A performance study of crossover operators for the SAT problem

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The balance between intensification and diversification is a key point on evolutionary computation. The performance of an evolutionary algorithm [1] strongly depends on the design and on the management of its operators along the search. Most of the approaches focus on intensification and use exclusively the quality of the population as a unique criterion to guide the search [2]. Some other works try to introduce this balance between intensification and diversification, but this balance is kept fixed all over the search [3]. Before developing such an approach, we have to study the behavior of search operators and their potential skills in intensification and diversification [4].

In our study we choose the study of crossover operators in the case of the SAT problem. The satisfiability problem (SAT) [5], as one of the six basic core NP-complete problems, has been the deserving object of many studies in the last two decades. In addition to its theoretical importance, SAT has a large number of practical applications such as VLSI test and verification [6], the design of asynchronous circuits [7], sports planning [8] and so on.

For experimental purposes, we use an evolutionary algorithm GASAT [9] that solves the canonical problem of satisfaction in propositional logic (SAT) [10] [11]. GASAT, a hybrid algorithm for the satisfiability problem (SAT) relies on the management of a population of individuals which are submitted to recombination and local search operators. A first version of GASAT has been presented in [12] with a simple local search process. This algorithm includes a recombination stage based on a specific crossover and a tabu search stage. Furthermore, More than 300 crossovers operators are defined by [13]. These operators are specific to the SAT problem and can defined by a combination of four basic features illustrated by table 1.

Table 1. Operators specific to the SAT problem

Steps	Basic features
1st-step	**Selection of clauses that are false in both parents**
2nd-step	**Action on each of the false clauses**
3rd-step	**Selection of clauses that are true in both parents**
4th-step	**Action on each of the true clauses**

At this stage, we deal with the required balance between intensification and diversification by introducing some dynamic strategies in a controller (AOS) defined by [14] [15], providing a fair experimental analysis of the controller behaviour. Such a study will help algorithm designers to better understand the actual effects of such adaptive control and to select the suitable components for achieving more autonomous algorithms.

This study is based on the application of Adaptive Pursuit strategy in the controller (AOS). The main idea: Updating probabilities such that the operator that currently has the maximal estimated reward is pursued. To achieve this, the pursuit method increases the selection probability and decreases all other probabilites. Here, the pursuit algorithm is extended to make it applicable in non-stationary environements. The pursuit algorithm is a rapidly converging algorithm for learning automata. At this stage, we conclude that the choice of each operators when performing promote intensification and/or diversification. Adaptive pursuit method introduced higher probability of applying best operator and higher expected reward, while ability to react swiftly at environmental changes remains intact.

The performance of the evolutionary algorithm is assessed by means of measures that evaluate the current state of search. Two well-known criteria are commonly used: diversification and intensification. Diversification reflects the trend to explore various areas of the search space. Intensification is related to the convergence of the search in a specific area. Results show that the change in generic algorithm parameters (Initial population size) and control strategies (Adaptive pursuit) causes a change in the management operators between intensification and diversification, these results help us to classify crossover operators. As a consequence, we use two measures previously introduced to control the balance between intensification and diversification, namely the average quality of the population and its genetic diversity.

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