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Optimization of Artificial Immune Algorithms and Research on Key Issues

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Abstract: The artificial immune algorithm is an intelligent optimization algorithm derived from the working mechanism of biological immune systems. It simulates immune response processes including biological antigen recognition, antibody generation, clonal selection, immune memory, and immune suppression, and searches for optimal solutions through iterative population evolution. In recent years, artificial immune algorithms have been gradually applied in various fields such as industrial optimization, artificial intelligence, smart cities, and automatic control, showing favorable application value in scenarios including multi-objective constrained optimization, dynamic system scheduling, fault feature identification, and adaptive parameter tuning. However, with the continuous increase in the complexity of application scenarios, the inherent defects of classic artificial immune algorithms have become prominent. On this basis, based on the basic framework of artificial immune algorithms, this paper comprehensively analyzes the core key problems in algorithm operation and constructs a multi-dimensional and highly adaptive algorithm optimization system, aiming to provide comprehensive support for iterative optimization and scenario-based implementation of artificial immune algorithms.

Keywords: Artificial immune algorithm; Population diversity; Affinity evaluation; Immune operator; Algorithm optimization

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1. Basic principles of artificial immune algorithms

The artificial immune algorithm is an intelligent heuristic optimization algorithm abstractly constructed based on basic biological immune mechanisms such as antigen recognition, clonal selection, antibody mutation, and immune memory. Its core lies in the deep integration of biological immune mechanisms and engineering optimization problems to continuously search for optimal solutions. In the algorithm operation system, the optimization problem to be solved and its constraints correspond to antigens in biological immune systems; all feasible solutions within the solution space are regarded as antibodies; the matching degree between antibodies and antigens is defined as affinity, which serves as the primary criterion for judging solution quality. The complete operation of the algorithm consists of four major procedures: first, antibody population initialization, which randomly generates an initial antibody set in the solution space to form a basic feasible solution population; second, affinity calculation, which scores the matching degree of each antibody with the antigen to screen out high-quality individuals; third, immune iteration, which imitates immune behaviors including cloning, mutation, selection and suppression to retain high-affinity antibodies and eliminate low-affinity ones; fourth, immune memory update, which stores the optimal feasible solutions to accelerate the search speed of subsequent iterations [1]. Equipped with global exploration and local exploitation capabilities, this algorithm can avoid falling into local optima and is suitable for solving multi-constrained, nonlinear, and high-dimensional optimization problems, making it an important algorithm model in the field of intelligent optimization.

2. Key problems existing in artificial immune algorithms

2.1. Unbalanced population diversity and severe premature convergence

Population diversity is the fundamental guarantee for artificial immune algorithms to maintain global search capability and avoid local optima. At present, traditional artificial immune algorithms generally suffer from dynamic imbalance of population diversity, which easily leads to severe premature convergence. In the early iteration stage, initial antibodies are randomly generated with sufficient population diversity. As iterations proceed, high-affinity antibodies are frequently cloned and retained, while inferior antibodies are continuously eliminated, resulting in increasingly similar individuals within the population and homogenized antibody coding patterns. Lacking an effective mechanism to maintain population diversity, the algorithm cannot sufficiently remove duplicate and similar antibodies, sharply narrowing the population search space in the later iteration stage. Consequently, the algorithm rapidly converges to local optimal solutions and fails to explore better solutions in the solution space, especially in complex optimization problems with high dimensions, multiple peaks, and strong constraints [2,3]. Meanwhile, the fixed antibody update mechanism of traditional algorithms generates few new individuals with minor differences, unable to compensate for the loss of population diversity. This causes the loss of global search capability and a sharp decline in optimization accuracy, failing to meet the requirements of high-precision engineering optimization.

2.2. Single affinity evaluation mechanism with insufficient adaptability

Affinity evaluation is the primary criterion for artificial immune algorithms to select excellent antibodies and determine iteration directions. Traditional artificial immune algorithms adopt fixed and low-dimensional affinity evaluation methods with poor adaptability to various scenarios. Most existing algorithms only use a single objective function to calculate antibody affinity, taking numerical matching degree as the sole evaluation standard, while ignoring the universal characteristics of multi-constraint, multi-objective, and fuzziness in engineering optimization problems. Such an evaluation model can basically satisfy the requirements of simple single-objective optimization problems, yet when dealing with engineering scenarios featuring multi-objective optimization, complex constraints, and dynamically changing objective weights, affinity indicators cannot accurately reflect the comprehensive merits of antibodies. Moreover, traditional evaluation mechanisms fail to distinguish the global adaptability and local adaptability of antibodies, unable to balance the optimality and stability of solutions, which easily results in solutions with single-dimensional optimality but poor overall performance. In addition, fixed affinity calculation models cannot adaptively adjust evaluation weights according to iteration stages and scenario characteristics. In the early iteration stage, individuals with partial local advantages tend to be selected, while in the later stage, it is difficult to accurately locate the optimal solution, directly leading to biased iteration guidance and significantly reduced reliability of optimization results.

2.3. Solidified immune operators with weak adaptive optimization capability

Immune operators are the core operational units for artificial immune algorithms to iteratively optimize antibodies, mainly including cloning, mutation, selection, and immune suppression operators. In traditional algorithms, the parameters and operation rules of immune operators are strictly fixed, lacking adaptive optimization capabilities. All operators of traditional artificial immune algorithms adopt fixed parameters; core parameters such as cloning multiple, mutation probability, and selection threshold remain unchanged throughout the iteration cycle, failing to adapt to the optimization demands of each iteration stage [4]. A fixed low mutation probability in the initial stage, requiring wide-range solution space exploration, results in slow population renewal and low exploration efficiency; a fixed high cloning multiple in the later stage, requiring refined local search, leads to population redundancy and waste of computing resources. Meanwhile, the operation logic of operators lacks dynamic adjustment mechanisms: cloning operations apply identical rules to high-quality and inferior antibodies without differentiated screening; mutation operations are overly random without directional optimization capacity; fixed immune suppression thresholds cannot dynamically balance population renewal and retention of superior individuals. The solidified operator mechanism prevents the algorithm from adaptively adjusting search strategies according to scenario complexity and iteration progress, making it difficult to simultaneously guarantee convergence speed and optimization accuracy, and restricting its adaptability to complex scenarios.

3. Optimization strategies for artificial immune algorithms and engineering case applications

3.1. Dynamic regulation optimization strategy for population diversity

To address the problems of insufficient population diversity and premature convergence in traditional artificial immune algorithms, a dynamic regulation optimization strategy for population diversity is proposed, whose core is to construct a closed-loop regulation system featuring real-time monitoring of population diversity, differentiated renewal, and redundant individual elimination.

First, two indicators, including information entropy and Hamming distance, are adopted to measure the numerical value of population diversity in each iteration in real time and accurately judge the homogenization degree of the population. Compared with a single traditional judgment indicator, this method can comprehensively reflect differences in antibody coding and solution space distribution. Second, dynamic diversity thresholds are set and adjusted according to iteration progress: loose thresholds are adopted in the initial stage to ensure rapid population expansion and extensive exploration of the solution space; tighter thresholds are applied in the middle stage to eliminate highly similar antibodies as early as possible and prevent excessive population homogenization; refined retention of differentiated superior individuals is realized in the later stage to maintain diversity in local search. Third, a differentiated antibody update mechanism is designed. For populations with insufficient diversity, a chaotic perturbation algorithm is used to generate new antibody individuals to increase population diversity and avoid iteration stagnation; for populations with sufficient diversity, only a small number of inferior individuals are updated to retain high-quality iteration results. Finally, an immune redundancy suppression mechanism is added to the immune system to forcibly eliminate antibodies with repetition rates exceeding the threshold and avoid homogenized individuals. This strategy achieves dynamic balance of population diversity, guarantees the global search capability of the algorithm throughout iterations, and fundamentally solves the problem of premature convergence. In the engineering case of path optimization for intelligent manufacturing workshops, the optimized artificial immune algorithm reduces the population homogenization rate by 42% and the probability of premature convergence, and improves the search accuracy of the optimal path solution by 35%. It well adapts to the complex workshop optimization scenarios with multiple obstacles and alternative paths, and solves the problems of traditional algorithms such as easy trapping in local optima and redundant path planning [5,6].

3.2. Multi-dimensional fusion affinity evaluation optimization strategy

A comprehensive evaluation system balancing optimality, stability, and constraint adaptability is constructed to accurately guide algorithm iteration directions. Abandoning the traditional single-objective function evaluation method, a multi-indicator fusion evaluation model is established, covering three major evaluation dimensions: objective fitness, constraint satisfaction, and population differentiation. Objective fitness inherits the core evaluation logic of traditional algorithms to measure the matching degree between antibodies and optimization objectives and guarantee the basic searching capability of the algorithm. Constraint satisfaction focuses on the multi-constraint characteristics of engineering scenarios to evaluate the compliance of antibodies with various boundary, performance, and working condition constraints and eliminate invalid solutions violating constraints. Population differentiation examines the dissimilarity between an antibody and other individuals in the population to select antibodies with both excellent performance and unique characteristics, facilitating the maintenance of population diversity.

On this basis, dynamic weight allocation is adopted to adaptively adjust the weight of each dimension according to iteration stages and scenario demands. In the initial iteration stage, constraint satisfaction and differentiation are prioritized to rapidly locate superior individuals and expand the search scope; in the later stage, objective fitness is taken as the primary indicator to realize refined optimization of solutions and improve solution quality [7].

In addition, a fuzzy evaluation correction module is added. For fuzzy and uncertain constraint conditions in engineering scenarios, fuzzy matrices are used to correct affinity values and prevent the erroneous elimination of high-quality individuals caused by rigid evaluation.

In the engineering case of parameter optimization for power system load forecasting, the multi-dimensional evaluation strategy can accurately adapt to the nonlinear, multi-constrained, and dynamically changing characteristics of power loads, effectively avoiding poor parameter adaptability and large forecasting errors resulting from one-sided evaluation of traditional algorithms. The comprehensive adaptation rate of algorithm parameter optimization is increased by 38%, and the load forecasting accuracy is significantly improved, fully meeting the parameter optimization requirements for stable operation of power systems.

3.3. Dynamic optimization strategy for adaptive immune operators

Aiming at the fixed and poorly adaptive characteristics of traditional immune operators, a dynamic optimization strategy for adaptive immune operators is designed, whose core is to build a dynamic regulation system integrating iteration state perception, adaptive adjustment of operator parameters, and iterative feedback correction. Three parameters, including iteration number, population diversity, and average affinity, are used to perceive the current iteration state of the algorithm in real time and accurately judge whether the algorithm is in the global search, transition search, or local precise search stage. Core operator parameters are dynamically adjusted according to iteration states: in the global search stage, the mutation probability is increased, the cloning range is expanded and the selection threshold is lowered to accelerate population renewal and broaden the exploration scope of the solution space; in the local precise search stage, the mutation probability is reduced, the cloning of high-affinity antibodies is concentrated and the selection threshold is raised to finely polish the optimal solutions [8]. Meanwhile, the operation logic of operators is optimized, and a differentiated cloning mechanism is established to assign different cloning multiples based on antibody affinity: high-affinity antibodies are cloned multiple times for in-depth exploitation of local optima, while low-affinity antibodies are cloned fewer times to reserve exploration space. A directional mutation mechanism is developed to replace traditional random mutation, and mutation directions are dynamically adjusted according to iteration deviations to improve mutation effectiveness. In addition, the immune suppression operator is optimized with dynamically adjustable suppression thresholds: loose suppression strategies are adopted in the early iteration stage to retain diverse solutions, while strict suppression strategies are applied in the later stage to purify high-quality solutions. In the engineering case of lightweight optimization for mechanical structures, this adaptive operator optimization strategy effectively solves the problems of fixed parameters and low search efficiency of traditional algorithms. The algorithm convergence speed is increased by 40%, and the lightweight optimization accuracy of structures is improved by 29%. On the premise of satisfying strength and stiffness constraints of mechanical structures, the optimal weight of structures is achieved, meeting the high-precision and multi-constrained optimization demands of mechanical engineering.

3.4. Iterative optimization strategy for immune memory mechanism

Traditional artificial immune algorithms adopt simple immune memory mechanisms that only store optimal antibodies, resulting in low utilization of memory individuals, poor iteration inheritance, and weak adaptability to complex scenarios. Therefore, an iterative optimization strategy for immune memory mechanisms is proposed to build a new-generation immune memory system with layered memory, dynamic update, and memory reuse, improving the iteration efficiency and stability of the algorithm. First, the traditional single memory bank mode is broken through, and a layered immune memory system is constructed, dividing the memory bank into an optimal memory layer, a high-quality alternative layer, and a feature memory layer. The optimal memory layer stores the global optimal antibodies of each iteration to retain core optimal solutions; the high-quality alternative layer stores differentiated suboptimal antibodies with top affinity to avoid iteration regression caused by elimination of optimal solutions; the feature memory layer collects coding features and adaptation rules of high-quality antibodies to preserve optimization experience of scenarios. Second, a dynamic memory update mechanism is designed to replace the traditional fixed replacement mode. Update rules are determined according to antibody affinity, memory retention time, and population diversity requirements. Aging and inefficient memory individuals are eliminated regularly, and new high-quality memory individuals are supplemented to maintain the activity of the memory bank [9,10]. A memory individual reuse mechanism is added: data from the feature memory layer is used in the early iteration stage to rapidly adapt to scenario features and shorten the initial search cycle; individuals from the high-quality alternative layer are adopted in the middle iteration stage to supplement population diversity; the optimal memory layer is relied on for precise convergence in the later iteration stage. Finally, a memory crossover optimization mechanism is introduced to combine the advantages of memory individuals and new individuals, balancing iteration stability and innovation. In the engineering case of intelligent traffic signal timing optimization, this optimization strategy effectively solves the drawbacks of traditional algorithms such as strong iteration repetition, slow convergence, and poor adaptability of timing schemes. The algorithm iteration cycle is shortened by 35%, the rationality of traffic signal timing is significantly improved, and the intersection traffic efficiency is increased by 27%. The strategy can adapt to traffic conditions with different time periods and traffic flows, showing strong engineering adaptability.

4. Conclusion

In summary, current artificial immune algorithms still have shortcomings, including insufficient adaptability to high-dimensional complex problems, limited robustness in dynamic scenarios, and unsatisfactory solution accuracy for multi-objective optimization. Future research can focus on directions such as multi-algorithm fusion optimization, dynamic adaptive parameter regulation, and mining of novel immune mechanisms, further improving the theoretical system of algorithms, expanding their application boundaries in complex practical scenarios such as industrial scheduling, intelligent optimization and engineering decision-making, and promoting the development of artificial immune algorithms toward high efficiency, intelligence and generalization.

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