A Grid-facilitated AIS-based Network Scheme for Many-objective Optimization

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ABSTRACT
Artificial Immune Systems (AIS), one of the promising artificial intelligence methods, has been widely adopted in the optimization domain. However, their application to many-objective domain is rather scattered. In this respect, we extend the AIS-based algorithm to many-objective situations using the immune network theory facilitated by the grid technique. The network operations are employed not only for managing the diversity, but also to strengthen the exploitation and exploration pressure. The suppression-triggered activation and the archive-driven activation are both introduced in this study to exploit the promising region and to explore along the local Pareto-front. In addition, Grid technique is introduced to reduce the computation complexity in the identification process of the sensory range. Coupled with the grid-facilitated network scheme, the proposed algorithm improves the exploitation and exploration capability in many-objective optimization problem.

Categories and Subject Descriptors
G.1.6 [**Numerical Analysis**]: Optimization -*Unconstrained optimization*

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search - *Heuristic methods*

Keywords
Optimization; Many-objective optimization; Artificial Immune Systems; Immune Network Theory

1. INTRODUCTION
Artificial immune systems (AIS), an engineering analogy of the biological immune system that imitates the human immune system, has established itself as one of the major methods inartificial intelligence. In field of optimization, AIS has been applied successfully to bi-objective and tri-objective problems. Problems with 4 to 5 objectives had been considered in some of the experiment. But, the algorithmic design did not anticipate the specific challenges given rise by the many-objective situation. This paper hence extends the potential of AIS to many-objective situation which adopts the AIS as the evolution framework and the immune network theory [5] to manage the evolution dynamics. Complete view of immune network theory is implemented in this study for managing the evolution dynamics and enhancing the search ability. 'Near' solutions are suppressed to reduce redundant search. Activation process aimed to enhance exploitation and exploration search to move both towards and along the local Pareto front. Activation may be triggered by suppression operation to exploit the local area to accelerate the exploitation process and may also be triggered by the archive to generate solutions along the local front. Effective pressure on both exploitation and exploration search is therefore expected.

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2. THE PROPOSED ALGORITHM
The basic structure of the proposed algorithm is very similar to other AIS-based optimization algorithms. The outline of the proposed algorithm is briefly depicted in figure 1.

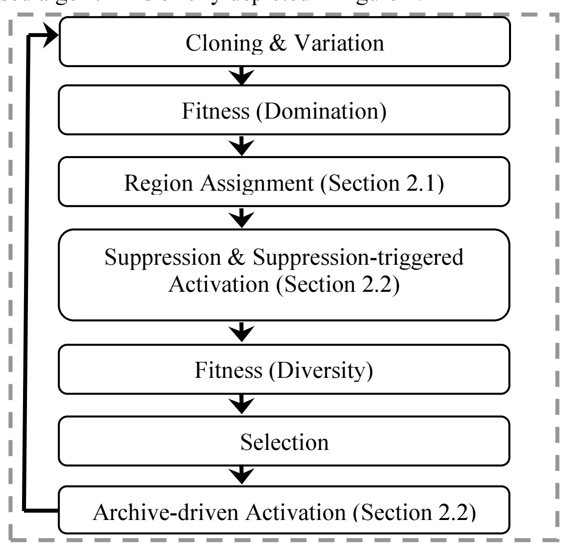


Figure 1: The organization of theproposed algorithm

2.1 Region Assignment
Grid determines the location of individuals in the objective space and in the decision variable space which is used as the identification of solutions within the sensory region for suppression and activation operation. The location and the size of a grid are desirable to be adapted and adjustable during the evolutionary process. Grid is considered to be a vector composing of grid location for every dimension in objective space and in decision variable space. The grid location in objective space ($G_o(i)$) and the grid location in decision variable space ($G_d(i)$) of any individual i is determined as

$$G_o^k(j)=\begin{cases}\left\lceil \dfrac{(f_k(x_j)-Min)}{[(Med-Min)/(div_o/2)]}\right\rceil & ,if\ f_k(x_j)\le Med\\ \left\lceil \dfrac{(f_k(x_j)-Med)}{[(Max-Med)/(div_o/2)]}+\dfrac{div_o}{2}\right\rceil & ,f\ f_k(x_j)>Med\end{cases}$$

$$G_d^p(j)=\left\lceil \frac{(g_p(x_j)-\phi_p)}{(\gamma_p-\phi_p)/div_d}\right\rceil$$ where $f_k(x_j)$ represents the objective value of the k^{th} objective for solution j, *max*, *med* and *min* represent the maximum, the median and the minimum values of objective k, $g_p(x_j)$ represents the value in the p^{th} decision variable for solution j, φ_p and γ_p represent the lower bound and the upper bound of the p^{th} decision variable, div_o and div_d represents the user defined number of division in objective space and in decision variable space

2.2 Suppression and Activation Operations

In general AIS-based algorithm, solutions with distance fall within the sensory range of another solution will be recognized by each other. The identification of recognized solutions needs to be conducted independently. To reduce computation complexity, the grid location found in the region assignment process is used as the determinant for the recognition requirement. Solutions with the same grid location are considered to be recognized by each other. This idea of recognition is applied to both the suppression process in the objective space and that in the decision variable space. When the grid location in both cases contains more than one solution, suppression operation will be performed within the grid location. Local dominated solution will be suppressed. If the capacity of the grid location exceeds the user-defined threshold, solution with smaller Euclidian distances will be removed to constraint the size. Potential redundant search are largely reduced.

Suppression in the decision variable space will also be used to trigger the suppression-triggered activation to direct the search to exploit potential local region. If one solution is able to dominate the other solution within the same grid location, such suppression will trigger the activation through the generation of new solution (sol_{n1}) on the high-potential solution space

$$sol_{n1}=sol_{p1}+(sol_{p1}-sol_{s1})\times r$$

where sol_{p1} and sol_{s1} represents the non-dominated and suppressed solutions vector respectively and r is a random variable.

Archive-driven activation is conducted after the selection process. The activation is achieved through the generation of new solution (sol_{n2}) based on the decision variable of the current best solutions. The new generated solutions will be moved to other grid location in the decision variable space to explore along the local front.

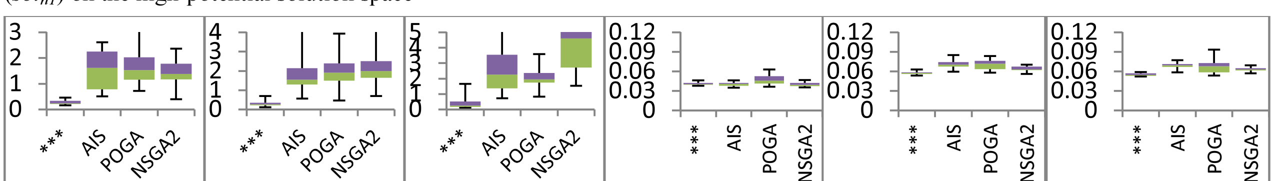
$$sol_{n2}=sol_{p2}+\frac{(\gamma_p-\phi_p)}{div_d}\times z\times R$$

where sol_{p2} represents the non-dominated solution vector, φ_p and γ_p represent the lower bound and the upper bound of the decision variable p, div_d represents the user defined number of division, m represent the number of objective, z is a vector of uniformly distributed random integer between -(div_d/2) and +(div_d/2) and R is a vector of random integer between 0 to 1

3. NUMERICAL EXPERIMENTS

The proposed algorithm is compared with general AIS-based algorithms (modified from MISA [1]), POGA [4] and NSGA-II [2]. Scalable test problem DTLZ-1 and DTLZ-2 [3] are used as the test problems. The result of IGD is given in Figure 2 with '***' represent our proposed algorithm.

In terms of the convergence performance (IGD), the result is promising. Among the experimented algorithms, the proposed algorithm achieves the smallest IGD in most time which represent that better group of solutions are generally identified in the proposed algorithm. As for the performance across different number of objectives, the proposed algorithm obtains similar convergence result in 4-objective, 6-objective and 8-objective cases. The impact on the increase in the number of objectives is small as compared to other experimented algorithms especially in DTLZ1. For the variability of the performance, it is obvious from the box plot that proposed algorithm has a very stable performance. The range in all instances is very small. The proposed algorithm could achieve good results consistently.



4-Objectives (DTLZ1) | 6-Objectives (DTLZ1) | 8-Objectives (DTLZ1) | 4-Objectives (DTLZ2) | 6-Objectives (DTLZ2) | 8-Objectives (DTLZ2)

Figure 2: Box Plot for Convergence measures

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