Chapter 2
A Complementary Cyber Swarm Algorithm

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ABSTRACT

A recent study (Yin et al., 2010) showed that combining particle swarm optimization (PSO) with the strategies of scatter search (SS) and path relinking (PR) produces a Cyber Swarm Algorithm that creates a more effective form of PSO than methods that do not incorporate such mechanisms. This paper proposes a Complementary Cyber Swarm Algorithm (C/CyberSA) that performs in the same league as the original Cyber Swarm Algorithm but adopts different sets of ideas from the tabu search (TS) and the SS/PR template. The C/CyberSA exploits the guidance information and restriction information produced in the history of swarm search and the manipulation of adaptive memory. Responsive strategies using long term memory and path relinking implementations are proposed that make use of critical events encountered in the search. Experimental results with a large set of challenging test functions show that the C/CyberSA outperforms two recently proposed swarm-based methods by finding more optimal solutions while simultaneously using a smaller number of function evaluations. The C/CyberSA approach further produces improvements comparable to those obtained by the original CyberSA in relation to the Standard PSO 2007 method (Clerc, 2008).

1. INTRODUCTION

Metaheuristics are master strategies that guide and modify slave heuristics to produce solutions beyond those that are normally generated for local optimality. Effective metaheuristics make a search plan of intensification and diversification to reach a good trade-off between solution quality and computational effort. Intensification exploits information about elite solutions that were previously found as a basis for focusing the search in regions anticipated to harbor additional solutions of high quality. Diversification promotes the exploration of regions appreciably different from those previously examined in order to produce new solutions with characteristics that depart from those already seen. Intensification and diversification work together to identify new promising regions when the slave heuristics stagnate in the executed search courses. Many intelligent algorithms fall in the territory of metaheuristics. Some exemplary algorithms (Luke, 2009) are genetic algorithms (GA), simulated annealing (SA), ant colony optimization (ACO), tabu search (TS), particle swarm optimization (PSO), scatter search (SS), greedy randomized adaptive search procedure (GRASP), variable neighborhood search (VNS), to name a few. A recent survey and descriptive analysis of metaheuristic algorithms can be found in Sorensen and Glover (2010).

Slave heuristics embedded in metaheuristic methods often adopt solution combination or neighborhood exploration processes to generate new solutions based on the current state of search. Solution combination approaches produce new solutions by exchanging information between candidate solutions (for example, crossover operation executed in GA) or by using candidate solutions as guiding points for producing new solutions (for example, by reference to the best experiences in PSO or the path relinking (PR) process used in SS). Alternatively, neighborhood exploration employs incremental changes, called moves, which progress from one solution to an-

other within local regions called neighborhoods that are considered relevant to the search (as by changing one or a small number of elements within a current solution). Sophisticated neighborhood concepts like ejection chains (Glover, 1996b; Rego & Glover, 2009) have been proposed for tackling a variety of complex problems and various types of multiple neighborhood strategies (Glover, 1996a; Mladenovic & Hansen, 1997; Sörensen, Sevaux, & Schittekat, 2008; Lu, Hao, & Glover, 2010) have been proposed for enriching the set of moves employed during the search. To avoid reversing the search course and prevent getting trapped in local optima, some solution attributes and move directions may be forbidden by means of tabu restrictions as proposed in tabu search, or multi-start mechanisms may be employed to initiate a new search thread in an uncharted region. There are other metaheuristic methods employing gradient-based or derivative-free supplementary procedures. The best of these methods are provided by Hedar and Fukushima (2006) and Duarte et al. (2007) for problems of moderate dimension, and by Hvattum and Glover (2009) and Vaz and Vicente (2007) for problems of large dimension. Duarte et al. (2011b) analyzes the performance of two path relinking variants: the static and the evolutionary path relinking. Both are based on the strategy of creating trajectories of moves passing through high quality solutions in order to incorporate their attributes to the explored solutions.

Methods that employ both solution combination and neighborhood exploration perform more effectively by carefully coordinating the slave heuristics with the master strategy employed. An illustration of this is provided, for example, by methods that integrate tabu search with classical direct search for global function optimization. Chelouah and Siarry (2005) proposed a continuous tabu simplex search (CTSS) method that uses the Nelder-Mead simplex algorithm to accelerate convergence towards a minimum within a detected promising region, while maintaining the tabu search (TS) restriction as a mechanism to search

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