Different Approaches for Cooperation with Metaheuristics

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Introduction

In optimization problems we search for the best solution (or one good enough) of a problem among a lot of alternatives. This kind of problems is common in our daily living. Every person constantly solves optimization problems such as finding the shortest path from home to work with traffic restrictions. Humans can find solutions to these problems efficiently because are small enough. However, these problems can become more complex, for example reducing the consumption of fuel of a fleet of plains trying to obtain more benefits. To tackle this kind of problems computational algorithms are required.

A first approach to solve this kind of problems is using an exhaustive search. However, although theoretically this method always finds the solution, it is not efficient, because its execution time grows exponentially. In order to improve this method appeared heuristics, which are intelligent techniques, methods or procedures that use expert knowledge to solve tasks, trying to obtain a good performance referring to solution quality and resources used.

Metaheuristics, term used first 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. The current trend in the field of metaheuristics is the design of new metaheuristics with the purpose of improving the solution for given problems. However, a very interesting line is to reuse existing metaheuristics in a coordinated system. In this article we present two different approaches for this view, one combining similar metaheuristics and the other combining different ones.

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. An interesting trend in this area is to obtain strategies which cooperate in a parallel way in order to solve a problem. This approach can be interesting for two reasons: firstly, larger problem instances may be solved, and secondly, robust tools may be obtained which offer high quality solutions despite variations in the characteristics of the instances.

There are different ways of obtaining this cooperation. The ant colony systems (Dorigo & Stützle, 2003) and swarm based methods (Eberhart & Kennedy, 2001) appear as one of the first cooperative mechanisms inspired by nature. However, the cooperation principle they have presented to date is too rigid for a general purpose model (Crainic & Toulouse, 2003). Another approach is parallel metaheuristics. In this field appear very interesting perspectives, for example, 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 as is the case in (Crainic, Toulouse & Gendreau, 1997) in Tabu Search and (Lee & Lee, 1992) in Simulated Annealing. More recently there have been multi-thread asynchronic cooperative implementations or multilevel cooperative searches (Crainic, Gendreau, Hansen & Mladenovic, 2004), (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. A good example of this is the paper (Le Bouthillier & Crainic, 2005). A whole new area of research opens up, in which questions arise, such as: What will be the role of each metaheuristic? or What cooperation mechanisms should be used?

This paper is focused on parallel metaheuristics, especially on Multi-search metaheuristics, following the classification of (Crainic & Toulouse, 2003), where several concurrent strategies search the solution space. Within this type we concentrate on those techniques in which each strategy exchanges information with the others during the execution.

Cooperative multi-search metaheuristics obtain solutions of a better quality than the solutions obtained by 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 owing to the intense exchange of the better solutions. So it would be interesting to find a way of controlling this exchange of information.

In this context we propose two approaches in order to control the exchange of information, one using memory in order 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 in which there is a coordinating agent modelled by a set of “ad hoc” fuzzy rules which receives information from a set of solver agents and sends instructions to each of them as to how to continue. Each solver agent implements the Fuzzy Adaptive Neighborhood Search (FANS) metaheuristic (Blanco, Pelta & Verdegay, 2002) as a clone. FANS is conceived as an adaptive fuzzy neighbourhood based search metaheuristic. Thanks to its characteristics, it is able to capture the qualitative behaviour of several metaheuristics based on environment search, and can thus 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 respect to the previous system lies on the way the rules are obtained 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 strategy 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.

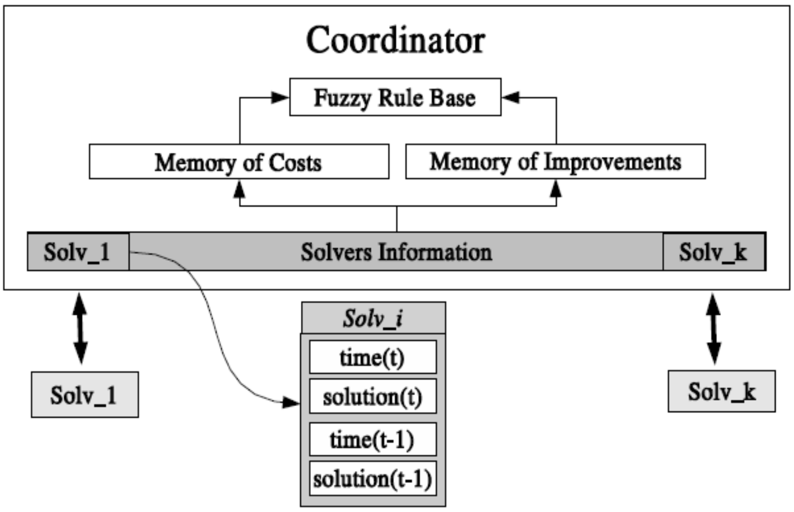

Fig 1. Diagram of the first strategy

The inner workings of the strategy are quite simple. In the first step, the co-ordinator determines the initial behaviour (set of parameters) for each solver, which models a particular optimization strategy. This behaviour is passed to each solver, which is then executed. For each solver, the co-ordinator keeps the last two reports containing their times, and the corresponding solutions at such times. From the solver information set, the co-ordinator calculates performance measures that will be used to adapt the fuzzy rule base. This fuzzy rule base is generated manually following the principle that *If a solver is working well, keep it; but if a solver seems to be trapped, do something to alter its behaviour*.

Solvers execute asynchronously by sending and receiving information. The co-ordinator checks which solver provided new information and decides whether its behaviour needs to be adapted using the fuzzy rule base. If this is the case, it will obtain a new behaviour which will be sent to the solvers. Solver operation is quite simple: once execution has begun, performance information is sent and adaptation orders from the coordinator are received alternately.

Each solver thread is implemented by means of the FANS metaheuristic. The three main reasons for this are:

- FANS is essentially a threshold-acceptance local search technique and is therefore easy to understand and implement, and does not require many computational resources.
- FANS can be used as a heuristic template. Each set of parameters implies a different behavior of the method, and therefore, the qualitative behaviour of other local search techniques can be simulated (Blanco, Pelta & Verdegay, 2002).
- The previous point enables different search schemes to be built, and diversification and intensification procedures to be driven easily. We therefore do not need to implement different algorithms but merely use FANS as a template.

A cooperative multi-search strategy using Data mining to obtain fuzzy rules

The idea of the second strategy is very similar to the first one, and can be seen on Fig. 2. Given a concrete problem to solve, we have a set of solvers to deal with it. Each solver implements a different metaheuristic, and has to solve the problem while coordinates itself with the rest of metaheuristics. In order to perform the cooperation we use a coordinating agent which will control and modify the behaviour of the agents. To perform the communication among the different metaheuristics we will use an adapted blackboard model. In this model each agent controls a part of the blackboard in which it can write the information about its performance, and periodically it writes the solution that it has found. The coordinator consults the blackboard in order to monitor the behaviour of each metaheuristic and to decide how it has to modify its behaviour.

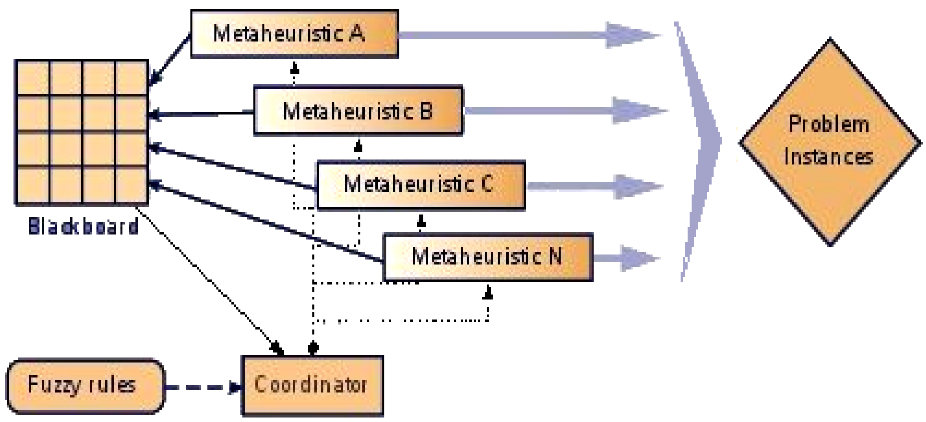

Fig 2. Diagram of the second strategy

To give intelligence to the coordinator we propose the use of a set of fuzzy rules obtained as a result of the methodological process proposed on (Cadenas, Garrido, Hernández & Muñoz, 2006), (Cadenas, Díaz-Valladares, Garrido, Hernández & Serrano, 2006), which is based on a process of intelligent knowledge extraction.

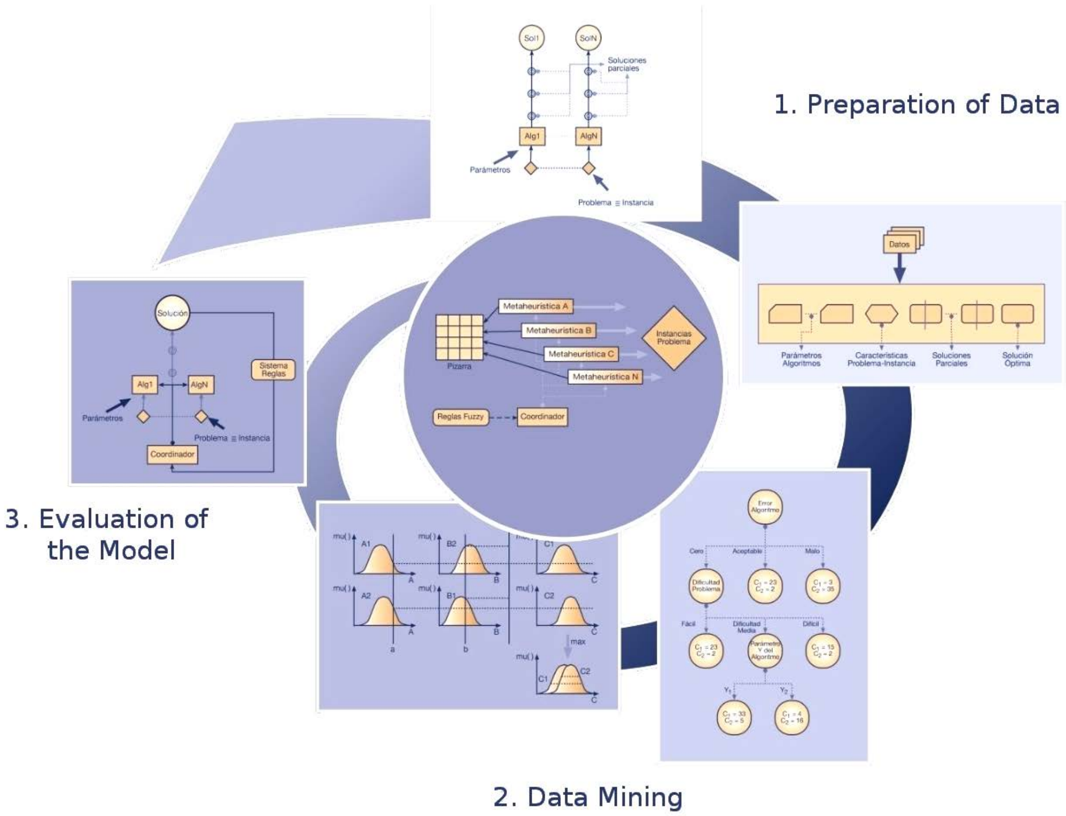

Fig 3. The knowledge extraction process

The process of knowledge extraction is shown in (Fig. 3). This process is divided in the following phases:

- Preparation of data. The aim of this phase is the obtention of a database containing useful information to what Data Mining could be applied in order to obtain the model of the coordinator. In this phase the metaheuristics that are going to be used are chosen and since our information sources come from the application of different metaheuristics to a problem, it is necessary to solve sets of instances of the problem using these metaheuristics, extracting from these executions interesting data such as the parameters of each metaheuristic or the solutions obtained. After that is advisable to apply a preprocess to the database in order to obtain those attributes and instances more relevant
- Data mining. In this phase, Data Mining is applied to the information obtained in the previous phase, in order to get the model of the coordinator of the system. The first step is choosing a Data Mining technique. After that this is applied to the database and from the models obtained a set of fuzzy rules is deduced.
- Evaluation. As final phase it would evaluate the behaviour of the coordinator using the rules previously obtained and would repeat the whole process using the data and adapting them to the new knowledge about the problem.

In this paper we present a synchronous implementation of this model in which three metaheuristics are used, a genetic algorithm, a tabu search and a simulated annealing.

The system obtained finally, operates as follows. First, the coordinator sets the initial set of parameters for each metaheuristic, according to the knowledge extracted from the data mining phase. After that each solver starts its search, periodically all the solvers stop and write their solutions, then the coordinator evaluates them and decides how it has to change the solutions and parameters of each metaheuristic using a fuzzy rule base. This rule base was formulated using the knowledge extraction process previously defined, using in the data mining phase fuzzy decision trees.

Results obtained by these approaches

These two strategies were tested solving the knapsack problem, whose mathematical formulation is

$$\max \sum_{j=1}^{n} p_j \times x_j$$

$$s.t. \sum_{j=1}^{n} w_j \times x_j \le C,\ x_j \in \{0,1\},\ j=1,\ldots,n$$

where n is the number of items, x_j indicates whether the item j is included or not in the knapsack, p_j is the profit associated with the item j, $w_j \in [0, \ldots, r]$ is the weight of the item j, and C is the capacity of the knapsack. We also assume that $w_j < C$, $\forall j$ (every item fits in the knapsack), and $\sum_{j=1}^{n} w_j > C$ (the whole set of items does not fit).

We chose this problem because of the fact that we can construct test instances varying hardness following three characteristics: size of instance, type of correlation between weights and profits, and range of the values available for the weights.

Finally we carried out the tests with an implementation of each system. The implementation of the system based on memory used six solvers each one implementing FANS with different parameters, and each solver was executed for 30 seconds (Memory based). The implementation of the system based on data mining, as said before, used three solvers each one implementing a different metaheuristic (a genetic algorithm, a tabu search and a simulated annealing), and each one was executed for 60 seconds (DM based). In order to test the performance of the systems we also executed each one of the metaheuristics individually (FANS, Tabu Search, Simulated Annealing, Genetic Algorithm) for 180 seconds. In table 1, we show the average error obtained for different types and sizes of instances, comparing the Memory based approach with individual FANS, and the DM based with the average results of the three metaheuristics that compose it. As we can see each one of the strategies outperforms its components.

Table 1: *The average error for the knapsack problem*

		Memory based	**FANS**	**DM based**	**Avg. Individual**
NC	1000	2.32	8.7	0,84	3,2
	2000	2.04	14.15	1,32	4,31
SC	1000	0.94	3.16	0,93	3,6
	2000	1.69	3.81	2,29	5,38
Circle	1000	6.73	10.42	5,14	15,44
	2000	8.10	13.41	12,11	18,26

Future trends

Several lines of research arise. For the first strategy, the topic of what kind of information is stored in the memory of the coordinator and how this is used to control the global search behavior of the strategy needs further research. For the second strategy the knowledge extraction process needs to be improved and tested with different data mining techniques. And for both strategies the improvement of the fuzzy rule base is another topic to be addressed.

One last consideration is the field of application. The knapsack problem is believed one of the “easiest” NP-hard problems, so it would be interesting to apply these strategies to more complex problems such as the p-median, p-hub median or the protein structure comparison.

Conclusion

This paper proposes two strategies to cope with the problems of convergence showed by cooperative multi-search metaheuristics. The first strategy suggests the use of memory in order to define a set of fuzzy rules which control the exchanges of solutions of a coordinated schema in which similar metaheuristics cooperate. The second strategy proposes the use of a knowledge extraction process to obtain a set of fuzzy rules which control the exchanges of solutions of a coordinated system with different metaheuristics. Both approaches have been tested and have demonstrated their good performance.

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Terms and Definitions

Optimization problem: A computational problem in which the object is to find the best solution from all feasible solutions.

Problem Instance: A concrete representation of a problem which has characteristics that distinguish it from the rest.

Heuristic: A method or approach which tries to apply expert knowledge in the resolution of a problem with the aim of increasing the probability of solving it.

Metaheuristic: A high-level strategy for solving a very general class of computational problems by combining user given black-box procedures — usually heuristics themselves — in a hopefully efficient way.

Cooperative Multi-search Metaheuristics: A parallelization strategy for metaheuristics in which parallelism is obtained from multiple concurrent explorations of the solution space and where metaheuristics exchange information during their execution in order to cooperate.

Knowledge Extraction/Discovery: The non-trivial process of identifying valid, novel, potentially useful and ultimately understandable patterns from large data collections. The overall process and discipline of extracting useful knowledge and includes data warehousing, data cleansing and data manipulation tasks right through to the interpretation and exploitation of results.

Data Mining: The most characteristic stage of the Knowledge Extraction process, where the aim is to produce new useful knowledge by constructing a model from the data gathered for this purpose.

Blackboard: A shared repository of problems, partial solutions, suggestions, and contributed information. The blackboard can be thought of as a dynamic "library" of contributions to the current problem that have been recently "published" by other knowledge sources.

Fuzzy Rules: Linguistic if-then constructions that have the general form "if A then B" where A and B are collections of propositions containing linguistic variables (A is called the premise and B is the consequence). The use of linguistic variables and fuzzy if-then rules exploits the tolerance for imprecision and uncertainty.

Parallel metaheuristics: Metaheuristics in which different threads search concurrently the solution space. They appear naturally in the develop of metaheuristics as a way of improving the acceleration factor in the search of solutions.