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An improved Harmony Search Algorithm embedded with a novel piecewise opposition based learning algorithm

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ABSTRACT

Harmony Search Algorithm (HS) is one of the most popular, music-inspired meta-heuristic algorithm. Since its conception HS has been used to solve many complex problems. However, this population based algorithm and its variants suffer from slow convergence speed to the globally optimal solutions. Hence they are computationally expensive. Opposition Based Learning Theory, a machine learning algorithm addresses this issue by considering both estimates and counter-estimates i.e. guess and counter-guess of a candidate solution, population and opposite population of a population based algorithm etc. simultaneously. Although this approach shows great promise, the problem of slow convergence rate in Harmony Search Algorithm is still not completely alleviated. We introduce some improvements over the Opposition based Learning Theory to accelerate the convergence rate of such algorithms. The proposed scheme employs a piecewise counter estimate updating technique while computing a candidate solution. In the present work, the proposed Opposition based Learning technique has been embedded in the framework of Harmony Search Algorithm. An exhaustive set of test functions is used in the experimental setup. The results obtained from the experiments are very promising.

1. Introduction

Machine learning algorithms learn from the available past data, estimate a candidate solution and try to improve upon that solution over multiple iterations. The heuristics used by many of these algorithms are inspired from nature. One of the most popular algorithm among these is Evolutionary Algorithm (EA) (Eiben JES, 2003; Coello Coello, 2013). There are several different kinds of EA present in the contemporary literature, such as Genetic Algorithm (Srinivas and Patnaik, 1994), Harmony Search Algorithm (Abdel-raouf, 2013), Swarm Intelligence (Vanitha and Padma, 2014), Ant Colony Optimization Algorithm (Dorigo and Blum, 2005), Differential Evolution (Storn and Price, 2017) etc. Each of these algorithms has their respective advantages and disadvantages, but they all have a common drawback. Their rates of convergence over the search space are very low, thus making them computationally expensive and infeasible for real-world applications. In the present work, we specifically focus on Harmony Search Algorithm (Abdel-raouf, 2013) and try to rectify its slow convergence speed.

Opposition based learning (OBL) theory, introduced by Tizhoosh (2005a) proposes modifications to improve upon the convergence rate of an Evolutionary Algorithm. By simultaneously considering both the candidate estimate and its corresponding *counter estimate* (Tizhoosh, 2005a) it selects the one which is closer to the global optimal value. Following basic algebra (Feller, 2008), there is a 50% chance that the corresponding *counter estimate* is closer to the desired solution than the candidate itself. Therefore intuitively, following OBL theory to select the fitter candidate solution helps to improve upon the quality of the candidate solution at each iteration; which accelerates the convergence rate of the EA algorithm in process. Since its conception, OBL theory has been applied to solve many real-world problems such as optimization of combined heat and power dispatch (Roy et al., 2014), biogeography based optimization for cardiac disease detection (Ovreiu and Simon, 2010), reducing training time for recurrent neural networks (Ventresca and Tizhoosh, 2007) etc. However, OBL theory, although remedies the problem of slow convergence rate of population based algorithms to some extent, it is far from being an ideal solution towards addressing it completely. Hence, an improvement over OBL theory, named *Piecewise Opposition based Learning* (POBL) algorithm is introduced in this paper. The proposed algorithm redefines the *counter estimate* or *opposite point* of a candidate solution. When computing the *counter estimate* of a candidate solution, instead of considering all of the components of the candidate solution at once, the proposed algorithm considers each component separately and updates them individually. A self-adaptive Harmony

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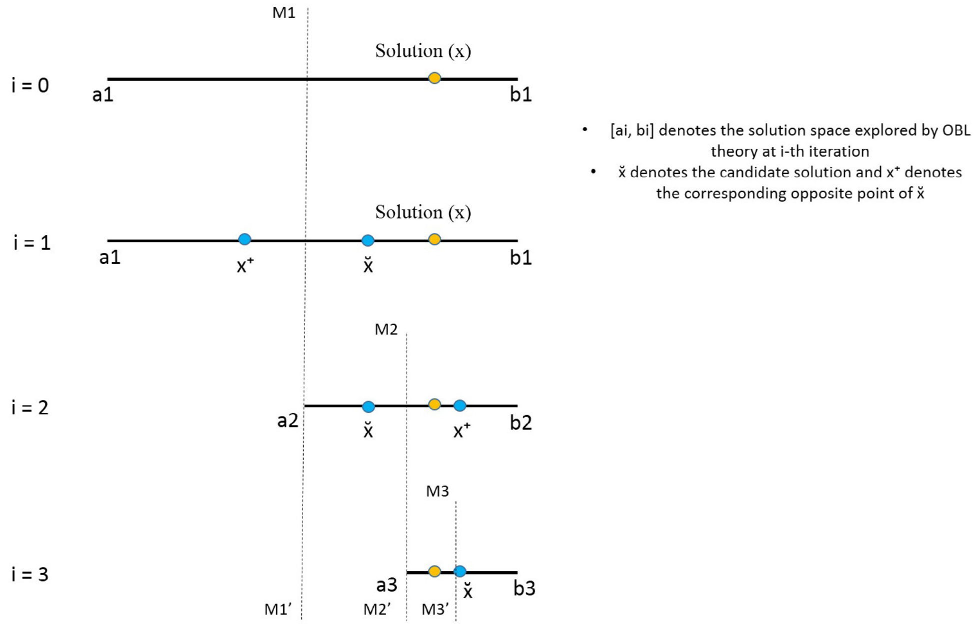

Fig. 1. Solving a problem using OBL theory by recursively halving of search interval based on proximity of $\breve{x}$ and x^+ *to the actual solution* x.

Search Algorithm employing the proposed POBL theory denotes one of the major contributions of the present work.

A set of benchmark test functions has been employed in the current experimental setup to evaluate the performance of the proposed algorithm. Several metrics suggested by contemporary researchers (Rahnamayan et al., 2008b) have been used to quantify the performance of the algorithm, which are: average number of function calls (NFC), success rate (SR), average success rate (ASR), and acceleration rate (AR). Definitions of each of these metrics are discussed later. A comparative analysis of the proposed algorithm against a set of popular, contemporary algorithms (Abdel-raouf, 2013) is also presented in this paper.

Organization of the rest of the paper is as follows: in Section 2, a brief introduction to Opposition based Learning theory is presented. Section 3 contains description of the proposed work. Experimental results and subsequent analysis are described in Section 4. A brief conclusion is made in Section 5. And finally, Appendix A describes the characteristics of the benchmark functions employed in our experimental setup and Appendix B describes an overview of the experimental results by embedding the proposed *piecewise opposition based learning* theory with EAs other than Harmony Search Algorithm.

2. An overview on opposition based learning theory

When solving a problem to determine the value of an unknown variable x, a learning algorithm generally starts with an estimate $\breve{x}$ of the solution. If the problem is complex and/or sufficient knowledge about the solution is not known beforehand, this solution is generally initiated by a random guess. At each iteration, the algorithm tries to improve upon this estimate $\breve{x}$ until it finally converges to the desired optimal solution or some predefined termination criteria is met. Therefore, the computational complexity of these algorithms renders to the quality of the initial random guess. For some cases, if the initial estimates are far from the actual solution, let us say at the *opposite location* (Tizhoosh, 2005b) of where the current candidate solution resides, it will take considerably more time for the algorithm to converge. To improve the poor quality of the initial guess, Tizhoosh (2005b) proposed to search for the candidate solution at all directions simultaneously. OBL theory takes a step towards the right direction following this intuition, by simultaneously considering the *counter estimate* x^+ of an estimate $\breve{x}$ at each iteration of the algorithm.

2.1. Definitions and notations

Definition 1. Let $P(x_1, x_2, \dots, x_n)$ be a point in n-dimensional space, where $x_1, x_2, \dots, x_n \in R$ and $x_i \in [a_i, b_i]\ \forall i \in 1, 2 \dots n$. The *opposite point* of P is defined by $P^+(x_1^+, x_2^+, \dots, x_n^+)$, where:

$$x_i^+ = a_i + b_i - x_i. \tag{1}$$

2.2. Opposition based learning

Let $P(x_1, x_2, \dots, x_n)$ be a point in an n-dimensional space with $x_i \in [a_i, b_i]\ \forall i \in 1, 2 \dots n$, is a candidate solution to an optimization problem. Assume $f(x)$ is the fitness function, used to measure the quality of a candidate solution. According to the definition described above, $P^+(x_1^+, x_2^+, \dots, x_n^+)$ is the opposite of $P(x_1, x_2, \dots, x_n)$ (as shown in Eq. (2)). Now, if $f(P^+) \geq f(P)$ (for a maximization problem), then point P is replaced with P^+; otherwise we continue with P. Hence, the point and its corresponding *opposite point* are evaluated simultaneously and compared at each iteration of the algorithm to continue with the fitter one. The working principle of opposition-based optimization is shown in Fig. 1. For the sake of simplicity and to introduce the notion of opposition based learning (OBL) theory to the readers, a one-dimensional problem, solved using OBL theory has been illustrated in Fig. 1.

As shown in Fig. 1, the algorithm starts with an interval $[a1, b1]$ and tries to find out the solution of the given problem based on repeated comparisons of the guess $\breve{x}$ and its corresponding opposite or counter guess x^+ with respect to an objective function. All of the components of candidate solution (x) gets updated at each iteration of OBL theory. The search interval is recursively halved at each iteration of the algorithm based on the proximity of the estimate and its corresponding counter estimate to the actual solution, until the final solution is close enough to the desired solution x. A slightly more complicated example of the workings of OBL theory in a two-dimensional solution space has been presented later in Fig. 2.

3. The present Work

In this section, the proposed *Piecewise Opposition based Learning* (POBL) technique is described in details. There are two stages (Rahnamayan et al., 2008b) of any Evolutionary Algorithm which can be