Arguments for ACO's Success

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Abstract. Very little theory is available to explain the reasons underlying ACO's success. A population–based ACO (P-ACO) variant is used to explain the reasons of elitist ACO's success in the TSP, given a globally convex structure of the solution space.

1 Reasons Underlying ACO's Success

For this work a TSP tour is denoted as r_x, the optimal tour as r^* and a population of m tours as $P = \{P_i\}$. Distance $\delta(r_x, r_y)$ is defined as the number of cities n minus the number of common arcs between tours r_x and r_y. Inspired in [1], Fig. 1 (a) presents the length of a tour $l(r_x)$ as a function of its distance to the optimal solution $\delta(r_x, r^*)$ for the whole space S of a randomly chosen TSP with 8 cities. Fig. 1 (b) shows the length of $r_x \in S$ as a function of its mean distance to a population $\delta(P, r_x) = \frac{1}{m}\sum_{i=1}^{m} \delta(P_i, r_x)$ of randomly chosen good solutions for the same problem. As previously found for different TSP instances [1], a positive correlation is observed. Consequently, the TSP solution space has a globally convex structure for all tested instances [1].

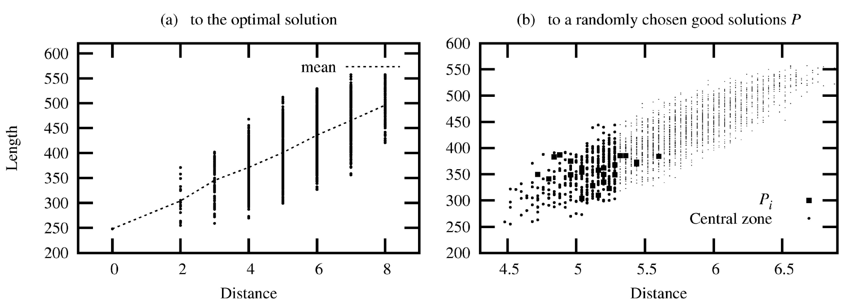

Fig. 1. Distance of the 2,520 solutions of the randomly chosen TSP with 8 cities

To understand the typical behavior of ACO, the n–dimensional TSP search space is simplified to two dimensions for a geometrical vision in Fig. 2. A population $P1 = \{P1_i\}$ of good solutions uniformly distributed is assumed in Fig. 2. Considering that the proposed variant of P-ACO [2] (called Omicron ACO or

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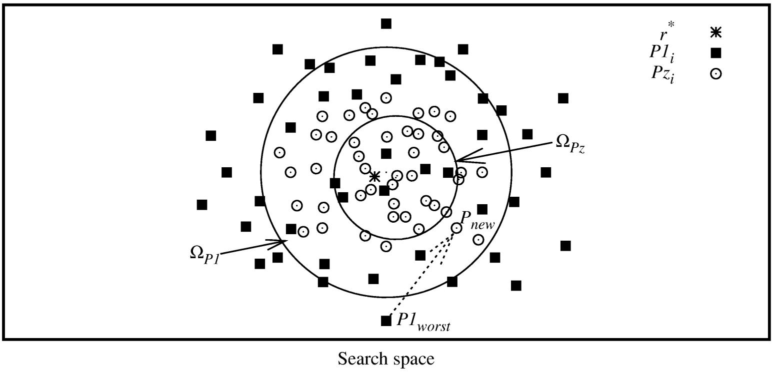

Fig. 2. Simplified vision of OA behavior

OA) gives more pheromones to the good solutions $P1_i$ already found, this can be seen as a search made close to each $P1_i$. Thus, OA concentrates the search of new solutions in a central zone of $P1$, denoted as Ω_{P1}, which is the zone close to all $P1_i$. Then OA typically replaces the worst solution of $P1$ ($P1_{worst}$) by a new solution P_{new} of smaller length. A new population $P2$ is created including P_{new}. This is shown in Fig. 2 with a dotted line arrow. As a consequence, it is expected that $\delta(P2, r^*) < \delta(P1, r^*)$ because there is a positive correlation between $l(r_x)$ and $\delta(r_x, r^*)$. Similarly, $\delta(P, P_{new}) < \delta(P, P_{worst})$ because there is a positive correlation between $l(r_x)$ and $\delta(P, r_x)$, therefore $\delta(P2) < \delta(P1)$ (where $\delta(P) = \frac{2}{m(m-1)} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} \delta(P_i, P_j)$ is the mean distance of P), i.e. it is expected that the subspace where the search of potential solutions is concentrated decreases. OA performs this procedure repeatedly to decrease the search zone where promising solutions are located, as seen in Fig. 1 (b). Considering population $Pz = \{Pz_i\}$ for $z >> 2$, Fig. 2 shows how Ω_{Pz} has decreased considerably as a consequence of the globally convex structure of the TSP solution space.

2 Conclusions

OA concentrates the search in a central zone Ω_P of its population P. In globally convex problems, good solutions are usually found in this region; therefore, OA concentrates its search in a promising subspace. Every time a good solution is found, it enters the population reducing the promising search zone iteratively.

References

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2. Guntsch, M., Middendorf, M.: Applying Population Based ACO to Dynamic Optimization Problems. In: Ant Algorithms, Proceedings of Third International Workshop ANTS 2002. Volume 2463 of LNCS. (2002) 111–122