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Micro-differential evolution: Diversity enhancement and a comparative study

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ABSTRACT

Differential evolution (DE) algorithm suffers from high computational time due to slow nature of evaluation. Micro-DE (MDE) algorithms utilize a very small population size, which can converge faster to a reasonable solution. Such algorithms are vulnerable to premature convergence and high risk of stagnation. This paper proposes a MDE algorithm with vectorized random mutation factor (MDEVM), which utilizes the small size population benefit while empowers the exploration ability of mutation factor through randomizing it in the decision variable level. The idea is supported by analyzing mutation factor using Monte-Carlo based simulations. To facilitate the usage of MDE algorithms with very-small population sizes, a new mutation scheme for population sizes less than four is also proposed. Furthermore, comprehensive comparative simulations and analysis on performance of the MDE algorithms over various mutation schemes, population sizes, problem types (i.e. uni-modal, multi-modal, and composite), problem dimensionalities, and mutation factor ranges are conducted by considering population diversity analysis for stagnation and pre-mature convergence. The MDEVM is implemented using a population-based parallel model and studies are conducted on 28 benchmark functions provided for the IEEE CEC-2013 competition. Experimental results demonstrate high performance in convergence speed of the proposed MDEVM algorithm.

1. Introduction

Accuracy enhancement as well as increase of convergence speed Q4 toward finding global solution(s) in optimization algorithms have motivated many researchers to develop more efficient evolutionary approaches. Such methods have solved many problems successfully such as smart grid design [1], vehicle navigation using ant colony optimization (ACO) [2], and communication system design using harmony search algorithm [3]. Differential evolution (DE) algorithm is one of the state-of-the-art global optimization algorithms, which is popular due to its simplicity and effectiveness. This algorithm works based on a set of individuals, called population, where an optimal size setting is imperative for a good performance [4].

Different variants of DE algorithm with large population size often grant more reasonable results than their small population size versions. A large population size supports a higher diversity for the population, which recombination of its diverse members offers a higher exploration ability to the optimizer to find global solution(s) [5–7]. The proposed diversity enhancement technique in this paper offers a better exploration of problem landscape. Most of the research works during past years were focused on developing complex approaches with a large populations size [49]. Utilizing a large population size intrinsically encompasses more function evaluations [5]. Therefore, using algorithms with a large population size may not be satisfactory for real-time or online applications [48,50].

Using a population size much smaller than the number of decision variables is sometimes more efficient than some of the state-of-the-art DE algorithms with a large population. The term micro-algorithm, denoted by μ-algorithm, refers to population-based algorithms with a small population size [7]. The micro-algorithms have been used in diverse applications, exceptionally due to their lighter hardware requirements and opportunity to operate in embedded systems with a memory saving approach [4]. Employing small population sizes decreases the number of function calls, but unfortunately due to lack of diversity, it also increases the risk of premature convergence as well as stagnation.

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The premature convergence problem refers to the situation where the population has converged to a sub-optimal solution of a multi-modal objective function [5]. This situation mostly occurs when the population has lost its diversity and cannot jump out of local optima. In this case, the algorithm progresses slower than usual and may stop any further improvement of the evolved candidate solutions [5,50].

The stagnation refers to either of the following scenarios occur: the population has not converged to any point and is still diverse; the algorithm cannot find a better solution as it proceeds, even if new individuals are entered to the population [5,50].

Based on the stagnation and premature convergence characteristics, it seems reducing the population size while raising the diversity of the population is a key point to achieve a faster convergence speed while maintaining a low risk of premature convergence or stagnation [5,50]. The DE algorithm is consisted of several manually tunable control parameters, where different adaptive proposals have been devised to avoid manual adjustments [80]. One way to increase the diversity of population while keeping its convergence toward global solution(s) is using parameter adaptive techniques.

One of the main criticisms for population-based algorithms is their computational cost. The core idea of this paper is to decrease the computational cost by reducing the population size and compensate the lack of diversity by randomizing the mutation scale factor. This idea is not only simple, but also introduces a typical interval for randomization of mutation scale factor (e.g. [0.1,1.5]) which relaxes the user from strict parameter setting of mutation scale factor to a constant value [37] (even the self-adaptive versions introduce a new hyper-parameter, the decay rate). The authors have recently proposed the idea of vectorized random mutation factor in DE algorithm for each decision variable of the problem, called MDEVM [50]. The fact that using randomized mutation scale factor acts randomly to select the mutation scale factor is right (from a hyperbox), which is the reason for added diversity while having many less individuals. But, it does not question the essential idea of DE, since still computes the differences between individuals in generating mutation vectors. The MDEVM has been applied on 3D sensor localization problem successfully [57].

The proposed transition from a scalar constant F to a scalar random F to a vectorized random $\mathbf{F}$ in DE has an interesting inverse in PSO [50]. In plain PSO [89], "velocities were adjusted according to their difference, per dimension, from best locations". This design guideline is further solidified in the 2007 standard for PSO [90]. As an extreme similar to scalar constant mutation factor in plain DE, there is also "Canonical Deterministic PSO" in which the update equation "system does not contain stochastic factors" [91]. It is noticeable that the role and effect of update weights in both DE and PSO is an interesting area for continued and coordinated study.

We have made the following contributions in this paper: (1) Conducted a comprehensive survey on micro-evolutionary algorithms; (2) Studied the proposed enhanced version of the MDE algorithm in [50], i.e. MDEVM, with population distributed implementation; (3) Mutation factor diversity analysis by Monte-Carlo simulations; (4) Presented population-based parallel model of MDEVM; (5) Conducted comparative study and analysis of MDE algorithms in terms of: variant mutation schemes and very-small population sizes (i.e. $N_P = \{2, 3, 4\}$), various problems types (uni-modal, multi-modal, composite), variant problem dimensions (i.e. $D = \{10, 30, 50, 100\}$) and mutation schemes, variant ranges for mutation factor, population diversity of the MDE algorithms in stagnation and trapping in local optimums, and variant stopping conditions for the MDE algorithm.

In the next section, the micro-population based methods are briefly surveyed. Then, a review of the DE algorithm is presented in Section 3. In Section 4, the proposed method is presented, and diversity enhancement in MDE using different structures of mutation scale factor is studied in detail. The simulation results and corresponding analysis are provided in Section 5. Finally, the paper is concluded in Section 6.

Table 1
Summary of related works in micro-population-based algorithms.

Population-based algorithm	Related research works
Genetic algorithm (GA)	[8,13,25,39–47]
Particle swarm optimization (PSO)	[9,10,51–68,77]
Differential evolution (DE)	[4,6,11,12,14–22,38,36,50,79]
Artificial bee colony (ABC)	[69,70]
Bacterial foraging optimization (BFO)	[71,72]
Artificial immune system (AIS)	[75]
Elitistic evolution (EEv)	[76]
Bat algorithm	[73]

2. Related works

Many research works have attempted to introduce efficient micro-algorithms. We can categorize such research works into four main groups which are micro-genetic algorithms (micro-GAs), micro-particle swarm optimization (micro-PSO), MDE, and other population-based approaches, Table 1. Another classification is according to different methods in helping realizing the effect of 'micro', such as population initialization and re-initialization, preserving individuals for the next generations, adaptive population size, adaptive local search, cooperative sub-population/sub-swarm, hybridization, and parameter adaptation techniques.

2.1. Population initialization and re-initialization

The idea of population reinitialization for micro-GA is one of the early works in the field [42]. In this approach, the best individual of each converged population, after a predefined number of generations, is replaced with a randomly selected individual in the population of the next iteration.

The micro-algorithms also have been employed in multi-objective optimization (MOO). The improved version of non-dominated sorting genetic algorithm (NSGA-II) with a specific population initialization strategy is embedded into the standard micro-GA to solve MOO problems [13]. A micro-GA with a population size of four and a reinitialization strategy is proposed in [39] which can produce a major part of the Pareto-front at a very low computational cost. Three forms of elitism and a memory are used to generate the initial population [39]. PSO is one of the well-known swarm intelligence algorithms, which its small population size versions have been developed recently [9,67,10]. A five-particle micro-PSO is used in [53] to deal with constrained optimization problems. This method preserves population diversity by using a reinitialization process and incorporates a mutation operator to improve the exploratory ability of the algorithm. The reported results present competitive performance versus the simple multi-member evolution strategy (SMES) and stochastic ranking (SR) method [53]. The micro-ODE is proposed and evaluated for an image thresholding case study [16]. Its performance is compared with the Kittler algorithm and MDE. The micro-ODE method has outperformed these algorithms on 16 challenging test images and has demonstrated faster convergence speed due to embedding the opposition-based population initialization scheme [16]. A 'micro' version of bacterial foraging optimization algorithms (BFOAs), called (μ-BFOA), is proposed in [71]. This method keeps the best bacterium unaltered, whereas the other population members are reinitialized [71]. This approach has outperformed the standard BFOA with a larger population size [71]. A micro-artificial immune system (Micro-AIS) with five individuals (antibodies), from which

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