Applications of Clonal Selection Algorithm Based on Tabu Criteria in Combinatorial Optimization

Yongfei Miao[1,a], Yufu Yin[2,b] and Yunpeng Wang[3,c]

[1]Wuhan University of Technology, Wuhan 430070, Hubei, China

[2]Air Force Engineering University, Xi'an 710051, Shanxi, China

[3]Dalian Air Force Sergeant School of Communication, Dalian 116600, Liaoning, China

[a]yongfei1900@163.com, [b]yf_yin2008@163.com, [c]yp_wang2000@163.com

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Abstract: Clonal selection algorithm has a shortcoming when solving the problem of combinatorial optimization, which is that the antibody diversity of population evolution declines in later stage. Therefore, this paper has improved the selection operator of this algorithm and introduced tabu criteria. What's more, the benchmark of a typical combinatorial optimization problem is combined to carry out simulation analysis on this algorithm. The result shows that the improved clonal selection algorithm owns a better global convergence, stability and quick convergence ability to solve combinatorial optimization problems.

Introduction

Combinatorial optimization concerns about finding out the best arrangement, grouping, sequence and selection of discrete time through the study of mathematical methods. It is a classic and important branch of operations research. And the issues it studies relate to many areas such as information technology, macro-economic management, industrial engineering, transportation, military technology, communication networks, etc. Lots of optimization questions in real life is to choose the best one from a limited number of conditions and so that most actual optimization problems can be classified as combinatorial optimization problems, for example, knapsack problem[1], traveling salesman problem(TSP)[2], job scheduling problem(JSP)[3-5] , robot path planning[6] , pattern recognition[7] and assembly sequence planning[8] and so on.

Over recent years, lots of papers have focused on Artificial Immune Systems (AIS), which have covered reviewing AIS in general, or much more specific aspects of AIS such as data mining , network security, the application of AIS, theoretical aspects and modeling in AIS. AIS have become known as an area of computer science and engineering which uses immune system metaphors for the creation of novel solutions to problems.

Within AIS, there are common and well understood algorithms based on specific aspects of immunology. Clonal selection algorithms are the most widely employed algorithms, which take their inspiration form how cells of the adaptive immune system (specifically, cells called B-cells) interact with the "antigen"(something that causes an immune response) and then undergo a process of cloning, mutation and selection. In this paper, a clonal selection algorithm based on tabu criteria (*CSAbT*) is presented, which aims to solve traveling salesman problem. This algorithm has improved the selection operator and adds in tabu search algorithm. The experiment results show that artificial immune algorithm has been greatly improved in the aspects of keeping the diversity of population and quickly converging to the optimal solution.

Section 2 mainly describes the proposed algorithm of solving TSP. Then experiments and experimental comparison results are presented in Section 3. Finally, section 4 makes a simple conclusion.

CSAbT in solving TSP problems

Traveling salesman problem, the most representative classic problem of combinatorial optimization, can be described as follows: to calculate the shortest path of going through all the cities on the basis of the given cities and the distances between every two cities. In graph theory, TSP can be described as follows: a graph is given, $G=(V,A)$ and V is the vertex set and A represents the side set, which is composed of the sides between every two vertices. The distances between every two vertices are given and the shortest circuit is required to be calculated. The one means the shortest circuit when every vertex is passed only once.

2.1 Antibody coding, calculation of the fitness and the affinity

Antibody coding adopts the form of float encoding method, which means forming coded string with city numbers. The fitness function of the antibody - antigen is defined as follows:

$$Dis_i = \sum_{i=1}^{N-1} d(v_i, v_{i+1}) + d(v_i, v_N) \tag{1}$$

$$Fit_i = 76.5L\sqrt{N} / Dis_i \tag{2}$$

Fit_i, Dis_i and $d(v_i, v_{i+1})$ represent sufficiency, path length and the distance between city i and city $i+1$. Then L means the side-length of the minimum square to surround all the cities and N is the number of the cities.

The Euclidean method is selected to measure the affinities among antibodies. The Euclidean distance between one individual $P_1(m_1, m_2, ..., m_N)$ and another individual $P_2(n_1, n_2, ..., n_N)$ can be calculated by this expression:

$$Dis_E(P_1, P_2) = \sqrt{\sum_{i=1}^{N}(m_i - n_i)} \tag{3}$$

It reflects that the smaller the Euclidean distance, the higher the individual affinity. And the Euclidean distance goes in zero when two individuals are just the same.

2.2 Immune selection operation

Set the measuring vector as K_{ky} while the fitness between the antibody and the antigen is normalized. Then we can see from Eq(4) that the higher the fitness between the antibody and the antigen, then the shorter the distance when the cities are passed by and the higher corresponding normalization metric parameters.

Set the measuring vector as K_{kt}, Then we can see from Eq(5) that the lower the affinity between the antibodies, the lower the degree of similarity between the antibodies and the farther corresponding Euclidean distance and the higher normalized parameter. Then selective probability P_s is defined as follows:

$$K_{ky} = \frac{Dis_i}{\sum_{i=1}^{N} Dis_i} \quad (i = 1, 2, ..., Popsize) \tag{4}$$

$$K_{kt} = \frac{\sum_{j=1}^{N} Dis_E(P_i, P_j)}{\sum_{i=1}^{N}\sum_{j=1}^{N} Dis_E(P_i, P_j)} \quad (i, j = 1, 2, ..., Popsize) \tag{5}$$

$$P_s = \lambda K_{ky} + (1-\lambda) K_{kt} \tag{6}$$

λ represents the selection ratio parameter of the fitness and the affinity. In the early period of algorithm iteration, the diversity of antibody is great and so that more excellent individuals are keen to be kept. In the later period of algorithm iteration, the differences among antibodies have lost and individuals with lower affinities are keen to be kept. Therefore, λ makes dynamic adjustment with the iteration and it will decrease gradually when the number of iterations increases.

2.3 Crossover, hypermutation and tabu operation

Crossover operator adopts Edge Recombination Crossover. Compared with other interleaved modes, it can make the next generation inherit good qualities from the parent much better.

Hyper-mutation operator is to clone the antibody cell at corresponding number according to the degree of the affinity between the antibody and the antigen.

$$N_i = \mathrm{int}\left(N_c \bullet \frac{f(X_i)}{\sum_{j=1}^{N} f(X_j)} \right) \tag{7}$$

Here N_c is the scale of the total antibody population after cloning, then $\mathrm{int}(\bullet)$ means integral function and $f(X_i)$ stands for the affinity value of the i individual. N_i is the cloning number of the i individual. Therefore it can be concluded that after the hypermutation, individuals with high affinities have generated more mirror images, preserved more good characteristics and enhanced the searching ability of solution space.

CSAbT has simulated the memory mechanism of good individuals and stored individuals with high affinities in the memory set. In the process of population iteration, the memory set will be updated if better individuals appear and the memory set will remain unchanged if the individual affinities of the offspring are lower than those of the memory set. On the one hand, the direction of convergence algorithm is ensured and the population will be on a global minimum of evolution. On the other hand, it will easily cause individual diversity reduction and serious population degradation. Especially in the later algorithm evolutionary, individual affinities of the population are similar or identical with those of the memory set, which make the algorithm do some circuitous search around local optimum points and so as to reduce the efficiency of algorithm convergence. Therefore, this algorithm has introduced tabu criteria, whose main idea is to mark obtained local optimum solution and to avoid from such local optimum solution during further iterative process. Add those individuals whose affinities won't increase during recent iterative process into tabu list. Individuals will not be added in the population if they are randomly generated in the neighborhood of the area where individuals in tabu list are generated. The individuals in tabu list will be amnestied if their tabu numbers exceed a certain threshold. Aspiration criteria aims to further expand search space and make good individuals participate in immune process again and ensure persistent search ability against the original space. So individuals which are added randomly have better spatial distribution and circuitous search can be reduced. Then more local optimum points can to be searched, the global search ability of the algorithm gets strengthened and the convergence speed is accelerated.

***CSAbT* procedure**
Step1: To read the data, create the distance matrix M_{TSP}*, initialize population size* N*, crossover probability* P_c *and tabu length* L *etc;*
Step2: To calculate the fitness K_{ky} *and the affinity* K_{kt} *of initializing population and generate the initial memory matrix* M_s *and the tabu list* T_l*;*
Step3: (while does not reach the termination condition)
Step3.1: To calculate selection probability P_s *according to individual fitness and affinity;*
Step3.2: To use the elitist selection strategy and generate new population according to selection probability P_s*;*
Step3.3: Population starts crossover and hypermutation, which means to carry out clonal expansion and variation according to selection probability; select the best M *individuals;*
Step3.4: To update the memory matrix M_s*, the tabu list* T_l *and tabu length* L*;*
Step3.5: If the tabu length is zero, add amnesty individual to the population;
Step3.6: To randomly generate individuals and replace individuals with low fitness of the population;
Step3.7:To calculate the shortest distance and average distance of the best individuals of the population;
Step4: To output the best individual in the memory matrix and the tabu list.

Figure 1. Procedure of *CSAb*T algorithm

Experiments and Results

In order to test the performance of *CSAbT* algorithm, some experiments are conduced on six TSP problems named *Ulysses16*, *Bays29*, *Att48*, *Eil51*, *Pr120* and *Gr202*, which come from international TSPLib benchmarks or from papers[9-11].

We use *CSAbT* to solve all the test TSP problems which are given above. *CSAbT* adopts an elitist selection operation as the selection operator, and adopts ordered crossover operator. The maximum iterations are set to be 2000 and all experiments run 20 times. Parameters are set as follows:

Parameters of *CSAbT*:

- Population size: N =100; Memory set size: CM =20; Tabu length: L =5;
- Crossover factor: P_c =0.4; Mutation factor: P_m =0.03;

Table 1 Experiment Results of *CSAbT*

Problems	**Optimal value Reported**	***CSAbT***	
		Optimum	***Worst***
Ulysses16	74.1087	73.9876	73.9998
Bays29	9074.148	9074.148	9197.0465
Att48	33523.7085	33523.7085	33784.027
Eil51	429.9833	429.5303	436.3626
Pr120	1666.5	1666.5	1694.8733
Gr202	549.99	503.1994	515.4646

Table 2 The shortest path obtained by *CSAbT*

Problems	**Shortest path**
Ulysses16	1 3 2 4 8 15 5 11 9 10 7 6 14 13 12 16
Bays29	1 28 6 12 9 26 3 29 5 21 2 20 10 4 15 18 14 17 22 11 19 25 7 23 8 27 16 13 24
Att48	1 8 38 31 44 18 7 28 6 37 19 27 17 43 30 36 46 33 20 47 21 32 39 48 5 42 24 10 45 35 4 26 2 29 34 41 16 22 3 23 14 25 13 11 12 15 40 9
Eil51	1 32 11 2 16 50 9 49 38 5 37 17 4 18 47 12 46 51 27 6 48 23 7 43 24 14 25 13 41 40 19 42 44 15 45 33 39 10 30 34 21 29 20 35 36 3 28 31 26 8 22
Pr120	1 76 59 15 30 29 120 32 92 28 45 78 86 94 81 22 66 31 117 85 18 19 25 108 43 79 52 33 100 58 91 68 65 69 113 107 20 46 50 44 75 14 87 74 105 40 72 38 7 56 41 42 98 17 118 49 13 51 11 23 9 103 119 3 82 2 115 21 93 53 64 109 88 97 12 95 77 39 63 5 27 80 101 102 48 110 112 106 114 73 57 83 67 37 62 99 10 35 104 36 84 6 89 55 47 71 26 4 34 116 70 8 54 90 96 111 24 60 16 61
Gr202	1 75 76 74 68 67 84 85 86 83 78 77 79 80 82 81 90 89 91 157 158 160 163 169 164 165 161 162 166 172 174 178 180 177 189 176 173 175 171 170 135 136 186 187 185 184 141 140 139 143 145 144 147 148 149 150 190 188 192 191 198 193 194 182 181 179 183 195 196 202 201 200 199 197 151 152 153 155 154 146 25 142 138 137 24 23 22 27 28 29 127 128 129 130 131 39 118 123 120 124 121 122 125 126 132 133 134 167 168 159 156 102 117 116 115 113 114 101 98 88 94 87 92 93 97 96 100 112 119 104 105 103 106 108 110 109 107 111 99 95 50 49 48 47 44 43 42 45 46 41 40 38 37 36 35 34 53 56 52 55 54 58 59 57 60 61 62 66 65 63 64 72 73 70 69 71 51 30 31 32 33 26 20 21 19 12 15 14 13 10 11 18 17 9 7 6 8 4 5 2 3 16

Take 51cities and 202 cities for example, their shortest path obtained by *CSAbT* is shown as follows:

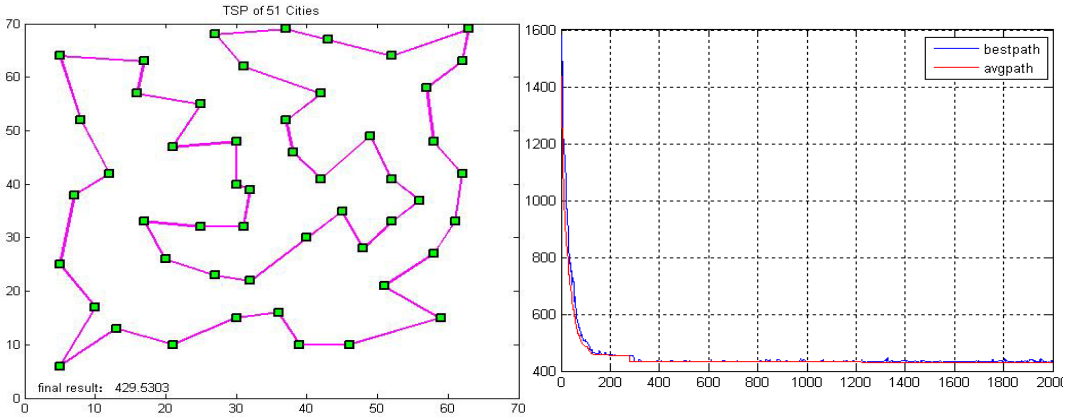

Figure 2. *CSAbT* in solving TSP(51 cities)

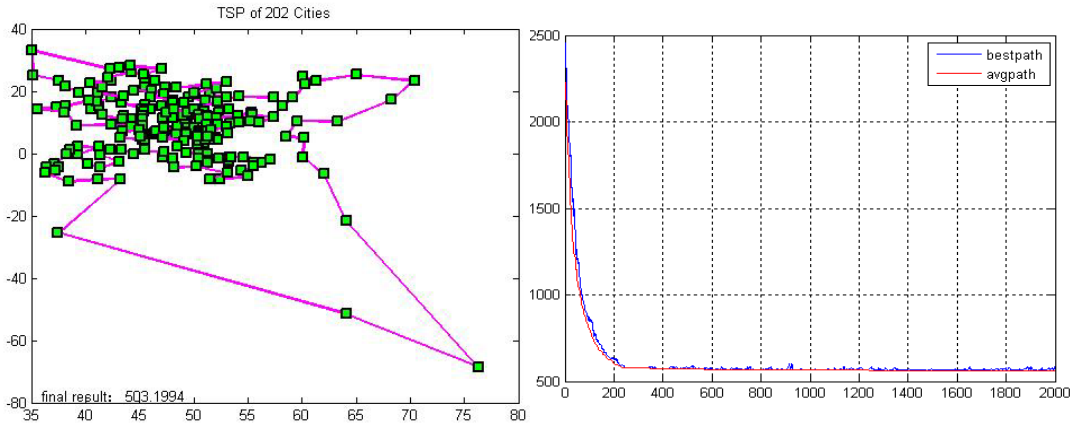

Figure 3. *CSAbT* in solving TSP(202 cities)

The computational results obtained by the *CSAbT* algorithm are reported in Table1-2. From the results we can see that *CSAbT* can quickly converge to the approximate solution and finally reach the global optimum. In most cases, *CSAbT* can find a better path than the optimal path which has been reported. In addition, the rate of convergence has been improved greatly. This shows that *CSAbT* is an effective algorithm to solve TSP.

Conclusions

This paper has put forward a clonal selection algorithm based on tabu criteria, which makes full use of the advantages of tabu algorithm and clonal selection algorithm. It has corrected some shortcomings of clonal selection algorithm, which are caused by circuitous search. For instance, the searching efficiency gets lower and it's easy to fall into the local optimal solution. The diversity of the population decreases in the later searching period and the degradation of population gets serious, etc. *CSAbT* has improved the convergence speed of the algorithm and better reflects these mechanisms such as parallel, self-organizing and immune memory of artificial immune system. The simulations demonstrate that this algorithm has well kept the diversity of the population, avoids trapping in local optimum problem and finally has reached the objectives of global optimization and rapid convergence. In a word, it shows an excellent performance.

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