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Adaptive hierarchical artificial immune system and its application in RFID reader collision avoidance

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ABSTRACT

This paper proposes an efficient adaptive hierarchical artificial immune system (AHAIS) for complex global optimization problems. In the proposed AHAIS optimization, a hierarchy with top-bottom levels is used to construct the antibody population, where some antibodies with higher affinity become the top-level elitist antibodies and the other antibodies with lower affinity become the bottom-level common antibodies. The elitist antibodies experience different evolutionary operators from those common antibodies, and a well-designed dynamic updating strategy is used to guide the evolution and retrogradation of antibodies between two levels. In detail, the elitist antibodies focus on self-learning and local searching while the common antibodies emphasize elitist-learning and global searching. In addition, an adaptive searching step length adjustment mechanism is proposed to capture more accurate solutions. The suppression operator introduces an upper limit of the similarity-based threshold by considering the concentration of the candidate antibodies. To evaluate the effectiveness and the efficiency of algorithms, a series of comparative numerical simulations are arranged among the proposed AHAIS, DE, PSO, opt-aiNet and IA-AIS, where eight benchmark functions are selected as testbeds. The simulation results prove that the proposed AHAIS is an efficient method and outperforms DE, PSO, opt-aiNet and IA-AIS in convergence speed and solution accuracy. Moreover, an industrial application in RFID reader collision avoidance also demonstrates the searching capability and practical value of the proposed AHAIS optimization.

1. Introduction

Biological immune system is a complex and powerful defense system which can keep the bodies of animals from the invasion of external pathogens. Inspired by the biological immune system, in the last two decades, the developed artificial immune systems (AIS) have attracted considerable attention as a promising intelligent approach to tackle with theoretical researches and engineering applications [1], such as numerical optimization [2,3], data mining [4,5], pattern recognition [6,7] and anomaly diagnosis [8,9]. Recently, many variations of AIS have been proposed, most of which are derived from four branches of theories related with AIS: clone selection theory [10], negative selection [11], danger theory [12] and artificial immune network [13]. In artificial immune networks, an immune cell can recognize not only the specific antigens but also the other immune cells, which leads to a negative response of suppressing the recognized immune cells [14]. As an important branch of artificial immune systems, artificial immune networks are increasingly employed to solve some practical problems in many industrial applications.

An earlier version of artificial immune networks has been proposed and named as aiNet by de Castro [13], which is aiming at clustering and filtering the redundant and rough data from real problems, and thus becomes popular for global optimization in filtering, control systems, pattern classification, disease prediction and many other applications [15]. Subsequently, aiNet has been improved much in various ways. For example, the aiNet applied to multimodal function optimization (*i.e.*, opt-aiNet) [16] has a well-designed convergence criterion and is capable of determining the population size automatically, combining exploitation with exploration of the affinity landscape, and stably locating local optimal solutions. Later, an improved algorithm named omni-aiNet [17] has been proposed to solve single and multiple objective problems with a single or multiple global optimal values, because it is able to adjust the population size dynamically and to avoid high levels of redundancy within the population. As well, cob-aiNet [18] employs the concept of concentration to guide the evolution of antibodies. On

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the other hand, an efficient artificial immune network with the elitist learning mechanism [19] and its improved algorithm [20] have been proposed by borrowing the elite strategy from PSO. These algorithms discriminate the elitist antibodies and the non-elitist antibodies during the mutation operation. To increase the adaptability, an improved adaptive artificial immune system (IA-AIS) [21] including the affinity-based cloning, the affinity-based mutation and the concentration-based suppressor, has been designed by taking advantage of the affinity data between an antibody and an antigen to guide the evolution of antibodies. Likewise, with the induction of elitist antibodies with higher affinity, an artificial immune network with social learning (aiNet-SL) [22] has been proposed and applied to optimize the coefficients of a finite impulse filter. All these achievements suggest that artificial immune systems, especially artificial immune networks, have been studied deeply and have a broad application foreground in the future.

However, the existing artificial immune systems are faced with such disadvantages as too many parameters which are lack of adaptability, the simple structure which is apt to result into slow convergence velocity and the fixed searching step length which is easy to cause poor convergence accuracy. Taking into account these issues mentioned above, this paper attempts to propose an efficient adaptive hierarchical artificial immune system (AHAIS) for complex global optimization. In the AHAIS optimization, a two-leveled structure will be designed, and the mutation operator will be redesigned. As well, a dynamic level updating strategy and an adaptive searching step length adjustment mechanism will be introduced. This proposed AHAIS optimization is expected to quickly capture the optimal solutions of complex optimization problems. Some comparative numerical experiments on benchmark functions are arranged among different evolutionary algorithms such as the proposed AHAIS optimization, differential evolution (SaDE/rand/1/bin) [23], particle swarm optimization [24], opt-aiNet and IA-AIS. Furthermore, an industrial application related with RFID reader collision avoidance is simulated. The experimental results will prove the high-performance and effectiveness of the proposed AHAIS optimization.

The remainder of this paper is organized as follows. Section 2 reviews the artificial immune systems, *i.e.*, opt-aiNet and IA-AIS. Subsequently, Section 3 gives the technical details of the proposed AHAIS optimization, including division of antibody population during initialization, differentiated mutation operators for two-leveled antibodies and dynamical updating mechanism of antibodies. Section 4 compares the performance between the proposed AHAIS optimization and the other existing evolutionary algorithms by a series of numerical simulations and a practical application. Finally, Section 5 draws some conclusions.

2. Reviews of artificial immune systems

By resorting to the biological functionalities of recognition, learning and memorization, the biological immune system is capable of killing the invasive pathogens timely. In detail, once invading the organism, the pathogen becomes the *antigen* and causes the immune response of biological immune system. When the antigen is detected by the immune cells for the first time, the immune cells will be activated and then propagate a number of cloned *antibodies* to destroy this antigen. During the propagation, the immune cells undergo the *affinity*-based somatic hypermutation, where the affinity is measured by the combination degree between an antibody and an antigen. As this biochemical reaction continues, the immune cells become mature and further differentiate as memory cells. When the same or similar antigen appears again, the memory cells will quickly identify and destroy the antigen. By imitating these principles of the biological immune system, artificial immune systems are developed to solve real-world problems. Corresponding to the biological immune system, for the sake of clear definition, several terms often used in artificial immune systems are required to be qualitatively described. The *antigen* refers to the objective problem to be solved which includes linear and non-linear constraints, the *antibody* refers to the feasible candidate solution of the objective problem and the *affinity* refers to the fitness value of the objective problem (antigen) related with the feasible candidate solution (antibody) [1,10,13].

2.1. The opt-aiNet optimization

As an extended algorithm of aiNet, the opt-aiNet optimization [14] has been developed to solve multimodal function optimization problems. In the cloning operator, the opt-aiNet optimization employs the *uniform cloning strategy*, where a fixed number of children antibodies are reproduced from a parent antibody. Then, all the cloned children antibodies but the parent one goes through an *affinity-based Gaussian mutation* (*AGM*) operator. But only one child antibody with the highest affinity among the cloned children antibodies is selected to enter the next generation. Once there is a very slight difference in the average affinity between two neighboring generations, a *similarity-based suppressor* will be activated. For any two antibodies whose Euclidean distance is less than a predefined suppression threshold, the antibody with lower affinity will be suppressed. To keep the diversity of population, some randomly generated antibodies are recruited. Repeat this iterative process until the termination condition is satisfied.

It is worth pointing out that the opt-aiNet optimization is capable of combining the exploitation with the exploration of the population, and at the same time shows the good stabilization of the population. Moreover, the dynamic searching mechanism for the optimal population size based on a certain suppression threshold is helpful to probe the local optima of objective problems. However, the opt-aiNet optimization is costly in computational time and not satisfactory in quality of solutions. Therefore, it can be concluded that a broad research space exists in improving the computational efficiency of the opt-aiNet optimization. Please see [14] for more details.

2.2. The IA-AIS optimization

In order to improve the adaptability of parameters in opt-aiNet, an improved adaptive artificial immune system (IA-AIS) [19] has been designed to deal with complex optimization problems. In IA-AIS, an *affinity-based* cloning operator is employed, where the antibodies with higher affinity are reproductive. On the other hand, a *controlled affinity-based Gaussian mutation* (*CAGM*) operator is used to make the antibodies with lower affinity mutate much more than those with greater affinity. In addition, the threshold can be adjusted dynamically and is proportional to the similarity between antibodies.

By utilizing the affinity data between an antibody and an antigen, the IA-AIS optimization performs well while not only mining the local information but also probing the potential information of the objective problem. Three redesigned operators (*i.e.*, the affinity-based cloning operator, the controlled affinity-based Gaussian mutation operator and the concentration-based suppressor) contribute to improve the performance of IA-AIS, which is profitable to probe the global optima quickly and accurately.

Note that both opt-aiNet and IA-AIS have a single level of candidate antibodies, so the good information from those better antibodies is neglected. In these two algorithms, each antibody is evolved only by learning from itself but any other better antibodies, which decreases the convergence speed to some degree. Moreover, both of these two algorithms use fixed mutation step length. When