An Evolved Autonomous Controller for Satellite Task Scheduling

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Abstract. A scheduling algorithm for satellites imaging tasks in a dynamic and uncertain environment. The environment is dynamic in the sense that imaging tasks will be added or removed from the given scenario and in addition, the parameters of individual tasks can change. The technique proposed develops an expert scheduling behaviour as opposed to a robust static schedule by using an evolutionary ALife methodology.[1]

1 Introduction

This paper is concerned with providing schedules for imaging satellites that make the most efficient use of the resources available. We employ a technique generally applied to robot collision avoidance systems to provide optimal schedules for imaging satellites which can be updated in real time and deal with uncertainty in the problem.

2 Principle

In this work we find near optimal schedules for imaging satellites using a technique known as a neural controller to form the decision making link between sensors and possible actions. A neural controller has actions and sensors that are fully connected to each other. The controller then performs the action that receives the greatest output from the sensors at any given time step. Each connection is weighted and the output for an action neuron is the accumulation of each connected sensory neuron multiplied by the weighting of the connection. This technique has been successfully used in industry to implement robot collision avoidance systems and in the development of walking robots [1]. Genetic algorithms were considered a good method to optimise the weights of a controller and have been successfully applied to the evolution of controllers for simple robots, such as Braitenberg vehicles [2] and Kerpera robots [3].

The neural controllers used to construct solutions to the problem have three actions that they can perform at each time step. Move the sensor 0.1 degrees, move the sensor -0.1 degrees or process (or continue processing) a task. The

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sensory inputs used by the neural controllers consist of 18 inputs which sense various attributes of a task such as the time it will take to image.

We represent each solution (set of weights) as a (genetic) string, each value in the string representing a weight. This string then represents the behavior of the neural controller. The fitness of each string is evaluated by running it in a simulation on multiple problems of tasks to be processed.

3 Conclusions

One neural controller was evolved with no uncertainty in its training set of problems, and another with some uncertainty. The controllers were evolved on problems that had time spans of up to 120 time steps with the number of tasks ranging from 20 to 50. The controllers were evolved using a large number of different problems. The evolved neural controllers are compared to a standard genetic algorithm approach that attempts to evolve a robust a plan for a single problem. The standard genetic algorithm evolves a plan over 500 generations with the fitness measure being the total task priority processed.

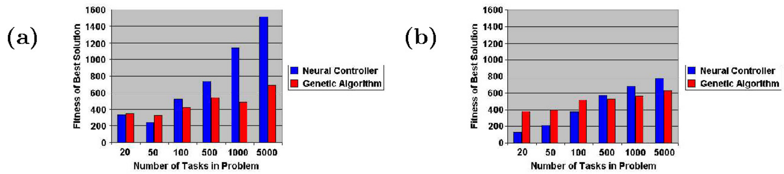

Fig. 1. (a): Neural controller technique compared with a standard GA technique on problems with no uncertainty. **(b):** with some uncertainty.

It can be seen in figure 1 that once the high cost of initially evolving a neural controller is completed it can produce good schedules instantly, this is a significant advantage over using a genetic algorithm. The neural controller can operate in real time and hence can respond immediately to any changes, which is a significant improvement over the genetic algorithm approach which would have to re-evolve a new plan to incorporate the changes.

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