Psychologically Motivated Clonal Algorithm based Approach to Solve Planning Problem

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Planning is a subject of interest to the Artificial Intelligence community. Genetic algorithms, neural networks, and simulated annealing are heuristic search methods often used to solve complex optimization problems. In this paper, we have proposed a novel intelligence paradigm to solve planning problems. This paper extends the Artificial Immune System (AIS) approach by proposing a new methodology termed as Psychologically Motivated Clonal Algorithm (PMCA). AIS approach is amalgamated with motivational theories to evolve a robust meta-heuristic. We have reported results for a planning problem related to a manufacturing system and compared these results with Genetic Algorithm. The results obtained have a significant improvement over the GA.

Keywords: Planning, Artificial Intelligence, PMCA, Manufacturing System

1. Introduction

Planning has always been the domain of experts due to its complexity, sophistication and flexibility. Planning can be modeled as an artificial intelligence problem with a wide range of real-world applications. In artificial intelligence, planning originally meant a search for a sequence of logical operators or actions that transform an initial world state into a desired goal state and take on a more discrete flavor. The task might be to solve a puzzle, such as the Rubik's cube or a sliding tile puzzle. Although such problems could be modeled with continuous spaces, it seems natural to define a finite set of actions that can be applied to a discrete set of states, and to construct a solution by giving the appropriate sequence of actions. Historically, planning has been considered different from problem solving; however, the distinction seems to have faded away in recent years. In this research, we do not attempt to make a distinction between the two. Determination of an optimal sequence of tasks is one of the frustrating issues associated with planning. Tasks can be executed using a variety of sequences. Thus, question of optimization arises.

Erol *et al.* (1995) carried out a comprehensive analysis of the complexity of domain independent planning algorithms and studied the conditions for the decidability of the problem. Blum and Furust (1997) proposed the Graphplan approach. The algorithm generates a planning graph showing all the possible operations at every time step. The coexistence of operations can also exist in the graph, when operations interact with each other. Experimentally, the Graphplan outperforms other general planning algorithms. The Efficiency of the universal planning algorithm was studied by Jonsson *et al.* (2000), and they proposed a randomized approach to universal planning under a restricted set of conditions. Simulation reveals that performance of the Stocplan is competitive with the Graphplan. Korf and Talyor (1996) presented the work on an accurate admissible heuristic function TAD^* search algorithm to solve a sliding-tile puzzle. Korf and Flener (2002) discussed the use of disjoint database heuristics in an evaluation function. Bonet and Geffener (2001) proposed a heuristic search planner to solve the planning problem and proved this search algorithm to be superior to the Graphplan.

It has been found that to achieve near-optimal solution Genetic Algorithm (GA) requires a high number of iterations. Further, they are prone to get entrapped in local optima. Thus, it is obligatory to have a solution approach that can solve a large-sized combinatorial problem in less number of generations and also reduce the burden on the CPU. This necessity motivated us to pursue underlying research and develop a meta-heuristic, namely- Psychologically Motivated Clonal Algorithm (PMCA). PMCA uses ideas gleaned from the Maslow's need hierarchy theory (Maslow, 1954), Vroom's Valence Expectancy Theory (Mitchell and Biglan, 1971) and the Artificial Immune System (Castero and Zuben, 2002). This research proposes how a candidate solution viz. antibody can be motivated to acquire different levels of needs with threshold motivational force. To prove the superiority of the proposed algorithm, it has been tested on a problem related to a manufacturing system, and an intensive comparison is carried out with GA.

The remainder of the paper is organized as follows: Section 2 describes the background of Psychologically Motivated Clonal Algorithm. The Proposed algorithm is presented in section 3. Experimentation is described in section 4. The results and discussion are provided in section 5. Finally, conclusions with future scope are included in section 6.

2. Background of Proposed Algorithm

2.1 Artificial Immune System

Biological systems have always fascinated researchers from a computational perspective. They serve as a source of inspiration for the development of many computational intelligence paradigms, such as Artificial Neural Network (ANN), Genetic Algorithm (GA) etc. In a very similar manner, the immune system has inspired the emergence of Artificial Immune System (AIS). AIS can be defined as an abstract or metamorphic computational system using ideas gleaned from the theories and components of immunology (Castero and Zuben, 2002).

As per the theory of clonal selection (Ada and Nossal, 1987), when a B-cell encounters a non-self antigenic with suitable affinity threshold, it proliferates and differentiates into memory and effectors cells. The detailed procedure of clonal selection is described in the next sub-section.

2.2 Theory of clonal selection

Clonal selection explains the response of the immune system, when a non-self antigenic pattern is recognized by a B-cell. Process of clonal selection is schematically shown in figure 1. When a non-self antigen with threshold affinity is recognized by a B-cell receptor, it is selected to proliferate and produces antibodies in high volume. Antigen stimulates the B-cell to proliferate and mature into terminal Antibodies (non-dividing) secreting cells, known as plasma cells. Proliferation in the case of immune cells is an asexual, amitotic process. The cells divide themselves (no crossover) to generate clones. During reproduction, the B-cell progenies undergo a hypermutation process that, together with strong selective pressure, results in B-cells with antigenic receptors presenting higher affinities with the selective antigen. This process is known as the maturation of the immune response.

B-cells, in addition to proliferating and differentiating into plasma cells, can differentiate into long-lived B memory cells with a long-life span. These memory cells are pre-eminent in future responses to the same or similar antigenic pattern.

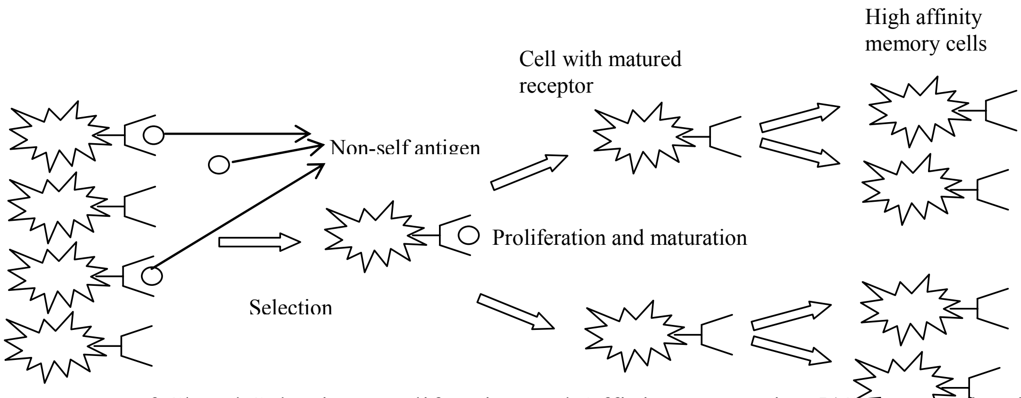

Figure1. Process of Clonal Selection, Proliferation and Affinity Maturation [(Castero and Zuben, 2002)]

2.3 Motivational Theories

The basic idea behind any algorithm is to produce an effective and efficient solution and thus, the overall aim is to improve the performance level of the candidate solution. This performance can be formally defined as the performance of product of ability and motivation.
Therefore, the performance level would be high if both crucial ingredients are high. After careful appraisal of clonal selection theory, we realized that it has the ability to produce a high quality solution but lacks in proper motivational strategies. Motivational theories such as Maslow's needs hierarchy theory and Vroom's valence expectancy theory have been amalgamated with the clonal selection theory to evolve a robust algorithm.

2.4 Maslow's Needs Hierarchy Theory

Maslow's theory has reasonable support for the hypothesis that human needs have some hierarchal order. The theory is based on the assumption that man is continuously wanting. As each need is never fully satisfied, its prepotency diminishes, and an other need emerges to replace it. Thus, at last some needs remain unsatisfied, which the man strives to satisfy. The theory hypothesizes that all people posses a set of five needs arranged in a hierarchy, as shown in figure 2. According to this theory, one can move up in the hierarchy if and only if the lowest needs level is fully or partially satisfied.

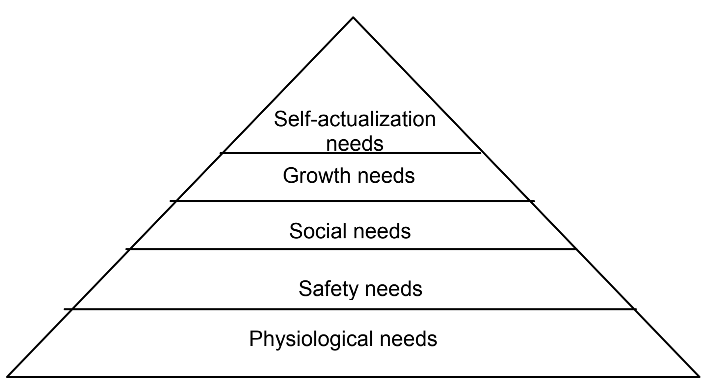

Figure 2. Maslow's Pyramid

Physiological Needs: The most basic survival needs for food, water, and shelter from the environment allow for our continued subsistence. In optimization, this needs to motivate for the generation for possible sequence based upon the problem environment.
Safety Needs: This refers to physical and physiological safety from external threats. From an engineering perspective, constraints (threats) are inherent features. At this level of need, a candidate solution is motivated to defend itself from imposed constraints. This is where evaluation of a candidate solution is carried out.
Social Needs: Next comes, social needs in hierarchy. The term "social" reflects the interaction between candidate solutions. From an engineering point of view, it refers to the selection of the candidate solution.
Growth Needs: Every individual desires to reproduce an entity of his own kind. Here, candidate solutions are motivated to diversify the search space.
Self-actualization needs: At this level an individual is motivated to maximize his potential. This level comprises needs for personal growth, for the development of one's full potential and to the fulfillment associated with the realization of one's capability. Self-actualization needs are unique; they can never be fully satisfied or fulfilled. This is true for any optimization problem as we always concentrate on finding a near-optimal solution rather than the global optima. According to the theory, the more self-actualization needs are fulfilled, the stronger they become. This is why a number of iterations are required to decide the near-optimal solution.
Maslow's need hierarchy theory helps in identifying the needs level for desired motivation but there must be some parameters which assist in determining whether a candidate solution is capable enough to enter the next needs level in hierarchy or not. To overcome this shortcoming, we incorporated the features of Vroom's valence expectancy theory in the proposed algorithm.

2.5 Vroom's Valence Expectancy Theory:

Vroom proposed a mathematical model to obtain a motivational force in terms of two parameters, namely valence and expectancy. Algebraically it can be expressed as:

Motivational Force=Valence x Expectancy

Valence means strength of an individual's preference to a particular outcome. The higher the value of the valence, the higher the motivational force. In optimization, valence is nothing but the value of objective function.

Another factor in determining the motivational force is expectancy, which is the probability that a particular action will lead to the need level. This can be obtained as the value of the objective function for a particular candidate solution upon the sum of the values of objective function of all candidate solutions in the pool.

3. Proposed Algorithm

Nomenclature:

j : a counter, varying from 1 to m.
k : a counter, varying from 1 to n.
Ab : Available set of Ab.
Ab_k : Ab's from Ab with highest affinities.
Ab_d : Set of the new antibodies that will replace d amount of the lower affinity Ab's from Ab.
Ag_m : Population of m Ag's, m=1,2,3…M.
v : value of antigenic affinity
f_k : Vector containing values of objective function, as the affinity of all Ab's

in relation to the antigen Ag_j.

C_k : Population of N_c clones generated from $Ab_{j,n}$.

C_k^* : The population after hypermutation.

f_k* : Vector containing values of antigenic affinity for matured clones.

N_c : The total number of clones generated for each of the Ag's = $\sum_{i=1}^{n} R$ $(\beta.\ N)$, i=1,2…n.

β : Multiplying factor

N : The total number of antibodies

$R(.)$: Operator that rounds its argument toward the closest integer.

e : Expectancy= $v_k/\Sigma f_k$

e^* : Expectancy of matured clones= $v_k/\Sigma f_k^*$

$f(v,e/e^*)$: Motivational force

Need level 1. *Physiological needs*: Defining the problem-specific objective function is a pre-requisite. Randomly generate an initial population of antibodies depending upon problem-environment.

Need level 2. *Safety needs*: Here, the initial population is exposed to threats posed by antigens.

2.1 Randomly choose an antigen Ag_j from Ag_m and expose it to all Ab.

2.2 Based on objective function, determine the vector f_k that contains the affinity of Ag_j to the entire N, Ab's in Ab.

2.3 Evaluate motivational force *f(v,e)*. If the motivational force is greater then the set value than move to the next level, otherwise go to need level 1.

Need level 3. *Social needs*: Here, interaction is done between antibodies so as to identify the relationship with each other.

3.1 Select n highest affinity Ab's from Ab to compose a new set Ab_k of high affinity Ab's in relation to Ag_j.

3.2 Then, selected Ab's will be cloned independently and proportionally to their antigenic affinities, generating a repertoire C_k of clones (the higher the antigenic affinity, the higher the number of clones generated for each n selected Ab's).

Need level 4. *Growth needs*: Set C_k is submitted for hypermutation, inversely proportional to the antigenic affinity, generating a population C_k^* of matured clones (the higher the affinity, the smaller the mutation rate).

4.1 Evaluate motivational force *f(v,e*)*of the matured clones. If the motivational force is greater than the set value, then move to next level; otherwise, go to need level 3.

After satisfaction of need level 4, it is not only desirable but also inevitable to check needs level 2 once again for these entities as they are new denizens of society. Thus, they must be exposed to the threats and properly evaluated as per the objective function.

Need level 2$^{/}$. *Safety needs*: Determine the affinity f_k^* of the matured clones C_k^* in relation to an antigen. Now, all of n Ab's are selected to compose the memory set. Again check the motivational force at this level if it is less than the desired value, then that particular candidate solution is rejected.

Need level 5. *Self-actualization needs*: Finally replace the d lowest affinity Ab's from Ab_d and choose the best among them to fulfill the self-actualization level. As discussed earlier, this level becomes stronger after a number of generations. Thus, the process repeats itself till N=Ngen (the maximum number of the generation). These levels need no more motivation as it is the pinnacle that a candidate solution can achieve.

4. Experimentation

To validate the proposed algorithm, we tested it on a planning problem related to a manufacturing system. Furthermore, an intensive comparison is carried out with GA to prove the superiority of the algorithm.

4.1 Problem Description

In order to illustrate the efficacy of our concepts and techniques, we have considered a case study. There are 3 servers and 8 tasks to be executed, unit processing time of each task, time allotted for different tasks on servers and precedence relationship between tasks are incorporated as in Table 1 and 2.

SERVERS	TASKS							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1	0	0	1	0	0	1	3
2	0	2	0	0	3	0	0	0
3	0	0	2	0	0	2	0	3

Table 1. Processing time of the Tasks on different servers

TASKS	TIME	FOLLOWERS
1	1	8
2	2	-
3	2	6, 8
4	1	7
5	3	-
6	2	-
7	1	-
8	3	-

Table2. Precedence relations and processing time of different tasks

The objective is to minimize the balancing cost of task assignment of products. He and Kusiak (1997) used a set of equations using idle time and waiting time to derive the balancing cost.

5. Results and Discussion

The main idea behind proposing the Psychologically Motivated Clonal Algorithm was to facilitate the faster interchange of information between antibodies with rejection of infeasible solutions. Further, results obtained reveal a high quality near-optimal solution in less time. The Psychologically Motivated Clonal Algorithm starts converging at 1312^{th} generation with a balancing cost of 11.7, whereas GA converges at the 5000^{th} generation with a balancing cost of 16.4. Thus, the PMCA converges much earlier with a convergence rate of 281% times faster than GA, with a better optimal value of balancing cost. Table 3 presents the comparative summary of the results obtained using Psychologically Motivated Clonal Algorithm and GA. The PMCA outperforms GA in all measures of benchmarking i.e. convergence trends, average number of feasible solutions and value of optimal balancing cost.

Performance measures	**PMCA**	**GA**
Average number of generations to achieve convergence over 100 runs	1312	5000
Average number of near-optimal solutions	1168	971
Average balancing cost of feasible near optimal solutions	58	86.16
Minimum value of balancing cost	11.7	16.4

Table 3. Comparison of PMCA with GA

6. Conclusion

Planning is generally more difficult than a typical search problem. It involves larger search spaces, and the existence of a solution is not guaranteed. Furthermore, the size of the optimal solution cannot be easily anticipated. Most existing planning algorithms suffer these drawbacks. In this research, planning has been addressed using a novel evolutionary technique, the Psychologically Motivated Clonal Algorithm (PMCA).

The alluring characteristics of this algorithm are motivational forces, needs level, and clonal selection. PMCA performs its search through the mechanisms of somatic mutation and receptor editing, balancing the exploitation of the best solutions with the exploration of the search-space. Thus, it can be characterized by its co-operative and competitive approach. As antibodies are competing with each other to enter the memory set, while the whole solution is co-operating to achieve a final solution. The results obtained disclose that PMCA outperforms in all measures of benchmarking over GA, such as rate of convergence, computational speed, and quality of solution. Although the problem addressed here appears to be relatively simple, it is just considered to show the efficacy of the proposed algorithm. We are in the process of applying it to more complex configuration problems, adding more constraints with multiple objectives and various planning problems related to manufacturing, such as set-up planning, assembly planning, cellular manufacturing etc. Furthermore, fine-tuning of the parameters with different specific problems could improve the results, and hence, the issues of future work.

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