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A novel hybrid Cultural Algorithms framework with trajectory-based search for global numerical optimization

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ABSTRACT

In recent years, Cultural Algorithms (CAs) have attracted substantial research interest. When applied to highly multimodal and high dimensional problems, Cultural Algorithms suffer from fast convergence followed by stagnation. This research proposes a novel hybridization between Cultural Algorithms and a modified multiple trajectory search (MTS). In this hybridization, a modified version of Cultural Algorithms is applied to generate solutions using three knowledge sources namely situational knowledge, normative knowledge, and topographic knowledge. From these solutions, several are selected to be used by the modified multi-trajectory search. All solutions generated by both component algorithms are used to update the three knowledge sources in the belief space of Cultural Algorithms. In addition, an adaptive quality function is used to control the number of function evaluations assigned to each component algorithm according to their success rates in the recent past iterations. The function evaluations assigned to Cultural Algorithms are also divided among the three knowledge sources according to their success rates in recent generations of the search. Moreover, the quality function is used to tune the number of offspring these component algorithms are allowed to contribute during the search. The proposed hybridization between Cultural Algorithms and the modified trajectory-based search is employed to solve a test suite of 25 large-scale benchmark functions. The paper also investigates the application of the new algorithm to a set of real-life problems. Comparative studies show that the proposed algorithm can have superior performance on more complex higher dimensional multimodal optimization problems when compared with several other hybrid and single population optimizers.

1. Introduction

Many real-life problems can be formulated as single objective global optimization problems. In single objective global optimization, the objective is to determine a set of state-variables or model parameters that offer the globally optimum solution of an objective or cost function. The cost function usually involves D decision variables: $\vec{X} = [x_1, x_2, x_3, \ldots, x_D]^T$. The optimization task is essentially a search for a parameter vector $\vec{X}^*$ that minimizes the cost function $f(\vec{X})$ $(f : \Omega \subseteq \Re^D \rightarrow \Re)$ where Ω is a

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non-empty, large but bounded set that represents the domain of the decision variable space. In other words, $f(\vec{X}^*) < f(\vec{X}),\ \forall \vec{X} \in \Omega$. The focus on minimization does not result in a loss of generality since $\max\{f(\vec{X})\} = -\min\{-f(\vec{X})\}$.

Recently there has been a growing interest in utilizing population-based stochastic optimization algorithms for the solution of global optimization problems, due to the emergence of important real-world problems of high complexity [27,35,47]. These stochastic search algorithms do not require that the fitness landscape be differentiable.

While many population-based stochastic algorithms have been developed for the solution of real-valued optimization problems, they can often get trapped in locally optimal basins of attraction when solving problems with complex landscapes. One approach to the solution of this problem is through the combination, hybridization, of algorithms with complementary properties in a synergistic fashion. Hybridization offers a great potential for developing stochastic optimization algorithms with search properties that are superior in performance to their constituent algorithms in terms of both resiliency and robustness [6,7,16,32]. For example, a new optimization algorithm called the Big Bang-Big Crunch (BB-BC) algorithm was introduced which is based on both the Big Bang and the Big Crunch Theories [12]. The algorithm is used to generate random points in the Big Bang phase that will be substituted for a single representative point via a center of mass in the Big Crunch phase. The algorithm exhibited an enhanced performance over a modified Genetic Algorithm that was also developed by the same authors. More recently, a novel heuristic optimization method namely, Charged System Search (CSS), was proposed [25]. The algorithm is based on principles from statistical mechanics and physics, especially Coulombs law from Newtonian laws of mechanics and electrostatics. The theory behind this hybrid algorithm makes it suitable for non-smooth or non-convex domains as it does not need information about the continuity nor the gradient of the search space.

Other evolutionary algorithms embrace the concept of hybridization in different ways. In these approaches multiple optimization algorithms are run concurrently, as in AMALGAM-SO [43]. This algorithm merges the strengths of Covariance Matrix Adaptation [4], Genetic Algorithms, and Particle Swarm Optimization. It employs a self-adaptive learning strategy that determines the number of individuals for each algorithm to use in each generation of the search process. The algorithm was tested on the IEEE CEC2005 real parameter optimization [40] and was shown to generate promising results on complex high dimensional multimodal problems.

Still other hybrid algorithms also demonstrate competitive performance when one of the algorithms is used to tune the parameters for the other. [46]. In [46], CoBiDE utilizes covariance matrix adaptation in order to establish an appropriate coordinate system for the crossover operator that is used by the Differential Evolution Component (DE). This helps to relieve the dependency of the DE on the coordinate system to a certain extent. Moreover, bimodal distribution parameter setting were proposed to control the crossover and mutation parameters of the DE. The algorithm demonstrated improved results on a set of standard functions and a wide range of engineering optimization problems.

The authors of PSO6-Mtsls [17] utilized an improved version of PSO where a multiple trajectory search algorithm was used to coordinate the search of individuals in the population. Each particle received local information from 6 neighbors and was guided by a trajectory.

Data intensive hybrid approaches frequently use Cultural Algorithms. Nguyen and Yao [32] proposed a hybrid framework consisting of Cultural Algorithms and iterated local search in which they used a shared knowledge space that is responsible for integrating the knowledge produced from pre-defined multi-populations. Knowledge migration in this context was used to guide the search in new directions with less communication cost. Another technique that hybridized Cultural Algorithms with an improved local search is presented in [5]. Coelho and Mariani [7] suggested using PSO as a population space in the cultural framework for numerical optimization over continuous spaces in order to increase the efficiency of the search. Another approach used an improved particle swarm algorithm with Cultural Algorithms was introduced by Wang et al. [44]. Bacerra and Coello [6] proposed an enhanced version of Cultural Algorithms with differential evolution so as to enhance diversity in the population of problem solvers during the optimization process. Although the results obtained by their algorithm were similar (in quality) to other approaches to which it was compared, it was able to achieve such results with a fewer number of function evaluations. Xue and Guo [50] introduced a hybridized Cultural Algorithms with Genetic Algorithms in order to solve multi-modal functions.

Another hybrid approach employs Cultural Algorithms to extract useful knowledge from a Genetic Algorithm population space for the solution of job shop scheduling problems [45]. A similar hybridization was used in [21] for the optimization of real world applications. In [3], the authors introduced a hybrid approach that combines Cultural Algorithms with a niching method for solving engineering applications. An improved Cultural Algorithms based on balancing the search direction is also presented in [2]. Other significant examples of hybridizing Cultural Algorithms with other techniques can be found in [16].

While hybridization has its advantages it also comes with a potential cost. First, there needs to be a way to balance the component algorithms in terms of exploration and exploitation [18,35]. Second, with more algorithms under the hood, the optimization engine may require more computational resources in the worst case. It is important Thus, keeping the hybrid algorithm simple can help to limit the number of Function Evaluations (FE) needed to solve a problem [1,6].

In this paper, we propose a simple yet powerful, hybrid evolutionary algorithms that synergistically combines the features of two global optimizers: Cultural Algorithms (CA) and multiple trajectory search (MTS) for multimodal optimization. The Cultural Algorithms (CA) is an evolutionary algorithm (EA) that provides a powerful tool for solving data intensive problems [1,37] and has successfully handled many optimization problems and applications [1,20,34,37]. It can be defined as an evolutionary model that consists of both a belief and population space with a set of communication protocols that combine the interaction of the two spaces.