e-04	9.1566e-04	9.1575e-04	7.5087e-04	2.4052e-04	0.1526 e-03	0.1526 e-03	142
	CGA	0	0	0	0	0	-0.0839	-0.3983	6

g9	CEA	0	0	0	0	0	-0.1968	-0.2823	6
	GA	0	0	0	0	0	0.0839	0.4288	5
g10	CGA	1.3366e-41	1.3366e-41	3.9463e-37	1.7375e-37	1.9778e-37	-0.7630 e-04	-0.7630 e-04	11
	CEA	4.8118e-45	1.6943e-41	1.6943e-41	1.6200e-41	3.3577e-42	-0.0091	-0.0015	15
	GA	5.2160e-29	7.6683e-22	2.2810e-20	3.8371e-21	5.8580e-21	-0.0009	-0.0015	10
g11	CGA	-1.0000	-1.0000	-1.0000	-1.0000	7.8505e-16	3.1418	3.1418	27
	CEA	-1.0000	-0.9999	-0.9999	-0.9999	8.6618e-06	3.1418	3.1418	16
	GA	-1.0000	-0.9995	-0.9986	-0.9995	3.5878e-04	3.1418	3.1418	19
g12	CGA	0.9980	0.9980	0.9980	0.9980	6.5252e-14	-31.9848	-31.9829	93
	CEA	0.9980	0.9980	0.9980	0.9980	3.6126e-11	-31.9778	-31.9798	20
	GA	0.9980	0.9980	0.9980	0.9980	1.9323e-10	-31.9775	-31.9775	99
g13	CGA	3.0000	3.0000	3.0000	3.0000	3.1201e-09	0.0000	-1.0000	65
	CEA	3.0000	3.0000	3.0000	3.0000	4.1948e-08	0.0000	-1.0000	21
	GA	3.0000	3.0000	3.0000	3.0000	1.2456e-05	0.0000	-1.0000	114
g14	CGA	-1.0316	-1.0316	-1.0316	-1.0316	4.7386e-06	0.0896	-0.7125	43
	CEA	-1.0316	-1.0316	-1.0316	-1.0316	9.9630e-06	-0.0897	0.7131	24
	GA	-1.0316	-1.0316	-1.0316	-1.0316	1.3930e-05	-0.0897	0.7184	48
g15	CGA	0.3979	0.3979	0.3979	0.3979	1.3339e-08	9.4248	2.4749	112
	CEA	0.3979	0.3979	0.3979	0.3979	1.1516e-06	-3.1416	12.2751	21
	GA	0.3979	0.3979	0.3979	0.3979	1.9852e-06	9.4250	2.4752	90

Table 5: Comparison results of the best value, the median, the worst value, average, and standard deviation of the functions f_1 to f_{15} for 50 independent runs using CGA,CEA and GA methods

Fun ctio n	Met hod	Best	Med ian	Wor st	Ave rage	S.D	x_1	x_2	Con verg ence
f1	CGA	-449.9998	-449.9901	-449.9901	-449.9924	0.0030	-39.3068	58.8855	45
	CEA	-449.9989	-449.9565	-449.9229	-449.9578	0.0244	-39.2782	58.9014	10
	GA	-449.9745	-449.9120	-449.7904	-449.8864	0.0498	-39.2447	59.0448	1000
f2	CGA	-450.0000	-450.0000	-449.9987	-449.9998	4.1997e-04	35.6202	-82.9080	67
	CEA	-449.9942	-449.8769	-449.8063	-449.8830	0.0558	35.6727	-82.8978	10
	GA	-449.9964	-449.9494	-449.9454	-449.9586	0.0189	35.6588	-82.9953	998
f3	CGA	-449.9942	-449.9668	-449.9668	-449.9692	0.0058	-32.2347	64.9836	42
	CEA	-447.0247	-446.9247	-446.2247	-446.7718	0.3217	-30.5043	64.6693	10
	GA	-449.9895	-449.8582	-449.8582	-449.8749	0.0441	-32.2809	64.9920	77
f4	CGA	-449.9999	-449.9943	-449.6849	-449.9821	0.0012	35.6344	-82.9252	1000
	CEA	-449.9958	-449.9040	-449.7769	-449.8975	0.0689	35.6161	-82.9465	10
	GA	-449.9997	-449.9865	-449.9657	-449.9853	0.0100	35.6169	-82.9126	1000

f5	CGA	-310	-310	-310	-310	0	100	100	20
	CEA	-310	-310	-310	-310	0	100	100	4
	GA	-309.8292	-309.0295	-308.4863	-309.0329	0.3597	100.0000	99.9939	123
f6	CGA	390.0000	390.0001	390.0004	390.0002	9.7598e-05	81.0241	-48.3932	67
	CEA	390.0000	390.0125	390.0049	390.0058	0.0037	81.0254	-48.3912	18
	GA	390.0001	390.1423	390.3480	390.1501	0.0963	81.0176	-48.4058	95
f7	CGA	-179.9919	-179.6063	-178.2872	-179.8255	0.3884	-271.9132	-13.3285	54
	CEA	-179.9866	-179.6100	-179.1093	-179.6018	0.2142	-271.8144	-13.3803	10
	GA	-140.7319	-139.7547	-139.6343	-139.8996	0.3557	1.9318	0.1282	258
f8	CGA	-139.8350	-136.4446	-135.7379	-136.7568	1.1469	-31.9936	15.0032	3
	CEA	-139.6152	-135.4985	-134.6663	-135.9566	1.2842	-31.9924	15.0095	3
	GA	-137.3716	-131.0882	-129.1634	-131.5795	2.1122	-31.8037	15.7205	3
f9	CGA	-329.9997	-329.9539	-329.9056	-329.9552	0.0281	1.9017	-1.5644	3
	CEA	-329.9977	-329.8700	-329.7644	-329.8822	0.0715	1.8994	-1.5612	3
	GA	-329.9164	-329.0696	-328.8314	-329.2013	0.3453	1.9035	-1.5847	3
f10	CGA	-329.9988	-329.7047	-329.5676	-329.8058	0.0836	1.9018	-1.5626	56
	CEA	-329.9964	-329.7202	-329.5477	-329.7277	0.1476	1.9030	-1.5626	8
	GA	-329.9728	-328.8565	-328.4160	-328.9917	0.4484	1.8939	-1.5664	547
f11	CGA	90.0025	90.0230	90.0261	90.0214	0.0056	-0.1367	0.1186	273
	CEA	90.0400	90.0246	90.0280	90.0230	0.0044	-0.1365	0.1186	18
	GA	90.0400	90.0924	90.1021	90.0911	0.0129	-0.1365	0.1186	390
f12	CGA	-459.9998	-459.9750	-459.9479	-459.9743	0.0145	-1.1443	-1.9036	34
	CEA	-459.9988	-459.9921	-459.9905	-459.9930	0.0024	-1.1442	-1.9037	16
	GA	-459.9990	-459.9547	-459.9503	-459.9638	0.0159	-1.1451	-1.9033	64
f13	CGA	-130.0000	-130.0000	-130.0000	-130.0000	1.8583e-05	0.2466	-0.8516	72
	CEA	-130.0000	-129.9994	-129.9942	-129.9986	0.0016	0.2497	-0.8462	10
	GA	-130.0000	-129.9999	-129.9999	-129.9999	2.7233e-05	0.2488	-0.8465	165

f14	CGA	-299.9902	-299.9805	-299.9804	-299.9807	0.0014	-73.5714	-23.5492	3
	CEA	-299.9806	-299.9518	-299.9252	-299.9518	0.0217	-74.3038	-24.3275	3
	GA	-299.9805	-299.9528	-299.9236	-299.9514	0.0226	-71.2337	-25.2216	3
f15	CGA	120.0001	120.0014	120.0076	120.0017	0.0015	3.3252	-1.2834	58
	CEA	120.0008	120.0014	120.0018	120.0015	0.1309	3.3252	-1.2832	10
	GA	120.0002	120.0018	120.0018	120.0016	4.4508e-04	3.3253	-1.2837	111

Table 6: Comparison results - The number of generations for convergence of the functions g_1 to g_{15} using CGA,CEA and GA methods

F		g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	g_9	g_{10}	g_{11}	g_{12}	g_{13}	g_{14}	g_{15}
Method	CGA	48	95	111	57	68	85	36	77	6	11	27	93	65	43	112
	CEA	17	15	15	18	18	21	20	15	6	15	16	20	21	24	21
	GA	136	172	62	85	110	89	49	142	5	10	19	99	114	48	90

Table 7: Comparison results - The number of generations for convergence of the functions f_1 to f_{15} using CGA,CEA and GA methods

F		f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}
Method	CGA	45	67	42	1000	20	67	54	3	3	56	273	34	72	3	58
	CEA	10	10	10	10	4	18	10	3	3	8	18	16	10	3	10
	GA	1000	998	77	1000	123	95	258	3	3	547	390	64	165	3	111

F-Function

5. CONCLUSION

In this paper we have introduced a new operator for genetic algorithm which imitates the biological cloning process and have applied the integrated algorithm on a number of standard test cases. We have simulated the results for the standard GA as well as two new optimization methods obtained by integrating the new clone operator with the GA operators. The results of the three methods, namely proposed CGA method, proposed CEA method and standard GA, indicate that the former is capable of generating better solution quality than the other methods. It is seen that the CGA and CEA methods significantly improve the convergence rate and the quality of the solution. In conclusion, it can be said that the proposed operator reduces the number of searches within the solution space and enhances the convergence capability and the performance of the GA. The proposed method can also be analyzed using real coded GAs with specially designed operators and also be extended to higher dimensions. This will be considered in future work.

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