Adaptive Multiobjective Memetic Optimization

Hieu V. Dang, University of Manitoba, Winnipeg, Canada
Witold Kinsner, University of Manitoba, Winnipeg, Canada

ABSTRACT

Multiobjective memetic optimization algorithms (MMOAs) are recently applied to solve nonlinear optimization problems with conflicting objectives. An important issue in an MMOA is how to identify the relative best solutions to guide its adaptive processes. In this paper, the authors introduce a framework of adaptive multiobjective memetic optimization algorithms (AMMOA) with an information theoretic criterion for guiding the adaptive selection, clustering, local learning processes, and a robust stopping criterion of AMMOA. The implementation of AMMOA is applied to several benchmark test problems with remarkable results. The paper also presents the application of AMMOA in designing an optimal image watermarking to maximize the quality of the watermarked images and the robustness of the watermark.

KEYWORDS

Image Watermarking, Memetic Computing, Multiobjective Optimization, Neural Networks, Relative Entropy

1. INTRODUCTION

Multiobjective optimization deals with the function of more than one objective. In most practical decision making problems, there are multiple conflicting objectives or multiple criteria. Unfortunately, these real world problems are often difficult, if not impossible, to solve without advanced and efficient optimization techniques. This is because these problems are characterized by multiple objectives that are much more complex than single-objective problems. Consequently, a multiobjective optimization problem has been mostly solved as a single-objective optimization problem. However, this method approaches one solution instead of a set of optimal solutions.

An *evolutionary algorithm* (EA) mimics the nature's evolutionary principles to formulate search procedures. Such an EA is a population-based algorithm that uses a population of solutions in each iteration, instead of a single solution in classical methods. The outcome of EA is also a population of solutions. Thus, an EA can be efficiently used to capture multiple optimal solutions in its final population for multiobjective optimization problems. EAs have the important advantage of being able to sample multiple solutions simultaneously. This feature makes EAs common-used in multiobjective optimization (called multiobjective optimization using EAs - MOEA). Many MOEAs have been proposed in the literature. Most of them are based on the models of *genetic algorithms* (GA) (Deb, 2001). Recently, biologically inspired models, such as *particle swarm* (PS), *differential evolution* (DE), and *memetic algorithms* (MA) have been introduced for multiobjective optimization (Lee & Kim, 2013; Wang & Cai, 2012; Ishibuchi et al., 2009). The main difference between these approaches is in the method of generating new candidate solutions.

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The term "meme" was first introduced and defined by Richard Dawkins as the basic unit of cultural transmission or imitation (Dawkins, 1989). Inspired by Darwinian's evolutionary theory and Dawkin's theory of memes, the term *memetic algorithm* (MA) was first introduced by Moscato in 1989 (Moscato, 1989). In this work, Moscato viewed MAs as extentions of EA that adopt the hybridization between EA and an individual learning procedure performing local refinements. The use of MA for multiobjective optimization (*mutiobjective memetic optimization algorithm*, MMOA) has attracted much attention and effort in recent years. In the literature, MMOA has been demonstrated to be much more effective and efficient than MOEAs and the traditional optimization searches for some specific optimization problem domains (Krasnogor & Smith, 2006; Kenedy & Eberhart, 2001; Ishibuchi et al., 2009; Neri & Cotta, 2012; Chen et al., 2011; Bergmeir et al., 2012; Dang & Kinsner, 2014). The performance of MMOA not only relies on the evolutionary framework, but also depends on the local searches.

Several studies have shown that multiobjective optimization based on evolutionary algorithms (MOEA) scale poorly with regard to increasing the number of objectives (Khare et al., 2003; Hugh, 2005; Fabre et al., 2010; Fabre et al., 2009). The main reason is that the principle of Pareto dominance, which is mostly used as a ranking criterion in MOEAs, is less effective when the number of objectives in MOEAs increases. Therefore, only Pareto ranking based MOEAs is not sufficient for solving multiobjective optimization problems. Currently-proposed MMOAs use Pareto-dominance ranking as a convergence measure to guide learning processes. On the other hand, diversity preservation is another critical issue of *multiobjective optimization problems* (MOPs). The diversity preservation is performed based on diversity assessment criteria (e.g., density, distance, or distribution based criteria). When the number of objectives in an MOP increases, the diversity criterion plays the key role in selecting the solutions. In this context, an effective diversity assessment criterion can help a multiobjective optimization algorithm (e.g., MOEA, MMOA) converges well. Thus, the need for an effective mechanism of diversity preservation is also critical. Besides, in MMOA, local searches are adopted for individual learning. Individual refinements can help improve the convergence; however, it can destroy the diversity of the population if our technique has neither a wise criteria for guiding the searches nor a well-designed learning mechanism.

In this paper, we introduce an effective information-theoretic criterion based on the multiscale relative Rényi entropy. This information-theoretic criterion is used to guide the adaptive selection, clustering, and local learning processes in our *adaptive multiobjective memetic optimization algorithms* (AMMOA). The AMMOA framework is proposed based on the observation from the real human cultural evolution that the individuals have gone through a hierarchical social learning structure. They first learn from their small communities to grow to compete with others in their local communities. The best individuals from small communities then contribute to the bigger community. They learn and compete with each other to improve the community. AMMOA framework adopts two layers of local learning with adaptive factors. This framework uses the proposed information-theoretic criterion to guide the adaptive selection, clustering, and local learning processes to improve the convergence and diversity of the obtained optimal population. The short version of this work is presented in the conference paper (Dang and Kinsner, 2016). The main contributions of this work are as follows.

a. An effective information-theoretic criterion is proposed to guide the adaptive processes such as the selection, clustering, and local learning processes in adaptive multiobjective optimization techniques.
b. A framework of adaptive multiobjective optimization algorithms (AMMOA) and its implementation with the adaptive tournament selection, fuzzy-clustering, and Tabu local searches, all guided by the proposed information-theoretic criterion, are introduced with remarkable results.
c. A robust online stopping criterion based on the proposed information-theoretic criterion is introduced for AMMOA.

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