Abstract:
In this work an approach of integration of clonal selection algorithm and immune memory based on self-organizing map (SOM) is presented to solve optimization problem. Immune memory lays the foundation for a rapid and massive secondary response of immune system. Management of immune memory is important for improving performance and quality of optimum search using immune algorithm. The adaptive functionality of SOM is applied for emulation of the dynamic behavior of immune memory. From results obtained using proposed approach SOM-based management of immune memory can keep balance between exploration and exploitation for good solution quality and search performance. Besides SOM can improve the clonal selection algorithm in performance for multi-modal optimization search.

Keywords:
Clonal selection algorithm; Self-organizing map; Immune memory; Topology optimization

1. Introduction

Biological inspiration can be converted into computation paradigms for specific task or optimization. The development of concepts has been successfully implemented in many theoretical fields such as artificial neural networks, evolutionary algorithms, swarm algorithms. Among the evolutionary algorithms, artificial immune system is a biologically-inspired computation paradigm that emerged in recent years. Researchers applied the features of human immune systems in the developed systems including distributed memory, adaptive self-organizing, parallel processing, and decentralized control. Artificial immune systems (AIS) have been applied to many complex theoretical and engineering problems such as function optimization, pattern recognition, machine learning, anomaly detection, computer security, control engineering, web mining, power systems, transportation systems [1-9].

The first immune algorithm for optimization may be the work of Fukuda[10]. But the AIS for optimization have been popularized mainly by the development of CLONALG algorithm [11] using clonal selection principle. CLONALG can perform multi-modal optimization and deliver good approximations of global optimum. The capability of finding global solution and different local solutions is important for multi-modal optimization. The balance between exploration and exploitation is a critical issue for good solution quality and search performance for evolutionary algorithms [12]. Exploration refers to locating the entire feasible region for promising global solutions while exploitation refers to the search for improved solutions in promising subregions already identified. Intelligent balance between these two aspects may drive the search process towards better optimum solutions and/or faster convergence rates. Issue of how and when to control the balance perceptively have not been comprehensively addressed yet.

Human immune system relies on the prior formation of an incredibly diverse population of B cells and T cells [13]. The specificity of both the B-cell receptors and T-cell receptors for binding the epitope of antigen, is created by a remarkable genetic mechanism. Each receptor is created to recognize the epitope that may never have been present in the body. Clones of antigen-specific lymphocytes of B-cell and T-cell provide the basis of the immune response. Clonal selection theory [14] elucidates the essential adaptive immune response of living organisms in protecting themselves against attack from an extremely large variety of antigens (e.g. bacteria, viruses, and other pathogenic organisms). When a B cell is activated by binding an antigen, it starts to clone itself and subsequently triggers a somatic hypermutation process. Once these B cells encounter their cognate antigens and receive additional signals from accessory cells such as the T-helper cell they further proliferate, become plasma cells, and eventually mature into memory cells. The resulting plasma cells can reproduce large volumes of antibodies specific to particular antigens, leading to antigenic neutralization and elimination. In addition to maturing into plasma cells, some B cells also, after antigen interaction,
form groups of long-life B memory cells which are circulated throughout the host organism. When encountered with the same or similar antigen again, these B memory cells are able to respond and eliminate the threat effectively by recognizing it, reproducing, and changing into plasma cells that produce antibodies rapidly.

The clonal selection principle as it pertains to adaptive immune response provides several concepts that are important from a computational point of view. One of these concepts is clonal expansion of activated B cells, which produces clones independently and proportionally to the affinity between B cells and available antigens. This gives the B cells that recognize the present antigens a better chance to survive and makes those that do not recognize the present antigens die via apoptosis. Thus the immune system can eliminate those antigens efficiently with minimal resources. Another important concept is somatic hypermutation, which involves a programmed process of mutation affecting the variable regions of antibodies’ genes. Such mutations are expected to have wider variations in the antigen-matching genes and may occasionally lead to an increase in the affinity of antibodies to the available antigens. It is also observed that the somatic hypermutation process is made at a rate inversely proportional to the antibody’s affinity with antigens. Thus, B cells with low-affinity antibody receptors may be further mutated in order to raise their affinity values quickly, whereas those with high affinity may be mutated less, retaining a good match to the antigen.

Immune memory lays the foundation for a more rapid and massive response the next time the antigen enters the body. But the majority immune-inspired optimization algorithms are concentrated on the clonal selection while the immune memory is only a concomitant which is simply modeled as the elitist selection. Therefore some studies[15-17] were focusing on the immune memory and second response mechanism for improving the optimization performance. A self-organizing map mechanism is introduced in this study to adaptively evolve the immune memory and control the balance between diversity and convergence.

Feature maps constitute basic building blocks in the information processing infrastructure of the nervous system. An essential property common to all these maps is the preservation of neighborhood relations. This distinct feature of the human brain motivated the development of the class of self-organizing neural networks. There are a number of ways to design an unsupervised learning network that self-organizes into a feature map. Self-organizing map (SOM) is an unsupervised learning algorithm proposed by Kohonen[18]. The principal goal of the SOM algorithm is to map an incoming pattern in a higher dimensional space into a lower dimensional space, and perform this transformation adaptively in a topological ordered fashion. The applications of SOM range widely from simulations used for the purpose of understanding and modeling of computational maps in the brain to subsystems for engineering applications[19–21]. Recently some researchers have exploited its ability in optimization search[22-24]. The modification about applying the SOM as an optimization search mechanism is that each weight vector represents a possible solution of the objective function. The winner will be determined with the best objective function and updating the weights of the winner and its neighbors. All weights will move to explore and exploit the potential space with optimum solution.

The SOM has been applied for both static data management and dynamic data analysis. Recently some studies have exploited its ability in optimization of dynamic system[25,26]. Immune response is an dynamic system to adjust the receptor antibody to match the epitope of antigen without monitor. Everyday, plenty of B-cells are excreted from the marrow and flow into the lymphoid recurrence. Once the invaded antigen is detected in the first time, B-cells will explosively produce antibodies to destroy the antigen. This is the primary response of acquired immune system. After the primary response, the mature cells are partially differentiated as memory cells, which are able to detect the invaded same or similar antigen in the future. This is the secondary response. Memory cells are more sharply stimulated by the particular antigen and they can destroy that antigen with less time. In order to emulate the mechanism of immune memory with limit computational resource, the SOM is applied to maintain a memory pool used for keeping memory cells, potential solutions of optimization problems.

For utilization of limited resource efficiently two operators, suppression and aging operators, are applied to population and memory. Suppression is triggered when the cells are highly concentrated or they are very similar. The concentration of cells falls down to a certain normal level through suppression and thus the diversity of cells are ensured. The suppression operator can be achieved through SOM. An aging operator is used. The aging operator eliminates old B cells in the populations to avoid premature convergence and to increase diversity in the current population.

In this paper, an approach of integration of clonal selection algorithm and self-organizing map based immune memory is presented to solve topology optimization of structure. Structural topology optimization, which aims to find the best structural configuration that meets different multidisciplinary requirements within a predefined design domain, is gradually becoming an integral part of the product development process. Such optimization is useful for inspiring completely new structural designs and offering suitable initial structural configurations for shape or sizing optimizations. However, due to its complexity and large
number of design variables, it is considered an intellectually challenging field. Among population-based optimization methods for structural topology optimization, genetic algorithms (GAs), which are simple to perform and do not have any demand regarding function derivatives, are some of the most widely implemented. However, despite the broad applicability and great potential of GAs for global search, they are frequently criticized as inefficient. One of the early reported approaches to apply immune algorithm (IA) to structural topology optimization was proposed by Luh and Chueh[27]. In their approach, the presented multi-modal immune algorithm (MMIA) emulates the features of a natural immune system to solve constrained multi-modal structural topology optimization problems. Although MMIA successfully extends IA to multi-modal structural topology optimization, the importance of design connectivity handling and hinge connection prevention in terms of population-based methods with binary representation for structural topology optimization were not considered in MMIA. Topology optimization is approached by keeping diversity using self-organizing map based memory management and accelerating convergence utilizing clonal selection algorithm. In addition to the final optimum solution, there are different designs with good objective function values for optional selection of design. It shows the capability of developed approach for multi-modal topology optimization of structure.

2. Implementation of proposed approach

In this study, only the antibody is taken into account. The antibody population consists of \( N_{pop} \) candidate solutions to a structural topology optimization problem. An antibody's genes are composed of a series of binary design variables with the same size as the element number of its corresponding design domain. The design domain and boundary conditions of a structural topology optimization problem are discretized into a fixed number of small square elements. The binary design variables corresponding to each antibody's genes are directly mapped to these elements within the design domain. A binary design variable with value of "1" represents a "solid element", determining the existence of material, while "0" represents a "void element", indicating the nonexistence of material in its corresponding element within the design domain. Also note that elements which are required to serve as support boundary conditions or load applications are not included in the binary design variables of each antibody in this study.

Based on the clonal selection principle, each antibody produces clones independently with fixed number. The hypermutation operator in an IA is directly responsible for introducing random changes to antibodies. Its mutation strategy in global search is to offer a larger design step size to raise the affinity values of inferior antibodies more rapidly and to escape local optima. In local search, the strategy is to offer a smaller design step size to allow better antibodies to gradually attain global optima. In general, this operator is performed by point mutation at a rate inversely proportional to the affinity of antibodies. A higher mutation rate does not necessarily guarantee a larger design step size for structural topology optimization problems, but rather increases the probability of destroying the structural performance or connectivity of a structural topology design. To reduce the risk of structural topology design destruction by the hypermutation operator, a modified hypermutation operator using element stress is applied in this study.

According to the basic idea that antibodies have limited life spans, the aging operator is designed to eliminate old antibodies and replace them with new randomly generated ones with the intention of maintaining diversity in the antibody population. During the search process, the age of each antibody is counted at each generation. When the age of an antibody exceeds a predefined age limit, it is considered an old antibody and is erased from the current population, regardless of its affinity value. As an antibody undergoes the cloning expansion and obtains a clone with a better affinity value, it is substituted by the clone and its age is reset to 0. This way, an equal opportunity is given to each antibody to evolve so that diversity is maintained and new areas of the search space can be potentially explored. To improve convergence efficiency in a structural topology optimization problem, each antibody is forced to be unique, and the best antibodies are retained in the population.

The concept of organizing information spatially, where the similar concepts are mapped to adjacent areas, constitutes a trademark of the SOM. A very relevant characteristic of the SOM is the development of an ordered network in which the nearby neurons will share similarities, this way similar patterns will activate similar area in the SOM. A SOM is a single layer neural network, where neurons set along an n-dimensional grid. In most applications this grid is 2-dimensional and rectangular. The concept of input space and output space are important because they constitute the core of the SOM activity. The SOM can be though as a tool for mapping a vector in input space onto output space and preserve the topological relations observed in the input space. In order to verify the developed program for SOM, a data set randomly generated is used as the training for SOM. The map at initialization state is shown in Figure 1a while the map after 1000 iteration of training is shown in Figure 1b.
Another data set of 24 topology configurations of structure is used for study some characteristics of using SOM with topology configuration of structure, as shown in Figure 2. The results of training using different learning and 4x4 grid are shown in Figure 3. The results of another test with same training data using 10x10 grid are shown in Figure 4. In comparison of results between 4x4 grid and 10x10 grid, it is shown that the difference of SOM maps using 4x4 grid is smaller than difference of 10x10 grid. But the gray area in SOM map of 10x10 grid is less than gray area of 4x4 grid. The SOM can use small data set to explore large space and it is applied to search optimum design of structure.

The SOM is also applied to maintain adaptively the diversity of population and immune memory during search process of topology optimization of structure. In the process the new created antibody is projected onto SOM map for similarity comparison first and the comparison of objective function values is followed. If the new design is the winner, then the weights of the winner and its neighbors will be updated. All weights will move to explore and exploit the potential space with optimum solution. The better solutions are treated as memory cell. Because the neighborhood radius is also adaptively changed during the process, there is no memory cell in some grids of map at iteration stage. There is no winner in that grid when the comparisons of similarity and objective function are made using corresponding neighborhood radius. The adaptive SOM map and memory cells are shown in Figure 5.
3. Numerical results and discussions

Topology In this section, the performance of the proposed algorithm was tested by implementing it on minimum compliance and minimum weight benchmark structural topology design problems. A minimum compliance design problem can be constructed as the following:

\[
\text{minimize } C(X) \\
\text{subject to } \frac{V(X)}{V_0} = \text{Volfract}
\]  

(1)

where \(C(x)\) is the compliance of a structural topology design, and \(V(x)\) and \(V_0\) are the material volume and the design domain volume, respectively. \(\text{Volfract}\) is a pre-defined volume fraction. In this structural topology optimization, a 2 × 1 benchmark cantilever problem was investigated below. Its boundary conditions are depicted in Fig. 6 and the final results are shown in Fig. 7. Compliance of the best solution is 63.9602. A performance comparison was made with the optimal designs reported by bit-array GA[28], enhanced GA [29] and TSAGA [30], which have minimum compliance values of 65.26, 64.41 and 64.81 respectively. SOM enhance the population diversity in search process and quality of optimum solution at final stage.

4. Conclusions

Integration of clonal selection algorithm, immune memory and self-organizing map is successfully applied to solve optimization problem. The adaptive functionality of SOM is applied for emulation of the dynamic behavior of immune memory. The SOM helps to maintain adaptively the diversity of population and immune memory during search process of optimization. From results obtained using proposed approach SOM-based management of immune memory can keep balance between exploration and exploitation for good solution quality and search performance. SOM can also improve the clonal selection algorithm in performance for multi-modal optimization search.

References


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