An Effective Memetic Algorithm for the Close-Enough Traveling Salesman Problem

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1 Introduction

The Close-Enough Traveling Salesman Problem (CETSP) [3] is a variant of the popular Traveling Salesman Problem (TSP). The CETSP can be defined as follows. Given a set of N targets $V = \{v_1, v_2, ..., v_N\}$ and a depot p_0 in the Euclidean plane, each target v_i has a disk neighborhood $\mathcal{N}_i$ of radius r_i. The objective is to find the shortest Hamiltonian cycle $S = \{p_0, p_1, p_2, ..., p_N, p_0\}$ that starts and ends at the depot p_0 and passes through a point p_i in the disk neighborhood $\mathcal{N}_i$ of every target v_i. The CETSP has a number of applications in the real world, such as automated meter reading with radio frequency identification (RFID), solar panel diagnostic reconnaissance, and laser welding robot path planning, etc.

2 Memetic algorithm for the CETSP

We proposed an effective memetic algorithm (MA-CETSP) for solving the CETSP. Our MA-CETSP algorithm comprises three main original components : a dedicated multi-step crossover tailored to the CETSP, which can better capture the connectivity between the points in a solution, leading to more meaningful and feasible offspring solutions ; a powerful VND-based local optimization procedure where a set of designed search operators, including sequence-only, position-only, and joint optimization operators, are applied sequentially to ensure thorough and intensive exploitation, resulting in a refined and accurate solution ; a fitness-and-distance based population management procedure which can maintain the balance between intensification and diversification. MA-CETSP also integrates a preprocessing procedure to reduce the input problem and a mutation operator to promote diversity.

3 Computational results

The proposed algorithm was evaluated on the set of 62 popular benchmark instances from [4] with different sizes from 10 to 1000 targets. There are three groups of instances. The first group (G1) consists of 27 instances with different overlap ratios, the second group (G2) comprises 21 instances with fixed overlap ratios (2%, 10% and 30%) (G2_0.02, G2_0.1 and G2_0.3), The third group (G3) comprises 14 instances with arbitrary radii. We used the best-known solutions (BKS) ever reported in the literature and three state-of-the-art algorithms (GA [2], (lb/ub)Alg [1], and SZVNS [5]) as reference methods for comparison.

Table 1 presents a summary of the computational results for the different groups of benchmark instances and provide a general overview of the performance of our MA-CETSP algorithm. Each instance was solved 20 times and the best result was considered. The line *#Instances* indicates the number of instances in the corresponding group, and the line *#Optima* shows the number of instances whose optimal solutions are known. The lines *#Wins*, *#Ties*,

TAB. 1 – Summary of computational results.

Group		G1	G2_0.02	G2_0.1	G2_0.3	G3	Total
#Instances		27	7	7	7	14	62
#Optima		9	0	4	7	3	23
MA-CETSP vs BKS	#Wins	**13**	**6**	**3**	0	**8**	**30**
	#Ties	14	1	4	7	6	32
	#Losses	0	0	0	0	0	0
	p-value	-	-	-	-	-	7.98E-08
MA-CETSP vs GA	#Wins	**13**	**6**	**6**	0	**8**	**33**
	#Ties	14	1	1	7	6	29
	#Losses	0	0	0	0	0	0
	p-value	-	-	-	-	-	1.32E-08
MA-CETSP vs (lb/ub)Alg	#Wins	**17**	**7**	**5**	**1**	**12**	**42**
	#Ties	10	0	2	6	2	20
	#Losses	0	0	0	0	0	0
	p-value	-	-	-	-	-	8.75E-10
MA-CETSP vs SZVNS	#Wins	**21**	**6**	**7**	**5**	**10**	**49**
	#Ties	6	1	0	2	4	13
	#Losses	0	0	0	0	0	0
	p-value	-	-	-	-	-	2.36E-11

and *#Losses* respectively indicate the number of instances where MA-CETSP achieves better, same, and worse results compared to the references. Furthermore, to confirm the statistical difference in the results, we conducted a Wilcoxon signed-rank test with a confidence level of 0.05, and the corresponding *p-values* are shown in the table. Table 1 clearly shows that the MA-CETSP algorithm provides comparable or better results compared to BKS and all reference algorithms. MA-CETSP obtained all 23 known optimal values and 30 new best upper bounds out of the remaining 39 instances. The *p-values* (<< 0.05) indicates that the proposed algorithm statistically performs better than the reference algorithms.

4 Conclusion

We have proposed an effective memetic algorithm for the CETSP. Compared to the existing algorithms, the results demonstrated the superiority of our algorithm on 62 benchmark instances. For future work, it would be interesting to adapt and extend our approach to other CETSP variants, thus extending its application to a wider range of real-world problems.

Références

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