A Co-Evolutionary Hybrid ACO for Solving Traveling Salesman Problem

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ABSTRACT

Ant Colony Optimization (ACO) is an approximate method proposed recently. Many ACO based approaches and hybrid methods have been proposed for solving the traveling salesman problem (TSP); However, the balance between intensification and diversification is also difficult to solve. In this paper, we propose a co-evolutionary hybrid method (CEACO-GA) by adopting multiple colonies which perform ACO or GA algorithms, and a co-evolutionary strategy among colonies which is to enhance the interaction among colonies by communication between ACO and GA colonies, thereby to control the population diversity. The number of colonies that perform GA operations is used to adjust the balance between intensification and diversification. The CEACO-GA is tested on various problem instances in the TSPLIB standard library, and the results of numerical calculation show that the the CEACO-GA has more outstanding performance comparing to other algorithms.

CCS CONCEPTS

• **Computing methodologies**; • **Theory of computation** → **Approximation algorithms analysis**;

KEYWORDS

ant colony optimization, genetic algorithm, co-evolutionary strategy, hybrid, traveling salesman problem

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1 INTRODUCTION

Ant colony optimization (ACO) [1] is a swarm intelligence algorithm for optimization problems. The ant system (AS) is the first ACO algorithm, proposed by Dorigo [1], and was used to solve the the traveling salesman problems (TSP) [2] as an example application. As same as other computational intelligence methods [3], the ACO algorithm has attracted the attention of more researchers, and many other ACO algorithms have been proposed, such as Ant Colony System (ACS) [4], Rank-based AS (ASrank) [5] and Max-Min AS (MMAS) [6]. In the ACO, the intensification and diversification is two main characteristics [7], many works were done on this topics. On this topics, traditional ACO algorithms mainly take manipulations on pheromone trails by using different pheromone update rules. As to other methods, hybrid methods also attracted the attentions of many researchers nowadays[8]. Gülcü et al. [9] proposed a parallel cooperative hybrid algorithm, called PACO-3Opt based on ant colony optimization. Zhang et al. [10] propose a ACO algorithm based on congestion and coevolution, called CCMACO.

In this paper, we propose a new hybrid method called CEACO-GA which has multiple ACO colonies and GA colonies and adopt co-evolutionary by performing communication between ACO and GA colonies. We use problem instances in the TSPLIB standard library [11] to test the performance of the CEACO-GA. The results of numerical calculation show that the the CEACO-GA has more outstanding performance comparing to other algorithms.

2 ANT COLONY OPTIMIZATION FOR TRAVELING SALESMAN PROBLEMS

In ACO methods, each ant randomly select a city, and then decides the city to go to independently using the rule depend a probability function, until all cities have been selected. we use τ_{ij} as the pheromone in the edge between city i and j, the probability that the $k-ant$ go to city j from city j is given by:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}}{\sum_{l\in J_i^k(t)}\tau_{il}^{\alpha}(t)\cdot\eta_{il}^{\beta}} & \text{if } j\in J_i^k(t)\\ 0 & \text{otherwise}\end{cases} \tag{1}$$

where $\eta_{ij}=1/d_{ij}$ is the heuristic information and d_{ij} is the distance between $i-citie$ and $j-citie$. The α and β is used to denote the weights of the pheromone and heuristic information. J_i^k is the set of cities that must be visited. After all ants completed Exploration process, the pheromone is updated using the following function:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{2}$$

note that $\rho\in(0,1)$ is the pheromone evaporation rate, and $\Delta\tau_{ij}^{k}$ is the amount of pheromone that ant k deposits on the edges it has visited. It is defined as follows:

$$\Delta\tau_{ij}^{k}=\begin{cases}1/L^{k} & \text{if } (i,j)\in T^{k}\\ 0 & \text{otherwise}\end{cases} \tag{3}$$

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where L^k is the tour lengthT^k created by $k - ant$.

3 CO-EVOLUTIONARY HYBRID ANT COLONY OPTIMIZATION (CEACO-GA)

Although many efforts were down on ACO based algorithm for TSP, the performance is also not very good because of the difficulty of adjusting the balance between the intensification and diversification. To overcome the deficiencies, we propose a co-evolutionary hybrid ant colony optimization (CEACO-GA) in which a co-evolutionary strategy among multiple ACO colonies and GA colonies is adopted.

GA is also a population-based search algorithm as well as ACO. It applies recombination and selection strategies to a population of solutions to produce better and better solutions. When applying to optimization problems, GA provides the advantages to perform global search and hybridize with other heuristics [13]. In GA, New populations are generated from generation to generation. A chromosome with a better fitness value will be selected with a higher probability in the next generation. As a result, GA can converge to the best solution after some generations.

3.1 Framework of Co-Evolutionary Hybrid Ant Colony Optimization (CEACO-GA)

In the proposed CEACO-GA, we introduce multiple colonies which perform ACO in some colonies (ACO colonies) and GA in other colonies (GA colonies). Communication between ACO and GA colonies is adopted to realize the co-evolution among multiple ACO colonies and GA colonies. The communication disturb the relatively stable pheromone distributions of ACO colonies after certain search iterations, so as to enhance the diversification of the method, and also the communication also enhances the quality of individuals of GA colonies. On the other hand, as too much emphasis of diversification from GA colonies could make the algorithm unstable, we decrease the GA colony number gradually as the communication proceeds, to modify the weight of intensification and diversification. The framework of the the CEACO-GA is depicted in Figure 1.

As shown in Figure 1, the CEACO-GA adopts two groups of colonies. One includes ACO colonies and the other includes GA colonies. Initially, the number of GA colonies is set equal to that of ACO colonies as $n = m$, and the population size of each colony is set to p. In this figure, A_i represents an arbitrary colony of the m ACO colonies, while G_i represents an arbitrary colony of the n GA colonies. Each ACO colony performs ACO while each GA colony performs GA to search solutions simultaneously. After a certain calculation period, two ACO colonies A_r, A_s and one GA colony G_t are randomly selected and communication among them are performed to produce new ACO and GA colonies (A'_i and G'_i). For the first communication period, through $m = n$ times of selections and communications, new colonies are produced and prepared for the next communication period. From the second communication period, the GA colony number is decreased as the following equation.

$$n = \mu \cdot n \tag{4}$$

where $\mu \in (0, 1)$ is a parameter that adjusts the balance of intensification and diversification. In order to depict the detailed procedure, we give the outline of the the CEACO-GA as Figure 2.

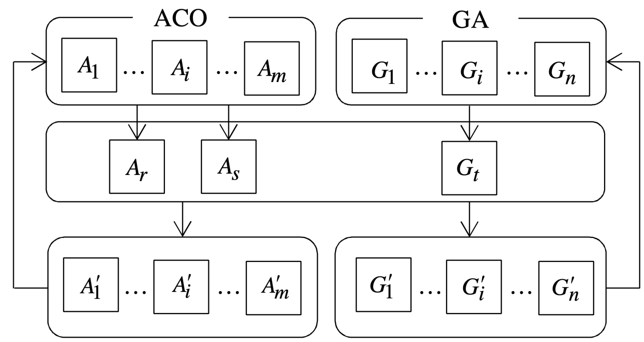

Figure 1: The framework of the CEACO-GA.

The same as in the traditional ACO, in the proposed CEACO-GAS, each ant select the city to builds a solution using the probability given by Eq. 1. On the other hand, each individual of GA colony evolve using GA operations. In this paper, we use PMX [14] for TSP. As to mutation operation, we swap two random selected cities in a solution to get a new solution.

3.2 Communications among Colonies

The proposed CEACO-GA perform communication between ACO and GA colonies to realize the co-evolutionary strategy which is to enhance the interaction among different colonies, and thereby to control the population diversity. In the proposed CEACO-GA, the communication is achieved through immigration. ACO always fall into local optima. However GA has the advantage to perform global search. Immigrations from GA colonies to ACO colonies enable ACO colonies to search the local solution space intensively, while improving ACO to globally search the solution space and move out of the local optimum. On the other hand, immigrations from ACO colonies to GA colonies enable better individuals to enter the GA colonies and improve the search performances of GA colonies.

As depicted in Figure 1, communications are performed among the randomly selected A_r, A_s and G_t. We first sort the solutions of A_r, A_s and G_t respectively so that the first individuals of A_r, A_s and G_t have the best solutions, respectively. Next we describe the immigration strategy among these colonies in detail. After the solution searches by ACO and the solution evolvements by GA, we replace the worst v solutions in A_r and A_s by the best $2v$ solutions in G_t as described in Eq.5 and Eq.6, and then average the pheromone distributions of A_r and A_s to produce a new pheromone distribution $\tau_{ij}^{A'_i}$ in the new colony A'_i as described in Eq.7.

$$\tau_{ij}^{A_r} \leftarrow \tau_{ij}^{A_r} - \sum_{k=u-v+1}^{u} \Delta\tau_{ij}^{k,A_r} + \sum_{k=1}^{v} \Delta\tau_{ij}^{k,G_t} \tag{5}$$

$$\tau_{ij}^{A_s} \leftarrow \tau_{ij}^{A_s} - \sum_{k=u-v+1}^{u} \Delta\tau_{ij}^{k,A_s} + \sum_{k=v+1}^{2v} \Delta\tau_{ij}^{k,G_t} \tag{6}$$

$$\tau_{ij}^{A'_i} \leftarrow (\tau_{ij}^{A_r} + \tau_{ij}^{A_s})/2 \tag{7}$$

```
Algorithm: The CEACO-GA Algorithm
  set parameters
  for i=1 to m do
    initialize pheromone distribution i
  end-for
  while( n > 1 ) do
    for i=1 to m do
      while (a certain calculation period ) do
        construct ant solution
        execute local search procedure
        update pheromones by traditional ACO
      end-while
    end-for
    for i=1 to n do
      evolve solutions by GA
    end-for
    for i=1 to n do
      randomly select A_r, A_s and G_t
      perform communication among A_r, A_s and G_t
           to obtain A_i' and G_i'
    end-for
    for i=n+1 to m do
      randomly select A_r, A_s
      perform communication among A_r, A_s
           to obtain A_i'
    end-for
    n ← μ · n
  end-while
```

Figure 2: The outline of the CEACO-GA in pseudo-code.

where the colony population size $p > 2v$, and $\Delta\tau_{ij}^{k,A_r}$, $\Delta\tau_{ij}^{k,A_s}$ and $\Delta\tau_{ij}^{k,G_t}$ are defined as follows.

$$\Delta\tau_{ij}^{k,A_r} = \begin{cases} \frac{1}{L_{A_r}^k} & \text{if } (i,j) \in \text{the } k_{th} \text{ ant in } A_r \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$\Delta\tau_{ij}^{k,A_s} = \begin{cases} \frac{1}{L_{A_s}^k} & \text{if } (i,j) \in \text{the } k_{th} \text{ ant in } A_s \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

$$\Delta\tau_{ij}^{k,G_t} = \begin{cases} \frac{1}{L_{G_t}^k} & \text{if } (i,j) \in \text{the } k_{th} \text{ individual in } G_t \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

In the meantime, we replace the worst $2v$ individuals of G_t by the best v solutions in A_r and the best v solutions in A_s to produce a new colony G_i'.

Through the communication described above, we can enhance the ability of adjusting the balance in search process of the hybridization between ACO and GA.

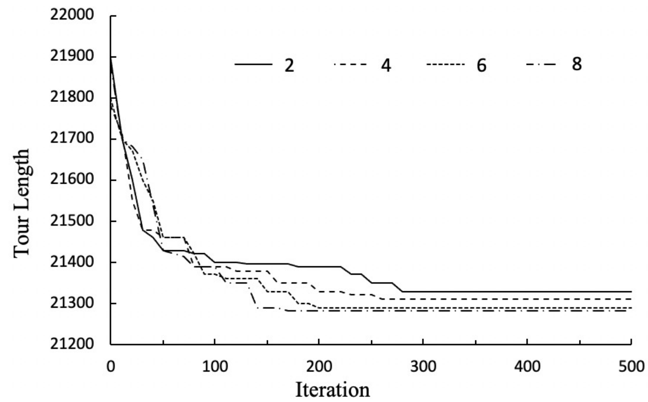

Figure 3: Variation of solution after communication.

Table 1: Results on 10 TSPs by the proposed CEACO-GA

Instances	Size(City)	BKS	Best	Average	RD
Eil51	51	426	**426**	426.0	0.00
Berlin52	52	7542	**7542**	7542.0	0.00
St70	70	675	**675**	675.1	0.01
KroA100	100	21282	**21282**	21326.3	0.21
Eil101	101	629	**629**	631.8	0.45
Lin105	105	14379	**14379**	14398.1	0.13
Ch150	150	6528	6532	6553.9	0.40
KroA200	200	29368	29378	29651.3	0.96
Rd400	400	15281	15527	15592.3	2.04
Rat575	575	6773	6883	6993.1	3.25

4 SIMULATION RESULT

In order to assess the effectiveness of the proposed method, extensive simulations were carried out over 10 different TSP instances which are available from the TSPLIB benchmark library [11]. The basic parameters setting of the CEACO-GA is as ($\alpha = 1, \beta = 2, \rho = 0.5$, colony size $p = 30$). Besides, we set the colony number m to 10, the immigration number v to 6.

As an another parameter, μ in Eq.4 plays an important role in adjusting the weight of intensification and diversification, too small or too large μ leads to too slow or too rapid decreasing of the GA colony number. Using different μ we did a lot of experiments to decide the appropriate μ, we found $\mu = 0.75$ makes the best result. In the proposed CEACO-GA, communication between ACO and GA colonies is adopted to realize the co-evolution among multiple ACO colonies and GA colonies. To show the effect of the communication among colonies on the search process, we did experiments on KroA100 and give Figure 3 to depict the variation of tour length after the 2nd, 4th, 8th, 10th communication period. From this figure we know that the curves converge to a smaller tour length as the the communications proceed. So we can conclude that the communication among colonies affects the search process effectively.

The simulation results of the CEACO-GA are summarized in Table 1. In Table 1, the column "best" is the best solution found by the CEACO-GA. Beside the tour length, the quality of the solutions can

Table 2: Simulation Result Using Different Ant Numbers on rl1323

Instances	BKS	CEACO-GA			CCMACO[10]			PACO-3Opt[9]		
		Best	Avg.	*RD*(%)	Best	Avg.	*RD*(%)	Best	Avg.	*RD*(%)
Eil51	426	**426**	426.0	0.00	**426**	427.8	0.42	**426**	426.4	0.08
Berlin52	7542	**7542**	7542.0	0.00	**7542**	7554.2	0.16	**7542**	7542.0	0.00
St70	675	**675**	675.1	0.01	**675**	679.1	0.61	676	677.9	0.42
KroA100	21282	**21282**	21326.3	0.21	**21282**	21488.3	0.97	**21282**	21326.0	0.21
Eil101	629	**629**	631.8	0.45	**629**	640.6	1.84	**629**	630.6	0.25
Lin105	14379	**14379**	14398.1	0.13	-	-	-	**14379**	14393.0	0.10
Ch150	6528	6532	6553.9	0.40	6532	6592.4	0.99	6570	6601.4	1.12
KroA200	29368	29378	29651.3	0.96	29399	29834.8	1.59	29533	29644.5	0.94
Rd400	15281	15527	15592.3	2.04	-	-	-	15578	15613.9	2.18
Rat575	6773	6883	6993.1	3.25	6950	7215.7	6.54	7003	7012.4	3.53

also be evaluated by the average solution and the relative deviation (*RD*)[15]. The average solution and the relative deviation (*RD*) is also shown in the table. The relative deviation *RD* is defined in Eq. 11 where BKS means the best-known solution.

$$RD = \frac{Average\ Solution - BKS}{BKS} \tag{11}$$

From Table 1, we can know that the CEACO-GA found 6 the best-known solution (BKS) in 10 TSP, which are shown in bold in column "best". Besides, the relative deviation is less than 3.25% for all TSP instances, which means that the CEACO-GA can obtains robust solutions.

To verify the performance of the proposed CEACO-GA, two previous ACO based algorithms in the literature whose characters and features are briefly explained in section introduction are selected to compare with the CEACO-GA: CCMACO [10] and PACO-3Opt [9]. Table 2 presents the comparison of the CEACO-GA with these methods.

Form the table, we can know that the PACO-3Opt [9] have relatively bad results. According to the best, the proposed CEACO-GA found same solution on Eli51, Berlin52, St70, KroA100, Eil101 and Ch150 as CCMACO [10]. On the other hand, according to the relative deviation of the average solutions on these instances the proposed CEACO-GA has much smaller value than CCMACO [10]. Besides, on the instances KroA200 and Rat575, the proposed CEACO-GA outperforms other algorithm in both the best and average solutions.

5 CONCLUSIONS

In this paper, a co-evolutionary hybrid ant colony optimization (CEACO-GA) has been proposed and evaluated using TSP. In the CEACO-GA, besides multiple colonies of ant colony we introduced multiple colonies that perform GA. Communication among colonies improved the performance of the CEACO-GA algorithm through enhancing the diversification of ACO and the quality of GA. The proposed CEACO-GA was evaluated using TSP instances, and compared with other resent methods. The results of numerical calculation show that the the CEACO-GA has more outstanding performance comparing to other methods.

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