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PAPER

Quantum Interference Crossover-Based Clonal Selection Algorithm and Its Application to Traveling Salesman Problem

Hongwei DAI[†a)], **Yu YANG**[†], **Cunhua LI**[†], **Jun SHI**[†], **Shangce GAO**[††], *Nonmembers*, *and* **Zheng TANG**[††], *Member*

SUMMARY Clonal Selection Algorithm (CSA), based on the clonal selection theory proposed by Burnet, has gained much attention and wide applications during the last decade. However, the proliferation process in the case of immune cells is asexual. That is, there is no information exchange during different immune cells. As a result the traditional CSA is often not satisfactory and is easy to be trapped in local optima so as to be premature convergence. To solve such a problem, inspired by the quantum interference mechanics, an improved quantum crossover operator is introduced and embedded in the traditional CSA. Simulation results based on the traveling salesman problems (TSP) have demonstrated the effectiveness of the quantum crossover-based Clonal Selection Algorithm.

key words: *clonal selection algorithm, quantum interference crossover, traveling salesman problem, hybrid model*

1. Introduction

Biology-inspired computing, using the biology system as a source of inspiration for solving computation problems, has gained much attention in the past few decades. Unlike the traditional optimization methods, which emphasize accurate and exact computation at the cost of spending much more computation time, the biology-inspired computing, such as Genetic Algorithm (GA) [26], [34], Evolutionary Algorithm (EA) [6], [33],and Ant Colony Optimization (ACO) [4], [13] etc, have better convergence speeds to the optimal or near optimal results.

More recently however, there has been a growing interest in the use of the natural immune system as a source of inspiration to the development of artificial computational systems. This emerging field of research is known as Artificial Immune System (AIS) [11]. Based on the different immune theories, various algorithms such as Danger Theory (DT) models [2], [3], Negative Selection Algorithms [5], [17], Immune Network Theory-based model [15], Clonal Selection Algorithms (CSA) [12], [18] are proposed and also applied on patter recognition [9],intrusion detection [10], [21], optimization problems [1], [14] and so on.

Among those model mentioned above, the CSA [12], based on the clonal selection principle proposed by Burnet [8], has received a rapid increasing interest and has been verified as having a great number of useful mechanisms.

Although CSA is very attractive from the viewpoint of a novel biology-inspired algorithm, this algorithm suffers from several problems, such as premature convergence and difficulties in reaching high-quality solutions in reasonable time [35].

According to the clonal selection theory, only the high affinity immune cells will be selected to proliferate, while the immune cells with low affinity must be efficiently deleted or become anergic (inactive). In addition, hypermutation is allowed to enhance the affinity of the selected immune cells. However, the random rearrangement of gene segments during hypermutation process frequently produces autoreactive immune cells. That is, the random hypermutation is little effective to improve the affinity. To overcome the low efficiency problem of the random hypermutation, a novel clonal selection algorithm [18] has been proposed by considering the Receptor Editing (RE) mechanisms. The receptor editing operator allows the immune system to rescue the low affinity immune cells before deletion. This also provide a chance to the immune system to enhance its search performance.

It is no doubt that the receptor editing-based clonal selection algorithm has better searching efficiency and can improve the searching ability within reasonable time. However both the traditional CSA and receptor editing-based CSA do not have their cells' (individuals) information exchanged due to the asexual proliferation. As an approach for solving such a problem, crossover operator is known to be useful.

In this paper, the quantum interference crossover [27] which has been proved for solving multicast routing problem [24] is introduced and further improved for information exchanging. It is natural to expect that quantum interference crossover-based information exchanging would be effective for premature convergence problems appearing in both CSA algorithms mentioned above.

The organization of the remaining content is as follows: Sect. 2 reviews the clonal selection theory and quantum interference crossover. Section 3 describes the quantum interference crossover-based clonal selection algorithm. In Sect. 4, simulations based on traveling salesman problem are performed to demonstrate the performance of the proposed algorithm. Finally, concluding remarks follow in Sect. 5.

2. Clonal Selection Theory and Quantum Interference Crossover

In this section, we fist introduce the natural immune system. Followed by this, clonal selection theory and recep-

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[†]The authors are with the School of Computer Engineering, Huaihai Institute of Technology, Lianyungang, 222005 China.

[††]The authors are with the Faculty of Engineering, University of Toyama, Toyama-shi, 930–8555 Japan.

a) E-mail: hongweidai@hotmail.com

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tor editing will be reviewed. Finally, quantum interference crossover is introduced.

2.1 Immune Cells and Natural Immune Systems [20], [28]

The natural immune system, one of the most intricate biological systems, is a complex of cells, tissues and organs that work together to protect the host against attacks by foreign invaders. Lymphocytes are small leukocytes that possess a major responsibility in immune system. B lymphocyte and T lymphocyte are two main types of lymphocytes. We also call them B cells and T cells. They are rather similar, but differ with relation to how they recognize antigens and by their functional roles.

B cells work mainly by secreting substances called antibody (Ab) as a response to antigen. Each B cell is programmed to make one specific antibody. Once a naive B cell (a cell that never previously encountered antigen) first encounters an antigen that matches its membrane-bound antibody, the binding of the antigen to the antibody caused the cell to divide into memory B cells and effector B cells called plasma cells. The effector B cells secrete antibodies to deal with the current antigen, however the memory B cells play an important role in further response to the same or related antigens.

Helper T cells (Th) and suppressor T cells (Ts) are two main types T cells. Th cells are essential to the activation of other immune cells. Suppressor T cells (Ts) are vital to normal operation of immune system too. Without their modulation, the immune system can mistake self for nonself and launch abnormal activation against the host's own cells. The result is called autoimmune disease. On the other hand, the immune response to a seemingly harmless foreign substance such as ragweed pollen will result in allergic reactions.

2.2 The Principle of Clonal Selection Theory and Receptor Editing

The clonal selection theory, proposed by Burnet in 1959 [8], is developed to explain the essential features which contain sufficient diversity, discrimination of self and non-self and long-lasting immunologic memory.

When an immune system is exposed to an antigen, some B cells can recognize the antigen with different certain affinities which reflect the degree of match and become active. Activated B cells will be stimulated to proliferate and eventually mature into terminal antibody secreting cells, called plasma cells. Proliferation of the B cells is a mitotic process whereby the cells divide themselves, creating a set of clones identical to the parent cell. The proliferation rate is directly proportional to the affinity level, i.e. the higher affinity levels of B lymphocytes, the more of them will be readily selected for cloning and cloned in larger numbers.

According to the clonal selection theory, random point mutation is performed during the maturation process. However, frequently, a large proportion of the cloned population becomes dysfunctional or develops into harmful anti-self

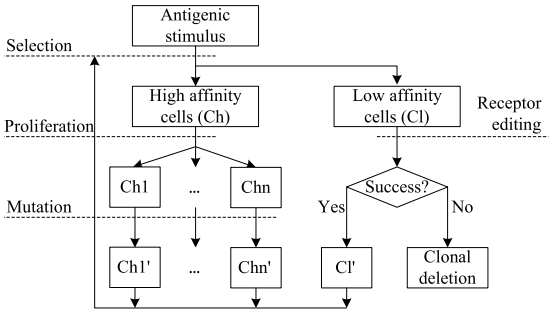

Fig. 1 Clonal selection process with receptor editing.

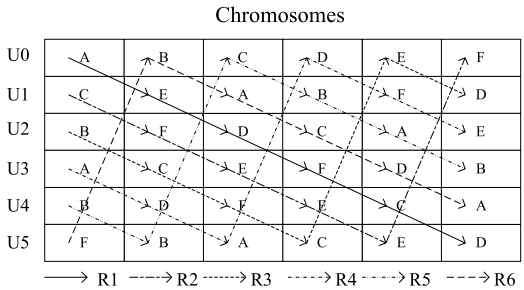

Fig. 2 Classical quantum interference crossover.

cells after the mutation. Moreover, the authors [29] interpret that clonal deletion, previously regarded as the major mechanism of central B cell tolerance, has been shown to operate secondarily and only when **receptor editing** is unable to provide a non-autoreactive specificity.

Recent investigations [19], [31], [32] indicate that receptor editing has played a major role in shaping the lymphocyte repertoire. Both B and T lymphocytes that carry antigen receptors are able to change specificity through subsequent receptor gene rearrangement. Figure 1 illustrates the clonal selection process including receptor editing mechanisms.

2.3 Quantum Interference Crossover

Quantum computing is a research area that includes concepts like quantum mechanical computers and quantum algorithms. It was proposed by Benioff [7] and Feynman [16] in the early 1980s. Because of its unique computational performance, there has been a great interest in the application of the quantum computing.

The classical quantum interference crossover was first proposed by Narayanan [27]. Figure 2 presents the quantum interference crossover process.

Because the method in this paper is just applied for solving traveling salesman problems, we set the population size equal the number of cities, i.e. 6. The number of universes u is also qual to the number of cities. The populations in each universes obey identical rules to the classical case, and evolve in parallel. However, there is one difference - the universes can interfere with one another in each generation [27]. Unlike other crossover, only genes (cities) in the

different universes (visiting tour) with the same list index position have the possibility of crossover.

See Fig. 2, let us consider the following chromosome in U0: | A | B | C | D | E | F |. This chromosome represents the following visiting tour in traveling salesman problem: A→ B → C → D → E → F → A. The interference crossover can be described as follows: take the 1st city of tour one, 2nd city of tour two, 3rd city of tour three, etc. No duplicates are permitted within the same universes, if a city is already presented in the visiting tour, choose the next alphabetical city not already contained. This way, we can get new visiting tours R1 = A → E → D → F → C → B → A, R2 = C → F → E → A → B → D → C, R3 = B → C → F → D → A → E → B, R4 = A → D → B → E → F → C → A, R5 = B → C → D → E → A → F → B, R6 = F → B → A → C → D → E → F. For example, in the tour R4, we select the 1st city *A* in U3, the 2nd city D in U4. The 3rd city A in U5 will be replaced by its next alphabetical city B for duplication. The same way, the 4th city D will be replaced by E and the 6th city E will be replaced by city C.

Obviously, the classical quantum interference crossover is just a crossover operator based on the list index position. Naturally, the city in different visiting tours with the same list index position can not be expected to reduce the current tour length.

As an approach for overcoming such a problem, a distance-based quantum interference crossover is proposed. Figure 3 illustrates the improved quantum interference crossover. We will introduce the new crossover operator as follows.

First, take the 1st city C of tour 1 (U1). Then compare the two edges $\overline{DC}$ and $\overline{CA}$ that conjunct with city C. City D will be selected if Dis(D,C) < Dis(C,A). Next, compare the two edges $\overline{FD}$ and $\overline{DB}$ and select city F if Dis(F,D) < Dis(D,B). Like this way, we can get a new tour C → D → F → E → C → B. The 5th city C will be replaced by city A for duplication. Then a closed visiting tour C → D → F → E → A → B → C is constructed. If the number of duplication city is greater than one, the duplication cities will be replaced by the fittest one through distance comparing.

It is clear that new visiting tours generated by both the classical quantum crossover and the improved quantum crossover include the information come from different old tours. As a result, the quantum crossover-based clonal selection algorithms is expected to be effective for premature convergence problems.

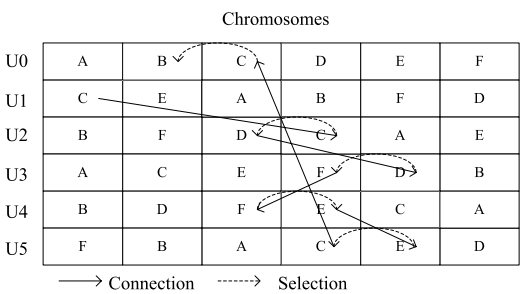

Fig. 3 Improved quantum interference crossover.

3. Quantum Interference Crossover-Based Clonal Selection Algorithm

In this section, according to what mentioned above, we propose an improved clonal selection algorithm named QCCSA by combining quantum crossover with clonal selection algorithm. Figure 4 illustrates the new algorithm.

Before explaining the procedure of the proposed algorithm, we introduce the conception of shape-space model which is a useful mathematical tool to quantitatively describe the interaction among antigens and immune cells [30]. According to this model, either an antigen or an immune cell can be represented by a set of coordinates in a N-dimensional shape-space. So we can express the immune cell's receptor gene sequence as $S = (s_1, s_2, \ldots, s_N)$. The random point mutation process described in the clonal selection theory and receptor editing process can be illustrated as follows:

$$s_1 \ldots \rightarrow s_{i-1} \rightarrow \mathbf{s_j} \rightarrow s_{i+1} \ldots s_{j-1} \rightarrow \mathbf{s_i} \rightarrow s_{j+1} \ldots \rightarrow s_N$$
$$\Uparrow$$
Random point mutation
$$\Vert$$
$$s_1 \ldots \rightarrow s_{i-1} \rightarrow \mathbf{s_i} \rightarrow s_{i+1} \ldots s_{j-1} \rightarrow \mathbf{s_j} \rightarrow s_{j+1} \ldots \rightarrow s_N$$
$$\Vert$$
Receptor editing
$$\Vert$$
$$\textbf{Inversion}(\overrightarrow{\mathbf{s_i} \rightarrow s_{i+1} \ldots s_{j-1}} \Rightarrow \overrightarrow{s_{j-1} \ldots s_{i+1} \rightarrow \mathbf{s_i}})$$
$$\Downarrow$$
$$s_1 \ldots \rightarrow s_{i-1} \rightarrow s_{j-1} \ldots s_{i+1} \rightarrow \mathbf{s_i} \rightarrow \mathbf{s_j} \rightarrow s_{j+1} \ldots \rightarrow s_N$$

It should be noticed that receptor editing on heavy chains occurs mostly by deletion of the intervening gene sequence while in the case of light chain receptor gene editing can occur either by deletion or by inversion of the intervening gene fragment. Obviously, the deletion operation can

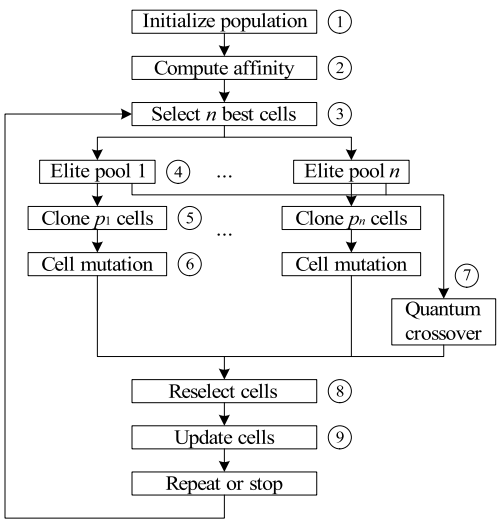

Fig. 4 Flowchart of the proposed algorithm.

not construct a closed feasible tour in the case of solving traveling salesman problem. We just use the inversion operator.

Then the whole produce of the proposed algorithm can be represented as follows:

Step 1 Initialize the population of cells, that is, creating an initial pool of m cells $(C_1, C_2, \ldots, C_m)$ randomly.

Step 2 Compute the affinity of all antibodies $(A(C_1), A(C_2), \ldots, A(C_m))$ and then sort them in a descending order, where $A(.)$ is the function to compute the affinity.

Step 3 Select the n $(n \leq m)$ best (fittest) cells based on their affinities from the m original cells. These cells will be referred to as the elites.

Step 4 Place each of the n selected elites in n separate and distinct pools $(EP_1, EP_2, \ldots, EP_n)$. They will be referred to as the elite pools.

Step 5 Clone the elites in each elite pool with a rate proportional to its fitness, i.e., the fitter the antibody, the more clones it will have. The amount of clone generated for these antibodies is given by Eq. (1):

$$p_i = round\left(\frac{(n-i)}{n} \times M\right) \tag{1}$$

where i is the ordinal number of the elite pools, M is a multiplying factor which determines the scope of the clone and $round(.)$ is the operator that rounds its argument towards the closest integer. After this step, we can obtain $\sum p_i$ antibodies just as $(EP_{1,1}, EP_{1,2}, \ldots, EP_{1,p_1}; \ldots; EP_{n,1}, EP_{n,2}, \ldots, EP_{n,p_n})$.

Step 6 Subject the clones in each pool through either random point mutation or receptor editing processes. Some of the clones in each elite pool undergo the random point mutation process and the remainder of the clones pass the receptor editing process. The mutation number (P_{hm} and P_{re} for random point mutation and receptor editing, respectively) are defined as follows:

$$P_{hm} = \lambda \cdot p_i \tag{2}$$

$$P_{re} = (1-\lambda) \cdot p_i \tag{3}$$

where λ is a user-defined parameter which determines the complementary intensity between the random point mutation and receptor editing. In our previous work [18], we had demonstrated that an equivalent level of $P_{hm} : P_{re}$, that is, $\lambda = 0.5$ will lead the clonal selection algorithm to a better performance. After this step, we obtain $\sum p_i$ mutated cells just as $(EP'_{1,1}, EP'_{1,2}, \ldots, EP'_{1,p_1}; \ldots; EP'_{n,1}, EP'_{n,2}, \ldots, EP'_{n,p_n})$

Step 7 According to the improved quantum interference crossover process described above, subject the selected n cells $(C_1, C_2, \ldots, C_n)$ through crossover. We can get n new cells $(QC_1, QC_2, \ldots, QC_n)$.

Step 8 Select the fittest cell from each elite pool and quantum crossover generated cells CB_i $(D(CBi) = max(D(EP_{i,1}), \ldots, D(EP_{i,p_i}), D(QC_i)))$, $i = 1, 2, \ldots, n$, where $D(.)$ is the distance function.

Step 9 Update the parent cells in each elite pool with the fittest cells selected in Step 8 and the probability $P(C_i \rightarrow CB_i)$ is according to the role followed by:

$$P = \begin{cases} 1 & D(C_i) < D(CB_i) \\ 0 & D(C_1) \geq D(CB_1) \\ \exp\left(\frac{D(CB_i)-D(C_i)}{\alpha}\right) & \text{otherwise} \end{cases} \tag{4}$$

In Eq. (4), α is a user-defined parameter to maintain the diversity of the population [18].

The produce will be terminated when the iteration number reaches a pre-specified maximal generation number G_{max}. Otherwise, it returns to Step 3.

4. Simulation on TSP and Discussion

In this section, for testing the performance of the proposed algorithm, we use the improved quantum crossover-based clonal selection algorithm (IQCCSA) to solve the Traveling Salesman Problems taken from TSPLIB [22]. The proposed IQCCSA algorithm is written in C++ language and run on a 1.8 GHz processor with 512 M memory. Except for special statement, all simulation results are integer number and over 10 replications. Table 1 lists the TSP instances to be solved by the proposed algorithm.

4.1 The Traveling Salesman Problem

TSP, one of the typical NP-hard combinatorial optimization problems, can be described as follows: find an optimal route (shortest) for visiting n cities and returning to the point of origin.

As mentioned above, the gene sequence of immune cell can be expressed as a set of coordinates in a N-dimensional shape-space. That is $C = (c_1, c_2, \ldots, c_N)$. Naturally, we can use different gene sequences denote the solutions of a N-city TSP. If $d(i, j)$ denotes the distance between city i and j which is symmetric and known, the object of TSP is to find a permutation π of the set $\{1, 2, 3, \ldots, N\}$ that minimizes the quantity [23]:

$$C(\pi) = \sum_{i=1}^{N-1} d(\pi(i), \pi(i+1)) + d(\pi(N), \pi(1)) \tag{5}$$

Table 1 Problems to be solved by the proposed algorithm.

Problem	Size	Type	Optimum	G_{max}
eil51	51	EUC_2D	426	1000
st70	70	EUC_2D	675	1000
eil76	76	EUC_2D	538	1000
rd100	100	EUC_2D	7910	1000
eil101	101	EUC_2D	629	1000
lin105	105	EUC_2D	14379	1000
pr107	107	EUC_2D	44303	1000
pr124	124	EUC_2D	59030	1000
bier127	127	EUC_2D	118282	2000
pr136	136	EUC_2D	96772	2000
pr152	152	EUC_2D	73682	2000
rat195	195	EUC_2D	2323	2000
kroA200	200	EUC_2D	29368	5000

Table 2 The meaning of the user-defined parameters and their values.

Parameter	Meaning	Values
N	city number	
m	number of initial antibodies	N
n	number of elite pools	N
M	scope of clone	50
α	diversity maintenance parameter	100
λ	complementary intensity between hypermutation and receptor editing	0.5
G_{max}	maximum number of generation	*

*:see Table 1

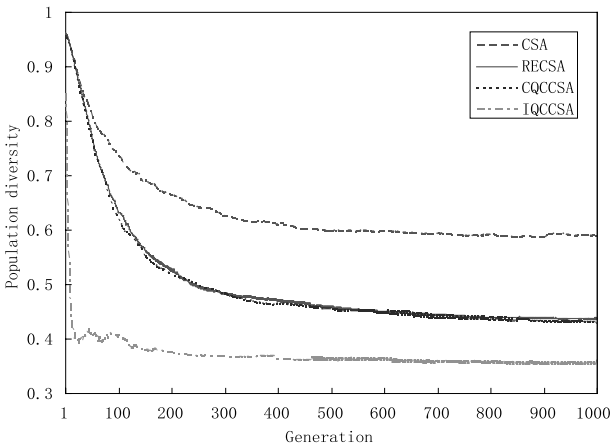

Fig. 5 Population diversity of different algorithms when solving eil51.

4.2 Diversity vs Balance of Exploration and Exploitation

Premature convergence is one of the main difficulties with the CSA. It has been observed that this problem is closely related to the problem of losing diversity in the population. Here, the diversity is defined as the mean edge-distance between the best tour and all other tours. Edge-distance means different edges between two tours [25].

The meaning of the parameters used in the proposed algorithm and their values are illustrated in Table 2.

The population diversity of a 51-city problem eil51 for different algorithms is shown in Fig. 5. Four algorithms CSA, RECSA, CQCCSA, and IQCCSA mean Classical Clonal Selection algorithm [12], improved clonal selection theory by considering Receptor Editing [18], Classical Quantum Crossover-based RECSA, and Improved Quantum Crossover-based RECSA respectively.

From Fig. 5, we can easily find that the CSA has a better population diversity than RECSA. However, simulations on different traveling salesman problems performed in [18] had demonstrated that the RECSA has a better convergence performance than the CSA and can generate shorter visiting tour for solving TSPs. It seems that the diversity is not the only key. Naturally, the question whether the improved quantum crossover-based CSA (IQCCSA) which has a worse population diversity than the classical quantum crossover crossover-based CSA (CQCCSA) is possible to generate better solutions than CQCCSA would be asked.

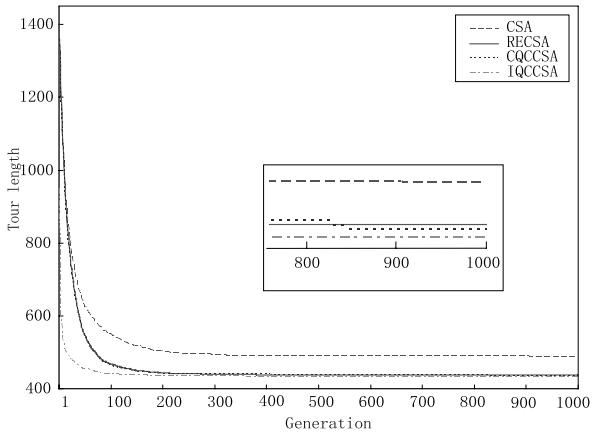

Fig. 6 Convergence process of different algorithms when solving eil51.

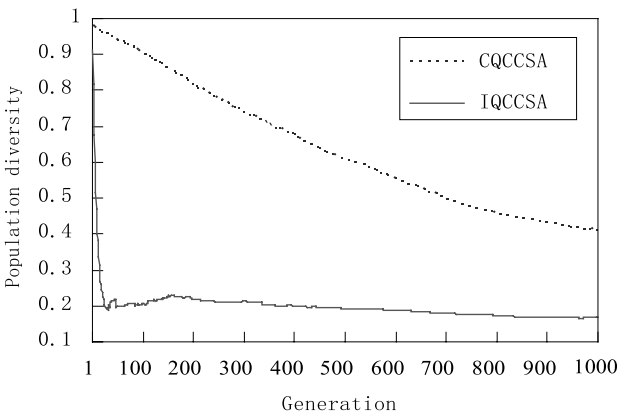

Fig. 7 Population diversity of different algorithms when solving pr124.

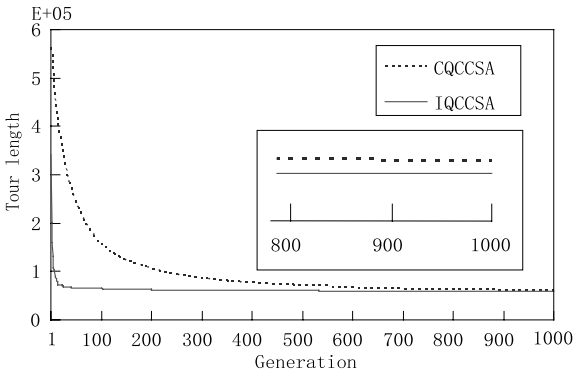

Fig. 8 Convergence process of different algorithms when solving pr124.

Figure 6 illustrates the convergence ability of those four algorithms. From this picture, it can be seen that the IQCCSA has a better convergence performance than the CQCCSA, as well as CSA and RECSA.

We also apply the CQCCSA and the IQCCSA to TSP pr124. The simulation results of population diversity and convergence process are shown in Fig. 7 and Fig. 8.

According to the simulation results illustrated in Fig. 5, Fig. 6, Fig. 7, and Fig. 8, it can be concluded that the im-

Table 3 Experimental results of RECSA, CQCCSA, and IQCCSA for TSPs from eil51 to kroA200.

Problem	Size	D_{opt}	RECSA			CQCCSA			IQCCSA		
			PDB	*PDM*	*T*	*PDB*	*PDM*	*T*	*PDB*	*PDM*	*T*
eil51	51	426	1.41	2.63	2.82	0.94	2.28	3.38	0	1.69	6.23
st70	70	675	0.30	2.39	4.90	1.19	2.61	5.92	0.44	1.76	13.94
eil76	76	538	3.35	4.54	5.81	3.16	4.55	7.11	1.30	2.70	16.82
rd100	100	7910	4.55	5.85	9.54	3.24	5.68	11.96	2.28	3.17	34.66
eil101	101	629	5.25	6.60	9.63	4.29	5.93	12.15	3.50	4.59	33.33
lin105	105	14379	2.48	5.39	10.35	1.38	4.64	13.02	0.61	2.12	40.86
pr107	107	44303	2.11	3.40	10.66	2.81	3.69	13.47	2.35	2.94	39.09
pr124	124	59030	1.65	4.42	13.91	0.92	4.48	17.81	0.64	1.33	58.20
bier127	127	118282	1.55	4.41	27.22	3.70	4.91	36.39	1.20	2.24	115.89
pr136	136	96772	4.39	6.28	31.72	4.45	5.86	42.26	6.48	7.36	159.45
pr152	152	73682	2.82	3.50	38.58	2.47	3.58	52.15	0.47	1.33	211.85
rat195	195	2323	10.55	13.12	60.12	12.44	13.42	83.58	2.41	2.91	457.65
kroA200	200	29368	4.46	6.59	158.74	5.11	6.70	217.29	1.32	1.95	1194.98
Average			3.45	4.81	29.54	3.55	5.26	39.73	1.77	2.78	183.30

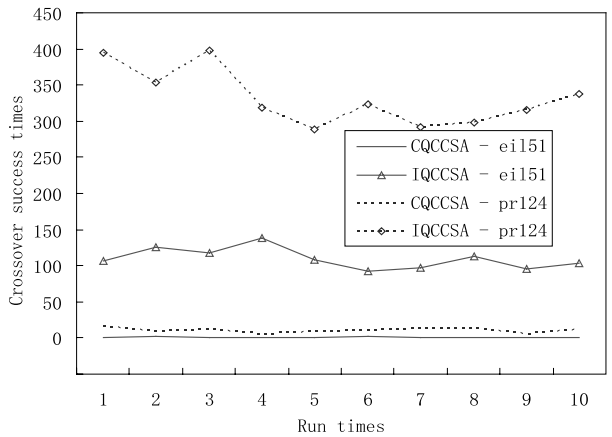

Fig. 9 Crossover success times when solving eil51 and pr124 (10 runs).

proved quantum crossover-based clonal selection algorithm IQCCSA has a good balance between exploration and exploitation.

In addition, in order to compare the improved quantum crossover with the classical crossover, we also investigate the crossover effectiveness when solving two TSPs eil51 and pr124. Figure 9 shows the crossover success times of two algorithms. It is clear that the distance-based improved quantum crossover is more effective than the position-based classical quantum crossover.

4.3 Simulation Results on Other TSPs

In addition to the parameters defined in Sect. 4.2, two parameters *PDM* and *PDB* which indicate the percentage deviation from the optimal tour length D_{opt} of the mean distance D_m and the best distance D_b respectively are defined as follows:

$$PDM = \frac{D_m - D_{opt}}{D_{opt}} \times 100 \tag{6}$$

$$PDB = \frac{D_b - D_{opt}}{D_{opt}} \times 100 \tag{7}$$

The parameter T which denotes the average computation time for 10 runs is also defined.

In order to confirm the effectiveness and the robustness of our method to TSP, we apply our method to TSPs from eil51 to kroA200 and also compare our method with RECSA and CQCCSA. Table 3 shows the experimental results of the TSPs.

In Table 3, the first three columns indicate the TSP instance, the problem size, and the optimal solution(D_{opt}). In the rest columns, we list the simulation results of three algorithms - the improved clonal selection algorithm (RECSA) [18], the classical quantum crossover-based RECSA (CQCCSA), and the improved quantum crossover-based RECSA (IQCCSA) respectively. T means computation time. From Table 3, we can find that the proposed algorithm IQCCSA has a superior ability to search better solutions than the RECSA and CQCCSA.

5. Conclusions

In this paper, we proposed an improved quantum crossover-based clonal selection algorithm (IQCCSA). An improved quantum interference crossover operator was introduced for information exchange among different solutions. Unlike the classical quantum interference crossover which selects a city in the different solutions with the same list index position, the improved distance-based quantum interference crossover has a superior convergence ability. Simulation was carried out and also compared with other clonal selection algorithms. Experimental results showed that the improved algorithm is more effective for traveling salesman problems and can search the global optimal or near-optimum solutions. In addition, through comparing the convergence performance with the population diversity, it can be concluded that the improved algorithm is more effective for balancing the exploration and exploitation abilities in the whole searching space.

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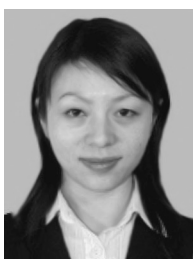
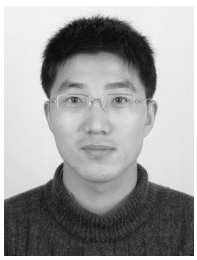
Hongwei Dai received the B.S. degree and an M.S. degree from Xi'an Jiaotong University, Shaanxi, China in 1999 and 2002, and a D.E. degree from University of Toyama, Toyama, Japan in 2007 respectively. From 2002 to 2003, he was a lecture in the Institute of Mechatronics and Information at Xi'an Jiaotong University, Shaanxi, China. In 2008, he joined Huaihai Institute of Technology. His current research interests are artificial immune system (AIS) and artificial neural networks.



Yu Yang received the B.S. degree form China University of mining and technology, Jiangsu, China in 2002 and an M.S. degree from Toyama University, Toyama, Japan in 2005. From 2005 to 2008, she was an engineer in Tele Electric Supply Service Inc., Toyama, Japan. In 2008, she joined Huaihai Institute of Technology, Jiangsu, China. Her main research interests are neural networks and artificial immune system.

Cunhua Li is PhD. of Engineering, Professor, Senior member of China Computer Federation, Dean of Computer Engineering School, Huaihai Institute of Technology. His major research interests are data mining, pattern recognition, image processing and artificial immune system.

Jun Shi associate professor, vice dean of Computer Engineering School, Huaihai Institute of Technology. Her main research interests are data mining, database technology and optimization problem.



Shangce Gao received the B.S. degree from Southeast University, Nanjing, China in 2005, and an M.S. degree from University of Toyama, Toyama, Japan in 2008 respectively. Now, he is working toward the D.E. degree at University of Toyama, Toyama, Japan. His main research interests are multiple-valued logic, artificial immune system, and artificial neural networks.

Zheng Tang received the B.S. degree from Zhejiang University, Zhejiang, China in 1982 and an M.S. degree and a D.E. degree from Tshinghua University, Beijing, China in 1984 and 1988, respectively. From 1988 to 1989, he was an Instructor in the Institute of Microelectronics at Tshinhua University. From 1990 to 1999, he was an Associate Professor in the Department of Electrical and Electronic Engineering, Miyazaki University, Miyazaki, Japan. In 2000, he joined University of Toyama, Toyama, Japan, where he is currently a Professor in the Department of Intellectual Information Systems. His current research interests include intellectual information technology, neural networks, and optimizations.