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Coevolutionary multitasking for concurrent global optimization: With case studies in complex engineering design

Mei-Ying Cheng [a], Abhishek Gupta [b], Yew-Soon Ong [b,*], Zhi-Wei Ni [c,*]

[a] Business School, Huzhou University, 313000, China
[b] School of Computer Science and Engineering, Nanyang Technological University, Singapore 639798, Singapore
[c] School of Management, Hefei University of Technology, 230009, China

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ABSTRACT

Recent research efforts have provided hints towards the innate ability of population-based evolutionary algorithms to tackle multiple distinct optimization tasks at once by combining them into a single unified search space. On the occasion that there emerges some form of complementarity between the tasks in the unified space, *multitask optimization* can bring about favourable leaps in the genetic lineage through automated gene transfer, thereby leading to notably accelerated convergence characteristics. In this paper, we further emphasize the efficacy of multitasking across problems through an algorithmic realization based on a coevolutionary framework. It is contended that the mechanics of cooperative coevolution are particularly well suited for exploiting the commonalities and/or complementarities between different (yet possibly related) optimization tasks in a single multitasking environment. To this end, we label the resultant approach as *coevolutionary multitasking* for concurrent global optimization. Further, in order to effectively navigate continuous search spaces of varying degrees of complexity, we employ the particle swarm algorithm as a sample instantiation of a base optimizer for a real-parameter unification scheme. Based on a series of numerical experiments carried out for synthetic functions as well as real-world optimization settings in engineering design, we demonstrate the efficacy of multitask optimization as a paradigm promising enhanced productivity in future decision making processes.

1. Introduction

The concept of multitasking has been applied with much success in the field of machine learning for at least the past two decades (Caruana, 1997, 1998). The motivation behind the idea is essentially to exploit the useful information from related tasks by performing learning with a shared representation. In recent studies, such as Gupta et al. (2016c, b), it has been shown that similar ideas can naturally be extended to the domain of global optimization as well. In particular, it is revealed that latent complementarities that may exist between function landscapes of distinct optimization tasks can be autonomously harnessed by unleashing the power of implicit parallelism of population-based search (Bertoni and Dorigo, 1993) in a multitasking environment. An intuitive explanation of what it might mean for function landscapes to be complementing shall be presented in the next section of the paper. Interestingly, in contrast to traditional tabula rasa optimization where the search process starts from scratch for every new problem (assuming no prior knowledge from previous or related problem-solving exercises), *multitask optimization* provides the necessary means for exploiting the potentially rich stream of knowledge (in the form of data) generated during the evolutionary search of different optimization tasks. Ignoring this knowledge may often be regarded as counterproductive, a fact that has arguably been limiting the true productivity of present-day search algorithms.

In Gupta et al. (2016c), the notion of multitasking in global search was formalized under the label of *multifactorial optimization*, where the nomenclature emphasizes the fact that each task in a multitasking environment represents an additional *factor* influencing the evolution of a single population of artificial search agents (or individuals). Subsequently, a simple *multifactorial evolutionary algorithm* (MFEA) was proposed based on the observation that while navigating a unified search space $\boldsymbol{Y}$ encompassing the heterogeneous search spaces $\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X}_K$ of K distinct optimization tasks, it is intuitively probable that a randomly generated or genetically modified solution that is unsuitable for one task may turn out to be of high quality with respect to some

* Corresponding authors.
E-mail addresses: qyc12117@126.com (M.-Y. Cheng), abhishekg@ntu.edu.sg (A. Gupta), asysong@ntu.edu.sg (Y.-S. Ong), zhwnelson@163.com (Z.-W. Ni).

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other task. Similarly, it is also possible that a solution in the unified space is good for more than one task at the same time. In both the aforementioned cases, the MFEA provides the scope for enhancing overall efficiency of the search process by allowing multiple tasks to be bundled together and facilitating *implicit genetic transfer* between them through small adjustments to traditional evolutionary operations (Ong and Gupta, 2016).

The design of the MFEA follows bio-cultural models of *multifactorial inheritance* (Rice et al., 1978; Cloninger et al., 1979), which essentially describe the manner in which diverse and complex development traits emerge among offspring belonging to the same species as a consequence of the interactions between various genetic and cultural/environmental factors. Although this is found to be a suitable metaphor for accommodating multitask settings, we note that computational analogs of multifactorial inheritance, for the purpose of optimization problem-solving, is in itself a largely unexplored subject in the field of evolutionary computation (EC). Accordingly, the key purpose of the present paper is to demonstrate that effective multitasking behaviour can be naturally derived from existing concepts in EC, without any pressing need to invoke the concept of multifactorial inheritance. In particular, we build upon well-established coevolutionary theory that has recently found widespread interest among EC researchers. In biology, the term *cooperative coevolution* is often used to explain a relationship where two organisms of different species work together, each benefiting from the mutual interaction (Chandra et al., 2017; Wiegand et al., 2002). In other words, when changes in the genetic compositions of at least two distinct species or subpopulations mutually affect the evolution of each other, coevolution is said to have occurred (Stearns and Hoekstra, 2000). With this background, it is conjectured that, assuming K optimization tasks in a multitasking environment to constitute K subpopulations in a unified ecosystem $\boldsymbol{Y}$, computational analogs of the mechanisms of coevolution may be well suited for tackling them concurrently (i.e., on the same machine, within the same algorithm, and at the same time). Most importantly, the scope for automatic exchange or transfer of potentially useful knowledge nuggets across distinct (but possibly similar) optimization problems is facilitated via the *explicit* reciprocity between subpopulations in coevolution. This feature highlights a promising implication of population-based search algorithms that, to the best of our knowledge, is yet to be thoroughly investigated in the literature. Furthermore, in order to effectively navigate a continuized form of the unified search space $\boldsymbol{Y}$, we exploit the intrinsic parallelism of swarm intelligence by applying an instantiation of particle swarm optimization (PSO) (Kennedy, 2011; Engelbrecht, 2016) as the base solver within the coevolutionary framework for multitask problem-solving. At this juncture, it is important to note that while similar combinations of PSO with coevolution can be found in the literature (Goh et al., 2010; He and Wang, 2007; Van den Bergh and Engelbrecht, 2004), they are usually considered for the limited case of high dimensional single-task optimization problems – possibly comprising of several interdependent components (Bonyadi et al., 2016) – where the single problem is decomposed into manageable lower dimensional subtasks. Our novel proposition for multitask problem-solving is therefore referred to hereafter as *coevolutionary multitasking* and its associated algorithm is labelled as *multitasking coevolutionary particle swarm optimization* (MT-CPSO).

For a complete exposition of the ideas discussed heretofore, the rest of the paper has been organized as follows. In Section 2, we highlight the main motivation behind this paper, namely, the scope for improving productivity in decision making processes. In Section 3, an overview of the classical PSO algorithm with some genetically-inspired enhancements for tackling complex single-task optimization is presented. Thereafter, the MT-CPSO, which combines the mechanism of PSO with cooperative coevolution for the purpose of effective multitask problem-solving is presented, highlighting its distinction from the existing MFEA. In Section 4, numerical studies on solving a batch of synthetic test functions for optimization, as well as multi-constrained practical (engineering design) benchmarks, are carried out. Next, in Section 5, the efficacy of multitasking is further emphasized with a real-world case study from the composites manufacturing industry. Finally, a summary of the work, concluding remarks, and directions for future research are provided in Section 6.

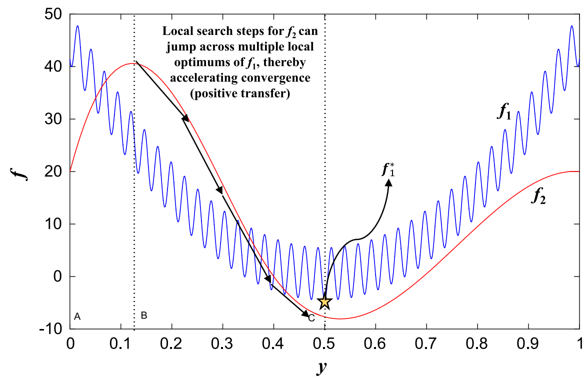

Fig. 1. An illustration of two distinct optimization tasks in a one-dimensional unified search space. We find that the comparatively smooth landscape of f_2 can aid minimization of the more rugged f_1 by allowing the search to leap across multiple local optimums.

2. Practical motivation

In today's fast-paced world, a crucial skill for satisfactorily responding to the many pressing demands on our time is the ability to multitask. In fact, with the increasing volume, velocity, and complexity of problem-solving scenarios faced across different real-world settings, multitasking is perhaps the only way to enhance our productivity to meet all requirements, albeit at the often tolerable cost of a slight reduction in the quality of output achieved. In summary, the potential for *productivity enhancement* through effective multitask problem-solving is the key motivation driving the propositions in this paper.

From the standpoint of global optimization, productivity enhancement is achieved when the accelerated convergence characteristics of a solver leads to high quality solutions within notably shorter periods of computation time. In fact, studies (Gupta et al., 2016c, b) have shown that there exist complementary optimization tasks which when bundled together and solved concurrently in a single multitask setting can lead to significantly improved performance for all constitutive tasks at once (i.e., in comparison to solving them in isolation in the form of traditional single-task optimization). Needless to say, a rigorous *a priori* prediction of the presence of such complementarity is challenging (if not impossible) in many cases where no prior knowledge about the objective function landscape is available. However, within a particular real-world domain of application, it is often possible for the practitioner to make a well-informed qualitative judgement about the potential success of multitasking, given a prior understanding of the underlying similarities between tasks (Gupta et al., 2016c; Ong and Gupta, 2016).

In order to emphasize the above, we consider the case of two minimization tasks T_1 and T_2 with objective/cost functions f_1 and f_2, respectively, that have high *ordinal correlation* (Kendall, 1938). To elaborate, we make the extreme assumption that for any pair of points $\boldsymbol{y}_1$ and $\boldsymbol{y}_2 \in \boldsymbol{Y}$, $f_1(\boldsymbol{y}_1) < f_1(\boldsymbol{y}_2) \Leftrightarrow f_2(\boldsymbol{y}_1) < f_2(\boldsymbol{y}_2)$. Thus, it can be seen that on bundling the two tasks in a multitasking environment, any series of steps leading to a cost reduction of T_1 will automatically lead to a cost reduction of T_2 *for free*, and vice versa, without the need for additional function evaluations. In other words, at least within the family of functions characterized by high ordinal correlation, multitask optimization can be immediately seen to provide the scope for *free lunches* (Wolpert and Macready, 1997, 2005).

Even for the more general case where optimization tasks do not possess high ordinal correlation, the process of multitasking can lead to the exploitation of underlying complementarities between them. This feature can be illustrated by referring to Fig. 1. Therein, we focus on