Information Sciences 267 (2014) 58–82

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Cluster-based differential evolution with Crowding Archive for niching in dynamic environments

Rohan Mukherjee [a], Gyana Ranjan Patra [a], Rupam Kundu [a], Swagatam Das [b,*]

[a] Department of Electronics and Telecommunication Engineering, Jadavpur University, Kolkata 700 032, India
[b] Electronics and Communications Sciences Unit, Indian Statistical Institute, Kolkata 700 108, India

ARTICLE INFO

Article history:
Received 9 March 2013
Received in revised form 14 September 2013
Accepted 19 November 2013
Available online 8 January 2014

Keywords:
Multimodal optimization
Dynamic optimization problem
Niching
Clustering
Crowding
Archive

ABSTRACT

Real world optimization problems may very often be dynamic in nature, i.e. the position or height of the optima may change over time instead of being fixed as for static optimization problems. Dynamic Optimization Problems (DOPs) can pose serious challenges to the evolutionary computing community, especially when the search space is multimodal with multiple, time-varying optima. Some recent experimental studies have indicated that the process of evolutionary optimization can benefit from locating and tracking of several local and global optima instead of the single global optimum. This necessitates the integration of specially tailored niching techniques with an Evolutionary Algorithm (EA) for grouping of similar individuals in optimal basins of the landscape against drift and other disruptive forces as well as for making such individuals track the basins whenever dynamic changes appear. Motivated by such requirements, we present a multipopulation search technique involving a clustering strategy coupled with the memory-based Crowding Archive for dynamic niching in non-stationary environments. The algorithm uses Differential Evolution (DE) as its basic optimizer and is referred here as the Cluster-based DE with Crowding Archive (CbDE-wCA). It is equipped with a few robust strategies like favorable solution retention and generation, clearing strategy to eliminate redundant solutions, and crowding to restrict individuals to local search. The performance of the proposed algorithm has been tested on two different instances of the Moving Peaks Benchmark (MPB) problems. Experimental results indicate that CbDE-wCA can outperform other state-of-art dynamic multimodal optimizers in a statistically significant way, thereby proving its worth as an attractive alternative for niching in dynamic environments.

1. Introduction

Several optimization problems in the real world are dynamic in nature. The characteristics of the functional landscape of these dynamic problems changes with time i.e. optima of the problem to be solved shifts their locations over time and, thus, the optimizer should be able to track the optima continually by responding to the dynamic environment [18,26]. Practical examples of such situations are price fluctuations, financial variations, and stochastic arrival of new tasks in a scheduling problem, and machine breakdown or maintenance. Under dynamic environments, converging tendency of a conventional EA imposes severe limitations on performance of the EA. If the population members of the EA converge rapidly, they will be unable to effectively respond to the environmental changes. Therefore, in case of DOPs the main challenge is to maintain

* Corresponding author.
E-mail addresses: rohan.mukherjii@gmail.com (R. Mukherjee), gyana.patra@gmail.com (G.R. Patra), rupam2422@gmail.com (R. Kundu), swagatam.das@isical.ac.in (S. Das).

0020-0255/$ - see front matter © 2014 Published by Elsevier Inc.
http://dx.doi.org/10.1016/j.ins.2013.11.025

the diversity and at the same time to produce high quality solutions by tracking the moving optima. Over the past two decades or so, researchers from the evolutionary computing community have been attempting to develop efficient algorithms, which can provide acceptable solutions to DOPs. Some of the most prominent approaches to adapt a conventional EA for dynamic optimization include diversity preserving schemes [7,14,17,45], memory-based schemes [3,13,43,44], multipopulation schemes [4,15,20,46,47], multi-objective optimization methods [6], hybrid approaches [19,23], change prediction methods [34], and problem change detection approaches [31].

Recently several researchers have advocated for detecting multiple optimal or near-optimal solutions (than merely the single global optimum) to solve DOPs in an effective manner [2,20,22,28]. The advantages are twofold. Firstly, locating and tracking a set of promising solutions (forming spatially diverse domains of attraction on the fitness landscape) enhances the chances of detection of the global optimum after the occurrence of a dynamical change. This is because usually one of the current near optimal solutions possesses relatively higher possibility of becoming the global optimum solution in the next environment than the other candidate points of the population. Secondly, for a multimodal landscape, if multiple global optima are known and if the currently focused global optimum does not remain the same due to a change in the environment, the implementation can be quickly switched to another solution while still maintaining an optimal system performance. These facts motivate us to adopt niching techniques in dynamic environments and attempt modifying an existing powerful EA like DE to detect and track multiple optima (local and global) of a dynamic multimodal function with greater accuracy. Most of the real world problems happen to be multi-modal with multiple local or global solutions co-existing in time. A single-peak global optimizer in these cases will face two main difficulties. Firstly it will lose its explorative power and fail to obtain best solution when dominance of the best solution shifts with dynamic change of the fitness landscape. Secondly a global optimizer may get trapped in local optima more often than an optimizing technique that incorporates additional mechanisms to preserve the diversity of the population. A global optimizer can converge to any of the several possible optima and lose its explorative power, thus, leaving the global solution unexplored. In an on-line dynamic optimization problem, for example controlling the parameters of a robot while it is being operated, this may give rise to a serious issue. It might hamper the entire operation as the obtained parametric set may be useless. However, a multimodal optimizer can easily avoid such problem as it is tailored to search in such space that is characterized by local optima. In a dynamic scenario, the demand of such specific mode of optimization is more desired as the primary concern is to maintain the diversity of the population while the search progresses. The population can never be allowed to stagnate to a particular optima, rather search the entire space for any emerging new optima. Thus, to handle DOPs which in most cases involve numerous optima, a dynamic *niching* optimizer is likely to be more helpful than a single-peak global optimizer.

Niching is a generic term referred to as the technique of finding and preserving multiple stable *niches*, or favorable parts of the solution space possibly around multiple solutions, so as to prevent convergence to a single point. There exists a wealth of research works on integrating niching techniques with EAs for locating multiple optima of a static multimodal function. A detailed account of such studies can be found in [52] and the references therein. Recently researchers have turned their attention to niching techniques for detecting multiple peaks in dynamic environments (see for example [28,33]). Differential Evolution (DE) [10,36,37] has emerged as one of the most powerful real-parameter optimizers currently in use. DE implements similar computational steps to that of standard Evolutionary Algorithms (EAs). However, unlike traditional EAs, DE-variants perturb the current-generation population members with the scaled differences of randomly selected and distinct population members. Therefore, no separate probability distribution is used to generate offspring. A well-known variant of DE with niching is the Crowding DE (CDE) algorithm [38] where the offspring, as generated by DE, competes with its nearest member of the population to preserve diversity and spatial information within the population. Although CDE provides satisfactory results for simpler and low-dimensional, static, and multimodal functions, the fine-tuning ability of the algorithm is limited. Its performance degrades considerably on high-dimensional and complex multimodal landscapes [30,38].

In this article we propose a clustering and re-clustering scheme based modified CDE algorithm to detect and track multiple peaks on a time-varying functional landscape. Current population is grouped together according to their proximity with other members based on Euclidean distance measure. The clustering technique adds explorative capability to the algorithm as different clusters are used to search in different parts of the landscape. Moreover CDE stages of mutation, recombination and crowding based selection are restricted to individual clusters enhancing local exploitative capability of the population. Here the selection of proper clustered local environment for each solution essentially demands an efficient grouping technique which is attained using Fuzzy C-Means with decisive cluster selection by the solutions on basis of maximum membership function.

The proposed Cluster-based DE with Crowding Archive (CbDE-wCA) integrates CDE with a clustering scheme, and a Crowding Archive based favorable solution retention technique to tackle multimodal landscapes in DOPs. Moreover favorable solution generation technique and a clearing technique add to the advantages of the algorithm. Experimental results in terms of the offline error and number of peaks discovered are compared with several state-of-the-art methods. The comparison results reflect the superiority of the proposed algorithm, thus, establishing it as an attractive alternative means for detecting and tracking multiple peaks on a dynamic functional landscape.

The remaining paper is organized as follows. Previous approaches are reviewed in Section 2. Section 3 gives a brief idea and motivations behind formulation of our algorithm and also discusses its uniqueness. An insight on the previous works that directly influence our algorithmic framework has been taken in Section 4. The different components of the algorithm