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Cloud Computing Task Scheduling Based on Cultural Genetic Algorithm

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Abstract. The task scheduling strategy based on cultural genetic algorithm(CGA) is proposed in order to improve the efficiency of task scheduling in the cloud computing platform, which targets at minimizing the total time and cost of task scheduling. The improved genetic algorithm is used to construct the main population space and knowledge space under cultural framework which get independent parallel evolution, forming a mechanism of mutual promotion to dispatch the cloud task. Simultaneously, in order to prevent the defects of the genetic algorithm which is easy to fall into local optimum, the non-uniform mutation operator is introduced to improve the search performance of the algorithm. The experimental results show that CGA reduces the total time and lowers the cost of the scheduling, which is an effective algorithm for the cloud task scheduling.

1 Introduction

Cloud computing is progressed with the development of computer and network technology, which is the outcome by combining with distributed technology, parallel computing and virtual technology. The basic principle of cloud computing is that the computer system divides tasks submitted by users into several independent subtasks. The appropriate scheduling strategy is used to allocate the subtasks to the nodes of resource center. When processing of all subtasks is completed, the processing results in resource nodes are returned to users by the merge strategy [1,2]. Therefore, the task scheduling scheme in cloud environment is one of the key technologies of cloud computing, which affects the whole performance of the cloud computing platform. A large number of studies show that the problem of cloud task scheduling is related to NP, which has been studied by many scholars. Literature [3] puts forward to a task scheduling algorithm in cloud computing for solving the cloud task scheduling based on improved genetic algorithm, which can obtain smaller time and lower cost for completing task. Literature [4] adopts the particle swarm optimization (PSO) to take the quality of service of users into account, which has achieved good results in the field of scheduling of resources of cloud task after finishing a large number of scientific computing. Literature [5] uses the strategy of solving the cloud task scheduling by dynamic self-adapting ant colony algorithm (ACO), which overcomes the deficiency of ant colony algorithm in solving the cloud task scheduling, including the slow rate of convergence and easy caught in local optimum. Literature [6] comes up with a genetic simulated annealing algorithm for task scheduling with dual fitness, which can effectively balance the demands of the users for the attributes of tasks and improve the users' satisfaction in the cloud computing platform. However, due to the heterogeneity of the cloud computing platform, any single intelligent group algorithm is easy to fall into local optimum, premature and other defects, and the improvement of the algorithm is focused on the nature of the algorithm itself, ignoring the guiding role of the formation of knowledge in the process of evolution.

Cultural algorithm is a kind of intelligent optimization algorithm based on the double layer evolution mechanism of knowledge, which obtains useful knowledge and information through the evolution space of micro-level (main population space) and reserves it in the evolution space of macro level (belief space), and utilizes those knowledge to guide the evolutionary process of main population space [7]. In order to improve the efficiency of task scheduling in the cloud platform, a task scheduling method based on genetic algorithm is presented. The main population space of the algorithm conducts searches by using the basic genetic algorithm, and the belief space uses the genetic algorithm with the non uniform mutation operator in each iteration to improve the search ability of population, which reduces the total time of the task and decreases the scheduling cost, and improves the efficiency of task scheduling.

2.Descriptions About the Cloud Task Scheduling

At present, most of the cloud computing platforms adopt MapReduce model for parallel computing. Cloud task scheduling is to employ appropriate scheduling policies so as to reasonably distribute the tasks to the compute nodes for operation, which enables to minimize time span, lower the cost, and maintain load balancing of the resource utilization after finishing tasks [8].

If users submit Job tasks to the cloud computing center in a certain time, the jth task is divided into $Task_j$ subtask by Map Computing, $TotalTask$ is the total number of tasks and $Machine$ is the number of computing nodes, therefore,

$$TotalTask = \sum_{i=1}^{Job} Task_i \tag{1}$$

In this paper, we use the ETC matrix [9] to record the execution time of each sub task, $ETC[i, j]$ means the execution time of sub task on jth resource, employ $cost[r]$ for the cost of task execution of rth resource at the unit time. Consequently, total time of all the sub tasks and the total cost of all the sub tasks are as follows:

$$TotalTime = \max_{m=1}^{Machine} \sum_{i=1}^{TotalTask} machine(mi) \tag{2}$$

$$TotalCost = \sum_{m=1}^{Machine} \left(\sum_{i=1}^{TotalTask} machine(mi) \cdot cost(m) \right) \tag{3}$$

Therefore, targeting at the cloud task scheduling with minimum span of total time and lowest total cost, the mathematical model of the target function can be described in the formula(4):

$$Total = min(TotalTime) + min(TotalCost) \tag{4}$$

3.Task Scheduling of CGA in Cloud Computing

3.1 Algorithm Framework

CGA is a hybrid intelligent algorithm which is formed by the mutual combination of the framework of cultural algorithm and genetic algorithm. CGA sets up two kinds of evolutionary space, namely, main population space and belief space. The main population space and belief space respectively use basic genetic algorithm and the improved genetic algorithm to carry on the independent evolution. In the evolution process, the belief space will periodically take advantages of the synchronous transmission to receive the excellent individuals of the population space in order to update its own space, and it will also use its own knowledge to guide the evolution of population space regularly. Through the dual evolution and mutual promotion of the main population space and belief space, it can obtain better global search ability. In order to improve the search performance of the cultural genetic algorithm, the belief space will adopts the genetic algorithm with the non-uniform mutation operator to increase diversity of the main population and avoid premature phenomenon. In this paper, the framework of the cultural genetic algorithm is shown in figure 1:

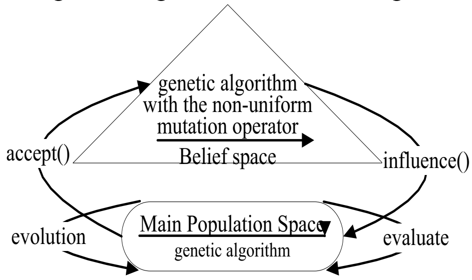

Figure 1. The framework of the cultural genetic algorithm

3.2 Encoding and Decoding

As for the solution of cloud task scheduling by CGA, it needs to establish a mapping relationship between the solution of the problem and the individual of the algorithm, and use the right way to express (the encoding way of task). The current encoding modes of the chromosome often include direct encoding and indirect encoding. In this paper, we use indirect encoding mode to encode the node occupied by each sub task. Since the length of the chromosome depends on the number of sub tasks, therefore, a chromosome corresponds to a task scheduling strategy. For example, if users submit Job=3 in a certain time, the number of sub tasks for each task will be $Task_1 = 2$, $Task_2 = 4$, $Task_3 = 3$ respectively, and the total number of tasks will be TotalTask=9, the number of nodes machine=3. Therefore, the chromosome (3,2,3,1,2,3,1,2,2) is a feasible scheduling scheme as shown in figure 2.

	$Task_1$		$Task_2$				$Task_3$		
Sub task	1	2	3	4	5	6	7	8	9
Resource	3	2	3	1	2	3	1	2	2

. **Figure 2.** Encoding mode of chromosomes

After producing chromosomes, it is necessary to decode them in order to obtain the distribution of the sub tasks on each node. After the above chromosomes are decoded, there are $machine_1 = \{4,7\}$, $machine_2 = \{2,5,8,9\}$, $machine_3 = \{1.3.6\}$

3.3 Initialization of the Population

Genetic algorithm is extremely sensitive to the initial population. What's more, it has a great influence on the convergence rate of the algorithm and the global optimization. The traditional genetic algorithm generate the initial population by adopting the random method, which is easy to produce local optimization. In order to accelerate the convergence rate of the algorithm and achieve global optimal solution, the individual similarity is introduced to ensure the initial population to distribute uniformly in solution space.

If we set the population size for $size$, the length of individual chromosomes for $totalTask$, the number of machine resources for $machine$, ith chromosome produced for $x_i = \{x_{i,1}, x_{i,2}, ..., x_{i,m}\}, (1 \le i \le size, 1 \le m \le totalTask)$, the Hamming distance between two individual chromosomes is as follows

$$Difference(i,j) = \sum_{m=1}^{totalTask} | x_{im} - x_{jm} |, (i, j) \in (1,2,...,size) \quad (5)$$

Thereinto $| x_{im} - x_{jm} | = \begin{cases} 1, x_{im} = x_{jm} \\ 0, x_{im} \ne x_{jm} \end{cases}$,similarity: $sim(i,j) = \frac{Difference(i,j)}{L}$,threshold detection: $\mu = \frac{L-C}{L}$, C represents as regulation parameter.Two individual chromosomes can enter the initial population on the condition that similarity $sim(i,j) > \mu$.

The initial population generated through the above method can ensure that individuals in the population largely differ from each other. When the size of the population is large, the initial population can distribute uniformly in solution space in a large scale, thus reducing the probability of local optimization and improving the ability of global search.

3.4 Fitness Function Model

In CGA, the selection of fitness function can directly affect the convergence rate of the algorithm and the search of the optimal solution. In this paper, we comprehensively consider the target function of task scheduling in cloud computing, which takes the minimum total cost and the lowest total cost of the task as the target. In order to facilitate the calculation, we modify appropriately the fitness function formula (4). If $TotalTime_i$ is the total time of the sub task in x_i chromosome and $Total\,cost_i$ is the total time, we will conduct normalized processing to them respectively in order to balance the proportion of the total time and the total cost of the task.

$$finishTime(i) = \frac{TotalTime(i) - min(TotalTime)}{max(TotalTime) - min(TotalTime)}$$

$$finishcost(i) = \frac{Totalcost(i) - min(Totalcost)}{max(Totalcost) - min(Totalcosst)} \quad (6)$$

In this paper, we use the formula (7) as the fitness of the algorithm.

$$fitness(i) = \omega_1 \cdot finishTime(i) + \omega_2 \cdot finishcost(i) \quad (7)$$

In the formula, ω_1, ω_2 are weights and $\omega_1 + \omega_2 = 1$, which can be set according to the specific needs.

3.5 Cultural and Genetic Operation

3.5.1.The Design of Main Population Space and Belief Space

CGA includes encoding and the design of the main population space and belief space, in which the evolution of main population space is handled by using basic genetic algorithm, while the evolution of the belief space is processed by using the improved genetic algorithm.

(1)Evolution strategy of main population space. The evolution process of the main population space mainly includes three parts of operation, including the selection, crossover and mutation. In order to improve the convergence rate of the algorithm, the chromosome with the highest fitness value directly enters into the next generation, and the rest of the chromosomes are operated and selected by the roulette algorithm.

(2)Evolution strategy of belief space. The evolutionary method of belief space adopts an improved genetic algorithm. In the operation for selection, the optimal individual enters into the next generation directly so as to improve the convergence rate of the algorithm. For the sake of improving the diversity of the population and ability of local search, the non uniform operator is introduced. In this paper, the non uniform mutation operator in the formula (8) is used for mutation.

$$x'_{i,k} = \begin{cases} x_{i,k} + \Delta(t, |x_{best,k} - x_{i,k}|) & if\ \gamma = 0 \\ x_{i,k} - \Delta - x_{i,k} - x_{best,k}|) & if\ \gamma = 1 \end{cases} \quad (8)$$

$x_{j,k}$ is the kth dimensional component in ith individual of chromosome, $x_{best,k}$ is the kth dimensional component in the individual of current optimal chromosome, γ randomly chooses 0 or 1, and the function $\Delta(t, y)$ returns a value between [0,y].

$$\Delta(t,y) = y*(1-r^{(1-t/T)^b}) \quad (9)$$

where r is the random number between [0,1], T is the maximum number of iterations, b is the system parameter to determine the degree of non-uniformity, whose value is between [1,5], while this paper chooses 3 for the system parameter.

3.5.2 Design for Receiving Operation

In the iterative process of the cultural framework, 5% chromosomes of first-class in the main population space replace the worst chromosomes of same number in the belief space in every $accept_{step}$. The calculation method of $accept_{step}$ in this paper is as follows:

$$accept_{step} = step_{min} + iter/T \cdot step \quad (10)$$

3.5.3 *Design* for Affecting Operation

In order to make full use of the guidance of information in the process of evolution, the cultural algorithm is the evolutionary process of the main population space, which is periodically guided by the excellent individual in the belief space. This paper adopts the accommodation mode of self-adaption dynamic changes as follows:

$$influence_{step} = step_{min} + (T - iter)/T \cdot step \quad (11)$$

3.6 Algorithm Procedure

CGA for the process of cloud task scheduling is shown in figure 3:

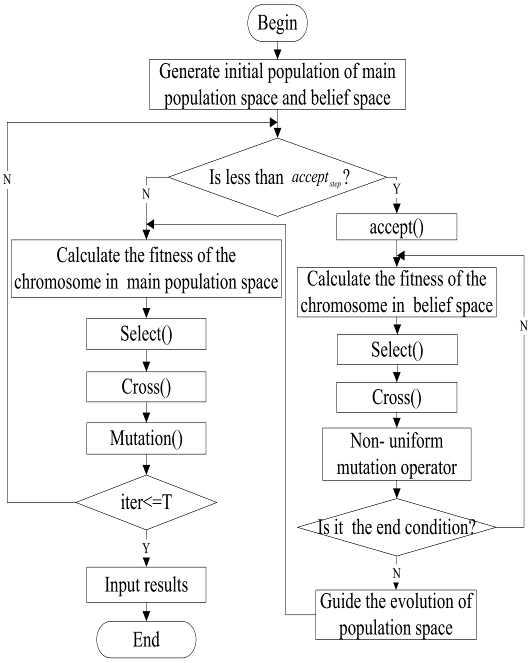

Figure 3. The Process of Cloud Task Scheduling by CGA

4 Experimental Simulations

4.1 Experimental Parameters

In order to verify the performance of the algorithm, the experiment is carried out simulation in the environment of cloud computing simulation platform-CloudSim[10]. The ETC matrix is generated randomly by Matlab 2012b, the number of nodes is 8, and the number of tasks respectively is 40, 80,120,160, and 200. The operating system for testing algorithm is win7 with CPU of 4 core and 2GHZ, and memory of 4G. The number of main population space and belief space respectively are 100 and 30, the number of iteration is T=200, weights ω_1 and ω_2 are 0.6 and 0.4 respectively, the step length of dynamic regulation is $step = 10$, the crossover probability is p_c =0.9 and mutation probability is p_m =0.05. Unit price for calculating each node (cost array) is shown in fig. 2.Other parameters are set up according to the specific conditions. The genetic algorithm (GA) and particle swarm optimization (PSO) are compared for 50 times of operation under the same conditions. The average value of each case is regarded as the ultimate scheduling result.

Table 1: Unit Price of Each Node for Operation

Node No.	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Unit price for operation	0.5	0.8	0.9	0.3	0.7	0.6	0.4	0.2

4.2 Experimental Results and Performance Analysis

Figure 4 and figure 5 show the iterative process of optimal total time and lowest total cost by using basic GA, PSO and CGA. We can see from Figure 4 that the completion time of the three algorithms is the same in the early iteration, but with the increase of the number of iterations, the convergence rate and accuracy of CGA are more superior than the scheduling results of PSO and GA. In Figure. 5, we can observe that the total cost of CGA to finish tasks is less than PSO and GA.

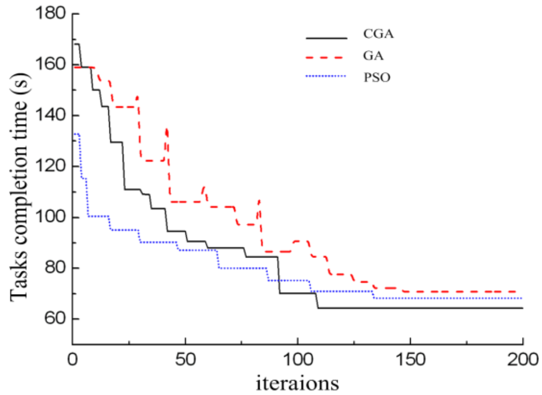

Figure 4.Total time for completing task when task=160

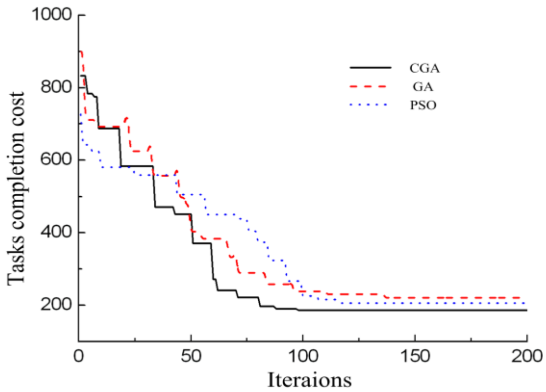

Figure 5. Total cost for completing task when task=160

Figure 6 and Figure 7 are comparison charts of total time and total cost for completing different task. In the chart, we can observe that the scheduling results of those three algorithms are basically the same when the number of task is small. However, with the increase of the number of tasks, the scheduling results of CGA are better than the other two algorithms in terms of the total time for completing task as well as the total cost for completing task. The comparison results show that the CGA integrates the advantages of the cultural algorithm and genetic algorithm, and especially makes full use of the guiding role of knowledge in the process of evolution. By adopting a mutation strategy of the non-uniform operator, it can speed up the convergence rate of the algorithm and searching precision and improve the scheduling efficiency of cloud task

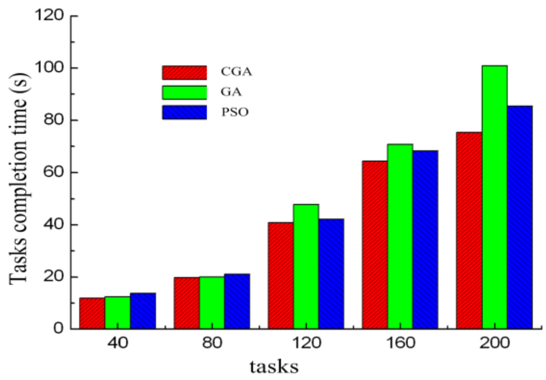

Figure 6. Total Time for completing different tasks.

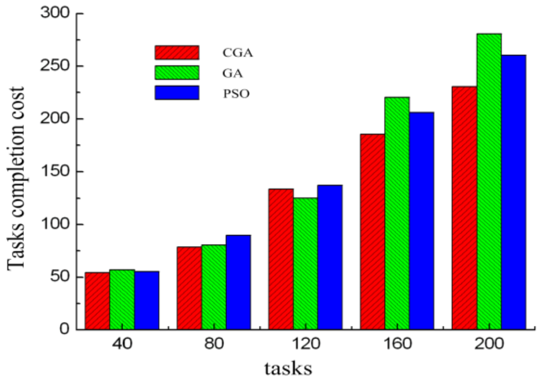

Figure 7. Total cost for completing different tasks

5 Conclusions

This paper takes the total completed time and the cost of cloud tasks as the scheduling objectives, applies a scheduling policy with the foundation of the improved cultural genetic algorithm dispatch users' task under the cloud computing platform. CGA fully integrates the advantages of genetic algorithm and cultural algorithm, which introduces the individual similarity to ensure that the initial population evenly distributes in the solution space. Moreover, the non uniform mutation operator conducts variation so as to improve the diversity and local search ability. The experimental results show that CGA reduces the total time and lowers the cost of the scheduling, which is an effective algorithm for the cloud task scheduling.

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