Improved Clonal Algorithm and Its Application to Traveling Salesman Problem

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Abstract

To explain the essential features such as sufficient diversity, discrimination of self and non-self, and also long-lasting immunologic memory of adaptive immune responses, Burnet and Talmage developed the clonal selection theory. In their model, only the high affinity immune cells are selected to proliferate. Those cells with low affinity must be efficiently deleted or be set as inactive. However, recent results suggest that low affinity cells would survive occasionally by altering their receptors. In this paper, in addition to combine receptor editing with clonal selection, a self-crossover operator is also implemented to improve algorithm's performance. Simulation on traveling salesman problems shows that this novel algorithm provides a better performance compared to the classical clonal selection algorithm.

Keyword: *Immune System, Clonal Selection Algorithm, Traveling Salesman Problem*

1. Introduction

Over the past few years, the researchers have paid their attention not only to nervous system, but also to other biological systems as the source of inspiration to the development of computational tools. Among those biological systems, immune system has received an ever increasing attention. Artificial immune system, as a new computational paradigm, has been investigated and applied in various areas [4], [2], [18].

In this paper, we will first review the clonal selection theory, explain an important immune mechanism and the receptor editing, which are both allowed to be implemented to enhance the affinity during maturation process. In addition, a self-crossover operator is also introduced to improve the novel algorithm's performance. Following that, simulations on traveling salesman problems are performed to verify this new algorithm's performance.

2. Background of Immune System

The sufficient diversity had to deal with a universe of antigens, discrimination of self from non-self and long-lasting immunologic memory which are the three essential features of adaptive immune responses. In order to describe these features, Burnet and Talmage developed the clonal selection theory [1], [15]. It establishes the idea that only those cells that recognize the antigens proliferate can be selected against those which do not.

In brief, clonal selection theory includes three processes: clonal selection process, proliferation process, and maturation process. When an antigen invades the host, it will be recognized by immune cells of the immune system with a certain affinity (degree of math). In immune responses, the invaded antigen imposes a selective pressure on the antibody by allowing only those cells which specifically recognize the antigen to be selected for proliferation and differentiation. In the selection stage, B cells with high affinity are activated. These activated cells are then stimulated to proliferate producing large numbers of clones. In the final stage these clones can mutate and turn into plasma cells that secrete high numbers of antibodies or memory cells that retain the antigenic pattern for future infections. It is a general observation that the antibodies present in the memory response have, on average, a higher affinity than those of the early primary response. The maturation of the immune response is a continuous process, in which the body over a number of exposures will build up a large collection of targeted memory cells that can act quickly to eliminate a pathogen [17].

Early experiments and works with transgenic mice supported the clonal selection theory where clones of cells with low affinity are deleted and occasional clones that survive become anergic (inactivation) [11]. Although the maturation process in clonal selection theory produces a small number of high affinity matches, a large number of low affinity cells are also generated.

Recent studies [16], [12], [10] show that the immune system practices molecular selection of receptor in addition to clonal selection of lymphocytes. That is to say, instead of the expected clonal deletion of all low affinity immune cells, occasionally cells were found that had undergone receptor editing. Those immune cells had deleted their low affinity receptors and developed entirely new receptors by the recombination of gene fragments.

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3. Improved Clonal Selection Algorithm

Before introducing the improved clonal selection algorithm, it is necessary to review the classical *CLONALG* algorithm. Simply, we call *CLONALG* algorithm *SCA* (simple clonal algorithm).

SCA was proposed by Castro and Zuben in [5] and was later enhanced in other paper [4]. This algorithm takes a population of antibodies by repeating exposure to antigens. After over a number of generations, it develops a population with a higher affinity to the presented antigen.

In this paper, we extend the *SCA* by combining classical clonal selection theory with receptor editing. The main advantage of the improved algorithm is that receptor editing can prevent the immune system from becoming ``premature'' and also increase the affinity.

In Burnet's clonal selection theory, immune memory would be provided by expanding the size of an antigen-specific clone, and the affinity can be enhanced by random somatic hypermutation. An alternative is using receptor editing to provide an additional mean of introducing diversity in immune cells during the process of affinity maturation.

3.1 Somatic Hypermutation and Receptor Editing

Fig.1 illustrates the conceptual graph of the somatic hypermutation and receptor editing. If a particular immune cell *C* is selected during the primary immune response, the immune system explores the local area around *C*, by random somatic hypermutation, with small alterations in the shape of the antigen-binding site. The higher affinity mutated immune cell will be selected. As a result, after a series of small steps, the selected immune cell reaches a maximum value (*C*'). According to the clonal selection theory, low affinity cells are deleted. Hence, facing the enormous number of different antigens, an immune cell undergoing somatic hypermutation might become stuck at a local optimal and can not improve its affinity any further.

As mentioned above, receptor editing allows the immune system to rescue immune cells before deletion. This may provide a chance to immune system to escape from the local optimum.

The authors [6] also pointed out that receptor editing permitted an immune cell to take large leaps through the landscape. However, some studies demonstrated that receptor editing might promote not only tolerance but also the autoreactive [16]. In other words, in most cases, receptor editing will land the immune cells in a locale C_L where the affinity is lower than current affinity. Occasionally, the editing will produce a higher affinity immune cell C_H. The higher affinity cell can then improve its affinity to a better state C'_H by somatic hypermutation .

In generally, random somatic hypermutation is good for exploring local optimum, whereas receptor editing may help immune system escape from local optima. Thus a conclusion can be presented that random somatic hypermutation and receptor editing might play complementary roles in affinity maturation process [6].

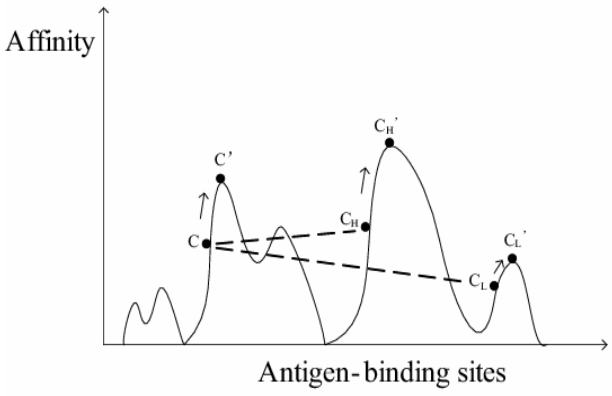


Fig.1. Conceptual graph of the hypermutation and receptor editing

3.2 Improved clonal algorithm (*ICA*)

Shape-space model [13] is a useful mathematical tool to quantitatively describe the interaction among antigens and immune cells. Mathematically, 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 R = (r_1, r_2, ..., r_N).

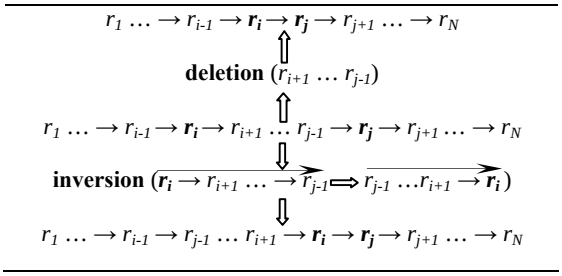
Immune cells have the unique ability to acquire large numbers of random somatic hypermutation in the variable segment of gene sequence. For example, gene position *i* and *j* are selected randomly, then the somatic hypermutation process can be expressed like this:

Somatic hypermutation

$$r_1 \rightarrow r_2 \ldots \rightarrow \mathbf{r_i} \rightarrow r_{i+1} \ldots \rightarrow \mathbf{r_j} \rightarrow r_{j+1} \ldots \rightarrow r_N$$
$$\Downarrow$$
$$r_1 \rightarrow r_2 \ldots \rightarrow \mathbf{r_j} \rightarrow r_{i+1} \ldots \rightarrow \mathbf{r_i} \rightarrow r_{j+1} \ldots \rightarrow r_N$$

As to the receptor editing, it is necessary to introduce the unique structure of antibody molecule. Antibody is composed of heavy and light chains, each of which is further subdivided into constant and variable regions [14]. The editing on heavy chains occurs mostly by deletion of the intervening gene sequence. Whereas, in the case of light chains, receptor gene editing can occur either by deletion or by inversion of the intervening gene fragment [8]. If receptor gene position *i* and *j* are selected, the novel gene sequences based on deletion and inversion can be illustrated as following:

Receptor editing



Considering the operation of the deletion can not produce legal visiting path in TSP, we adopt the operation of the inversion in receptor editing process to generate new visiting path in TSP. The pseudo code of proposed algorithm can be described as below:

```
initialization();
for i= 1 to NG
  for j = 1 to NCS
    somatic hypermutation();
    evaluation();
    if (D < cDis)
       cDis = D;
       update() :
  else
       receptor editing();
       evaluation();
       if (D < cDis)
          cDis = D;
          update() :
       else
          clonal deletion();
          CC + +
       end if
    end if
    if (CC > CMAX)
       self crossover();
       CC = 0;
    end if
  end for
end for
```

The parameters in algorithm are:

- *NG*: the number of generations (iterations)
- *NCS*: the number of clone population size
- D_{opt}: shortest distance of optimal solution
- D, D_m, D_b: distance, mean distance, and best distance generated by this algorithm (replicated 10 times). cDis means current distance
- *PDM*, *PDB*: the percentage deviation from the D_{opt} of the mean distance D_m and best distance D_b. Here,

$$PDM = 100 \times \frac{D_m - D_{opt}}{D_{opt}}, \quad PDB = 100 \times \frac{D_b - D_{opt}}{D_{opt}}$$

- *CC:* the counter of inactivation
- *CMAX*: the criterion of self-crossover
- P_{pm}, P_{re}: probability of point mutation (somatic hypermutation) and receptor editing, $P_{pm}+P_{re}=1$
- *T*: average operation time

In natural immune system, the proliferation of immune cell is asexual, a mitotic process. That is, the immune cells divide themselves without crossover. However, to enhance algorithm's performance, we add crossover operator to the novel algorithm. Unlike the conventional crossover mechanism, a self-crossover mechanism is adopted here. This self-crossover alters the genetic information within a single potential gene sequence selected randomly from the mating pool to produce an offspring [9].

4. Simulation on TSP

Traveling Salesman Problem (TSP) is a classical optimization problem, defined as a task to find the shortest path for visiting N cities and returning to the original point. The TSP is known to be NP-hard and cannot be solved in polynomial time. Hence, GA (Genetic algorithm) and other problem-independent algorithms are usually used to find an optimal or a suboptimal solution [3]. In this paper, we use the improved algorithm to solve this classical optimization problem.

Table 1. Parameter sensitivity (eil51, *N*=51)

Parameter	Value	*PDM*	*PDB*	*T*(*s*)
CMAX	*N*	72.09	46.24	12.55
	10N	14.06	6.10	12.52
	50N	7.44	3.76	12.75
	200N	6.24	3.99	12.93
	500N	9.13	5.16	12.47
	infinity	9.41	5.16	12.25
P_{pm} : P_{re}	1.0:0.0	34.15	25.82	11.90
	0.8:0.2	8.45	6.34	12.06
	0.6:0.4	6.99	3.05	12.53
	0.5:0.5	6.24	3.99	12.93
	0.4:06	7.65	1.64	12.59
	0.2:08	8.87	3.99	12.83
	0.0:1.0	11.83	4.22	13.09

4.1 Parameter analysis

In order to evaluate the sensitivity of our algorithm with parameters mentioned above, we use the parameters: *NG*=3000, *NCS*=10**N*, *CMAX* = 200**N*, P_{pm}/P_{re} = 0.5:0.5. The city number *N* equals to 51 (eil51 problem) after limited simulation experimentation.

As we know the parameters *NG* and *NCS* possess an obvious feature. The bigger the value of *NG* and *NCS*, the better solutions we can acquire. We can expect to get a desired suboptimal solution with a reasonable computational cost (computational time).

However, neither the parameter *CMAX* nor the proportion of point mutation and receptor editing has such obvious feature as *NG* and *NCS*.

Table 1 shows the computation results, where the value of the parameter *CMAX = infinity* denotes that there is no self-crossover in the algorithm.

First, we will analyze the parameter *CMAX*. In algorithm it is a parameter which determines the criterion for crossover operation. In other words, *CMAX* reflects the relationship between mutation and crossover. As shown in Table 1 of the simulation results, we can found that the algorithm can not present a better solution without self-crossover. On the other hand, when *CMAX = N*, the algorithm produces a more unsatisfied solution. We attempt to deduce this phenomenon to that too frequent crossover may cause the algorithm to ignore the suboptimal.

In Table 1, except the pure point mutation (P_{pm} : P_{re} = 1.0 : 0.0) and pure receptor editing (P_{pm} : P_{re} = 0.0 : 1.0), we can not draw any conclusions directly there. In order to investigate the relationship between P_{pm} : P_{re} and this solution, we also run our algorithm on Berlin52 TSP and get results as shown in Table 2.

Simulation results in Table 2 demonstrate that the algorithm can produce better solutions when the probability of point mutation P_{pm} and receptor editing P_{re} are in equivalent level, for example when P_{pm} : P_{re} = 0.5 :0.5.

Table 2. Parameter analysis of P_{pm} and P_{re} (berlin52, *N*=52)

Parameter	Value	*PDM*	*PDB*	*T*(*s*)
P_{pm} : P_{re}	1.0:0.0	37.66	25.87	12.78
	0.8:0.2	8.10	3.73	12.96
	0.6:0.4	10.31	7.77	13.13
	0.5:0.5	7.43	4.23	13.34
	0.4:06	8.39	5.42	13.55
	0.2:08	9.59	6.58	13.62
	0.0:1.0	16.17	11.44	13.83

4.2 Application to other TSPs

In this section, we apply this novel algorithm to different traveling salesman problems and compare it with *SCA* and the algorithm combining point mutation with receptor editing without self-crossover.

It should be noticed that all the results of simulation are from over 5 replications of the algorithm. According to the documentation file in [7], all TSPs are defined on a complete graph and all distances are integer numbers. That is to say, the distance between two cities is calculated by the Euclidean distance and expressed as integer number, not as a real number. Except for special statement, all simulation results in this section are integer number.

Table 3 indicates the simulation results of different TSPs generated by *SCA*, algorithm combining point mutation with receptor editing, and algorithm combining point mutation with receptor editing added self-crossover operator. Obviously, receptor editing allows the immune system to rescue immune cells before deletion. This also provides a chance for immune system to escape from local optimum. In addition, self-crossover operator also enhances the performance of algorithm.

Table 3. Simulation results for the problem from eil51 to rat195

Problem	Size	D_{opt}	*SCA*			*pm + re*			Novel algorithm *pm + re + self crossover*		
			PDM	*PDB*	*T*(*s*)	*PDM*	*PDB*	*T*(*s*)	*PDM*	*PDB*	*T*(*s*)
eil51	51	426	37.61	32.86	11.93	10.00	4.46	12.28	6.24	3.99	12.94
st70	70	675	54.49	36.74	23.63	10.70	9.04	23.21	8.80	4.44	24.93
eil101	101	629	56.53	43.08	49.79	11.80	7.95	47.77	11.45	8.11	48.09
pr124	124	59030	146.37	120.19	69.81	8.03	3.20	70.86	6.81	2.21	72.03
rat195	195	2323	105.17	86.40	174.18	16.54	13.17	175.58	14.48	12.18	176.13

5. Conclusions

In this paper, we extended the traditional clonal selection algorithm by combining with receptor editing. Unlike the traditional clonal deletion, receptor editing allows the immune cells to delete their low affinity receptors and develop entirely new receptors by gene sequence recombination. Receptor editing allows the immune system to rescue immune cells before deletion. This also provides a chance for immune system to escape from local optimum. In addition, self-crossover operator is also added to enhance algorithm's performance. Simulation results with traveling salesman problems also shows the proposed algorithm has better performance than traditional clonal selection algorithm and the algorithm including point mutation and receptor editing without self-crossover.

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