The Fitness Landscapes Exploration Based on the Parallel Simulated Annealing Algorithm

Shanshan Cui[1], Jing Zhao[1], Bin Shi[2]
[1]College of Information and Computer Engineering, Chuzhou Vocational and Technical College, China
[2]China Railway Fourth Bureau, China

Abstract: Taken the complexity of managing forests into account, researchers regard the virtual forest environment as an experimental area, and manage the forests efficiently by way of the simulated annealing algorithm. More specifically, this paper evolves the forests from the current forest states to the most desired one using the most efficient path. Due the traditional simulated annealing algorithm converges slowly and has long execution time, this paper takes on a parallel method and its optimization strategy based on simulated annealing. As it is expected, increasing the number of processes is positive in any case; an important supplement to global search is local optimization. All above present that the parallel strategy can be efficient and low cost management of forest landscape.

Keywords: Parallel Algorithm; Simulated Annealing Algorithm; Multiple Markov Chaint

1. Introduction

The forest ecosystem is one of the most important ecosystems on earth. Forest biodiversity is a primary measure in the relationships between different ecological resources [1]. Each location represents the possible genetic combinations on the landscape. The range of heights represents the fitness of survival. There are a great many peaks and valleys. Also, there is some inter-relationship between different height values. The slightly different combinations will be close to each other, and the fitness between them will be similar. The possible range in decisions is depicted as a landscape of many peaks and valleys. The modeling evolution is a process to find the highest point in the fitness landscape according to the desired state. In this paper, evolve the forests from the current forest states to the most desired one using the most efficient path [2].

In the fitness landscapes, a benchmark or starting point needs to be determined firstly. Then several elements are defined to describe this benchmark condition. These elements are being changed, in order to move from the benchmark to the search for the highest point of fitness in the model. Reeves and P. F. Stadler applied the fitness [3] ,[4].

2. Description of the Problem

Fitness landscape [5], [6] is determined by two parameters N and K. Through the control of N and K, the researcher observes the effect of the complexity of the system evolution. Here, N is the number of elements of the form system. Each element decides a feature of system. The comprehensive performance of N features decides whether a system is good or not. System quality is measured by the values of fitness. In particular, the system has N elements, and each system elements di (i=1, 2…N) is with two kinds of state. These two states are represented by binary numbers 0 and 1, and each form is an N-vector consisting of binary numbers, such as N-vector (0... 1, 1, and 1). 2N vectors are randomly assigned to different values, which is the fitness. Then N and K are mapped to a three dimensional space, which forms a fitness landscape. Therefore, fitness landscapes are essentially graphic made of all possible states of the system. Evolution of complex forest system is through the variation of elements (a transition from state one to another)，which improves the total value of the degree of adaptation system continuously. Specific performance is for the fitness landscape of “Climbing process” (Holland, 1992). For example, the forest system has four elements (N=4). The current state is 4-vector (0000); and the final state of evolution (the desired state) is 4-vector (1111). There are many paths that can reach the desired status from the current status.All

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In the NK model, K represents the interaction size between system elements. A factor in the occurrence of variation, not only will cause it to determine the system to adapt to changes in the value of the system, but also related to other K elements of the system to determine the degree of adaptation to change. Overall fitness values vary depending on the changes in two parts. In particular, interaction between all paths is pij (j=1, 2… K). fi is the cost of the paths from the current state to the desired state. The purpose is to find the optimal route.

3. Parallel Simulated Annealing

The designed system is an algorithm [7], including a local optimization stage and a global optimization stage. Design the above stages and work in parallel. Partial optimization section is used to design the value of N (N vector) for each route inserted during the global optimization section. On the other hand, for the part of global optimization, we use the entire path set. In these two stages, the new solution is used to search for variants of Simulated annealing.

In the process of obtaining the optimal routes, many search methods can be selected. Search pattern refers to the subject adopted by way of adaptation. The NK model is concerned with the optimization process and evolution path. The main existing search pattern includes local search, greedy search, long jump search, cognitive search and imitate search. In the paper, we use the imitate search as the search pattern. Specifically, determine a benchmark point in fitness landscapes. After a change of multiple elements, compare with the benchmark point. And then search for the optimal performance point. This way is for the study of imitation success rate. Compared with others, determining the search direction is the biggest advantage.

3.1 Parallelization in Local Optimization

A large number of possible evolutionary pathways are provided to approach the optimal solution, in the exponential behavior of the local optimization stage. In local optimization, select the value of N (N vector) for each route. The N (N vector) values of each path of the optimal solution obtained after global optimization are optimized using the optimization algorithm. This is called local optimization, which helps to leave a local minimum in the system. SAM is used as a search algorithm, and the same route construction method is used in global optimization. Firstly, for each route, apply SAM to every value of N (N vector). The values of these arguments are basically similar to those used in global optimization. Once the first stage is executed, it generates a gain matrix. Then, this will be used to select routes with greater benefits. Repeat the process until the best beneficial solution no longer appears. Just calculate the complete gain matrix for the first time, and only calculate one row and one column for the remaining process.

3.2 In Global Optimization Parallelization With Synchronous Communication

When synchronization is applied to Simulated annealing, each thread processor starts with the initial solution X0. The total amount of individual communications does not rest with the number of procedures. Each processor has a set of time periods or target dates for communication throughout the entire process. Every time communication occurs, each processor will start with the optimum overall solution and continue until now. Reduce communication to pass the arrangement and values of functions obtained by each processor to the main processor and receive the best solution found so far.Specifically, each processor passes its local optimal value to the main processor. By comparing these values, determine the current local optimal value (minimum value). At the next temperature level, the current local optimal value is considered as the initial solution for each thread. Repeat the process until the termination condition is reached.

In the analysis of parallel algorithms the formation of the Markov chain is uneven. This unevenness demonstrates the difference in probability from one solution to another is affected not only by the solution of the corresponding cost values and the current temperature, but also by the local optimal

values produced by the algorithm as it evolves to the optimal solution. Based on this idea, using master-slave structure provides an improved parallel algorithm at different temperature levels.

The development of search results is seen as a solution exchange between processes, and development occurs when processes freely penetrate the search space. Let's execute the process between cooperation points ω， The sequence of annealing steps is called a free exploration chain. When using different numbers of processes, the parallel cost of the algorithm remains unchanged, but the premise is that the collaboration cost is ignored. However, regarding collaboration costs, the quantity of annealing steps taken in the process among collaboration points decreases as the number of processes increases to maintain a constant cost of parallel computing. Therefore, cost is not always inversely proportional to the number of processors.

4. Experimental Studies

Obviously, in the fitness landscape, the distribution of solutions is not isotropic. For example, in each direction of the search space, they are not uniformly scattered and there are relatively large numbers of solutions, which increases the probability of the algorithm completing calculations with the optimal solution within that range. Local optimization is considered the optimal solution after performing some iterations in global optimization, i.e. the initial solution. At the same time, it uses optimization selection strategies to improve the quality of global solutions.

5. Main Text

The experimental results prove the importance of optimization strategy in parallelizing such applications. There are two algorithms, one is local algorithm, the other is global optimization algorithm of synchronous communication. Whether the global or the local optimization in any set (R, RC and C), the more the solutions are, the less the cost of finding the efficient path is; meanwhile, the cost is roughly proportional to the number of threads. Using this analysis method can allow forecasting that will protect the forest ecosystems and achieve sustainable business objectives, which are closely related to manage the forest. This type of analysis has both theoretical value and practical applications. However, if the cooperation cost is not ignored,the cost is also related to the period of communication ω and multiple annealing steps L2. So researchers need a great many tests to obtain the minimum cost for parameters L2, p, and ω Different values of appear.

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