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An Immune Inspired-based Optimization Algorithm: Application to the Traveling Salesman Problem

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Abstract

The clonal selection is a mechanism used by the natural immune system to select cells that recognize the antigens to proliferate. The proliferated cells are subject to an affinity maturation process, which improves their affinity to the selective antigens. The concept of clonal selection is a vitally important one to the success of the human immune system, and it provides an excellent example of the principles of selection at work. The Positive and negative selection is another interesting mechanism in the immune system that work together to both retain cells that recognize the self peptides, while also removing cells that recognize any self peptides. In this paper, a cloning-based algorithm inspired by the clonal and the positive/negative selection mechanism of the natural immune system is presented. This algorithm is inherently parallel and the cloning strategy employs greedy criteria which lends to an adaptive approach. The well known TSP is used to illustrate the approach with experimental comparison with Ant approach. Simulations demonstrate that this approach generates good solutions to traveling salesman problem and greatly improve the convergence speed compared to the Ant-based optimization approach.

Keywords : Optimization, Immune system, Clonal and negative/positive selection, Ant colonies, Traveling salesman problem.

1. Introduction

Optimization, a key topic in the areas of engineering and science, is referred to a process of finding the best solution in the most effective way to a given problem, eventually with some constraints. Most known optimization problems like a Traveling Salesman Problem (TSP) have been shown to be NP-hard. Approaches proposed in the literature to solve the NP-hard problems have been divided into two classes: exact approaches and heuristic approaches [Puchinger and Raidel, 2005]. Both approaches have their specific properties, advantages, and disadvantages. Exact approaches give exact solution to the studied problem, but they work reasonably fast only for relatively small problem sizes. Among the exact approaches, we find branch-and-bound, dynamic programming, Lagrangian relaxation based methods, and linear and integer programming based methods [Nemhauser and Wolsey, 1988]. Heuristic approaches deliver either apparently or probably a good solution, but which could not be proved to be optimal. Heuristic approaches include [Puchinger and Raidel, 2005], among others, simulated annealing [Kirkpatrick et al., 1983], tabu search [Glover and Laguna, 1997], iterated local search [Louren et al., 2002], variable neighborhood search [Hansen and N. Mladenovic, 1999], and various population based models such as evolutionary algorithms [Back et al., 1997], scatter search [Glover et al., 2000],

memetic algorithms [Moscato and Cotta, 2003], and various estimation of distribution algorithms [Larranaga and Lozano, 2001]. Other approaches incorporate exact algorithms in heuristics algorithms [Minaux, 2002]. An important classification of existing approaches combining exact and heuristic algorithms for combinatorial optimization is proposed in [Puchinger and Raidel, 2005].

In this paper, an optimization approach inspired by the clonal and positive/negative selection mechanisms of the natural immune system is presented. The clonal selection mechanism is used by the natural immune system to define the basic features of an immune response to an antigenic stimulus [De Castro and Zuben, 2000]. To illustrate the proposed algorithm, we consider the traveling salesman problem that exemplifies a prominent class of problems in combinatorial optimization [Bakhouya et al., 2006]. The problem can simply be stated as follows: the traveling salesman must visit every city exactly once and then return to the starting city. More precisely, the TSP is the problem of finding a shortest tour which visits all cities [Dorigo and Gambardella, 1996, 1997; Applegate et al., 1998]. The question is: given the cost of travel between all cities, what is the tour with smallest cost?

Formally, let's consider a graph *G=(N,E)*, where *N* is a set of nodes representing cities and *E* is a set of arcs connecting these nodes. The distance between the city *i* and the city *j* is denoted δ_{ij} . Therefore, a TSP problem consists of finding a minimal length Hamiltonian circuit in the graph *G*. An Hamiltonian circuit of graph *G* is a closed tour visiting once and only once all the $n = |N|$ nodes of *G*, and its length is given by the sum of the lengths δ_{ij} of all arcs *(i,j)* that it is composed.

Various exact approaches such as branch-and-bound [Volgenant and Jonker, 1982] and linear programming [Hoffman, 2000; Dantzing et al., 1954] are proposed to solve a TSP problem. Exact approaches for solving such problems require algorithms that generate both a lower bound and an upper bound on the true minimum value of the problem instance. Algorithms that construct feasible solutions, and thus upper bounds for the optimum value, are called heuristics. Many heuristic approaches, such as Genetic Algorithm [Davoian and Gorlatch, 2005], Tabu Search [Fiechter, 1990], Simulated Annealing [Aarts et al., 1988] and Neural Networks [Potvin, 1993], are proposed to resolve the traveling salesman problem [Raymond, 1969; Walshaw, 2002]. At the heart of every search methods, such as local search, simulated annealing, tabu search, swarm or genetic-like algorithms [De Castro and Zuben, 2000, Belal et al, 2006, Wang et al., 2004], is a strategy that generates variations of solutions to explore the search space. A new solution is accepted if it improves the value of the objective function.

Approaches inspired by natural systems, such as ant colonies [Dorigo and Gambardella, 1996] and the natural immune system [Wang et al., 2004], have been also used to solve different combinatorial optimization problems. For example in [Dorigo and Gambardella, 1996], Ant-based optimization approach for the traveling salesman problem presents some attractive characteristics due to the use of trail mediated communication that determines a synergistic effect. More precisely, communication through a pheromone increases the probability of finding an optimal solution. Even though the number of ants at each cycle is maintained constant, their repetitive behavior allows the growth of the amount of pheromone on shorter paths.

In this paper, an algorithm based on the clonal selection with a negative/positive selection mechanism that replaces the repetitive synergistic effect of the Ant-based optimization approach is presented. More precisely, by cloning action, an agent do not need to choose between two or more paths, but it clones itself and its clone moves to neighboring node selected at random [bakhouya et al., 2006]. Moreover, the number of search agents is not constant and changes during the course of the algorithm due to cloning/suppression operations.

One of the main challenges today in optimization is to derive inherently parallel, dynamic and adaptive search algorithms. The proposed approach is inherently parallel and the cloning strategy according to greedy criteria lends to adaptive algorithms to environment changes [bakhouya et al., 2006].

The rest of the paper is organized as follows. Section 2 presents an overview of the Ant-based optimization approach. In section 3, we present the immune system principles. The proposed immune-based optimization approach is presented in section 4. Section 5 presents computational results. Conclusion is given in section 6.

2. Ant colony approach

Ant colony approach is a general purpose heuristic which can be used to solve different combinatorial optimization problems [Dorigo and Gambardella, 1996]. In this approach, the search activities are distributed over artificial ants, which mimic the behavior of real ants. Recall that real ants are capable of finding the shortest path from food source to the nest without using a global controller [Belal et al., 2006]. They are capable to adapt to dynamically changes in the environment, i.e., if the environment changes, the ants will look for a new shortest path.

To solve the traveling salesman problem, a set of cooperating agents (i.e., artificial ants) are positioned at a starting cities selected randomly [Parpinelli et al., 2002]. At each time step they "move" to new cities and cooperate locally with each other to find good solutions. This cooperation does by using an indirect communication mediated by the pheromone. The pheromone trail is modified by agents in a local and a global manner. More precisely, while building a solution, agents visit edges and change their pheromone level. After all agents have completed their tours, the global updating is performed. After an agent has made a tour, it dies, i.e. it is deleted, and new ants can be generated after that. The search for a better solution in ant colony is done collectively and repetitively. Each ant can discover a solution or a part of a solution while moving in the solution space and the optimal solution can be found only by the cooperation of whole ant colony (i.e., the collective intelligence).

Such as presented in [Dorigo and Gambardella, 1996, 1997], Ant-based optimization approach for traveling salesman problem presents some attractive characteristics due to the use of trail mediated communication that determines a synergistic effect. More precisely, communication using the pheromone as a communication medium increases the probability of finding an optimal solution. However, the number of ants at each cycle is maintained constant but their repetitive behavior allows the growth of the amount of pheromone on shorter paths.

3. Immune system: an overview

The immune system defends the body against harmful diseases and infections. It is capable of recognizing most antigens' attacks by some certain important immune cells, called B-cells. B-cells circulate through the blood and lymphatic network waiting to encounter antigens (the foreign molecules belonging to pathogens that invade the body). Each antigen has a particular shape that is recognized by the receptors present on the B-cell surface. More precisely, B-cells synthesize and carry on their surfaces molecules, called antibodies, that act like detectors to identify antigens. Thus the quality of the antibody is crucial for the immune system to successfully recognize the antigen. If a B-cell is useful to recognize the antigen, it may be stimulated to clone (i.e., proliferate or clonally expand). More

precisely, a B-cell with better fitting receptors and binding more tightly the antigen, replicate more and survive longer. This process of amplifying, using proliferation, only those cells that produce a useful B-cell type is called clonal selection [Rodin et al., 2004; Wang et al., 2004; Forstdyke, 1995]. Clones are not perfect, but they are subjected to somatic permutations that result in children having slightly different antibodies from the parent. Clonal selection guarantees that only good B-cells (i.e., with higher affinity with the antigen) can be cloned to represent the next generation [Rodin et al., 2004; Hofmeyr, 1999, 2000]. However, clones with low affinity with antigen do not divide and will be discarded or deleted. Hence, the clonal selection enables the body to have sufficient numbers of antigen-specific B-cells to build up an effective immune response.

Positive and negative selections are interesting mechanisms of the immune system that work together to both retains cells that recognize the self peptides, while also removing cells that recognize any self peptides [Middlemiss, 2006]. More precisely, during positive selection, those cells that demonstrate a relatively weak affinity to the self peptide are induced to die. This results in the removal of cells that are unable to recognize self molecules. During the negative selection, cells with a strong affinity to the self peptide are also induced to die. The result of this positive and negative selection is a repertoire of cells with receptors that can be considered to have a better affinity for the self peptide.

The immune system receives similar attention like other biological-inspired approaches to develop artificial systems called artificial immune systems. The use of the immune system capabilities in artificial systems depends on the nature of the problem. They are a great source of inspiration in many different areas including network security [Hofmeyr, 1999], parallel processing [King et al., 1999], image processing [Rodin et al., 2004], robotic [Watanabe et al., 1999], TSP [Hui et al., 2003; Toma et al., 2003; Endo et al., 1998] and many other areas [Bakhouya, 2005; Dasgupta, 1999]. In optimization field, the Artificial Immune Optimization (AIO) methods have been applied to deal with numerous challenging optimization problems. A concise survey on the recent progresses of the theory as well as applications of the AIO schemes are introduced and discussed in [Wang et al., 2004]. More precisely, the existing AIO methods have been classified into three main categories: Genetic-aided approaches, selection principle-based approaches and immune networks-based approaches. Genetic-aided approaches are similar to genetic algorithm (GA) in which the somatic mutation and gene recombination operations are modeled by means of two GA operators, crossover and mutation [Smith et al., 1993; Forrest et al., 1993; Toma et al., 2001]. In selection principle-based methods, the selection mechanism is introduced to the activated B-cells to generate another intermediate population in order to preserve useful B-cells instead of exploring the whole search space [Gaspar et al., 2000]. More precisely, the selection considered by these methods concerns the somatic permutation mechanism that is exploited to search for even better solution by starting from the already interesting solutions [Forsdyke, 1995]. Immune network-based approaches are inspired by Jerne's idiotypic network principle, which suggests that B-cells are stimulated and suppressed not only by antigens but also by other interacted B-cells [Wang et al., 2004; Toma et al., 2000].

In the rest of this paper, an optimization approach is presented. This approach is based on clonal selection principle with negative/positive mechanisms that replace the repetitive synergistic effect of Ant-based optimization approach. More precisely, only those cells that recognize antigens are selected to proliferate (i.e., to clone) and change their affinities to selective antigens. Recall that, such as presented above, in Ant-based optimization approach, the path that was more frequently chosen by other ants in the past will have a greater probability of being chosen by the ant. Therefore, trails with greater amount of pheromone are synonyms of shorter paths.

4. The cloning-based approach

In this section, we will present how a clonal and negative/positive selection mechanisms can be put to work in an environment (i.e., simulated world) inhabited by artificial agents to solve optimization problems. We present also how this approach can be used to solve the traveling salesman problem.

4.1. Description of the approach

Mapping between the immune system and an optimization problem is done as follows. The immune response represents solutions and antigens represent the problem to solve. More precisely, B-cells are considered as artificial agents that roam around and explore an environment. The optimization problem represents the pathogen. In other words, the optimization problem is described by an environment of antigens. The positive and negative selection mechanism is used to control the agent proliferation by eliminating useless or bad solutions. Hence, the positive/negative selection rules can be considered as "a reinforcement learning mechanism" that not only selects suitable solutions, but also regulates the agent population size that growth due to the cloning operation [Bakhouya et al., 2006].

Immune system	**Optimization problem**
Pathogen	Problem (environment of antigens) (e.g., city graph wherein nodes represent antigens)
Immune response	Solution (e.g., shortest path)
B-cells	Agents
Clonal selection	Creating new agents in order to explore the environment (i.e., proliferation)
Positive/negative selection	Selection of useless/bad agents to kill themselves (i.e., apoptosis)

Table 1: Mapping between the immune system and an optimization problem.

Recall that in the immune system the number of cells directed against an antigen increases by proliferation operation when this antigen is present in the body and reduces when it is eliminated. During this operation, a cell changes its morphology such as change of the life duration. So, the proliferation increases the number of agents that improve the affinity with the antigen in order to inhibit and destroy it. In other words, the proliferation corresponds to the creation of new agents. The new created agents are structurally and behaviorally close to their creators but not exactly the same to allow the adaptation of the system. The apoptosis corresponds to the programmed cellular death. This mechanism occurs when a cell is not adapted to the antigen elimination. Thus, useless cells are destroyed.

Using the immune-based collective behavior, a clonal and positive/negative selection, the population size of agents in the system is regulated dynamically in order to search the optimal solution to a given problem. In fact, an agent which is estimated unsuitable can be destroyed before being proliferated. The decision is made locally on the agent level; no global controller is necessary.

4.2. Application to TSP

Let us consider the well known TSP problem. The environment is the city graph wherein nodes represent antigens. B-cells are agents that progress from a city to neighboring cities and can clone or destroy themselves based on positive/negative selection criteria. The algorithm starts with an initial agent at the source city. At each algorithm cycle, an agent could clone itself and the newly spawned clone moves to neighboring cities. When an agent reaches a city that belongs to its already visited cities set, the positive selection rule is triggered and the agent kills it (i.e., useless solution). Otherwise, the agent clones it and the clone acquires a copy of the already visited cities set from its parent. When all survival agents have accomplished their tour (i.e., reach the source city), the negative selection rule is triggered and among these B-cell agents that constitute the immune response, the one that held the best tour is selected (i.e., useless agents are destroyed).

In order to stop the cloning operation, a better way is to try and develop a tight lower bound of the optimal solution. This lower bound will then act as a stop sign for the search terminating an agent once the upper bound of the partial solution being investigated overlaps the lower bound of the optimal solution. This significantly reduces the useless tours to be explored and consequently reduces the agent's population size. In our case, an agent is allowed to continue its travel if the distance carried is less than to the starting tour generated initially. The initial tour is generated randomly and has an impact to regulate the agent's population. In other words, when an agent reaches a node, the agent clones itself. During its travel, an agent carries the list of visited cities. An agent carried a larger distance kill itself at any city as soon as this condition is detected. This condition ignores a particular path of the TSP graph as soon as it becomes impossible for the path to get a better solution.

Formally, Let $C = \{a,..., z\}$ be a set of cities, $A = \{(x,y): x, y \in C\}$ be the edge set, and $\delta(x,y)$ be a cost measure associated with edge $(x,y) \in C$. Let's also consider that the vectors, composed of elements in the set $C = \{a,..., z\}$, represent the possible tours. Each component of the vector represents a city. The total length of each tour gives the affinity measure of the corresponding vector. The TSP is the problem of finding a minimal affinity value closed tour that visits each city once. Using the proposed approach, the agent behavior is described as follows:

```
Initialization
Create a mobile agent A
A.citiesList= Cities // the set of cities
A.souceCity = Random(Cities) // agent is positioned on a starting city
A.visitedList = {} // the set of visited cities
A.mAffinity = dist // maximal affinity generated at random
A.currentCity =Null // the city in which the agent is positioned
A.LastCity = A.currentCity // the city lastly visited
A.cAffinity=0 // current affinity of the actually tour
//Agent terminates if all cities are visited
while (A.CitiesList ≠ Null) do
  A.cAffinity= A.cAffinity+ δ(LastCity, currentCity)
   if(A.currentCity ∉ A.visitedList and A.cAffinity < A. mAffinity)
      A.visitedList.Add(currrentCity)
      A. citiesList.Remove(currrentCity)
         // the agent clones itself and moves with its clone
            A.LastCity= currentCity
            B=A.clone() // if there at least two neighbors
```

```
        // n1 is selected at random from neighbors such as n1 ∉ visitedList
A.currrentCity = n1; B.move()
// n2 selected at random from neighbors such as n2 ∉ visitedList-{n1}
B.currrentCity = n2 ; A.move()
      endFor
  else
   // positive selection, the agent not make a tour and kills itself
      A.die()  //useless solution
   endif
done
// negative selection, agent die itself if an other agent that have a better tour
   A.die() // bad solution
```

It's worth noting that the positive selection is applied if an agent not build a tour or its affinity becomes greater that the affinity of a tour generated initially at random. Also, the negative selection is applied if all suitable agents build a tour (i.e., a feasible solution to the TSP). In this case, only the agent having a smaller affinity will have remained and is considered the most suitable solution.

5. Computational results

In this section, series of tests aimed to demonstrating the immune-based optimization algorithm to solve the TSP are described. This algorithm is implemented with Java and run on a Pentium III 1GHz personal computer with single processor. The cities are given coordinates in the plane of simulator and then the tour length is measured by the sum of pixel distances between each pair on the tour. The TSP graph is generated randomly. Figure 1, 2, 3, and 4 shows the resolution of the problem with 10, 25, 50 and 100 cities respectively. For example, as depicted in figure 1, for the problem with 100 cities, the total distance of the optimal tour is 7.132 with the convergence speed (i.e., CPU) equal to 593 ms.

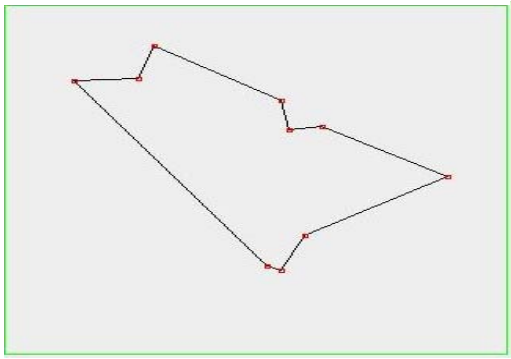

Fig.1: The optimal tour of 10-cities problem

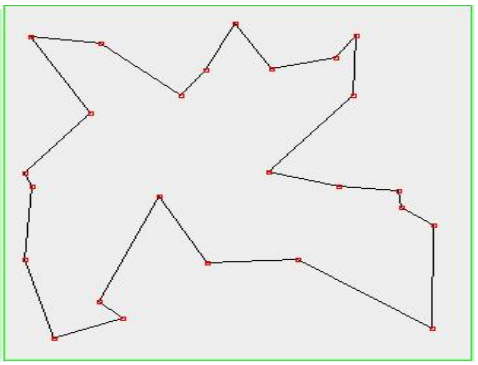

Fig.2: The optimal tour of 25-cities problem

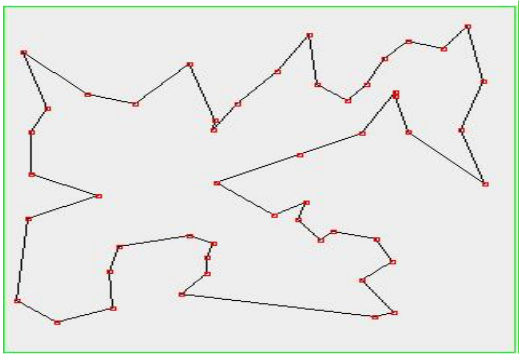

Fig.3: The optimal tour of 50-cities problem

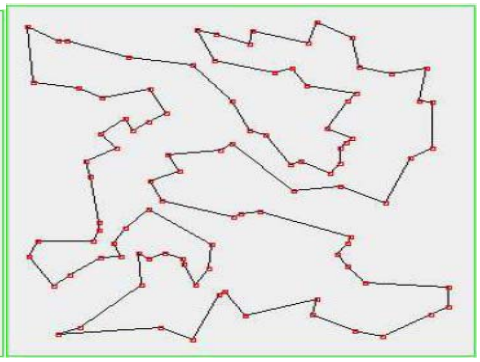

Fig.4: The optimal tour of 100-cities problem

The result reported in table1 shows the cost and the CPU time of the tours found by the proposed immune-based optimization algorithm.

Number of cities	cpu Time	Tour distance
10	0	2,978
20	15	3,296
30	27	3,296
40	32	5,376
50	94	6,208
100	593	7,132
150	1602	8,534
200	4076	9,634
500	12298	11,498
1000	274355	15,234

Table 1: Costs and execution times of tours computed by the cloning algorithm

We have implemented the ant-based optimization algorithm proposed in [Dorigo and Gambardella, 1996, 1997] in order to compare it with immune-based optimization algorithm. The result reported in table 2 shows the cost and the CPU time of the tours found by this algorithm. We conclude that the ant optimization algorithm needs a large amount of computation time to the tour finding routine rather that the immune-based algorithm.

Number of cities	cpu Time	Tour distance
10	15	3,219
20	78	3,385
30	94	3,336
40	1375	5,903
50	3406	6,458
100	9743	7,585
150	94446	9,505
200	606745	10,556
500	2359753	12,357
1000	4350567	15,654

Table 2: Costs and execution times of tours computed by the Ant algorithm

Compared to the immune-based optimization approach, we find that when city number grows, the immune-based algorithm can find the best solution each time and the running time is better than using ant-based optimization algorithm. For example, using immune-based optimization algorithm, the total distance of the tour in 100-city problem is 7,132 and is achieved with 593 ms, comparing with the result provided with ant-based algorithm (tour=7,585, time=9743ms).

6. Conclusion

In this paper, a cloning-based algorithm inspired by the natural immune system is presented. This algorithm is inherently parallel and the cloning strategy employs greedy criteria which lends to an adaptive approach. The well known TSP is used to illustrate the approach with experimental comparison with ant algorithm. Despite these already promising results, the proposed approach is still in its infancy and can be improved. Further research will include mathematical formulation and convergence proof together with experimental comparisons with other evolutionary algorithms using benchmarks suites.

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