A Genetic Planning Method and its Application to Planetary Exploration

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Abstract

This paper describes a genetic algorithm planning method for autonomous robots in unstructured environments. It presents the approach and demonstrates its application to a laboratory planetary exploration problem. The method represents activities of the robot with discrete actions, or action modules. The action modules are assembled into action plan with a Genetic Algorithm (GA). A successful plan allows the robot to complete the task without violating any physical constraints. Plans are developed that explicitly consider constraints such as power, actuator saturation, wheel slip, and vehicle stability. These are verified using analytical models of the robot and environment.

The methodology is described in the context of planetary exploration similar to the NASA Mars Pathfinder mission. More aggressive missions are planned where rovers will explore scientifically important areas that are difficult to reach (e.g., ravines, craters, dry riverbeds, steep cliffs). The proposed approach is designed for such areas.

1. Introduction

This paper describes a genetic algorithm planning method for autonomous robots in unstructured environments. It presents the approach and demonstrates its application to a laboratory planetary exploration problem. The method represents activities of the robot with discrete actions, or action modules. The action modules are assembled into a sequence, or action plan, with a Genetic Algorithm (GA). A successful action plan allows the robot to complete the task without violating any physical constraints of the robot or task. These constraints are verified using analytical models of the robot and environment.

The genetic algorithm planner is applied to planetary exploration rovers similar to the pathfinder mission [1]. More aggressive missions are planned where rovers travel several kilometers, manipulate science samples, and operate semi-autonomously [2]. They will explore scientifically important areas that are difficult to reach (e.g., ravines, craters, dry riverbeds, steep cliffs) and the proposed approach is designed for such areas. Also, limited on-board computational power requires efficiency.

2. Background

One robot planning approach called behavior control is very reactive; robots quickly respond to sensor inputs but do not plan into the future [3, 4]. Other approaches consider the problem more globally by representing it as a search {e.g. probabilistic map building [5], potential fields [6], tangent graphs [7], visibility graphs [8]}. Many search techniques are used including gradient decent [9], A* [10], simulated annealing [11], greedy [12], and GAs.

Some planning techniques use GAs to support fuzzy-based [13], potential field [14] or grid cells [15] planning. The efficiency of a GA has been compared to greedy search [15], hill climbing, and simulated annealing [18]. Genetic programming is a similar, but less structured, approach that incorporates learning [16, 17]. The proposed method is similar to GA approaches used in more constrained problems [15, 19, 20, 21] and has similarities to genetic programming in that it allows plans of variable length and is capable of reusing previous motions.

Research has addressed planning for planetary exploration. One behavior-based method has been shown to be successful in relatively low-density obstacle fields. However, it requires the operator to provide closely-spaced task goals [4, 22]. Another method uses classic local tangent graphs to search the area observed by the robot's sensors [23]. An advantage and limitation of these approaches is that they do not require an extensive model of the robot or environment. Unlike the proposed approach, they do not explicitly consider physical constraints and therefore are limited in challenging terrain.

3. The Action Planning Method

An example robot, task (climb a step >1/2 limb length), and plan are shown in Figure 1. Example modules are "move body forward 2 cm" (#001) or "move leg #4 forward 2 cm" (#401). The action plan developed is 71 modules in length.

The search for the correct sequences of action modules is performed with a standard steady-state genetic algorithm (GA). A chromosome (list of modules) represents an action plan. An initial random population of random length chromosomes is generated. Then the GA uses crossover, mutation, and fitness operators to evolve better plans through subsequent generations. The crossover operator combines attributes of two action plans to create new plans for the next generation. A mutation operator inserts random modules to maintain diversity. Fitness is determined using an analytical model of the robot and an environment model created using on-board sensors.

The method to assign fitness and perform crossover is very important to the planner's success. To assign fitness, a plan is simulated until failure or task completion. The beginning (successful) portion of the plan determines fitness so "partial credit" is given to partially successful plans. In crossover, a method is used that preserves the beginning portions of each plan. Therefore, the successful portion is generally maintained, and change is more likely on the unsuccessful portion.

These attributes allow the planner to "learn" since it is possible to reuse a portion of a successful plan by adding it to the end of another. To highlight this characteristic of the method, the robot in Figure 1 was asked to climbing four sequential steps. The search created a plan that included 514 modules in 63 generations with 1000 plans per generation, Figure 2.

This solution was analyzed to find repeated patterns using the Rabin-Karp pattern-matching algorithm. A pattern of 12 modules was identified corresponding to each step, Figure 2. The repeated patterns were then included in the action inventory as "higher-level" modules. Using these modules improves convergence and fitness, Figure 3.

4. Action Planning for Planetary Exploration

The planning method was applied to planetary exploration. The parameters of NASA's prototype Lightweight and Survivable Rover-1 (LSR-1) are used [25]. The LSR-1 is a rocker-bogie mobility design similar to Pathfinder's Sojourner rover. It has 25 cm diameter wheels, is 100 cm in length, 70 cm wide, and 45 cm high. A laboratory rover and test area was constructed that is structurally similar to the LSR-1 but is about one-third the size, Figure 4 a). The action modules are shown in Table 1.

Table 1: Action Module Inventory for Planetary Exploration Tasks

Module #	Action	Module #	Action
101	move forward 10cm	1001	move arm +x 2cm
102	move back 10cm	1002	move arm -x 2cm
103	turn left 5°	1003	move arm +y 2cm
104	turn right 5°	1004	move arm -y 2cm
105	circle (r=50cm) left 10cm	1005	move arm -z 2cm
106	circle (r=200cm) right 10cm	1006	move arm +z 2cm
107	circle (r=50cm) right 10cm	3000	turn to sample
108	circle (r=200cm) right 10cm	3001	turn from sample
901	Transmit video	3002	grasp sample
902	end video	3003	release sample
910	sweep sensors	2020	retract science tray
920	Sleep	2010	deploy science tray
921	Communicate with ground station	4000	Recharge with solar array

A computationally efficient analytical model of the rover and environment was created for on-board implementation. The rover will move at slow speeds (≈3 cm/s) so dynamic effects are negligible. Modeling details can be found in [24, 26].

The environment model was created with realistic rover sensors. In the laboratory tests, the model consisted of a terrain map constructed with a vision-based laser triangulation method [27]; see Figure 4 b). This is similar to NASA proposals for future missions [2, 25]. Characteristics, such as coefficients of friction, were estimated experimentally but would be made using visual data during a mission.

In the example task (Figure 4), the rover is required to travel to the top of a hill (five meters) in one Martian day and is tasked to acquire up to five pre-designated science objectives. This is a challenging task since the rover must cross a ditch approximately one wheel diameter (25 cm) in width and climb a hill that is 2.5 wheel diameters (63 cm) high with slopes from 25º to 70º.

The fitness function used defines the relative importance of reaching the target, the energy consumed, the number of science samples obtained, the stability margin, actuator saturation, required time, and other constraints (1). Vehicle stability is estimated by the angle the vehicle must rotate to tip, normalized by the angle to tip on flat ground [28]. One advantage of genetic optimization is that many objectives can be considered [24, 29, 30].

$$f = \frac{\alpha_1}{D} + \alpha_2 A + \alpha_3 \sum_i S_i - \alpha_4 T - \alpha_5 E + \alpha_6 \delta \qquad (1)$$

Where: D = final distance to the target
A = number of science samples
S_j = stability margin for time j
T = time required
E = the energy consumed
δ = 1 if task complete
α_I= weighting factor
m = plan length

The genetic planner used a population of 50 individuals and solved the problem in 13 generations with a run time of two hours on an 80486 processor (similar to proposed on-board capabilities). The generated plan moves the rover to the target while acquiring two science samples and maintaining a stability margin >40%, Figure 5. This shows a trade between time required (i.e., power) and the samples obtained.

5. Summary and Conclusions

This paper describes a genetic planning method for field robots. The methodology divides the activities of the rover into discrete actions, then a genetic algorithm searches for the proper sequence of actions that allow the task to be completed. Action plans are evaluated using a physical model of the robot and its environment. The approach is limited by the accuracy of the model.

The action planning process was applied to practical planetary exploration tasks. A laboratory demonstration showed that successful action plans could be developed for a real system using realistic sensor data and an environment model. On-board implementation and sensor integration need further study.

6. Acknowledgements

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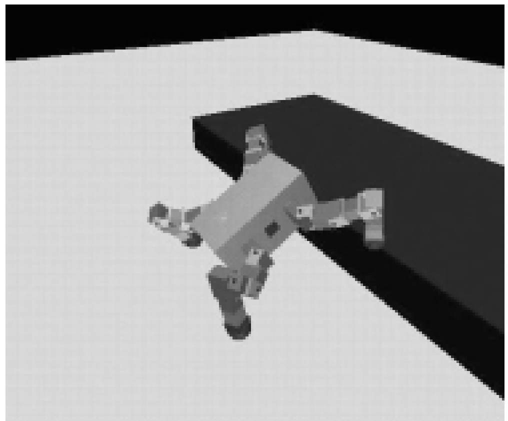

#	Actio n
1	101
2	1
3	401
4	1
5	101
6	301
7	5
8	14
9	1
10	410
11	310
12	14
: : :	: : :
68	13
69	1
70	401
71	301

Figure 1: A Step Climbing Task

8	13
9	5001
10	5001
11	14
12	5001
13	5001
14	13
15	5001
16	13
17	6006
18	5001
19	5001
20	5001
21	5001
22	14
23	5001

34	13
35	5001
36	14
37	5001
38	5001
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46	5001
47	14
48	14

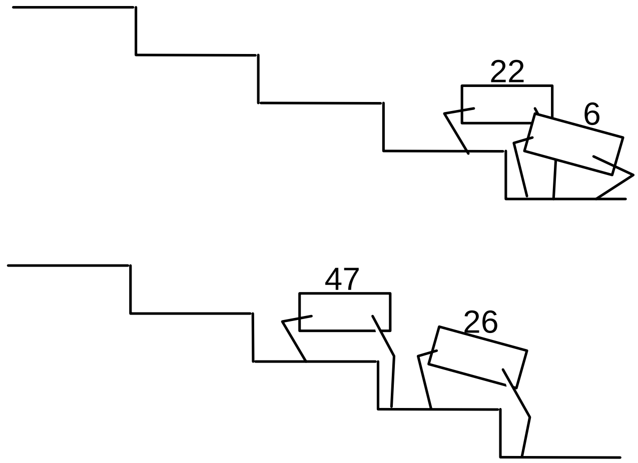


Figure 2: Action Plan for the Stair Task

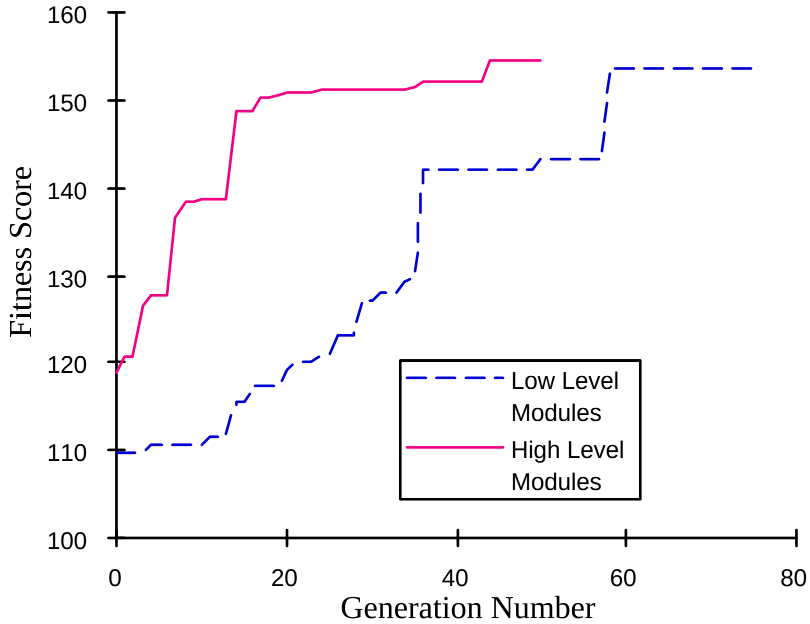
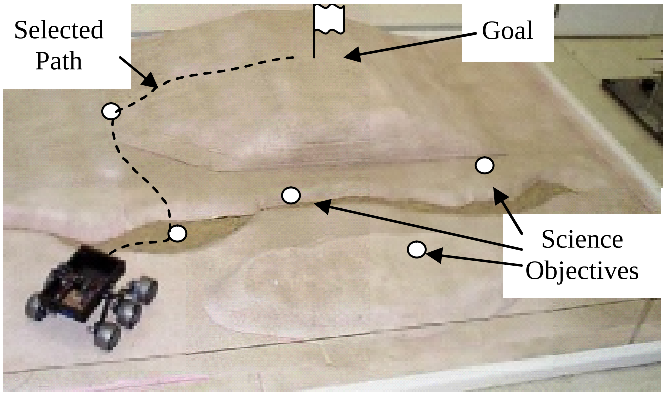
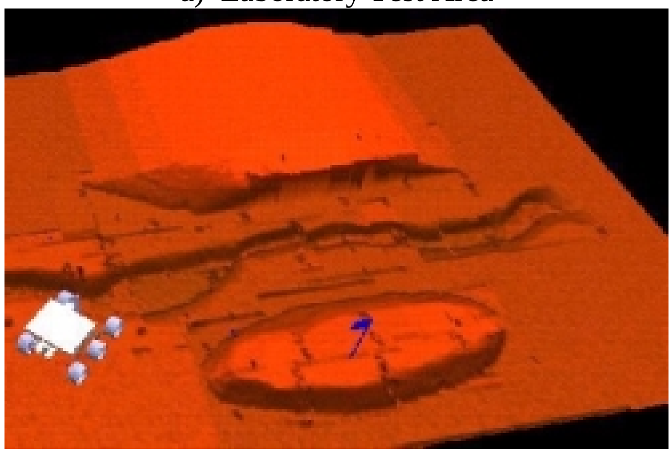


Figure 3: Convergence for the Stair Task



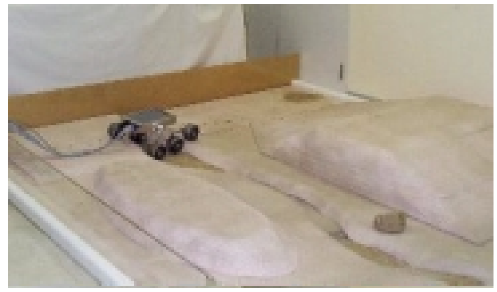
a) Laboratory Test Area



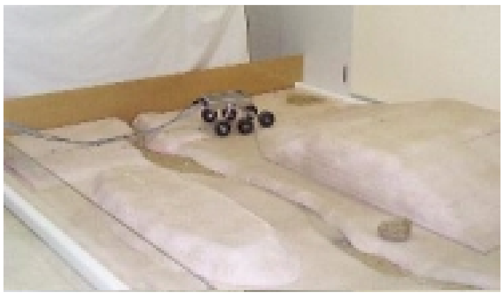
b) Model of Laboratory Test Area

Figure 4: Laboratory Test Area and a Model of the Area

Frame 1



Frame 2



Frame 3

Frame 4

Figure 5: Laboratory Demonstration of a Mobility Task