Different Approaches for Cooperation with Metaheuristics

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INTRODUCTION

Working on artificial intelligence, one of the tasks we can carry on is optimization of the possible solutions of a problem. Optimization problems appear. In optimization problems we search for the best solution, or one good enough, to a problem among a lot of alternatives.

Problems we try to solve are usual in daily living. Every person constantly works out optimization problems, e.g. finding the quickest way from home to work taking into account traffic restrictions. Humans can find efficiently solutions to these problems because these are easy enough. Nevertheless, problems can be more complex, for example reducing fuel consumption of a fleet of plains. Computational algorithms are required to tackle this kind of problems. A first approach to solve them is using an exhaustive search. Theoretically, this method always finds the solution, but is not efficient as its execution time grows exponentially.

In order to improve this method heuristics were proposed. Heuristics are intelligent techniques, methods or procedures that use expert knowledge to solve tasks; they try to obtain a high performance referring to solution quality and used resources.

Metaheuristics, term first used by Fred Glover in 1986 (Glover, 1986), arise to improve heuristics, and can be defined as (Melián, Moreno & Moreno, 2003) 'intelligent strategies for designing and improving very general heuristic procedures with a high performance'. Since Glover the field has been extensively developed. The current trend is designing new metaheuristics that improve the solution to given problems. However, another line, very interesting, is reuse existing metaheuristics in a coordinated system. In this article we present two different methods following this line.

BACKGROUND

Several studies have shown that heuristics and metaheuristics are successful tools for providing reasonably good solutions (excellent in some cases) using a moderate number of resources. A brief look at recent literature (Glover & Kochenberger, 2003), (Hart, Krasnogor & Smith, 2004), (Pardalos & Resende, 2002) reveals the wide variety of problems and methods which appear under the overall topic of heuristic optimization. Within this, obtaining strategies which cooperate in a parallel way is an interesting trend. The interest is on account of two reasons: larger problem instances may be solved, and robust tools, that offer high quality solutions despite variations in the characteristics of the instances, may be obtained.

There are different ways of obtaining this cooperation. One way are ant colony systems (Dorigo & Stützle, 2003) and swarm based methods (Eberhart & Kennedy, 2001) appear as one of the first cooperative mechanisms inspired by nature. Nevertheless, the cooperation principle they have presented to date is too rigid for a general purpose model (Crainic & Toulouse, 2003). Another way are parallel metaheuristics, where very interesting perspectives appear. This is the line we will follow.

There have been huge efforts to parallelize different metaheuristics. Thus we may find synchronic implementations of these methods where the information is shared at regular intervals, (Crainic, Toulouse & Gendreau, 1997) using Tabu Search and (Lee & Lee, 1992) using Simulated Annealing. More recently there have been multi-thread asynchronic cooperative implementations (Crainic, Gendreau, Hansen & Mladenovic, 2004) or multilevel cooperative searches (Baños, Gil, Ortega & Montoya, 2004) which, according to the reports in (Crainic & Toulouse, 2003) provide better results than the synchronic implementations.

However, it seems that a cooperative strategy based on a single metaheuristic does not cover all the possibilities and the use of strategies which combine different metaheuristics is recommended. The paper (Le Bouthillier & Crainic, 2005) is a good example. A whole new area of research opens up. Questions such as, 'what will be the role of each metaheuristic?' or 'What cooperation mechanisms should be used?' arise.

Within parallel metaheuristics, we will focus following the classification of (Crainic & Toulouse, 2003) on Multi-search metaheuristics, where several concurrent strategies search the solution space. Among them, we concentrate on those techniques, known as Cooperative multi-search metaheuristics, where each strategy exchanges information with the others during the execution.

Cooperative multi-search metaheuristics obtain better quality solutions than independent methods. But previous studies (Crainic & Toulouse, 2002), (Crainic, Toulouse & Sansó, 2004) demonstrate that cooperative methods with a non-restrictive access to shared information may experiment problems of premature convergence. This seems to be due to the stabilization of the shared information, stabilization caused by the intense exchange of the better solutions. So it would be interesting to find a way of controlling this information exchange.

In this context we propose two approaches in order to control the exchange of information, one using memory to cope with this problem, and the other using a process of knowledge extraction.

The first approach (Pelta, Cruz, Sancho-Royo & Verdegay, 2006) proposes a cooperative strategy where a coordinating agent, modelled by a set of 'ad hoc' fuzzy rules, receives information from a set of solver agents and sends instructions to each of them telling how to continue. Each solver agent implements the Fuzzy Adaptive Neighbourhood Search (FANS) metaheuristic (Blanco, Pelta & Verdegay, 2002) as a clone. FANS is conceived as an adaptive fuzzy neighbourhood based metaheuristic. Its own characteristics allow FANS to capture the qualitative behaviour of several metaheuristics, and thus, can be considered as a "framework" of metaheuristics.

The second approach (Cadenas, Garrido, Liern, Muñoz & Serrano, 2007) uses the same structure but combines a set of different metaheuristics which cooperate within a single coordinated schema, where a coordinating agent modelled by a set of fuzzy rules receives information from the different metaheuristics and sends instructions to each of them. The difference with the previous system lies on the way the rules are obtained. Here, as a result of a knowledge extraction process (Cadenas, Garrido, Hernández & Muñoz, 2006), (Cadenas, Díaz-Valladares, Garrido, Hernández & Serrano, 2006).

TWO COOPERATIVE MULTI-SEARCH METAHEURISTICS

A Cooperative Multi-Search Metaheuristic Using Memory and Fuzzy Rules

The idea of the first strategy can be explained with the help of the diagram in Fig. 1. Given a concrete problem to solve, we have a set of solvers to deal with it. Each solver develops a particular strategy to solve the problem independently, and the whole set of solvers works simultaneously without direct interaction. In order to coordinate the solvers there is a coordinator which knows all the general aspects of the problem concerned and the particular solver features. The coordinator receives reports from the solvers with the obtained results, and returns orders to them.