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Group counseling optimization

M.A. Eita*, M.M. Fahmy

Tanta University, Egypt

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ABSTRACT

In this paper, a new population-based optimization algorithm – which we call a group counseling optimizer (GCO) – is developed. Instead of mimicking the behavior of living organisms such as birds, fish, ants, and bees, we emulate the behavior of human beings in life problem solving through counseling within a group. This is motivated by the fact that the human's thinking is often predicted to be the most reasonable and influential. The inspiration radiates from the various striking points of analogy between group counseling and population-based optimization which we have discovered, as elucidated in Section 2. The algorithm is tested using seven unrotated benchmark functions and five rotated ones. Further, a comparison is made with the comprehensive learning particle swarm optimizer (CLPSO) which outperforms many other variants of the particle swarm optimizer. Using new eight composition benchmark functions, another comparison is made with the BI-population covariance matrix adaptation evolution strategy with alternative restart strategy (NBIPOP-$_{a}$CMA-ES) which is the winner of the competition on real-parameter single objective optimization at IEEE CEC-2013. The results are all highly promising, demonstrating the soundness and efficacy of the proposed approach. GCO is applied to real-world application which is spacecraft trajectory design problem. Also, the results show that GCO outperforms well-known optimizers.

1. Introduction

Optimization is the computational discipline devoted to the study of the 'best' solution of a problem [1,2]. It, mathematically, means either minimization or maximization of a certain objective function. Losses and drawbacks are to be minimized, whereas profits and merits are to be maximized. All of us seek optimum or, at least suboptimum, solutions because we often aspire to a better way of life. It is no exaggeration to assert that looking for a solution of an optimization problem is as old as human history itself.

A great many optimization approaches have been developed and consolidated over the decades. From 1960 onwards, attention has been particularly focused on the category of population-based optimizers [3]. A prominent property of the computational algorithms of this category is that an iterative policy is followed, which relies on a group, or population, of candidate solutions, not just one solution. During the iterations, a population of constant size is maintained, and the group of solutions is improved progressively. The adoption of successive solution groups is advantageous in that working in groups is generally more productive than individual efforts. Specifically, improving a solution in an iteration can benefit from other solutions in the group, in the sense that the new value of a solution (to be used in the next iteration) can be deduced through 'interaction' or 'cooperation' with other solutions in an algorithm-dependent manner. Having a group of solutions 'working together' is the key to the development of modern biology-inspired optimizers, in which the behavior of biological organisms is emulated. In other words, a biological 'metaphor' does stimulate the algorithm. In what follows, we refer to five famous example algorithms and their pertinent metaphors.

The genetic algorithm (GA) [4,5] emulates genetic evolution in biological organisms according to the theory of the Charles Darwin. It depends on the construction of an evolutionary computation scheme, using models of evolutionary processes such as 'natural selection', 'survival of the fittest', and 'reproduction'. In a world with limited resources, each individual enthusiastically competes with others for survival. Individuals having the best traits are more likely to survive and reproduce, and these traits will be passed on to their offspring. With time, desirable qualities are inherited from generation to generation, and they turn dominant in the population.

The particle swarm optimization (PSO) [6–8] began as a computer simulation of the social behavior of biological organisms living in groups such as a flock of birds, and a school of fish, where

* Corresponding author. Tel.: +20 403306059.
E-mail addresses: Mohammad.Eita@ejust.edu.eg, eta1232002@yahoo.com (M.A. Eita), mfn_288@hotmail.com (M.M. Fahmy).

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no leader can be recognized. Within such social groups, individuals are not very knowledgeable about the overall behavior of the group, nor are they fully aware of their environment. But they do have the capability of gathering as well as travelling and managing together, without any collision or apparent conflict. In doing all this, a plain principle is obeyed: imitation of successful activities of neighboring individuals. Intrinsic local interaction among individuals brings about intricate, graceful behavior that characterizes bird flocking, fish schooling, collective foraging, and many other aspects of living. In analyzing group dynamics of bird social behavior, inter-individual distances play a major role; that is, the synchrony of flocking behavior is conceived to hinge on the effort exerted by the birds to preserve optimum separation between themselves and their neighbors, so that cooperation of individuals becomes feasible and effective.

The ant colony optimization (ACO) [9] is based on the foraging behavior of ants. Such social insects are capable of finding the shortest path between their nest and a food source, with no visible, centralized coordinating mechanism. There exists an initial chaotic activity pattern in the search for food but, once a food source is located, activity patterns become well organized and ant groups come to go along the shortest path heading for the food source. In an infinitesimal time interval, all ants follow the same path. Here, through an orderly recruitment process, the ants that discovered a food source direct other ants toward it. Most ants indirectly communicate with each other by means of secreting a chemical scented substance called pheromone. When an ant locates a food source, it carries a food item to the nest and deposits pheromone along the trail. Forager ants decide which path to select on the basis of the concentration of pheromone on the various paths. The path with higher pheromone concentration has a greater probability of being selected. As more ants follow a specific path, the desirability of that path is strengthened by extra pheromonal secretion of the foragers, and thus more and more ants are attracted to it.

The artificial bee colony (ABC) optimization [10–12] is based on the foraging behavior of honey bees. A forager bee leaves the hive looking for a rich food source, a patch of flowers, to gather nectar from. For multiple food sources, forager bees are allocated among different flower patches in such a way as to maximize total nectar intake. The bee stores the nectar in her honey stomach, and a honey-making process begins with secreting an enzyme on the nectar. On returning to the hive, the bee unloads the nectar into empty honeycomb cells, and some extra enzymes are added to avoid fermentation and bacterial attacks. Then, the forager bee that has found a food source performs attractive movements, visualized to as a 'dance', around the place of the comb. Through dancing, she announces her information about the food source, such as how plentiful it is and where it is located. Other bees touch her with their sensory antennas and learn, moreover, the scent and taste of the food of the source. In this way, groups of bees are recruited to exploit the same source. ABC was improved to be able to detect the global optima *via* a lot of research works. Some of newly improvements can be found in [13,14].

The differential evolution algorithm (DE), which is considered an extension to GA, was originated by Storn and Price in 1997, for minimization problems in terms of a cost function [15]. It participated in the First International IEEE Competition on Evolutionary Optimization (ICEC'96), and proved to be the fastest evolutionary algorithm at the time (although it came third among deterministic methods). In this algorithm, use is made of concepts of mutation, crossover, and selection, but with specific mathematical definitions, generally different form those of the genetic algorithm. The guiding principle is that information from within a population of parameter vectors is utilized to produce a new vector population of the same size. The scheme of computations depends on using a weighted difference vector of two randomly chosen vectors so as to vary (perturb) some other third vector. The perturbation is done for every population vector, without resort to a predefined probability distribution function. This is the process of mutation in differential evolution. The vector resulting after perturbation is a mutant vector. Some of the components of the mutant vector are 'mixed' with some components of the target vector to form the so-called trial vector. This is the process of crossover. Over the past years, researchers enhanced the DE behavior through various ideas. Some of the recent enhancements exist in [16,17].

The above-mentioned algorithms, and many others, are useful and the accompanying metaphors are interesting. Yet the field of computational optimization is extensive and still open for further research work and advanced ideas with no foreseeable end. In the present paper, we do not concern ourselves with improving or even overcoming shortcomings of any one of these algorithms. Our main aim is to introduce a new population-based optimization algorithm inspired by an utterly different metaphor. Instead of mimicking the behavior of living organisms such as birds, fish, ants, or bees, we emulate the behavior of *human beings* in life problem solving through *counseling within a group* [18–20]. This is motivated by the fact that the human's thinking is, or should be, the most reasonable and influential. The subject of counseling is well known in sciences like psychology and sociology, but may seem rather obscure in computational optimization. The contribution of this paper is therefore twofold. First, we investigate some of the basic counseling concepts and procedures in an attempt to make counseling emerge as a convincing and appealing metaphor for population-based computational optimization. In this conceptual framework, we identify *twenty* striking items of significant analogy. Second, we utilize these metaphoric items to develop what we call a group counseling optimizer (GCO). The proposed algorithm is compared with the comprehensive learning particle swarm optimizer (CLPSO) [21], which outperforms several variants of the particle swarm optimizer, through use of seven unrotated benchmark functions and five rotated ones. An additional comparison is made with the BI-population covariance matrix adaptation evolution strategy with alternative restart strategy (NBIPOP-$_a$CMA-ES) [22,23], which is the winner of the competition on real-parameter single objective optimization at IEEE CEC-2013 [24], using new eight composition benchmark functions. Results, including error values and convergence characteristics, obtained for GCO are highly satisfactory, demonstrating that the link we have established between group counseling and computational optimization is healthy, authentic, and valuable. We point out that a preliminary version of GCO, with unrotated benchmark functions alone, has been published in [25]. A multi-objective version of GCO is recently published in [26], which gives promising results in solving multi-objective optimization problems. To test the applicability, GCO is applied to a real-world application. Also, the results show that GCO outperforms well-known optimizers.

The remainder of the paper is organized as follows: Section 2 introduces the analogy items between group counseling and the population-based optimization. In Section 3, the proposed algorithm, based on group counseling is introduced and the steps of GCO algorithm are explained in details. In Section 4, algorithmic comparison between GCO and other optimizers is presented. In Sections 5–7 the results of the experiments conducted on seven unrotated and five rotated and eight composition benchmark functions are given. A real world application of GCO is presented in Section 8. The conclusions are finally discussed in Section 9.

2. Analogy between group counseling and population-based optimization

People with problems often seek out another person as a sounding board: someone with whom they can talk over their