Parallel evolutionary computing and 3-tier load balance of remote mining robot [①]

GONG Tao(龚　涛), CAI Zi-xing(蔡自兴)

(School of Information Sceince and Engineering, Central South University, Changsha 410083, China)

Abstract: To realize nonferrous metals deposit mining remotely with mobile robot under unknown environment, parallel evolutionary computing and 3-tier load balance were proposed to overcome the efficiency problem of online evolutionary computing. A system of polar coordinates can be established on remote mining robot with the polar point of current position and the polar axis from the current point to goal point. With the polar coordinate system path planning of remote mining robot can be computed in a parallel way. From the results of simulations and analysis based on agent techniques, good computing quality can be guaranteed for remote mining robot, such as efficiency, optimization and robustness.

Key words: remote mining robot; parallel evolutionary computing; navigation; efficiency

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1 INTRODUCTION

With the development of science and technology, research and activity fields of human beings have been expanded from the land to the sea and the space. Space exploration and development with mobile robot has become one of the main ways for each main country to compete with each other on space resources. In 1997, Mars Sojourner robot with remote control of NASA has been applied to Mars plan successfully[1−3]. In China, moon exploration is being planned. Researching and developing moon exploration robot such as remote mining robot (RMR), is not only crucial for China to attain inside track in international competition, but also will push research on the frontier technologies including navigation control of RMR. In this paper RMR was studied on mobile robot navigation (MRN) under unknown environment.

Recently, path planning of cooperative mobile multi-robot system was discussed with the proposal of a novel cooperative co-evolutionary adaptive genetic algorithm[4]. Principles and advantages of evolutionary control in researches of mobile intelligent robots were studied[5]. Based on the behavior-based architecture, many new control ideas and control strategies of mobile robots were proposed[6−8]. But efficiency of online evolutionary learning of mobile robot is too low for too much data in navigation control under unknown environment, and has become a key bottleneck to develop remote mining robot. To overcome the disadvantages of traditional evolutionary computing (EC), co-evolutionary computing on parallel computer is proposed to solve efficiency problem in navigation control of remote mining robot under unknown environment. Then 3-tier architecture of navigation control system for remote mining robot is proposed to realize integration of remote control and real control, and load balance in 3-tier architecture is analyzed.

2 RMR SYSTEM MODEL

Under unknown environment, model of unknown environment with nonferrous metals deposit and location seeking of mobile RMR are necessary and crucial problems at the beginning of designing remote mining system (RMS).

2.1 Environment model of RMR

When mobile robot moves in unknown environment with nonferrous metals deposit, it may be given some goals to arrive, or may not have any goal place to go. For simplicity, suppose RMR have a goal of mining place, which can be detected by some sensors of the robot basing on the mining environment and RMR.

Let S be the position of the robot base in the mining environment with nonferrous metals and the start of RMR, let G be the goal of mining nonferrous metals deposit, and let P be current position of RMR (as shown in Fig. 1).
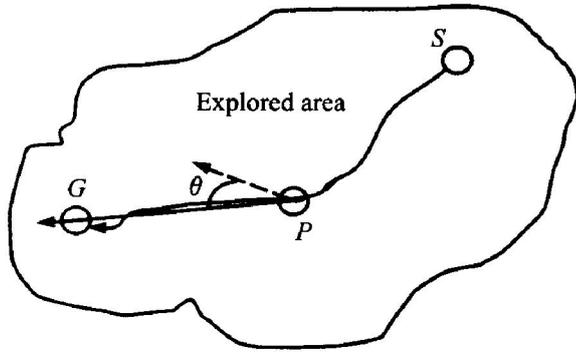
Fig. 1　Environment model of RMR

In Fig. 1, RMR is moving from point S to point G, and now it arrives at point P. Explored area represents the area RMR has explored. A system of polar coordinates can be established on RMR with the polar point of P and the polar axis from point P to point G. Then the angle θ represents the direction of the next step for RMR at point P.

When RMR moves, the position P of RMR also moves, and the polar coordinates also moves. But the polar axis always points to the goal of mining place. In general, RMR will check its direction and adjust the direction to minimize the path cost from the start S to the goal G, after a regular time t. So the angle θ will be checked and adjusted after a regular time t. t is selected according to accuracy requirement, parallel computing ability and hardware quality. But once RMR meets with some obstacles, the direction of RMR will be checked and adjusted immediately. So the navigation of RMR from the start S to the goal G of mining place with nonferrous metals deposit is an adaptive path-planning process to avoid obstacles.

2. 2　3-tier architecture of RMS

Because the environment is unknown and remote and so many data need huge parallel computer to deal with, the architecture of RMS is complicated and can be a 3-tier hierarchy(as shown in Fig. 2).

In Fig. 2, RMS consists of three tiers: 1) computer system of RMR, 2) computer system of the base, and 3) remote parallel computer. To make RMR easy to move about, computer system of RMR is micro-system or DSP chip. Computer system of the base may be middle-size computer because of the transport cost. And remote parallel computer can be huge and must have enough breadth of the communication network between the parallel computer and the remote mining environment. From 1) to 3), the scale of computer system is larger and larger, and the function of computer system changes from hardware to software. For tier 3, web control from the parallel computer to computers in the remote mining environment is the main computing mechanism, and can be developed with mobile agent techniques.
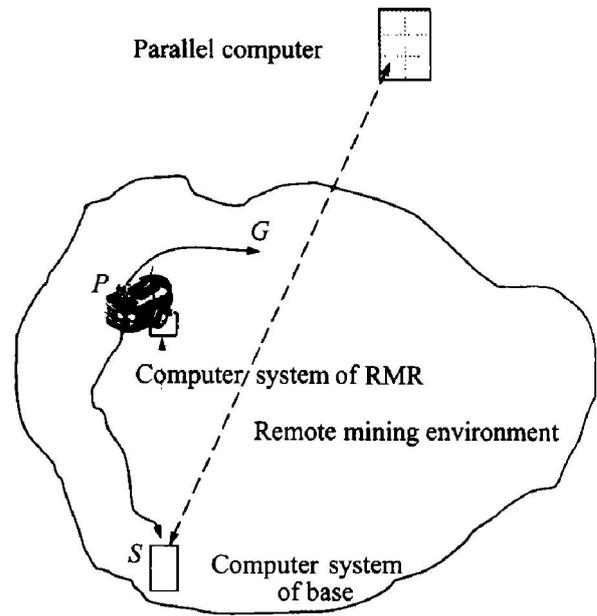

Fig. 2　3-tier architecture of RMS

The model of web mobile agent (WMA) consists of behavior controller, EC, wireless or wire communication and software interface.

1) Communication: WMA can move from one server to another.

Web mobile agent communicates with servers through tunnels of VPN (Virtual Private Network) wireless or wired.

Servers that support mobile agent service form a new safer and more efficient network, called mobile agent server network (MASN). Data transmitted between web mobile agent and servers may be encapsulated and packed, and then be unpacked.

2) EC: In the system, the architecture of evolutionary computation is described as Fig. 3.
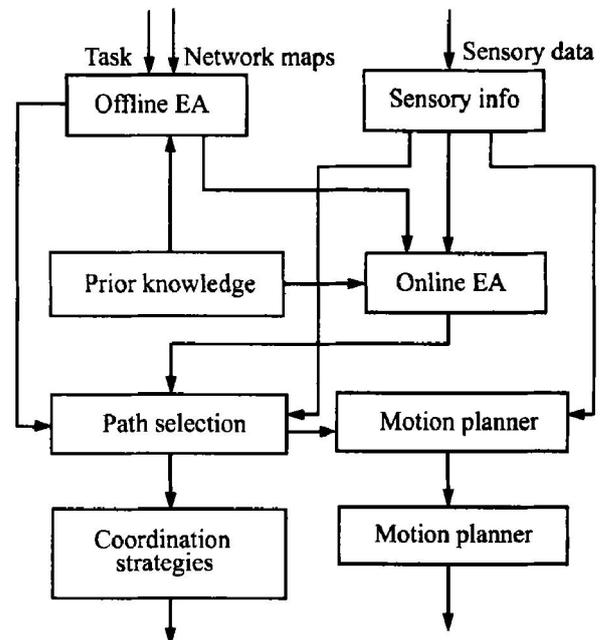

Fig. 3　Architecture of EC

The detail running procedure is as the following: off-line evolutionary algorithm module gives the path of off-line plan motion for the robot according to a prior knowledge, then the robot moves based on the planning path with its pose guaranteed by the motion planning module. The reflected behavior is started when it meets with unpredictable obstacle to ensure that the robot avoids it, then on-line evolutionary planning is started up and a new path is computed. At last the motion planner guarantees the implementation to keep robustness of the path tracking.

3) Behavior controller: In this system, the primitive behaviors, such as obstacle avoidance, balance maintaining, cruise, forward, backward are provided by the behavior-based modules.

4) Interface: WMA exchanges data packages, recognizes the format of data packages and unpacks them at the interface. Data from the packages can be sent into working environment of mobile agent and data will be loaded in EC.

2. 3   Load balance in RMS model

RMS model consists of 3-tier hierarchy computer systems. Tasks can be distributed to each tier of computer system. So load balance needs to be established to optimal performance of the whole RMS. When load on computer system of RMR is too heavy, the load can be divided and transmitted partly to computer system of the base and remote huge parallel computer system.

RMS is an active network, and mobile agent processes data of the network. Encapsulation and running of active data packages with mobile agent not only make full use of autonomy and mobility of mobile agent, but also provide more programmability and flexibility of RMS. Encapsulating data and programs from RMS into mobile agents make data packages more active and powerful. For example, active data packages can clone mobile agent, produce and distribute agent sons to realize multi-line distribution.

Mobile agent technique based on the center of data sends computing agent to data server node of RMS. In the application of different parallel and distributed heterogeneous platforms, especially in wireless computation environment, mobile agent model is convenient, effective, robust and intelligent. Mobile computers often disconnect with RMS. Mobile agent senses variances of the web world, plans its path autonomously and then moves to the destination to provide service.

Mobile agents have such advantages as the following: 1) Saving data flow when RMS is busy with data transition; 2) No need for fixed connection so as to support distributed applications; 3) Sensing the host server whenever the position of the host varies; 4) Path-planning autonomously with cooperative genetic algorithms; 5) Communicating with each other wherever they are in the RMS.

3   PARALLEL EC OF RMR

Suppose that there are n web mobile agents, they communicate wirelessly with servers and communicate wirelessly with each other[9]. All web mobile agents do path planning and take active services in the MASN with cooperative evolutionary algorithm (CEA), as shown in Fig. 4.
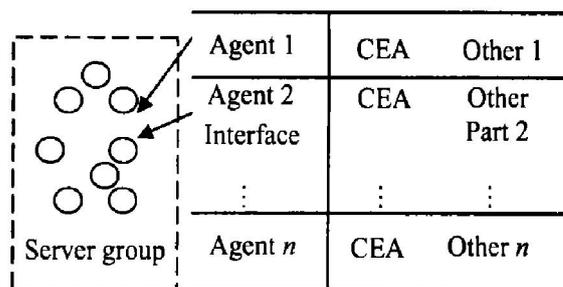

Server group	Agent 1	CEA	Other 1
	Agent 2 Interface	CEA	Other Part 2
	⋮	⋮	⋮
	Agent n	CEA	Other n

Fig. 4   Web mobile robot computing model

Main characteristic of CEA is that potential solutions of each sub-problem from sub-population evolve only in sub-population. While the interaction among all sub-problems is reflected by means of the definition of fitness function of each sub-population. As a result, the algorithm is very suitable for parallel computation, which decreases the run time of solution seeking. Meanwhile, in the evolutionary process of each sub-population, probability of crossover is adaptively determined to increase the convergence rate of the algorithm.

Web mobile robot computing model includes n WMA models, web world environment model and CEA. Because of wireless communication, portable computing devices and internet technology, mobile agents can move within the circle of wireless information center and valid mobile areas can be approached with enough rectangles.

Suppose RMR A starts the mining navigation from point S under unknown environment, avoids some obstacles $\{ O_i,\ i = 1, 2, \cdots, O,\ O$ is the total number of obstacles$\}$, and arrives at the goal G. As supposed above, RMR A can detect the position of G at any time, and then a system of polar coordinates can be established on RMR with the polar point of P and the polar axis from point P to point G. Moreover the angle θ represents the direction of the next step

for RMR at point P, and equals to the quotient of $360°$ divided by n (n is great enough). On the other hand, suppose huge parallel computer have m nodes (m is great and fit, in general $m < n$), and each node has 2 processors [10, 11], so the parallel computer can process $2m$ instructions for one time. Thus parallel EC of MRN under unknown environment is shown in Fig. 5.
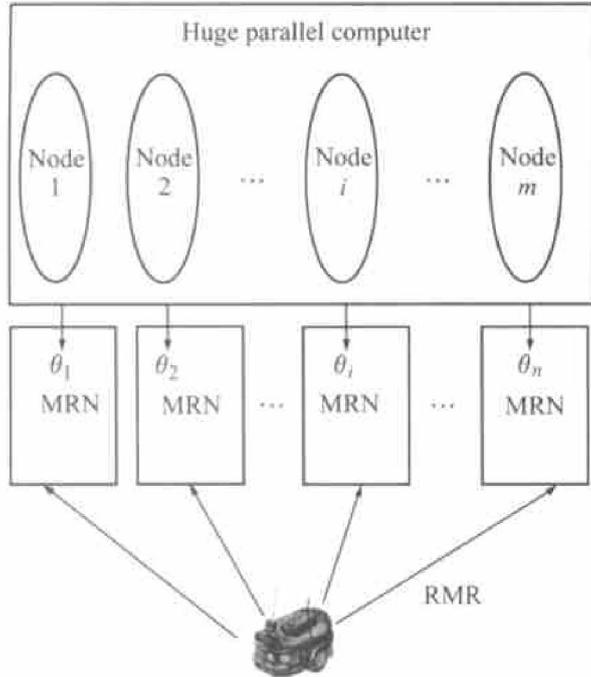

Fig. 5　Parallel EC of MRN on moon

In Fig. 5, huge parallel computer distributes n MRN computing problems with the direction θ_i to m computing nodes, and each node has 2 processors, so $2m$ processors compute the problem of MRN in parallel methods. Probably n is great enough. If the problem of n RMN is solved on single PC, the time needed is surprising. Let its time complexity be $PC(n)$. For huge parallel computer, the time needed decreases greatly with the increase of node number. Let the time complexity for huge parallel computer to solve the problem of n RMN be $PEM(n)$, then the following theorem can be created.

Theorem on complexity of parallel EC

Suppose parallel computer has m nodes, each node has 2 processors, then the relation between the time complexity of parallel computer to solve RMR direction problem and the time complexity of single PC to solve this problem can be the following:

$$PEM(n) = \begin{vmatrix} PC(\left|\dfrac{n}{2m}\right|) + O(m) & (2m \mid n = 0) \\ PC(\left|\dfrac{n}{2m}\right| + 1) + O(m) & (2m \mid n \neq 0) \end{vmatrix}$$

(1)

[Proof] Parallel computer solves RMR direction problem by two steps. The first step is to distribute n direction problems to $2m$ processors. If the remainder of n divided by $2m$ is not 0, then some processors

have more direction problems than the first processor. The second step for parallel computer is to compare the time complexity of each processor, and select the max time complexity. Because each processor is distributed and parallel, the total time complexity of parallel computer is the sum of the max time complexity of all processors and the time complexity to compare the time complexity of each processor. The time complexity to compare the time complexity of each processor is $O(m)$. Therefore, Eqn. (1) is right.

The following steps describe how CEA is applied to path planning of RMR system.

1) Encoding: The motion path of RMR is the segment between the original node and the object node [12, 13].

2) Initialization: Each sub-population is initialized locally, not influenced by other sub-populations.

3) Fitness function: Feasible and infeasible paths are evaluated by the $eval_f$,

$$eval_f(p) = w_d(p) + w_s(p) + w_c(p) \qquad (2)$$

where w_d, w_s, w_c denote the length, smoothness and safety expectation.

4) Selection: Roulette selection is adopted in each sub-population locally.

5) Crossover: To increase the convergence rate of the algorithm, probability of crossover is determined adaptively.

6) Mutation: Mutation is also performed in each sub-population locally. For the reason that the probability of mutation is always very low, it is prescribed in this algorithm.

7) Termination condition: In the case that the best individual in each sub-population has been the same for several generations, or most individuals in each sub-population are similar, or the best global solution for the whole problem has been relatively optimal, the algorithm terminates.

4　SIMULATION OF RMR NAVIGATION

In this section, path planning of a RMR system is discussed to illustrate how CEA can be applied to path planning of RMR system, shown as Fig. 6. The environment in which the RMR moves is shown in Fig. 6, where black rectangular and square blocks represent obstacles in the environment for simplicity. RMR starts from point S to the destination Q.

From 18 repeated simulations, it is shown that a sub-optimal solution of path planning of the RMR system is obtained after about 212 generations. The sub-optimal solution is shown in Fig. 6. The result of this simulation on two double-processor computers costs about one fourth time of that on one single-processor computer.

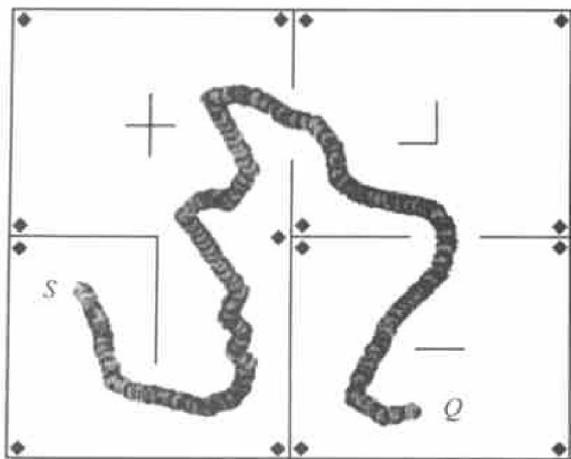From the above simulations, it can be seen that

Fig. 6 MRN under unknown environment

since the environment is randomly selected, and the algorithm can guarantee the above sub-optimal solution be obtained for each simulation, the CEA based on path planning of RMR system is convergent.

5 CONCLUSIONS

Efficiency and knowledge update problems of evolutionary learning in mobile robot navigation under remote unknown mining environment were analyzed, parallel evolutionary computation was proposed to solve the problems, and efficient parallel evolutionary computer was designed and verified. At last, with experiment and simulation mobile robot navigation under unknown environment based on parallel EC was tested available and effective.

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