Combining Local Search and Fitness Function Adaptation in a GA for Solving Binary Constraint Satisfaction Problems

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Binary constraint satisfaction problems (BCSPs) are defined by having a set of variables, where each variable has a domain of values, and a set of constraints acting between pairs of variables. A solution of a BCSP is an assignment of values to the variables in such a way that all restrictions imposed by the constraints are satisfied. Both genetic local search and genetic algorithms (GAs) with on-line adaptation of a penalty-based fitness function, separately, have produced promising results when they have been used to solve random binary constraint satisfaction problems [2, 3]. In this paper we investigate the effectiveness of the combination of these two approaches. We use the genetic local search algorithm recently introduced in [3], here called GLS. At each generation, the offsprings are improved by means of a local search procedure. The genetic operators and the fitness function do not use any heuristic information. We modify the algorithm by replacing the fitness function with the penalty-based fitness function used in the GA based on the SAW-ing method [2], here called SAW. The resulting algorithm is called GLS+SAW. We conduct extensive experiments on a large set of standard benchmark instances of random BCSPs. We generate problem instances from different BCSP classes, obtained by considering BCSPs with 15 variables, uniform domain size equal to 15, and varying density d (the probability of a constraint between two variables) and tightness t (the probablity of a conflict between two values of a constraint). When one of these parameters is changed, the BCSPs change from being relatively easy to solve to being very easy to prove unsolvable (phase transition). Table 1 contains the success rate SR (percentage of runs that find a solution) and, between brackets, the average number of fitness evaluations in successful runs (AES), for each combination of d and t. The results indicate that the addition of the SAW-ing method does not deteriorate the SR of GLS, while it decreases the AES for some classes of problems. Moreover, GLS+SAW has comparable SR and AES than one of the best GA based heuristic algorithms, the Microgenetic Iterative Descent Method Genetic Algorithm [1].

density	alg.	tightness 0.1	0.3	0.5	0.7	0.9
0.1	SAW	1(1)	1(1)	1(2)	1(9)	0.64(1159)
	GLS	1(10)	1(10)	1(10)	1(10.1)	0.70(16)
	GLS+SAW	1(10)	1(10)	1(10)	1(10)	0.70(25)
0.3	SAW	1(1)	1(2)	1(36)	0.23(21281)	0(-)
	GLS	1(10)	1(10)	1(17.9)	0.60(2547)	0(-)
	GLS+SAW	1(10)	1(10)	1(19.2)	0.60(2125)	0(-)
0.5	SAW	1(1)	1(8)	0.74(10722)	0(-)	0(-)
	GLS	1(10)	1(11)	1(2320)	0(-)	0(-)
	GLS+SAW	1(10)	1(11)	1(1791)	0(-)	0(-)
0.7	SAW	1(1)	1(73)	0(-)	0(-)	0(-)
	GLS	1(10)	1(26)	0(-)	0(-)	0(-)
	GLS+SAW	1(10)	1(31)	0(-)	0(-)	0(-)
0.9	SAW	1(1)	1(3848)	0(-)	0(-)	0(-)
	GLS	1(10)	1(376)	0(-)	0(-)	0(-)
	GLS+SAW	1(10)	1(436)	0(-)	0(-)	0(-)

Table 1: SR (AES) of SAW, GLS and GLS+SAW

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