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Hybrid biogeography-based evolutionary algorithms

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ABSTRACT

Hybrid evolutionary algorithms (EAs) are effective optimization methods that combine multiple EAs. We propose several hybrid EAs by combining some recently-developed EAs with a biogeography-based hybridization strategy. We test our hybrid EAs on the continuous optimization benchmarks from the 2013 Congress on Evolutionary Computation (CEC) and on some real-world traveling salesman problems. The new hybrid EAs include two approaches to hybridization: (1) iteration-level hybridization, in which various EAs and BBO are executed in sequence; and (2) algorithm-level hybridization, which runs various EAs independently and then exchanges information between them using ideas from biogeography. Our empirical study shows that the new hybrid EAs significantly outperforms their constituent algorithms with the selected tuning parameters and generation limits, and algorithm-level hybridization is generally better than iteration-level hybridization. Results also show that the best new hybrid algorithm in this paper is competitive with the algorithms from the 2013 CEC competition. In addition, we show that the new hybrid EAs are generally robust to tuning parameters. In summary, the contribution of this paper is the introduction of biogeography-based hybridization strategies to the EA community.

1. Introduction

Evolutionary algorithms (EAs) are optimization techniques that have become highly popular in recent decades (Simon, 2013; Yao et al., 1999; Wolpert and Macready, 1997; Neri and Cotta, 2012). One of the main reasons for their success is that they provide a general purpose mechanism to solve a wide range of problems. Many EAs have been proposed, including genetic algorithms (GA) (Ahn, 2006), evolution strategies (ES) (Beyer, 1994; Beyer and Sendhoff, 2008), ant colony optimization (ACO) (Dorigo et al., 2002; Dorigo and Gambardella, 1997), particle swarm optimization (PSO) (Bratton and Kennedy, 2007), differential evolution (DE) (Das and Suganthan, 2011), estimation of distribution algorithms (EDA) (Pedro and Lozano, 2002), immune system optimization (Hofmeyr and Forrest, 2000), artificial bee colony (ABC) optimization (Karaboga and Basturk, 2007), and many others (Simon, 2013).

Hybrid EAs are attractive alternatives to standard EAs. The combination of several algorithms in hybrid EAs allows them to exploit the strength of each algorithm. It has been shown that by properly selecting the constituent algorithms and hybridization strategies, hybrid EAs can outperform their constituent algorithms due to their synergy (Niknam and Farsani, 2010). This characteristic is a strong motivation for the study of hybrid EAs. Many hybrid EAs have been proposed to improve performance and to find global optima (Makeyev et al., 2010; Mongus et al., 2012). Although some of these improvements are significant, the development of new hybrid EA strategies is worthy of further investigation.

Current research directions in hybrid EAs involve several major areas. The first area is the application of hybrid EAs to special types of optimization problems, such as constrained optimization (Wang et al., 2009) and multi-objective optimization (Niknam, 2009). The second area is the application of hybrid EAs to real-world optimization problems (Liang et al., 2009; Lin et al., 2009). The third area is the determination of which EAs to combine in a hybrid algorithm (Lozano and Garcia-Martinez, 2010; Blum et al., 2011). The fourth area is the determination of how to hybridize a given set of EAs into a single algorithm (Gen and Lin, in press; Prodhon, 2011); that is, how to determine the hybridization strategy. The goal of this paper is to address the fourth research area. In general, we propose the application of EA information-sharing ideas to the hybridization of constituent EAs. That is, just as a single EA uses specific mechanisms to share information among candidate solutions, we use the same mechanisms to share information among constituent EAs in a hybrid EA. The information-sharing mechanism that we propose in this paper is based on biogeography-based optimization (BBO).

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BBO is an EA that was introduced in 2008 (Simon, 2008, 2011). It is modeled after the immigration and emigration of species between habitats. One distinctive feature of BBO is that in each generation, BBO uses the fitness of each candidate solution to determine the candidate solution's immigration and emigration rate. The emigration rate increases with fitness, and the immigration rate decreases with fitness. BBO has demonstrated good performance on benchmark functions (Ma, 2010; Boussaïd et al., 2012). It has also been applied to many real-world optimization problems, including economic load dispatch (Bhattacharya and Chattopadhyay, 2010), wireless network power allocation (Boussaïd et al., 2011, 2013a), flexible job shop scheduling (Rahmati and Zandieh, 2012), power system optimization (Jamuna and Swarup, 2012), antenna design (Singh et al., 2010), and others (Chatterjee et al., 2012; Wang and Xu, 2011).

The main contribution of this paper is to propose new EA hybridization strategies that are based on migration behaviors in biogeography. We propose biogeography-based hybridization at both the iteration level and the algorithm level. Although BBO has already been hybridized with other algorithms, this paper represents the first time that EAs have been hybridized with each other using biogeography-based migration. Our motivation for biogeography-based migration in hybrid EAs is twofold: first, we note the good performance obtained in past research with BBO; and second, we note the good performance obtained in past research with hybrid EAs. Given these two factors, we hypothesize that hybridization using biogeography-based operations will provide some advantages over other hybrid EAs. We demonstrate our hybridization approaches with several recently-developed EAs, and we analyze the optimization results with statistical tests.

In iteration-level hybridization we combine various EAs with BBO. In algorithm-level hybridization we combine various EAs using ideas from biogeography. Note that in algorithm-level hybridization, we do not necessarily combine a particular EA with BBO. Instead we use the BBO migration strategy to combine multiple EAs. In this approach, various EAs are taken as the baseline algorithms, and then we make use of the migration mechanism of BBO to adaptively improve the solutions. That is, the constituent EAs generate offspring individuals each generation, and then we use the BBO migration operator to exchange information between these individuals.

The recently developed EAs that we hybridize include covariance matrix adaptation evolution strategy (CMA-ES) (Hansen, 2006; Hansen et al., 2003), stud genetic algorithm (SGA) (Khatib and Fleming, 1998), self-adaptive differential evolution (SaDE) (Zhao et al., 2011), 2011 standard particle swarm optimization (PSO2011) (Omran and Clerc, 2011), PSO with linearly varying inertia weight (LPSO) (Shi and Eberhart, 1998; Chatterjee and Siarry, 2006), and PSO with constriction factor (CPSO) (Clerc and Kennedy, 2002; Eberhart and Shi, 2000). We choose these algorithms because they are some of the most recent and best-performing EA variants. The six algorithms that we choose form a representative set rather than a complete set. We could hybridize many other algorithms besides these six. However, the goal here is not to be exhaustive, but rather to present a general biogeography-based hybridization strategy and demonstrate it on a representative set of constituent algorithms and benchmarks.

The rest of this paper is organized as follows: Section 2 gives a brief overview of EAs, including the constituent algorithms used in the rest of the paper. Section 3 presents our new hybridization methods. Section 4 tests our new algorithms on the continuous optimization benchmark functions from the 2013 Congress on Evolutionary Computation (CEC) and on some real-world traveling salesman problems, and performs some robustness tests. Section 5 gives conclusions and directions for future research.

2. Evolutionary algorithms

This section presents the basic outlines of the constituent EAs used in this paper, including CMA-ES, SGA, SaDE, PSO, and BBO.

2.1. Covariance matrix adaptation evolution strategy (CMA-ES)

ES is an evolutionary algorithm based on the ideas of adaptation during recombination, mutation, and selection. There are many variants of ES, and CMA-ES is a recent ES variant that has demonstrated good performance (Hansen, 2006; Hansen et al., 2003). It is a non-elitist algorithm that first samples a number of new candidate solutions from a multivariate normal distribution and then updates the sampling distribution using the better candidate solutions. The update consists of two major mechanisms: step size control and covariance matrix adaptation. In step size control, the length of the path of the most recent iteration step is adjusted. In covariance matrix adaptation, the likelihood of successful steps is increased. The time scales of the two updates are independent. The step size can change fast to allow for fast convergence to a good solution. The covariance matrix changes on a slower time scale to maintain stability.

2.2. Stud genetic algorithm (SGA)

GAs are the most popular EAs, and were introduced as a computational analogy of adaptive biological systems. They are modeled on natural selection. There are many GA variants, one of which is the stud GA (SGA) (Khatib and Fleming, 1998). The basic idea of SGA is to use the best solution in the population as one of the parents in all recombination operations. That is, instead of stochastic selection of both parents, only one parent is selected stochastically, and the other parent is always chosen as the fittest individual (the stud). The benefits of this GA variation are improved optimization performance and computational efficiency.

2.3. Self-adaptive differential evolution (SaDE)

DE is a simple evolutionary algorithm that creates new candidate solutions by combining the parent solution and several other candidate solutions. A candidate solution replaces the parent solution if it has better fitness. This is a greedy selection scheme that often outperforms traditional evolutionary algorithms. SaDE is one of the best DE variants (Zhao et al., 2011). It uses a self-adaptive mechanism on control parameters F and CR. Each candidate solution in the population is extended with control parameters F and CR that are adjusted during evolution. Better values of these control parameters lead to better candidate solutions, which in turn are more likely to survive the selection process to produce the next solution and propagate the good parameter values. SaDE is highly independent of the optimization problem's characteristics and complexity, and it involves self-adaptation and learning by experience. SaDE demonstrates consistently good performance on a variety of problems, including both unimodal and multimodal problems.

2.4. Particle swarm optimization (PSO)

PSO is a swarm optimization algorithm that is inspired by the collective behavior of a flock of birds or a school of fish. PSO consists of a swarm of particles moving through the search space of possible problem solutions. Every particle has a position vector encoding a candidate solution to the problem and a velocity vector to update position. PSO relies on the learning strategy of the particles to guide its search direction. Traditionally, each particle uses its historical best value and the global best value of the entire