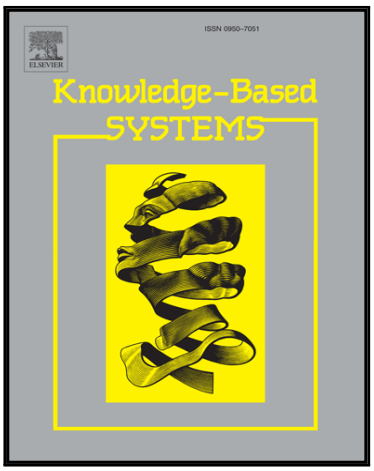

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PII: S0950-7051(16)30265-9
DOI: 10.1016/j.knosys.2016.08.005
Reference: KNOSYS 3632

To appear in: *Knowledge-Based Systems*

Received date: 21 December 2015
Revised date: 14 June 2016
Accepted date: 5 August 2016

Please cite this article as: Mostafa Z. Ali , Noor H. Awad , Ponnuthurai N. Suganthan , Robert G. Reynolds , A Modified Cultural Algorithm with a Balanced Performance for the Differential Evolution Frameworks, *Knowledge-Based Systems* (2016), doi: 10.1016/j.knosys.2016.08.005

A Modified Cultural Algorithm with a Balanced Performance for the Differential Evolution Frameworks

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Abstract

Numerous different methodologies have been introduced in the last few decades to provide efficient solutions for complex real-world problems and other optimization problems. This work focuses on the development of a simple hybrid cultural learning theme with a balanced performance for differential evolution frameworks. It is intended to be always efficient for a diverse set of optimization tasks. As different optimization algorithms behave differently depending on the problems, the combination of the best behaviors from different search strategies seems desirable. The proposed work explores the combination of the explorative/exploitative strengths of two heuristic search techniques, which discretely provide competitive results. Differential evolution is used as the population space for Cultural Algorithm, and is used to guide knowledge dissemination from the knowledge sources in the belief space. Here, a new influence function is introduced that adjusts the membership of each of the knowledge sources. The algorithm has been tested with the conditions and benchmark problems defined for the IEEE CEC2013 special session and competition on real-parameter single objective optimization. The paper also investigates the application of the new algorithm to a set of real-life problems concerning optimizing the weight a tension/compression spring and minimizing the fabrication cost of a welded beam engineering problem. The proposed algorithm appears to have a significant impact on the algorithmic functioning as it reliably augments the performance of the differential evolution frameworks with which it is integrated. Benchmark results for most of the synthetic functions from the special session show that the balanced hybrid obtains superior performance compared to the other competent algorithms. It scales well with the increasing dimensionality and converges in the close proximity of the global optimum for complex functions.

Keywords: Evolutionary algorithm, Cultural Algorithm, differential evolution, optimization, hybrid algorithm.

1. Introduction

Many real-life problems can be formulated as optimization problems. Hence, a considerable amount of research has been done to locate the global optimal solution to a problem. Generally, any optimization problem can be expressed as follows:

Minimize: $f(x)$, $X = \{x_1, x_2, ..., x_D\}, x_i \in [x_l, x_u]$ (1)

where $f(x)$ is the objective function being optimized over x, D is the dimension of the problem, and x_l, x_u are the lower and upper bounds for parameter x_i.

To solve such problems, many nature-inspired methods have been used such as Evolutionary Computation (EC) [1], Tabu Search (TS) [2], Genetic Algorithm (GA) ([3]), Simulated Annealing (SA) [4], Particle Swarm Optimization (PSO) [5], and Differential Evolution (DE) [6]. Cultural Algorithm (CA) provides a powerful tool for solving sophisticated problems and has successfully handled many optimization problems [7], [8]. It can be defined as a knowledge intensive evolutionary model with two components, namely a belief and population spaces, with communication protocols that coordinate the interaction of the two spaces. However, an issue facing all evolutionary algorithms is the potential for premature convergence and stagnation scenarios [9]. In order to overcome these issues researchers usually enhance the performance of their algorithms by introducing new and efficient techniques that