State-Of-The-Art on Reactive Search

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Abstract
Real-world problems have a rich structure and are very dynamic. An efficient scheduling system for the problem should be able to react quickly to such changes as soon as they happen. In order to address this issue, reactive search is one of the solutions. Response to such events is made available and parameter is tuned during the search itself. In this paper we overview reactive search in literature and its application on scheduling problems
Keywords:
scheduling, reactive search, parameter tuning.

1. Introduction

Batiti and Brunato (2007) defined reactive search as a methodology for solving complex optimization problems by integrating the machine learning techniques and optimization in an online manner. The word reactive refers to a ready response to events during the search through an internal feedback loop for self-tuning and dynamic adaptation (Batiti et al. 2008). In other word, reactive search provides a solution by including the parameter tuning mechanism within the search algorithm itself; it can automatically adjust the parameter and somehow learn during search process (Zenniki et al. 2007).
A scenario for applying reactive search is when we need to set some operating parameter on a system to improve its function. In order to complete this task, the best or accepted parameter values are usually found by a "trial and error" iterative process. How we set the parameters is going to give a better or worse outcome on the system. In reactive search, parameter setting is done by learning process (Batiti et al. 2008).

2. Machine learning in reactive search

'Learning' definition consists of remembering, or ability to gain knowledge or understanding of or experience and modication of a behavioral tendency by experience (Nilsson, 1997; Guggenberger 2007). Learning takes place when we have problem and not well kown at the beginning, and then the structure become more clearer and clearer when we have more experience with the problem (Batiti et al. 2008). As regards machines, we might say that a machine learns whenever it changes its structure, program or data based on its inputs or in response to external information in such a manner that its expected future performance improves.
The metaphors for reactive search are derived from the way human brain learns and make decisions based on previous experience or facts. One of the human learning processes is called 'observational learning' or famously known as 'learning by example'. Human brain learns by observation and repeats the learned subject by repetition. This is the main inspiration source for inserting machine learning into the optimization engine of reactive search. In searching for solutions, many alternative solutions are tested in the exploration of a search space. During the searching process, patterns and regularities appear and can be 'learned' for future used.
Some of the methodology used in machine learning can be used in analogic fashion to develop reactive search (Batiti et al. 2008). Machine learning technique can be used to analyze the behavior of an optimization algorithm and provides feedback by tuning its parameters. The parameter tuning itself is actually a typical 'learning' process, where experiments are designed in a focused way with the supports of statistical estimations (parameter identification) tools (Batiti & Brunato 2007).
In reactive search, parameter setting is done using memory and intelligence (Batiti et al. 2008). The memory is used to keep information collected during past and the ongoing exploration whereas the intelligence of the process is used to decide what the next step to be taken based on the information given. Learning scheme relates to the knowledge accumulated during searching to be used for self-adaptation in autonomic manner. Thus, we can eliminate human intervention and time-consuming in hand-made tuning process (Batiti & Protasi 1997).

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3. Previous technique used on Reactive Search

3.1 Local Search (LS)

Reactive LS is the integration of a simple history-based feedback scheme into local search for on-line determination of free parameters. Some of previous work applied local search algorithm to their reactive search. Batiti and Protasi (1997) proposed new reactive search algorithm for the approximated solution of the Maximum Satisfiability problem where a reactive scheme was complemented with a component based on local search. The algorithm determines ("learns") the appropriate value of the prohibition parameter by monitoring the Hamming distance along the search trajectory (algorithm H-RTS). The non-oblivious functions introduced in the framework of approximation algorithms are used to discover a better local optimum in the initial part of the search.

Hifi et al. (2005) proposed a reactive local search-based algorithm for the multiple-choice multi-dimensional knapsack problem. The Modified Reactive Local Search (MRLS) is an improved version of Reactive Local Search (RLS). The MRLS improves the quality of the solution obtained by the RLS. The core algorithm is based on the degrading strategy and deblocking strategy.

The degrading strategy is conducted through an exchanging process between several items. This strategy improves the current solution. The deblocking strategy is performed through diversification and changes of search direction. The changing of search direction allows the algorithm to explore different regions of search space when the obtained solutions seems to cycle.

The algorithm will compare the current configuration whether it has already been found during the search process. When the current solution saturates relatively all constraints, the approach requires other “escape” mechanism called “memory storage”. The memory storage is introduced in order to prevent the non desirable solutions from being picked as the solution. Applying MRLS by combining both deblocking strategy and memory list procedure give good result however the computational time become superior.

Afterward Hifi et al (2006) proposed a reactive local search-based algorithm for different kind of problem: disjuntively constrained knapsack problem (DCKP). A disjunctive constrain is a couple of items for which only one item is packed. They applied two complementary greedy procedures to construct starting solution. Furthemore, they also introduce degrading and deblocking procedures for avoiding local optima and for diversification. And as they did in their previous work, they add memory list to forbid the repetition of configuration.

3.2 Tabu Search (TS)

Tabu Search (TS) is a method that use adaptive memory to expand the local search (Glover and Laguna 1997). Batiti et al. (2008) refers a Reactive Tabu Search (RTS) as a class of heuristics that can automatically adjust their working parameters during the optimization phase. In the following we discuss the application of RTS on some problems

Toune et al. (1998) proposed a solution to the problem of service restoration of electric power distribution systems using RST. In their novel application of RST, the algorithm is designed to restore electric power to the out-of-service are as quickly as possible by proving solutions to the emergency control in distribution control centers. Restoring electrical power needs a high quality solution in the fastest time in order to address customer needs and emergency situation such as hospital. Toune et al. (1998) divide the out-of-service area to the available power source. The combinatorial optimization problem is addressed using the RTS and the results are encouraging as the speed (time) of computing and the effectiveness of the proposed algorithm is comparable to the conventional tabu search. Based on this result, Hiroyuki et al. (1999), continue the research using the same algorithm, i.e reactive tabu search and compare their algorithm with conventional TS, genetic algorithm, and parallel simulated annealing. The feasibility of the algorithm shows promising result.

Reactive TS is applied to solve servixe restoration in electrical power system (Toune et al. 1998). Service restoration is an emergency control in distribution control centers r\to restore out-of-service area as soon as possible when fault occurs in distribution system. Therefore it requires fast computation time and high quality solution for customer iroyuki et al. (1999) develops a reactive TS (RTS) for service restoration. Until recently the problem has been dealt with using conventional method such as branch and bound method, expert system and fuzzy reasoning. and compares RTS, Genetic Algorithm (GA), and Parallel Simulated Annealing (Parallel SA) for the problem. The feasibility of the proposed methods is shown and compared on a typical distribution system model with promising results.

Fescioglu-Unver & Kokar (2008) introduced two strategies to improve the RTS. The improved RTS is called Self Controlling Tabu Search (SC-Tabu). SC-Tabu is applied to achieve a self controlling software which is a heuristic search algorithm: the reactive tabu search (RTS). The RTS algorithm, the solutions are always being evaluated and modified during the search process.

However, the SC-Tabu uses a control theoretic approach. SC-Tabu regards the RTS algorithm as a plant to be controlled. Therefore, SC-Tabu will modify the algorithm parameters in order to control the intensification of the search. The second strategy of the SC-Tabu is to adjust several parameters based on the feedback coming from the search to achieve diversification during the search. These strategies adjust the parameters that are the unique signature of self controlling TS (SC-Tabu) algorithm. The improved algorithm (SC-Tabu) was compared to the RTS and Robust Tabu Search. The experiment results showed a significant difference between RTS, Robust Tabu and SC-Tabu after an experiment on different problem types of the quadratic assignment problem (QAP). The RTS performs well on random uniform problems while Robust Tabu Search performs well on real life like problems. The SC-Tabu is found to performed better on both types of problem as the algorithm adapts to different structures in order to find good solution.

Another example of RTS application is in classification as shown in Zennaki et al (2007) work. They investigate the utility of RTS to solve the primal Mixed Integer Programming Transductive Support Vector Machine (MIP-TSVM) formulation with relatively large problem dimensions. Preliminary results with a linear kernel show that their RTS implementation can effectively find optimal global solutions for TSVM.

Another interesting application of RST is in the cognitive neuroscience research. This field studies how language is processed, acquired, comprehended and produced by the human brain. One of the research tools in this field is to use computational models that try to simulate how language information is processed. An issue in developing computational model in psycholinguistics is the generation of meaningless "words" that match certain statistical and/or linguistic criteria. One of the techniques in generating nonwords is based on linguistic units such as syllables or morphemes. This technique will cause a vast amount of combinations when the size of the nonwords is increased. De Lara (2007) apply RTS algorithm for stimuli generation in order to generate nonwords of variables size. Such stimuli receive the name of pseudowords or nonwords in the Cognitive Neuroscience literature. The approach builds pseudowords by using a modified Metaheuristic algorithm based on a local search procedure enhanced by a feedback-based scheme. The experimental results show the proposed algorithm is able to perform effectively and has achieved its objective. The abilities of the algorithm suggest that the reaction and feedback mechanisms introduced by de Lara (2007) offers a good alternative to classic random generation techniques. These mechanisms make RST a robust algorithm against problem dimensionality and make it able to cope a complex combinatorial search and offer general solutions where the classic random generation techniques is not effective at. Another interesting feature of the algorithm is its robustness against problem dimensionality.

3.3 Comparison with Ant Colony

Sammoud et al (2006) compare the efficiency between the Ant Colony Optimization algorithm (ACO) with RST on two different kinds of complex graph matching problems. In Sammoud et al (2006) experiment, they come to a conclusion that ACO usually obtains better results but in terms of speed and time is slower than RST. However, it is suggested by the paper that the two algorithms complements each other. If a good solution is need in a short time while the instances are easy, RST is recommended in this kind of situation. But ACO is recommended if the instances is complex and we have more time for processing to achieve better solution.

3.4 Hybrid Techniques

Wassan (2007) proposed a heuristic approach based on the hybridization of RTS and adaptive memory programming (AMP) to solve the vehicle routing problem with backhauls (VRPB). The techniques are integrated within the Tabu Search framework in order to obtain maximum continuous balance of intensification and diversification. In this hybrid technique, the RTS with an escape mechanism is used to manipulate different neighbourhood schemes in order to get a balanced intensification and diversification during the search process. Wassan (2007) used the adaptive memory strategy to avoid local optima by searching back the unexplored regions. A set of elite solutions is maintained and will be used when appropriate with the RTS. The robust feature of the proposed algorithm is gained from the AMP behavior. AMP causes an early convergence when tested on most of the VRPB instances. Wassan’s work proved a successful strategy in producing better accuracy and consistency in solution results for various types of VRPB benchmark problems. They compare their algorithm against the best methods in the literature and report new best solutions for several benchmark problems.

Masegosa et al. (2009) propose hybrid reactive search and cooperative strategies to the uncapacitated single allocation p-Hub median problem. The cooperative strategy they applied is a standard version of simulated annealing. Concretely, they incorporate a rule based of reactrive search framework into a simple centralized cooperative strategy. They first investigate the perfomance of the strategy during the search process and confirm that the reactive control rule is capable of driving the diversification of the strategy. In such a way solvers can escape from local minima. They compare their proposed algorithm with (i) cooperative strategy utilizing the fuzzy rule and (ii) the cooperative strategy using both reactive rules reactive rule and fuzzy rule. The performance is assessed in term of qualtiy of the solution, convergence speed and how the rules modifes the threads. Masegosa et al (2009) experiments on instances of the Uncapacitated Single Allocation p-Hub Median problem have shown that the proposed hybridization achieves better results with respect to a strategy based on independent solver, and with respect to the same cooperative strategy based on a fuzzy control rule.

4. Conclusion

Most problems can be formulated in terms of search space and target in several different manners. A local search algorithm starts from a candidate solution and then iteratively moves to a neighbor solution. The search stops when no improvement is possible. However, it is impossible to know when the global minimum is found. Modern heuristic such as, Genetic Algorithm, Simulated Annealing and Tabu search noticed as efficient methods for solving large combinatorial optimization problems (Fudo et al. 1999).

The term reactive search refers to an algorithmic framework where optimization techniques are coupled with machine learning algorithms. Feedback scheme that modifies the search parameter according to the search result is called reaction, which is the core of reactive search technique. Reactive search technique automates parameter setting by taking into account the past search history (i.e. by learning). The machine learning component analyzes the behavior of the optimization algorithm and provides feedback by fine tuning its parameters (Masegosa et al. 2009). The main advantages of reactive search as listed by Batiti (2008) are as follows:

- Automation of the complete optimization procedure;
- Dynamic adjustment of search parameters at every search step which leads to faster overall optimization time;
- Enhanced reproducibility of the results.

Reactive TS, known as the prohibition-based search, is among the popular technique used, ranging from psycholinguistics, knapsack problem, vechicle routing problem, to service restoration in electric power distribution system which is a hard optimization problems. The propularity of reactive TS is it has a mechanism to continue the search after found the local minimum; guiding the basic heuristic beyond local optimality. One of the main component that make TS different from local search is it uses adaptive memory, which creates more flexible search behaviour (Glover and Laguna 1997). Reactive TS can automatically adjust the generic parameters of TS and somehow learn during the search process.

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