学 位 論 文 内 容 の 要 旨

博士の専攻分野の名称　博士（情報科学）　氏名　徐 卓然

学 位 論 文 題 名

A Study of Attraction Basin Sphere Estimation for Niching Evolutionary Algorithms
（ニッチング進化計算アルゴリズムのための Attraction Basin Sphere 計算法の提案）

In mathematics and computer science, an optimization problem is the problem of finding the best solution from all feasible solutions. However, knowledge of multiple solutions to an optimization task is especially helpful in engineering. For example, due to physical (and/or cost) constraints, the best results may not always be realizable. Multimodal optimization deals with tasks that involve finding all or most of the multiple solutions as opposed to a single best solution. Evolutionary Algorithms (EAs), benefit by being population-based, has the potential ability to locate multiple solutions. However, this is against the natural tendency of EAs, which will always converge to the best solution, or a sub-optimal solution. Finding and maintenance of multiple solutions is wherein lies the challenge of using EAs for multimodal optimization.

Niching is the technique that can help EAs to find and preserve multiple stable niches, or favorable parts of the fitness landscape possibly around multiple solutions, so as to prevent convergence to a single solution. However, most niching methods employ a radius parameter which is hard to correctly set in practice. The purpose of this study is to propose a new niching evolutionary algorithm (the combination of a niching method and an EA), which have the following new features:
1. The algorithm does not use the radius parameter.
2. The algorithm can create niches adaptively according to the fitness landscape.
3. The algorithm should overcome other niching methods on the ability of finding multiple solutions.
4. The algorithm should be efficient in computational time.
This thesis is organized into six chapters. In Chapter 1, I introduce the background and purpose of this thesis. I first give a review of Mathematical Optimization and Evolutionary Algorithms. Second, I introduce the concept of Multimodal Optimization. After that, I explain the mechanism of Niching Evolutionary Computation and introduce several classic niching methods.

In Chapter 2, I propose a niching method named as Attraction Basin Sphere Estimation (ABSE). Given several candidate solutions, this method can collect niching information about those candidates from fitness landscapes and adaptively adjust niching parameters. I combine this method with several EAs in the next three chapters.

In Chapter 3, I apply ABSE to genetic algorithms to create a niching genetic algorithm: Attraction Basin Sphere Estimation Genetic Algorithm (ABSEGA). It identifies optimal-like individuals (seeds) from the population, and uses ABSE to calculate niching parameters. The experiments are performed on benchmark tests. I compare ABSEGA with another adaptive niching method: Topological Species Conservation (TSC). The results indicates that ABSEGA has a similar ability to solve multimodal optimization problems as TSC. Considering the computational cost, ABSEGA is found to perform significantly more efficiently than TSC. Examining the randomly sampled parameter settings, the results are found to be insensitive to different parameter settings on most test functions.

In Chapter 4, I improve ABSEGA for Neuroevolution problems. The original ABSEGA does not work well on Neuroevolution problems, because those problems usually have a lot of local optimal solutions. ABSEGA may find multiple local optimal solutions instead of multiple global optimal solutions. I propose a method to calculate the Importance of solutions. Importance measures the possibility of a solution to be a global optimal solution. So the algorithm can use Importance to find multiple global optimal solutions. The newly proposed method is named as ABSEGA2. I first examine ABSEGA2 with some state-of-the-art algorithms including dADE, DE, CMA-ES with a simple archive and NEA2 on benchmark tests. Second, I examine ABSEGA2 in a robotic arm problem, in which I evolve an artificial neural network (ANN) to control the arm to catch balls. I compare ABSEGA2 with a radius-based method Dynamic Fitness Sharing (DFS) and the Standard Genetic Algorithm and those state-of-the-art algorithms. The results show that ABSEGA2 has a high ability to escape local optimal and find relatively better solutions. The experiments also show that the calculation of Importance plays an important role on keeping diversity on complex tasks.

In Chapter 5, I combine ABSE and CMA-ES, a very powerful local optimization method. The proposed niching method is named as Attraction Basin Sphere Estimation CMA-ES (ABSE-CMA-ES). The algorithm is compared with the best 5 niching methods in CEC 2013 Niching Methods Competition. The results show that the proposed algorithm is significant better than the dADE/nrand/1, DE/nrand/2, CMA-ES with a simple archive and NVMO. It is also better than NEA2, but not in a significant way. ABSE-CMA-ES is better than ABSEGA and ABSEGA2. However, ABSEGA2 is only slightly better than ABSEGA.

Finally, I conclude this thesis and discuss future researches in Chapter 6.