A Novel Ant Colony System Based on Traditional Chinese Medicine Theory

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Summary
By applying the health protection method of "bu" and the treatment method "xie" from traditional Chinese medicine to ant colony system (ACS), a novel ant colony system (CACS) is proposed. The core of CACS lies in the construction of "bu" operator and "xie" operator. The "bu" operator is made up of the good solution elements pool and the "bu" operation. The "bu" operation is that ants select from the good solution elements pool first and only if there are no feasible candidates are the remaining normal solution elements considered when ants construct solutions. The "xie" operator consists of "xie" operation and abnormal solution elements pheromone trails update rule. The "xie" operation is to remove the abnormal solution elements from solutions after ants have completed the construction of solutions. The construction methods of "bu" operator and "xie" operator are demonstrated by TSP. To validate the superiority of CACS, CACS and ACS and the latest improved ant colony are compared as regards TSP. The simulation results show that CACS promises excellent performance not only in the convergence speed but also in the quality of solution.

Key words:
ant colony system; good solution elements pool; "bu" operator; "xie" operator; abnormal solution elements pheromone trails update rule.

Introduction

The Traveling Salesman Problem (TSP), where the task is to find the shortest closed tour through a given set of n cities with known inter-city distances such that each city is visited exactly once and the tour ends at the start city, is a well-known NP-hard problem [1]. Not only is TSP broadly applicable to a variety of routing and scheduling problem, but it is also usually considered as a standard test-bed for novel algorithmic ideas such as simulated annealing, tabu search, evolutionary algorithms, ant colony optimization (ACO) and so on, among which ACO inspired by the foraging behavior of real ant was first introduced by Dorigo and his colleagues [2, 3, 4] and has become one of the most efficient algorithms for TSP [3, 5].

ACO is a constructive meta-heuristic, where a solution is probabilistically built by iteratively adding solution elements to partial solutions until a complete solution is generated. Since at each step ants consider the entire set of possible elements before choosing just one, the vast majority of an ant algorithm's runtime is devoted to evaluating the utility of reachable elements. Meanwhile, because the choice of ants is impossible to come absolutely correct in each step, there exist abnormal solution elements in solution unavoidably. Therefore canonical ACO algorithm has the phenomena of low converging speed and degeneration.

A novel genetic algorithm based on cure mechanism of traditional Chinese medicine theory (CMGA), which applies two types of treatment methods of "bu" and "xie" of traditional Chinese medicine theory to canonical GA, was proposed in Ref. [6]. CMGA can restrain the degeneration and premature convergence phenomenon effectively during the evolutionary process while greatly increasing the convergence speed.

Being similar to CMGA, this paper leads the health protection and treatment methods of traditional Chinese medicine to ACS and presents a novel ant colony system based on traditional Chinese medicine theory (CACS). According to the idea and method of "bu" operation, the "bu" operator is designed to guarantee ants to construct solution with good solution elements first and only if there are no feasible candidates are the remaining normal solution elements considered and thus greatly improves the quality of solutions and reduces the size of search space. Meanwhile, by mimicking the idea and method of "xie" operation, the "xie" operator, which consists of "xie" operation and abnormal solution elements pheromone trails update rule, is designed to restrain the degeneration phenomenon effectively. The "xie" operation aims at removing abnormal solution elements from solutions, and the abnormal solution elements pheromone trails update rule is used to reduce the probability of ants selecting abnormal solution elements. The construction methods of "bu" operator and "xie" operator are demonstrated by TSP. To validate CACS, the comparisons with ACS and the latest improved ant colony for many TSP instances are performed. Conclusions are given in the end.

Manuscript received May 5, 2006.
Manuscript revised May 30 , 2006.

2. The Ant Colony System

The first ACO algorithm proposed is ant system (AS) [2], and since then Dorigo and other researchers have introduced many improved ACO algorithms based on AS, among which ACS has better performance and is a representative of ACO. The flowchart of ACS can be shown in Fig.1.

```
Initialize the pheromone on all edges
Loop /* at this level each loop is called an iteration */
   Each ant is positioned on a starting node
   Loop /* at this level each loop is called a step */
         Each ant applies a state transition rule to
         incrementally build a solution and a local
         updating rule
   Until all ants have built a complete solution
   A global updating rule is applied
Until End_condition
```

Fig. 1 The flowchart of ACS

In the following, we take TSP as an example to explain ACS. For the purpose of convenient expression, we first give some symbols: n and m are the total number of cities and ants respectively, τ_0 is the initial pheromone level.

Initially, m ants are placed on m cities randomly chosen, and there is the same pheromone level τ_0 on each edge. Suppose that an ant k is on city i and will chooses the next city j to move to, well then, the city j can be confirmed by applying the state transition rule of Eg.(1).

$$j = \begin{cases} \arg\max_{u \in J_k(t)} \{\tau_{iu}(t)[\eta_{iu}]^{\beta}\}, & \text{if } q \le q_0 \text{ (exploitation)} \\ J, & \text{otherwise (biased exploration)} \end{cases} \qquad (1)$$

where $\tau_{iu}(t)$ is the pheromone level on edge (i, u) at the t-th step, $\eta_{iu} = 1/d_{iu}$ is the inverse of the distance d_{iu} from city i to city u, $J_k(t)$ is the set of cities that remain to be visited by ant k at the t-th step, β is a parameter that determines the relative importance of pheromone versus distance(β >0), q is a random number uniformly distributed in [$0...1$], q_0 is a parameter ($0 \le q_0 \le 1$), and J is a random variable selected according to the probability distribution given in Eq.(2):

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}(t) \cdot [\eta_{ij}]^{\beta}}{\sum_{u \in J_k(t)} \tau_{iu}(t) \cdot [\eta_{iu}]^{\beta}}, & if\ j \in J_k(t) \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

where $p_{ij}^{k}(t)$ is the probability with which ant k in city i chooses to move to the city j at the t-th step.

The state transition rule resulting from Eq. (1) and Eq. (2) is called pseudo-random-proportional rule. This state transition rule favors transitions toward cities connected by short edges and with a large amount of pheromone. The parameter q_0 determines the relative importance of exploitation versus exploration: every time an ant in city i has to choose a city j to move to, it samples a random number q. If $q \le q_0$ then the best edge, according to Eq. (1), is chosen (exploitation), otherwise an edge is chosen according to Eq. (2) (biased exploration).

While building a tour of the TSP, ants visit edges and change their pheromone levels by applying the local pheromone-updating rule of Eq. (3).

$$\tau_{ij}(t+1) \leftarrow \tau_{ij}(t)(1-\rho) + \rho\Delta\tau_{ij} \qquad (3)$$

Where ρ denotes the local pheromone decay parameter (0< ρ <1), $\Delta\tau_{ij} = \tau_0$ denotes the amount of pheromone deposited on edge (i, j).

The role of the ACS local pheromone-updating rule is to shuffle the tours, so that the early cities in one ant's tour may be explored later in other ants' tours. In other words, the effect of local pheromone updating is to make the desirability of edges change dynamically: every time an ant uses an edge this becomes slightly less desirable (since it loses some of its pheromone). In this way ants will make a better use of pheromone information: without local pheromone updating all ants would search in a narrow neighborhood of the best previous tour.

The global pheromone updating is performed after all ants have completed their tours. The pheromone level is updated by applying the global pheromone-updating rule of Eq. (4).

$$\tau_{ij}(t+1) \leftarrow (1-\alpha)\tau_{ij}(t) + \alpha\nabla\tau_{ij} \qquad (4)$$

$$\text{where } \nabla\tau_{ij} = \begin{cases} (L_{gb})^{-1}, & \text{if edge}(i,j) \in \text{the best tour} \\ 0, & \text{otherwise} \end{cases}$$

0< α <1 is the global pheromone decay parameter, and L_{ab} is the length of the best tour from the beginning of the trial.

The global pheromone updating is intended to provide a greater amount of pheromone to shorter tours. Eq. (4) dictates that only those edges belonging to the best tour will receive reinforcement.

3 A Novel Ant Colony System Based on Traditional Chinese Medicine Theory

According to traditional Chinese medicine theory, there are two kinds of health protection and treatment methods, namely, "bu" and "xie". The "bu" is to supply the nutritional ingredient and tonic to body, while the "xie" is to clear the harmful materials and pathogen from body. One of the importance ways to keep fit is to take nutritional ingredient and tonic in usual live, namely, "bu". When a person is in sickness, he must accept “xie” treatment because there are much harmful materials and pathogen in his body. So, “bu” and “xie” methods can achieve the goal of curing diseases and increasing people's health level.

The quality of solutions in ACO can be considered as the index of health in medicine, by which the better solution indicate the strong body and the bad solution indicate the weak and patient. The improvement process of solutions in ACO is similar to the process of the on-going improvement of people's health condition. The health protection and treatment methods adopted by human being to improve health level enlighten us to employ the similar ones to improve the quality of solutions in ACO.

Based on the consideration above, a novel ant colony system based on traditional Chinese medicine theory (CACS) is presented. Its flowchart is shown in Fig.2. The core of CACS lies in the construction of “bu” operator and “xie” operator, the key of which is the acquisition of good solution elements pool and abnormal solution elements. The good solution elements are the ones to be included in the global optimal solution at a high probability. The abnormal solution elements are the ones to be impossibly included in the global optimal solution at a high probability. Usually, there exists some characteristics information in the pending problem. By the analysis of this information, we can create good solution elements pool and get abnormal solution elements. In the following, we take TSP for example to demonstrate their construction.

```
Initialize the pheromone on all edges
Constructing good solution elements pool
Loop /* at this level each loop is called an iteration */
   Each ant is positioned on a starting node
   Loop /* at this level each loop is called a step */
       Each ant applies a state transition rule and
        the “bu”  operator to incrementally build
        a solution and a local updating rule
    Until all ants have built a complete solution
    The “xie” operator is applied to each solution
    A global updating rule is applied
Until End_condition
```

Fig. 2 The flowchart of CACS

3.1 The Construction of “bu” Operator for TSP

As we all know, ACO is a constructive meta-heuristic. At each step, the quality of the solution elements selected by ants will directly influence the quality of solution. So, in order to construct better solutions, enlightened by “bu” methods, we should let ants construct solution with good solution elements first, which is similar to tonic and nutritional ingredient in medicine. This is the idea of “bu” operator, which is made up of the good solution elements pool and “bu” operation. The good solution elements pool must be constructed at first. The “bu” operation is that ants select from the good solution elements pool first and only if there are no feasible candidates are the remaining normal solution elements considered when ants construct solutions.

Estimating the lower bound for TSP by minimum 1-tree was introduced in Ref. [7], and the error between this lower bound and the length of global optimal tour doesn't exceed 10%. Therefore, minimum 1-tree seems to be well suited as a basis of measuring the probability of an edge belonging to a global optimal tour: edges that belong, or 'nearly belong', to a minimum 1-tree, stand a good chance of also belonging to a global optimal tour. Conversely, edges that are 'far from' belonging to a minimum 1-tree have a low probability of also belonging to a global optimal tour. A $\alpha-nearness$ was used for a measure reflecting the chances of a given edge being a member of Minimum 1-tree in Ref. [8]. On the basis of further investigation into minimum 1-tree and the $\alpha-nearness$, the good solution elements pool based on Minimum 1-tree (GPMT) is applied to ACS. The method of constructing GPMT can be described briefly in the following [9]:

Step 1: For each city of TSP, calculate the $\alpha-nearness$ of the *n-1* edges incident to this city (*n* is the total number of cities).

Step 2: Let $\alpha(i,j)$ denote the $\alpha-nearness$ of edge (*i, j*)(*i=1,…,n, j* $\neq$ *i, j=1,…,n*). For each city of TSP, arrange the *n-1* edges incident to this city according to their $\alpha-nearness$ in descending order. Then, the front *S* cities that are another end node of the *S* top edges make up of candidate set of this city (*S=1,…, n-1*).

On the basis of investigating the impact of various S value to the quality of GPMT, *S=6* is found out an appropriate value. The percentage of the edges of GPMT (*S=6*) shared with the global optimal tour for 23 instances of TSP from TSPLIB is shown in Table.1, where the average percentage of the former is 99.91%. So, GPMT (*S=6*) is a perfect selection for the good solution elements pool in TSP.

Table 1: The percentage of the edges of GPMT (*S*=6) shared with the global optimal tour for 23 instances of TSP

Name	Cities	The global optimal tour shared edges with GPMT (S =6)	%
a280	280	280	100
att532	532	532	100
berlin52	52	52	100
ch130	130	100	100
d198	198	197	99.49
ch150	150	150	100
eil51	51	51	100
eil76	76	76	100
eil101	101	101	100
gr120	120	120	100
fl1577	1577	1572	99.68
gr202	202	202	100
kroA100	100	99	99
kroC100	100	100	100
kroD100	100	100	100
lin105	105	105	100
lin318	318	318	100
pr1002	1002	999	99.70
pcb442	442	442	100
pr76	76	75	100
st70	70	70	100
rat783	783	783	100
tsp225	225	225	100
average			99.91

After GPMT (*S=6*) have been constructed, "bu" operation can be implemented, namely, ants select from GPMT (*S =6*) first and only if there are no feasible candidates are the remaining normal solution elements considered when ants construct solutions.

3.2 The Construction of "xie" Operator for TSP

Because the choice of ants is impossible to come completely correct in each step when they construct solutions, there exist abnormal solution elements in solutions unavoidably. We should remove these abnormal solution elements and reduce the probability of selecting them in next solution construction. By mimicking the idea and method of "xie" operation of traditional Chinese medicine, the "xie" operator, which consists of "xie" operation that removes the abnormal solution elements from candidate solutions and the abnormal solution elements pheromone trails update rule which reduce the pheromone trails on the abnormal solution elements, is designed.

In TSP, two crossed edges in a tour are identified as abnormal solution elements [6]. A cross can be removed from a tour by reversing the sub path between the two cities that belong to two crossed edges and aren't linked. Because the original city order of a tour is changed after a reversal is completed, the process of removing crosses of every two edges in a solution must be repeated for sufficient times so that all the crosses in this tour can be removed completely.

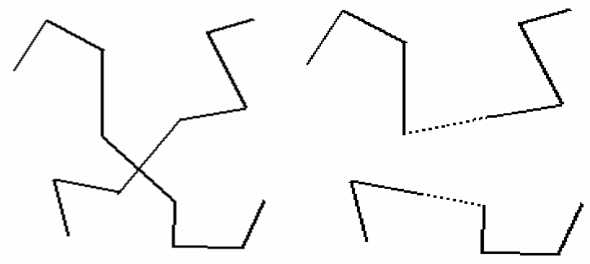

Fig. 3 A sub path including two crosses edges and removing operation

After the "xie" operation is completed to a solution, the abnormal solution elements pheromone trails update rule of Eg. (5) is applied. This allows ants to quickly discard the abnormal solution elements in next solution construction.

$$\tau_{ij}(t+1) \leftarrow \tau_{ij}(t)(1-e) \quad (5)$$

where e denotes the abnormal solution elements pheromone decay parameter($0< e <1$). τ_{ij} denotes the pheromone trails on the abnormal solution elements (edge P_i P_j)

4. The Simulation and Results

4.1 The Effect of "xie" Operator

A contrast before and after a solution (tour) cured by "xie" operation on berlin52.tsp is shown in Fig.5. The solution (tour) in the sub graph (a) of Fig.5 has many abnormal solution elements (crossed edges) and its length is 10812, and after it is cured by "xie" operation all abnormal solution elements (crossed edges) of the solution are removed and its length is reduced to 8125, which is shown in the sub graph (b) of Fig.4. It can be seen that the improvement effect of "xie" operation to the quality of solution is very remarkable.

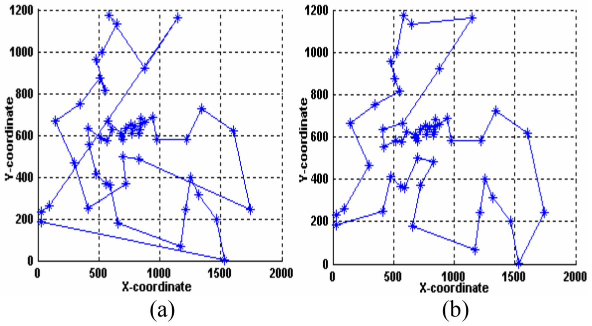

Fig. 4 A contrast before and after a solution (tour) cured by "xie" operation for berlin52.tsp

4.2 The Comparisons between CACS and MMACS

An ant colony optimization algorithm based on minimum 1-tree and hybrid mutation (MMACS), which adopted GPMT (*S=6*) and a self-adaptive hybrid mutation operator that consists of inversion mutation, insertion mutation and swap mutation, was introduced in Ref. [9]. In order to compare CACS with MMACS, some instances of TSP that are the same as ones used in MMACS are chosen in simulation. Comparisons of the final solution and convergence iteration number and convergence time between MMACS and CACS are shown in Table.2 (test results of MMACS are directly taken from Ref. [9]) and Table.3 respectively. It can be seen that CACS gains better convergence speed than MMACS.

Table 2: A Comparison of the Final Solution and Convergence Number between CACS and MMACS

Name	Optimum	Best length of MMACS	Best length of CACO	Convergence iteration number of MMACS	Convergence iteration number of CACO
Eil51	426	426	426	5	3
Berlin52	7542	7542	7542	4	1
Pr107	44303	44303	44303	8	3
Dl98	15780	15780	15780	71	63

Table 3: A Comparison of Convergence Time between CACS and MMACS

Name	Convergence time of MMACS(s)	Convergence time of CACS(s)
Eil51	0.001	0.001
Berlin52	0.001	0.001
Pr107	0.02	0.016

4.3 The Comparison between CACS and ACS

CACS and ACS are tested on five hard and large-scaled TSP respectively, and the experimental results are shown in Table.4, where each experiment consists of at least 20 trials; and the experimental results of ACS are directly taken from Ref. [3]. It can be seen from Table.4 that CACS makes not only the quality of solutions better than ACS but also the speed of convergence hundreds of times faster than ACS.

Table 4: Comparison between CACS and ACS

Name	Optimum	CACS best integer length	CACS number of tours generated to best	CACS average integer length	ACS best integer length	ACS number of tours generated to best	ACS average integer length
D198	15780	15780	630	15786	15888	585000	16054
Pcb442	50779	50802	24880	51048	51268	595000	51690
Att532	27686	27705	13437	27815	28174	830658	28523
Rat783	8806	8813	34410	8843	9015	991276	9066
Fl1577	22249	22298	25210	22345	22977	942000	23163

5. Conclusions

Enlightened by the health protection and treatment methods of "bu" and "xie" in traditional Chinese medicine, a novel ant colony system for TSP (CACS) is proposed. The constructions of "bu" operator and "xie" operator are demonstrated by TSP. The simulations and comparisons with conventional ACS and MMACS for TSP show CACS is a kind of competitive novel algorithms and can make the convergence speed dozens even hundreds of times faster under the precondition of improving the quality of solution because the search space is reduced greatly and the degeneration phenomena is restrained effectively.

The success of CACS and CMGA [6] suggests that it is a new and promising research way to get inspiration from medicine theory in the research field of intelligent computation. In the future, we will keep on with the research work along this way.

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