Recruiting Ant Colony System

Extending the ACS by a group recruitment strategy

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Abstract

We briefly describe an approach to extend the *Ant Colony System* by a group recruitment strategy. The underlying idea is very similar to the behavior of real ants, which use e.g. tandem-techniques to guide each other to large food sources. General investigations with small and medium sized colonies have shown that such strategies in combination with mass recruitment (pheromones) increase the food-supply rate.

Surprisingly, this quite natural mechanism can be easily adapted for *Ant Algorithms* and has inspired our idea of the *Recruiting Ant Colony System*. The experiments with the optimization of a *Traveling Salesman Problem* instance show that RACS improves the auto-catalytic process. It seems that our new algorithm converge faster and more stable than the original one.

Keywords: Ant Algorithms, Ant Colony System (ACS), combinatorial optimization problems, group recruitment, Traveling Salesman Problem (TSP)

1 Introduction

The class of *Ant Algorithms* was introduced by Marco Dorigo et al. [3, 4, 5]. Such kind of algorithms rely on foraging behavior of real ant colonies, in particular, by the communication of the individual agents through pheromones. A recent overview about the biological background can be found in [6]. Experiments with the *Traveling Salesman Problem (TSP)* show that these algorithms are well suitable for combinatorial optimization problems. Through the years several variations and improvements have been applied to the basic algorithm, e.g. Ant-Q [8], ACS [9, 13], $\mathcal{MAX}$-$\mathcal{MIN}$ Ant System [10, 11] and AS_{rank} [12]. The most approaches fit the so called ACO meta-heuristic [7] and can be used for practical applications, e.g. routing in telecommunication networks.

2 Group recruitment strategy

For a general introduction to the underlying recruitment strategies and their modeling for real ant colonies we refer the reader to [1, 2]. Sumpter and Beekman supposed in [2] that for small sized colonies a combination of mass recruitment (pheromones) and group recruitment (tandem guided) could be useful. Starting from this idea we have implemented and tested a first modification of the Ant System, called *Recruiting Ant System (RAS)*. The algorithm and some partial results [15] were presented on a seminar for "Artificial Life" at the University of Leipzig. Due to the promising results we have revisited our previous work and can finally present an interesting improvement for the *Ant Colony System (ACS)*.

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3 Recruiting Ant Colony System

Our model considers two different kinds of agents w.r.t. the real biological pattern:

1. **Search Ants:** Their job is to find large food sources in the environment by random search. For this purpose the common *action choice rule* of ACS is almost ideal.
2. **Transport Ants:** These agents wait in the nest until an acceptable food source is found. Then they follow with overwhelming probability the stored route of a recruiting search ant. If the track is lost, then a simple fall back to the classical orientation by pheromones appears. On the way the agents sometimes change their recruit label, i.e. they will act like recruited by a different search ant. Of course, the number of transport ants should be much larger than the number of search ants.

Recruiting algorithm for the Traveling Salesman Problem:

```
initialize pheromone array τ by value τ_0 (calculate τ_0 like ACS [9])
distribute m Search Ants randomly over the n cities
FOR t = 1 TO number of RACS-iterations
    /* Search Ants looking for good tours */
    FOR k = 1 TO m
        the kth ant is guided by τ like ACS
        local update of τ like ACS
        IF found tour is global best
            set Δτ_ij like ACS
    /* recruit r_1 Transport Ants for the r_0 iteration best Search Ants */
    /* (a) preparing pheromone sub-array */
    FOR k = 1 TO r_0
        initialize pheromone sub-array θ_kij by value 0
        set Δθ_kij := { 1/L_k  if the kth Search Ant moved from i to j
                       { 0      else
        update θ_kij by (1 − α) · θ_kij + α · Δθ_kij
        /* (b) instructing r_1 Transport Ants */
        FOR l = 1 TO r_1
            choose start city randomly
            set recruit label κ_{(k−1)·r_1+l} := k
    /* Transport Ants try to optimize tours */
    FOR k = 1 TO r_0 · r_1
        WHILE not all cities visited
            DO with probability ψ
                choose city random proportional by pheromone sub-array θ_{κ_k}
            DO with probability ψ − ψ^2
                choose city random proportional by pheromone array τ
            DO with probability (1 − ψ)^2
                set recruit label κ_k randomly from [1, ..., r_0]
        IF found tour is global best
            set Δτ_ij like ACS
    /* global update rule, similar to ACS */
    update τ_ij by (1 − α) · τ_ij + α · Δτ_ij
```

RACS has some similarities to AS_{rank} [12] and to AS with *elitist strategy* [6], but there are also complete new ideas, e.g. the group recruiting strategy, the usage of different pheromone arrays, and the change of the recruit label during the search.

4 Experiments and Results

We have only considered the TSP instance `st70` from the well known `TSPlib` [14].

ant algorithm	$T = 100$ avg. tour length std. deviation best tour	$T = 500$ avg. tour length std. deviation best tour	$T = 1000$ avg. tour length std. deviation best tour
AS70	716.981038 6.626357 701.504173	706.694384 4.454800 695.688021	703.600421 4.090950 695.362217
AS420	707.990482 4.623918 695.012480	701.714974 3.063929 692.222347	700.363662 2.635835 691.022638
RAS with $\xi = 0.00$	702.438273 12.611322 680.625303	698.114644 10.812993 678.115854	695.274270 10.295332 681.005292
RAS with $\xi = 0.05$	693.048182 3.742948 682.961533	687.098608 1.528757 682.093087	686.047880 1.326667 682.961533
RAS with $\xi = 0.10$	702.921183 3.843554 690.970097	695.049664 3.042670 684.472720	693.412571 3.122854 684.472720
ACS20	716.390465 14.776480 685.970361	711.655752 13.666000 683.104249	710.515404 13.752143 684.327621
ACS70	694.033039 9.875491 679.921935	686.871297 7.499485 **677.109609**	685.730690 7.317068 **677.109609**
ACS420	695.375406 9.107366 677.870036	687.517755 8.028459 **677.109609**	685.199858 6.883340 **677.109609**
RACS with $\psi = 1.00$	694.227542 9.987955 678.127746	685.108234 6.341046 **677.109609**	683.768535 6.403931 **677.109609**
RACS with $\psi = 0.95$	689.379314 12.369379 **677.109609**	683.413386 9.443083 **677.109609**	680.869586 6.506919 **677.109609**
RACS with $\psi = 0.90$	**682.366094** 5.816040 **677.109609**	**680.468348** 4.654106 **677.109609**	**680.485575** 5.265754 **677.109609**

Tabular 1: Results for 70-city problem Smith/Thompson (optimal tour = 675) average tour length (final best), standard deviation and best tour through 100 runs of the algorithms with the following parameters:
AS70: $\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.5$, $Q = 100.0$, $m = 70$ (uniform)
AS420: $\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.5$, $Q = 100.0$, $m = 420$ (uniform)
RAS: $\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.5$, $Q = 100.0$, $m = 70$ (uniform), $r0 = 5$, $r1 = m$ (random)
ACS20: $\alpha = 0.1$, $\beta = 2.0$, $\rho = 0.1$, $q_0 = 0.9$, $m = 20$ (random / at most one per city)
ACS70: $\alpha = 0.1$, $\beta = 2.0$, $\rho = 0.1$, $q_0 = 0.9$, $m = 70$ (uniform)
ACS420: $\alpha = 0.1$, $\beta = 2.0$, $\rho = 0.1$, $q_0 = 0.9$, $m = 420$ (uniform)
RACS: $\alpha = 0.1$, $\beta = 2.0$, $\rho = 0.1$, $q_0 = 0.9$, $m = 70$ (uniform), $r0 = 5$, $r1 = m$ (random)
(initial distribution of the ants). The best allover results are marked **bold**.

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