Chaos Genetic Algorithm Instead Genetic Algorithm

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Abstract: *Today the Genetic Algorithm (GA) is used to solve a large variety of complex nonlinear optimization problems. However, permute convergence which is one of the most important disadvantages in GA is known to increase the number of iterations for reaching a global optimum. This paper, presents a new GA based on chaotic systems to overcome this shortcoming,. We employ logistic map and tent map as two chaotic systems to generate chaotic values instead of the random values in GA processes. The diversity of the Chaos Genetic Algorithm (CGA) avoids local convergence more often than the traditional GA. Moreover, numerical results show that the proposed method decreases the number of iterations in optimization problems and significantly improves the performance of the basic GA. The idea of utilization of chaotic sequences for optimization algorithms is motivated by biological systems such as Particle Swarm Optimization (PSO), Ant Colony algorithms (ACO) and bee colony algorithms and has the potential to improve ordinary GAs.*

Keywords: *CGA, optimization problem, chaos evolutionary algorithm.*

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1. Introduction

In today's world, it is very important to solve complex nonlinear optimization problems. There are some efficient techniques to solve nonlinear optimization problems, such as a recursive quadratic programming, a projection method and a generalized reduced gradient method [29]. In these methods must be differentiable the objective function. But, in general, it is difficult to apply these methods to the problems. Since, firstly their objective function is complex and sometimes is not differentiable, secondly their objective function may have many local minimum or maximum.

During the past years many techniques have been proposed for optimization problem. Genetic Algorithm (GA) is one of the heuristic-based optimization techniques and successfully applied in many optimization problems. GA is probabilistic, robust and heuristic search algorithms premised on the evolutionary ideas of natural selection and genetic [17]. At present, the GA has been widely used in function optimization, combinatorial optimization, robotics, image processing and so on [7]. The main idea behind the design of a GA is to achieve robustness and adaptive process in the real world problems which are never static or predictable [26]. GA is different from most conventional calculus-based search algorithms in the following characteristics: No limitation on the continuity or discreteness of the search space, parallel computation of a population of solutions, using natural selection criteria, and no gradient information [14]. However, this method has a few disadvantages. The GA process may take a large number of iterations to reach the global optimal solution and also a key problem of GA is permeating convergence. Several methods have been proposed to overcome the shortcomings and improve the efficiency of GA [10, 33, 38]. Their effects are various in different problems. In order to, avoid these problems, it is necessary to find an effective approach to improve GA and to increase speed of convergence.

Recently the theories and application of nonlinear dynamic, especially chaos, have drowned more and more attention in many fields such as secure transmission, telecommunication and cryptography [31, 37]; nonlinear circuits [3], DNA computing [24], and image processing [8, 9]. Another field is the potential applications of chaos in various disciplines including optimization. Chaos Optimization Algorithm (COA) is a recently proposed population-based stochastic optimization algorithm which is used by chaotic map [19]. In [6] proposed the Chaos Genetic Algorithm (CGA) which uses logistic map to generate the initial population, it still can't mutation diversity of the population in some complicated cases. In [22], is proposed a novel feature selection method based on chaos GA that used two kind of chaotic mapping to maintain and enhance the global searching capability. In another research, Wang and Yoo [36] proposed a new hybrid GA based on chaos and PSO to solve key problems GA; their results show that, the proposed method improves both global convergence and convergence precision.

The rest of the paper is organized as follows: Section 2 has provided an introduction to GA. In section 3 we've introduced Chaos theory. In section 4 CGA has been described and finally, experimental results are presented in section 5.

2. Genetic Algorithm

GAs have been developed by John Holland at the University of Michigan in the early 1970's [28]. GA belongs to the larger class of Evolutionary Algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection and crossover. These algorithms encode a potential solution to a specific problem on a simple chromosome-like data structure and apply recombination operators to these structures so as to preserve critical information. In a GA, a population of strings (called chromosomes or the genotype of the genome), which encode candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem, evolves toward better solutions. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness) and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations have been produced or a satisfactory fitness level has been reached for the population.

Relying on multi-point search and algorithmic features, it is not easy to fall into local optimal solution but can converge to a universal optimal solution [18]. Since, GA is good at searching, it is used to solve complex nonlinear optimization problems. Choosing the proper parameters of GA such as, population size, crossover probability and mutation probability, is the key to affect the behavior and performance of GA. Hence, if the P_c is too large, the genetic pattern is much easier to be damaged and the individual structures with high fitness will be destroyed soon. But, if the P_c is too small, the search process will go slowly, even stagnate [5]. If the mutation probability P_m is too small, it is difficult to produce the new individual structures; but if the value of P_m is too large, the GA then becomes a pure random search algorithm [5]. However, increasing of population size can reduce the number of iterations to reach global optimum.

3. Chaos Theory

Chaos is a bounded dynamic behavior that it occurs in deterministic nonlinear system. Although, it appears to be stochastic, it occurs in a deterministic nonlinear system under deterministic conditions [2]. It is highly sensitive to changes of initial condition than a small change to initial condition can lead to a big change in the behavior of the system. Chaos theory is typically described as the so-called 'butterfly effect' detailed by Lorenz [23]. There are three main properties of the chaotic map, i.e.

- Ergodicity.
- Randomness.
- Sensitivity to initial condition.

The ergodicity property of chaos can ensure chaotic variables to traverse all state non-repeatedly within a certain range according to its own laws [32]. So, this is can be used as an optimization mechanism which avoids falling into local minimum solution [36]. The sensibility to the initial state, one of the most important characters of chaotic systems, can ensure that there are not two identical new populations even if the two best fit solutions obtained by sequential evolving procedures are very close [16]. So, such population not only reserves the best fit chromosome, but also maintains population diversity.

By using these properties, an effective approach was proposed for maintaining the population diversity and avoids the search being trapped in local optimum. In this paper, we use logistic and tent maps to generate the chaotic sequence. Chaotic sequences have been proven easy and fast to generate and store, there is no need for storage of long sequences [13]. In addition, an enormous number of different sequences can be generated simply by changing its initial condition. Moreover, these sequences are deterministic and reproducible [2]. We outline the two chaotic mappings as follows:

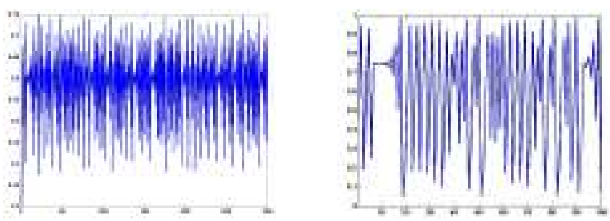
1. *Logistic Map* [25]: Is one of the simplest forms of chaotic mappings. Basically, this map is a polynomial mapping of degree 2, whose equation is the following:

$$X_{n+1} = rX_n(1 - X_n) \qquad X_n \in (0,1) \tag{1}$$

   Where, r is a control parameter which is between 0 and 4. Obviously, $X \in (0, 1)$ under the conditions that the initial $X_0 \in (0, 1)$ and that $X_0 \notin \{0.0, 0.25, 0.75, 0.5, 1.0\}$. When $3.57 < r \leq 4$, the system has proven to be chaotic state. In this paper, $r=4$ is used. Figure 1-b shows its chaotic dynamics, where, $X_0=0.4$.
2. *Tent Map* [27]: Is one of the known chaotic systems and it is a discrete-time dynamical system, whose equation is the following:

$$x_{n+1} = \begin{cases} \mu x_n & x_n < \frac{1}{2} \\ \mu(1 - x_n) & x_n \geq \frac{1}{2} \end{cases} \tag{2}$$

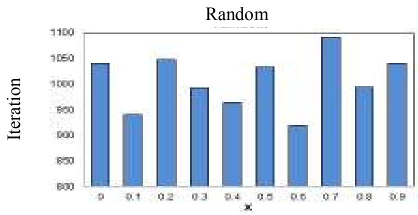
   Where, μ is a control parameter, when $1 < \mu < 2$, the system exhibits chaotic behavior. In this paper, we take $\mu=1.5$. Figure 1-a shows its chaotic dynamics, where, $x_0=0.3$.



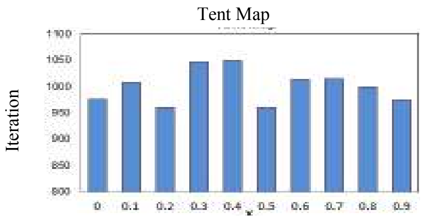
a) Dynamics of tent map. b) Dynamics of logistic map.

Figure 1. Dynamics of chaotic systems.

We have generated 10000 random value and chaos numbers between 0 and 1. Figure 2 shows the random values and Tent chaotic system output values, it is clearly the diversity of chaotic system values are better than the random values.



a) Distribution of 10000 numbers generated of random.



b) Distribution of 10000 numbers generated of tent map.

Figure 2. Distribution of 10000 numbers generated of random and tent map.

4. Chaos Genetic Algorithm

Recently, chaos theory and the generation of chaotic sequences instead of random ones have been adopted, which has led to very interesting results in many applications such as optimization of power flow problems [30], control systems [34], neural networks [15], cryptography [31, 37] and image processing [9] and others. Due to the easy implementation and special ability to avoid being trapped in local optima, chaos has been a novel optimization technique and chaos-based search algorithms have aroused intense interests [35]. Many researchers have found a close-knit relationship between chaos and cryptography [20, 21], and many of their properties can be found in traditional cryptosystems. Abdullah *et. al* [1] introduced a hybrid method based on GA and chaotic function for image encryption; their results show that the hybrid method can perform a high level of resistance against statistical invasions. In random-based optimization algorithms, are used chaotic variables instead of random variables. Experimental studies assert that the benefits of using chaotic signals instead of random signals are often evident although, it is not mathematically proved yet [4]. GA has aroused intense interest, due to the flexibility, versatility and robustness in solving optimization problems, which conventional optimization methods find difficult [6]. One of the major disadvantages of the GA is its premature convergence, especially while optimization problems have more local optima. In this situation, the solving procedure is trapped in the local optimum and most of the operators can't produce offspring surpassing their parents any more [16]. In this paper, CGA is proposed that combine the concept of chaos with GA.

The chaos as it was cited in pervious section is a general phenomenon is nonlinear system that has some properties such as randomness, ergodicity; regularity and sensitivity to initial condition. By use of these properties of chaos, we propose CGA based on two kinds of chaotic mapping. In improving the algorithm, we use chaotic mapping instead of random process. The standard GA uses random sequences in the initial population, crossover and mutation.

In the GA method, the initial population generated by a random approach might be unevenly distributed and away from the optimal solution. Hence, the algorithmic efficiency can be very low and more number of iteration is needed to find the global optimum. Therefore, we use the uniform distribution of the tent map to generate the initial population. Then, we use logistic map output instead of crossover and mutation each time a random number is needed. The flowchart of the proposed method has been shown in Figure 3.

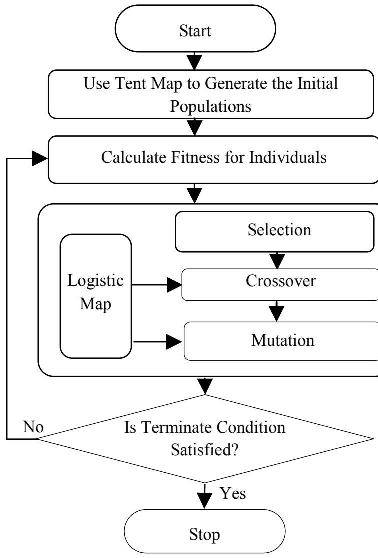


Figure 3. CGA flowchart.

5. Numerical Results and Discussion

The proposed method has been implemented in MATLAB by assistance of logistic and tent map chaotic systems and finally it has been tested on some famous benchmark functions which Table1 shows the main properties of the benchmark function used in the experiments.

To examine the performance of the proposed algorithms, 5 test functions are adopted in this paper and we compared the proposed algorithms with the standard GA and PSO algorithms. In PSO algorithms, swarm size is set to 25. For each method the Average (Mean), Best (Min), Worst (Max), Standard Deviation (SD) are calculated from the simulated runs and then they are compared. The sets of parameters were assigned for PSO i.e., $c_1=c_2=2$ and v_{max} is clamped to be 15% of the search space. Also, in GA and CGA algorithms, the population size is set to 100, crossover and mutation rate are set to 0.8 and 0.2 respectively. In

Table 1. Benchmark for simulation.

Function	Mathematical Representation	Range	Modality	Optimum
Zakharov	$f(x)=\sum_{i=1}^{n} x_i^2 + (\sum_{i=1}^{n} 0.5ix_i)^2 + (\sum_{i=1}^{n} 0.5ix_i)^4$	(-5, 10)	Unimodal	0
Ackley	$f(x)=20+e-20exp(-0.2\sqrt{1/n(\sum_{i=1}^{n} x_i^2)}-exp(1/n(\sum_{i=1}^{n} cos2\pi x_i))$	(-32, 32)	Multimodal	0
Rosenbrock	$f(x)=\sum_{i=1}^{n-1} (100(x_i^2 - x_{i+1})^2 + (x_i-1)^2)$	(-10, 10)	Unimodal	0
Rastrigin	$f(x)=\sum_{i=1}^{n} (x_i^2 - 10cos2\pi x_i + 10)$	(-5.12 , 5.12)	Multimodal	0
Griewank	$f(x)=1/4000\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} cos(x_i/\sqrt{i})+1$	(-600, 600)	Multimodal	0

these experiments, all the simulations were done 2000 generation. Two criteria are applied to terminate the simulation of the algorithms: Reaching maximum number and reaching to the global optimal solution.

These algorithms have been implemented in MATLAB and the results are shown in Table 2 in the 100 independent runs by each algorithm. To evaluate the performance of the GA, PSO and CGA are calculated the means of the fitness value (Mean), Best (Min), Worst (Max) and the SD. In this comparison, it can be seen that the proposed methods could as well as improve the disadvantages of the standard algorithms.

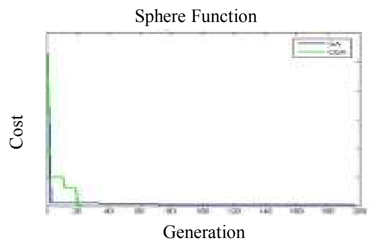
Table 2. Simulation results obtained from CGA and other methods using chaotic systems for benchmark functions.

Function		GA	PSO	CGA
Zakharov	**Mean**	0.006	0.00005	0.0000
	Min	0.0000	2.4433e-007	0.0000
	Max	0.0501	3.5513e-004	0.0000
	SD	5.9760e-04	3.7193 e-006	0.0000
Ackley	**Mean**	8.8818e-016	0.00005	8.8818e-016
	Min	8.8818e-016	2.4433e-007	8.8818e-016
	Max	8.8818e-016	3.5513e-004	8.8818e-016
	SD	0.0000	3.7193 e-006	0.0000
Rosenbrock	**Mean**	0.0120	0.1958	0.0000
	Min	0.0000	0.0128	0.0000
	Max	0.2000	0.5138	0.0000
	SD	0.0012	0.0091	0.0000
Rastrigin	**Mean**	0.0000	0.00024	0.0000
	Min	0.0000	5.2969e-005	0.0000
	Max	0.0000	0.0134	0.0000
	SD	0.0000	7.6349 e-004	0.0000
Griewank	**Mean**	0.0000	0.00075	0.0000
	Min	0.0000	3.5252e-006	0.0000
	Max	0.0000	0.007	0.0000
	SD	0.0000	1.5463 e-05	0.0000

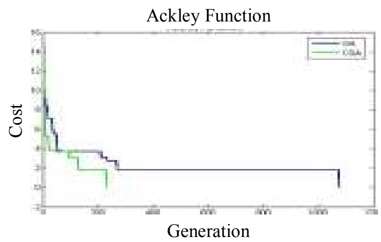
To further show the effectiveness of CGA, we carry out comparison with several other methods, such as Directed Search Simulated Annealing (DSSA) [11], Directed Tabu Search (DTS) [12], COA [18], GA and PSO. The results of these comparisons presented in Table 3. From Table 2, it can be seen that CGA can find global optima with small iteration numbers for every function. Figure 4 shows the performance of the CGA and GA for solving four functions. Obviously the convergence speed of CGA is faster than the basic GA.

Table 3. Average number of iterations in CGA and other methods.

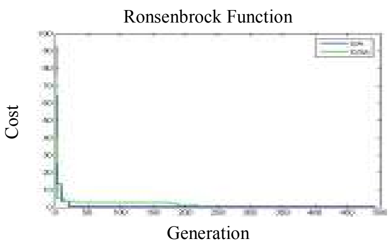
Method	Zakharov	Ackley	Rosenbrock	Rastrigin	Griewank
DTS	473	1748	201	NA	NA
DSSA	472	1058	863	252	1830
COA	495	347	925	NA	NA
PSO	1229	1254	1311	1928	946
GA	410	340.4	353	382	367
CGA	**334**	**318**	**315**	**304**	**302**



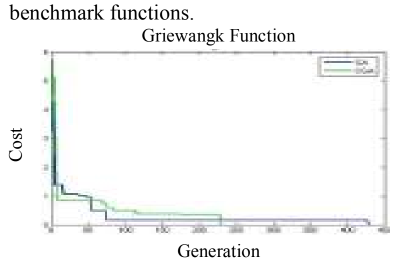
a. Fitness value for CGA and GA on Sphere benchmark functions.



b. Fitness value for CGA and GA on Ackley benchmark functions.



c. Fitness value for CGA and GA on Ronsenbrock benchmark functions.



d. Fitness value for CGA and GA on Griewangk benchmark functions.

Figure 4. Fitness value for CGA and GA on 4 benchmark functions.

6. Conclusions

In this paper, we have used chaos theory instead randomness in the standard GA. The proposed method uses some chaotic systems, such as logistic map and tent map; to generate chaotic variables each time a random number is needed by the classical GA algorithm to avoid local convergence. Simulation results have shown that the proposed method can perform significantly better than the basic GA. In particular the number of iterations to find the global optimized has been reduced. Similarly, utilizing chaotic sequences for many optimization algorithms are inspired from biological systems such as PSO, ACO and bee colony algorithm; have potential to improve by combining of chaotic systems.

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