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Parallel chaos optimization algorithm with migration and merging operation

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ABSTRACT

Chaos optimization algorithm (COA) utilizes the chaotic maps to generate the pseudo-random sequences mapped as the decision variables for global optimization applications. A kind of parallel chaos optimization algorithm (PCOA) has been proposed in our former studies to improve COA. The salient feature of PCOA lies in its pseudo-parallel mechanism. However, all individuals in the PCOA search independently without utilizing the fitness and diversity information of the population. In view of the limitation of PCOA, a novel PCOA with migration and merging operation (denoted as MMO-PCOA) is proposed in this paper. Specifically, parallel individuals are randomly selected to be conducted migration and merging operation with the so far parallel solutions. Both migration and merging operation exchange information within population and produce new candidate individuals, which are different from those generated by stochastic chaotic sequences. Consequently, a good balance between exploration and exploitation can be achieved in the MMO-PCOA. The impacts of different one-dimensional maps and parallel numbers on the MMO-PCOA are also discussed. Benchmark functions and parameter identification problems are used to test the performance of the MMO-PCOA. Simulation results, compared with other optimization algorithms, show the superiority of the proposed MMO-PCOA algorithm.

1. Introduction

As an inherent characteristic of nonlinear dynamics, chaos emerges in diverse areas of science and engineering [1]. Generally speaking, chaos has several important dynamical characteristics, namely, the sensitive dependence on initial conditions, ergodicity, pseudo-randomness, and strange attractor with self-similar fractal pattern [1–5]. Recently, chaotic sequences generated by means of chaotic maps have been used in the development of global optimization techniques, and particularly, in the specification of chaos optimization algorithm (COA) [2–9]. Due to the unique characteristic of chaos, COA carries out global exploration search at higher speed than stochastic ergodic searches that depend on the probabilities [5–9]. The main advantages of COA include: (a) COA escapes from local minima more easily than classical stochastic optimization algorithms such as genetic algorithm (GA), simulated annealing (SA) and some meta-heuristics algorithms including particle swarm optimization (PSO), ant colony optimization algorithm (ACO), differential evolution (DE), and so on [9]; (b) COA does not depend on the strict mathematical properties of optimization problems, such as continuity, differentiability; (c) COA is easy to be implemented and execution time of algorithm is short [2–5].

Recently, COA has also been hybridized with optimization algorithms, such as: hybrid chaos-BFGS algorithm [9], hybrid COA and quasi-Newton method [10], hybrid COA and GA [11], hybrid COA and PSO [12], hybrid COA and affine scaling search algorithm [13], hybrid COA with artificial emotion [14]. In addition to the development of COA and hybrid COA, chaos has also been integrated with optimization algorithms, such as: chaotic harmony search algorithm [15], chaotic ant swarm optimization [16], chaotic particle swarm optimization [17,18], chaotic evolutionary algorithm [19,20], chaotic genetic algorithms [21,22], chaotic-based hybrid negative selection algorithm [23], chaos embedded great deluge algorithm [24]. The above-mentioned chaos based optimization algorithms are mainly applied to complex or multidimensional functions problems, in addition, these algorithms have also been applied in various fields like parameter selection of SVM [4], parameter identification of synchronous generator [6], feature selection of text categorization [11], flow shop scheduling problem [15], feature selection [17], multi-reservoir optimization [20], etc. Various simulation results and applications in these references have shown the solutions diversity and global optimization capacity of chaos based optimization algorithms.

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Table 1
One-dimensional maps.

No.	Map	Definition	Range	Parameter
1	Chebyshev map	$x_{n+1} = \cos(\varphi \cos^{-1} x_n)$	$x_n \in [-1, 1]$	$\varphi = 5$
2	Circle map	$x_{n+1} = x_n + \vartheta - (\frac{\tau}{2\pi}) \sin(2\pi x_n) \mathrm{mod}(1)$	$x_n \in (0, 1)$	$\vartheta = 2.5, \tau = 5$
3	Cubic map	$x_{n+1} = \rho x_n(1 - x_n^2)$	$x_n \in (0, 1)$	$\rho = 2.59$
4	Gauss map	$x_{n+1} = 0, x_n = 0, x_{n+1} = \frac{1}{x_n} \mathrm{mod}(1), x_n \neq 0$	$x_n \in (0, 1)$	
5	ICMIC map	$x_{n+1} = \sin(\frac{\alpha}{x_n})$	$x_n \in (-1, 1)$	$\alpha = 2$
6	Logistic map	$x_{n+1} = \varphi x_n(1 - x_n)$	$x_n \in (0, 1)$	$\varphi = 4$
7	Sinusodial map	$x_{n+1} = \sin(\pi x_n)$	$x_n \in (0, 1)$	
8	Tent map	$x_{n+1} = \frac{x_n}{0.7}, x_n < 0.7, x_{n+1} = (\frac{10}{3}) x_n(1 - x_n), else$	$x_n \in (0, 1)$	

Since the chaotic motions are pseudo-random and chaotic sequences are sensitive to the initial conditions, therefore, the success of COA in solving optimization problems crucially depends on appropriate starting values. For this reason, parallel chaos optimization algorithm (PCOA) has been proposed in our former studies [25,26]. The population-based PCOA searches from diverse initial points, therefore, it easily escapes from local minima and detracts the sensitivity of starting values. Considering its poor exploitation ability, PCOA is combined with local search method in [25,26], like simplex search method (SSM) and harmony search algorithm (HSA). However, the local search method usually has slow efficiency. In addition, parallel individuals search independently without information exchange in the PCOA.

In view of the limitation of PCOA, a novel PCOA with migration and merging operation (denoted as MMO-PCOA) is proposed in this paper. In the MMO-PCOA, the so far parallel solutions are firstly selected according to the fitness. Then parallel individuals are randomly selected to be conducted migration and merging operation with the so far parallel solutions. The new produced candidate individuals compete with the original ones, and the individuals with better fitness will survive as the new solutions. By using migration and merging operation to exploit the fitness and diversity information of the population, MMO-PCOA can enhance search performance without hybrid with local search method. The main contribution of this paper is to establish a novel MMO-PCOA framework, which has the major advantages as follows: (a) The MMO-PCOA roots in population based PCOA, which easily escapes from local minima and detracts the sensitivity of initial conditions. Meanwhile, fitness and diversity information are considered by exploiting the so far parallel solutions. Therefore, a good balance between exploration and exploitation can be achieved in the MMO-PCOA. (b) The MMO-PCOA keeps the simple frame of twice carrier wave mechanism, without the need to combine with local search method. (c) The implementation of the MMO-PCOA is very simple, and there are few control parameters.

The rest of this paper is organized as follows. Section 2 briefly describes chaos and PCOA approach. Section 3 describes the proposed MMO-PCOA approach. Benchmark functions are used to test the performance of MMO-PCOA in Section 4. The proposed MMO-PCOA is also applied to the parameter extraction of solar cell models and parameter identification of chaotic systems in Section 5 and Section 6, respectively. Conclusions are presented in Section 7.

2. Chaotic map and PCOA approach

2.1. Chaotic map

For more than three decades, the unusual behavior of chaotic systems has attracted attention of different scientific communities. From the mathematical aspect, chaos is defined as a pseudo-random behavior generated by nonlinear deterministic systems [1]. In COA, the chaotic sequences from chaotic maps are mapped to produce the decision variables, instead of random sequences from random number generators during the process of global optimization [5]. The concept and search process of COA are based on the regularity of chaotic motion. The regularity of chaotic motion is usually represented by using one-dimensional map, which is the simplest system with the capability of generating chaotic behavior [10,13]. Eight well-known one-dimensional maps which yield chaotic behaviors are described in Table 1. These maps are used as the sources of chaos in the proposed MMO-PCOA.

2.2. PCOA approach

Compared to individual based COA, PCOA evolves a population of N parallel candidate individuals [25,26]. In the PCOA, multiple stochastic chaos variables (like population) are simultaneously mapped onto one decision variable, and the search result is the best fitness of parallel candidate individuals.

Consider an optimization problem for nonlinear multi-modal function with boundary constraints as:

$$\min f(X) = f(x_1, x_2, \ldots, x_n), \quad x_i \in [L_i, U_i]. \tag{1}$$

where f is an objective function, $X = (x_1, x_2, \ldots, x_n) \in R^n$ is a vector in the n-dimensional decision variable space, $x_i \in [L_i, U_i]$ is the feasible solution space, L_i and U_i represent the lower and upper bound of the ith variable, respectively. PCOA evolves a stochastic population of N candidate individuals with n-dimensional parameter vectors. The N is the population size, meanwhile, the number of parallel candidate individuals. In the following, the subscripts i and j stand for the decision variable and parallel candidate individuals, respectively.

The process of PCOA approach is based on the twice carrier wave mechanism, and the algorithmic description of the PCOA is summarized in Table 2. The first carrier wave part of PCOA is the raw search in different chaotic traces, and the second carrier wave part is refined search to enhance the search precision.

The λ_i in the second carrier wave part is an adjustable parameter which adjusts small ergodic ranges around parallel solution x_j^*, and $t > 1$ is a constant. The initial value of parameter λ_i is usually set to $0.01(U_i - L_i)$ [5].

3. MMO-PCOA approach

This section presents a novel MMO-PCOA which utilizes the fitness and diversity information of the population. The remarkable distinction of MMO-PCOA is the application of migration and merging operation for exploitation. Consequently, MMO-PCOA does not need combination with local search method.

3.1. Migration operation

In the PCOA, parallel candidate individuals search independently according to their respective chaotic sequences without information interaction. In the proposed MMO-PCOA, the migration operation is used to exploit the parallel solutions and to find new candidate individuals. The migration operation (denoted by M1) is illustrated in Fig. 1. The application of migration operation in the MMO-PCOA includes the following steps: