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

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Both genetic local search (GLS) 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 (BCSPs). In this paper we investigate the effectiveness of GAs that combine these two methods, more specifically, whether the use of a more involved fitness function improves the performance of GLS algorithms for random BCSPs. GLS has been recently used in a hybrid GA [3]; at each generation, the offsprings produced by the application of genetic operators are improved by means of a local search procedure. Next, we replace the fitness function with the fitness function from SAW-ing [2] and define an adaptive cost function (resulting in GLS+SAW). We conduct extensive experiments on a large set of standard benchmark instances of random BCSPs. Binary constraint satisfaction problems 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. In this paper we use randomly generated BCSPs that can be defined by four parameters: the number of variables n, the (uniform) domainsize m, the probability of a constraint between two variables d (density), and the probablity of a conflict between two values of a constraint t (tightness). The results indicate that the addition of the SAW-ing method does not deteriorate the succes rate (percentage of runs that find a solution, SR) of GLS, while it decreases the average number of fitness evaluations (AES) for some classes of problems. When comparing GLS+SAW with one of the best GA based algorithms, Microgenetic Iterative Descent Method Genetic Algorithm (MIDA) [1], we found that GLS+SAW is slightly better in both SR and AES.

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

References

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