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An island-model framework for evolving neuro-controllers for planetary rover control

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***Abstract*— Autonomous navigation and robust obstacle avoidance are prerequisites for the successful operation of a planetary rover. Typical approaches to tackling this problem rely on complex and computationally expensive navigation strategies based upon the creation of 3D maps of the environment. In contrast, this research proposes a simple artificial neural network relying on infrared sensory input as the control structure. This paper presents a unified framework for designing such control structures for a simulated rover, taking advantage of code parallelisation and the latest advances in global optimisation research. In particular, it details a 3D physics-based simulation of a planetary rover and a tool set for performing the optimisation of ANN parameters within the island model. This paper also presents preliminary results showing that the aforementioned framework can parallelise the controller design process without any loss in performance over traditional methods, and will outline research directions, which aim to take full advantage of this technique's potential.**

I. Introduction

In 1957, Sputnik, the first human-made satellite orbited Earth marking the beginning of the Space Age. This remarkable achievement is considered a monumental point in human history; for the first time humans had broken free from the constraints of Earth, triggering the enormous competition between the USA and Soviet Union that would result in numerous advancements in space exploration. Apollo 11 reached the apogee of this exciting era when, in 1969, 500 million people from all around the Earth witnessed the first humans land on the Moon. In the hope of reigniting this spirit, on 14th January 2004 the US government announced *Vision for Space Exploration*, a series of crucial milestones for the US space program. Robotic missions to the Moon and Mars were announced in preparation for the first crewed mission to Mars to be accomplished by 2020. The vision also outlined hopes of sending robotic and crewed missions to other scientifically important destinations within the Solar System. Likely destinations include the satellites of Saturn: Titan and Enceladus. Titan is the only natural satellite in the Solar System to have a dense atmosphere and the only celestial body other than Earth known to have a liquid surface [1]. Enceladus has an icy surface with cracks and geysers, suggesting the presence of a liquid ocean beneath the moon's surface.

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One of the key problems that exists in the domain of robotic space exploration pertains to the signal transmission delays that exist between the Earth and other celestial bodies, which make real-time remote control virtually impossible. Advanced autonomous capabilities are therefore vital for further advancement in space exploration. Mars Pathfinder, launched in 1997, was the first exploratory mission in which a semi-autonomous vehicle, Sojourner, landed on the Martian surface. After Mars Pathfinder, more sophisticated robots such as the rovers Spirit and Opportunity were landed on Mars in 2004. These rovers were designed to withstand harsh Martian conditions for only 90 days, however after five years they are still exploring Mars and bringing new discoveries [2]. NASA's next planned rover mission to Mars, named Mars Science Laboratory (MSL) is scheduled for launch in Autumn 2011. This mission involves a rover carrying more sophisticated instruments that will help answer questions about Mars' history, climate, geology, possible life and ultimately pave the way for future crewed missions. The rising interest in such missions is also strengthened by the fact that, alongside the NASA projects, several other projects are under development by the European Space Agency, as well as China and Japan.

As mentioned, the ability to act autonomously, in particular the ability to navigate efficiently within an unknown environment, is a basic requirement for any planetary robotic vehicle. In addition, since unknown terrain could be encountered containing obstacles such as rocks, slopes, terrain roughness or trenches, a robot is exposed to many potential dangers. Therefore, to avoid a mission failure, an autonomous planetary robot needs to be able to distinguish between different obstacles and actuate appropriate avoidance manoeuvres.

The above-mentioned rovers Sojourner, Spirit and Opportunity use stereo-cameras for navigation and obstacle avoidance. The two more recent robots, Spirit and Opportunity, are equipped with three sets of stereo-camera pairs. One pair is forward-facing, under the front solar panel. Another pair is rear-faced, under the back solar panel, while the last pair is situated on the mast and used primarily for navigation purposes. With the images taken by these cameras, a stereo algorithm calculate a 3D representation of the terrain in front of the robot, while other algorithms are used to calculate a 'traversability' map [3]. The information of this map is then used to calculate the next action of the robot. However, if these cameras fail there are no other means for the rovers to sense obstacles. For this reason, it is worth exploring other possible solutions that allow planetary rovers

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to navigate and avoid obstacles, besides the use of stereo-cameras. These alternative methods might represent useful complements in the sensory systems of a robot, which has to operate in difficult conditions in deep-space where any human intervention is prevented by the long communication delays.

To investigate such alternative sensing methodologies, a Mars rover physics simulator was developed using Open Dynamics Engine (ODE), an open source library for simulating rigid body dynamics (www.ode.org). The computer model of the rover is based on approximate dimensions of the MSL rover while its control system consists of an artificial neural network (ANN) whose synaptic weights are evolved using evolutionary computation techniques. This approach is commonly known as evolutionary robotics [4]. Evolutionary robotics is inspired by the Darwinian principle of selective *reproduction of the fittest* and attempts to develop sensory-motor control systems for autonomous robots in an automated manner. The selection of ANNs as controllers stems from their versatility, generalisation capabilities and tolerance to noisy sensory input.

It is acknowledged that within the field of evolutionary robotics, obstacle avoidance and navigation behaviours are well known and widely used to demonstrate the feasibility of the approach. The research detailed herein, attempts to extend the existing research to the domain of interplanetary robotics, in order to more fully demonstrate the potential and robustness of the approach. This requires consideration for the hypothetical complexity involved in a planetary exploration mission, along with all the tasks that entails, such as safely exploring an unknown environment, autonomously finding an efficient route over rough terrain and dealing with unknown obstacles, while at the same time taking into account the limited computational capability of the on-board hardware [5]. The accomplishment of these tasks requires 1) a control system capable of identifying and responding to different types of obstacles while navigating appropriately and safely over unknown terrain (i.e. the robot should be able to autonomously assess when a terrain is safe for navigation or when it is better to change direction), and 2) a low complexity algorithm capable of producing these behaviours using low-power hardware.

Navigation in rough terrain is a topic that has been addressed in different ways. A number of projects have employed behaviour-based navigation methods [6], [7]. In these studies, the whole behaviour of the robot is the outcome of a complex interaction between simple sub-behaviours predefined by the researchers. Some researchers have used the so-called 'arcs approach' [8], [9]. In the arcs approach, an algorithm is devoted to generating several candidate arcs, after which, one of the arcs is chosen on the basis of some criteria (i.e. the arc with the largest clearance or, after calculating the costs along each arc, the one with the lowest cost). The robot is then steered along the winning arc. In other works, the steering of the robot is calculated by creating a grid-type traversability map from the terrain immediately surrounding the robot [10].

In evolutionary robotics, the most recent studies that explicitly address the issue of navigation in rough terrain with obstacles, are mainly based on coordinated motion behaviour. This approach aims to solve the problem by means of evolving complex coordinated behaviours amongst simple interconnected mini-robots [11]. Another approach is based on the idea of reconfigurable robots, where robots can adopt different shapes in order to cope with different environmental conditions [12], [13], [14].

In contrast to the previous studies, the intention of this research has been to use a single robot, modelled on the MSL rover, to investigate whether it is possible to evolve neural network controllers capable of circumnavigating different obstacles. So far the authors have explored the feasibility of two alternative systems: The first is based on a simple neuro-controller with infrared sensors, utilising an evolvable sensitivity threshold to distinguish between rocks, roughness and holes [15]. The second is a biologically inspired active vision system, the architecture consisting of an artificial retinal matrix fed into a recurrent neural network. This system was found to be capable of detecting different environmental features and reacting appropriately based on visual stimuli [16].

Both of the previous studies with the rover were based on a classical sequential genetic algorithm (GA) where one genotype was evaluated after another. However, parallelisation of GAs can massively decrease the time required for the evolutionary process. This can be especially beneficial in computationally demanding problems, as in the case of the described setup, which requires 3D physics simulations. In order to implement parallel evolution, inspiration was taken from the field of evolutionary biology, namely the theory of *punctuated equilibria* [17], which states that speciation arises from brief periods of rapid evolution, punctuated by long periods of evolutionary stasis (see [18], [19]). One explanation for how this might occur postulates that the migration of individuals into new demes gives rise to a sudden influx of new genetic material, hence allowing for new adaptations. Cohoon and colleagues were inspired by this theory to develop an island migration model: a coarse-grained parallel approach to global optimisation [20], [21] (see [22] for an alternative model). The authors focused initially on a parallelisation of genetic algorithms, which was then complemented with the transfer of individuals between the different populations, ergo allowing for interaction between divergent gene-pools. This approach was found to lead not only to faster evolution, but often to better performance also. The island model paradigm has since been used to parallelise other global optimisation algorithms and applied with success to difficult and high dimensional problems [23]. The analogies between the effects of migration and the biological observations equally hold for the Evolutionary Robotics methodology since the exploration arises from migration and exploitation from evolution in separate islands. Migration introduces new ways of solving a problem in a pool of existing solutions, while preventing any one population converging to a local optima. This also allows for more complex ER tasks to be addressed, for example evolving populations for different tasks in different islands, where migration performs the transfer of genetic material and associated behaviours. A first demonstration of the evolution of neuro-controllers within the island-model framework is given in [24], where the authors show that a parallel evolutionary algorithm can solve a two robot coordination task while a sequential version becomes stuck in a local optima.

Taking the island model paradigm, the Mars rover simulator was completely re-implemented and integrated with the Parallel Global Multiobjective Optimiser (PaGMO) framework developed by the European Space Agency's Advanced Concepts Team (http://sourceforge.net/projects/pagmo). The new simulator can run any number of separate populations asynchronously in parallel, resulting in a significant decrease in the time required for evolution. In this paper, an integrated design framework is presented, consisting of the above-mentioned rover model equipped with eighteen infrared sensors and a neuro-controller, along with the generic optimisation toolbox (PaGMO). The system was evolved using the new island model, where eight independent populations were evolved in parallel, each island population evaluating against an environment containing different rocks, cliffs, holes and areas of rough terrain. Preliminary results from the experiments indicate that island migration, when applied to this task, significantly increases the speed of the evolution while maintaining the quality of the evolved solutions.

The following sections will delineate the methodology that was used, providing a detailed description of the rover simulator, its neural network controller and the island model together with the genetic algorithm (GA) parameters that were used to evolve the neural connection weights. The experimental set up used in each of the evolutions will be presented, along with the obtained results. The final section will outline ongoing work into the application of migration to more complex problems, such as adaptivity to multiple environments, sensor failure and the use of active vision systems for obstacle avoidance, classification and navigation; this work will empirically demonstrate that a powerful global optimisation framework combined with an artificial neural network can provide agents with the tools necessary to achieve increased autonomy, adaptivity and robustness.

II. Method

As mentioned in the introduction, the approach of this research is based in evolutionary robotics (ER), an approach which has gained significant momentum in recent years [4]. The ER approach emphasises the agent's embodiment, which means that an emerging behaviour is not only dependent on the various properties of the actual robot such as its size, speed, degrees of freedom, sensors and actuators, but also on the environment with which it interacts [25]. ER is an excellent technique that allows for the creation of artificial control systems that autonomously develop their skills in close interaction with the environment, exploiting very simple, but extremely powerful sensory-motor coordination [26].

To date, however, the complexity of evolved neuro-controller based agents is lower than systems designed and hand-coded using expert knowledge. In an attempt to overcome this problem the island migration paradigm has been applied in the evolutionary robotics domain resulting not only in significant time reductions but also in the production of better individuals [24]. In particular, the effects of migration can be considered the main factor helping to achieve better results through introducing (even radically) different solutions, evolved in mostly isolated populations. These migrant genotypes integrate with the native population, increasing exploration of the solution space and facilitate the study of more complex ER scenarios, for example, evolving populations for different tasks in different islands while exchanging genes and behaviours between these populations through migration. This research has integrated this promising model with the Mars rover physics simulator via the PaGMO libraries and evaluated its advantages in this preliminary study.

A. Simulator

The simulator consists of two logically separate parts: the controller, and the physics simulation of the rover and environment. The controller (see Fig.1) utilises the island model framework, dealing with the numerous parameters required for configuring the evolutionary process, neural network, sensory inputs, terrains, physical simulation, graphics and environmental properties. The physics simulator executes the actual simulation and returns a floating point value representing the fitness achieved by a particular genotype (the reader is reminded that within the Evolutionary Robotics methodology a controller is represented as a genotype undergoing optimisation). Therefore, the physics simulator as such is independent from the controller. In addition, as the Open Dynamics Engine does not require rendering, the simulator is in no way dependent on graphics. In the case where active vision sensing is used, an off-screen rendering mode has been implemented using pbuffers, making graphics fully optional.

B. Rover Model

The robot used in this experiment is a 3D simulation model of the MSL rover. The model cannot be considered an accurate or detailed representation of the actual rover, but only an approximate copy. This is mainly due to the lack of information on the rover's real dimensions, mass distribution and parts size, as well as many other details. According to the Centre National d'Etudes Spatiales [27], the dimensions of the real rover are 2900Lx2700Wx2200H mm and its mass is about 775 kg. The physics model of the rover was therefore built considering these details, and modelled on the several diagrams and pictures that were available. These limitations are not crucial to the study at this stage as the focus is to demonstrate the application of the ER approach in developing a suitable controller capable of performing complex obstacle avoidance tasks in unknown rough terrains.

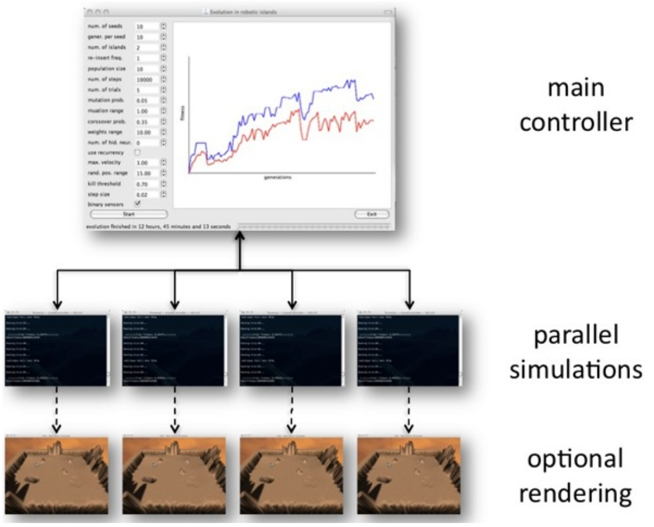

Fig. 1. Architecture diagram showing the controller running multiple simulations in parallel.

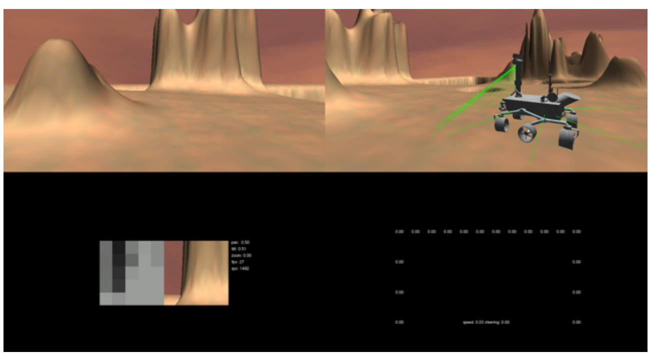

Fig. 2. Physics simulation of the Mars rover. The right section shows the user-controlled camera, the rover and the sensor inputs. The left section shows the rover's field of vision and information from the active vision system when in use.

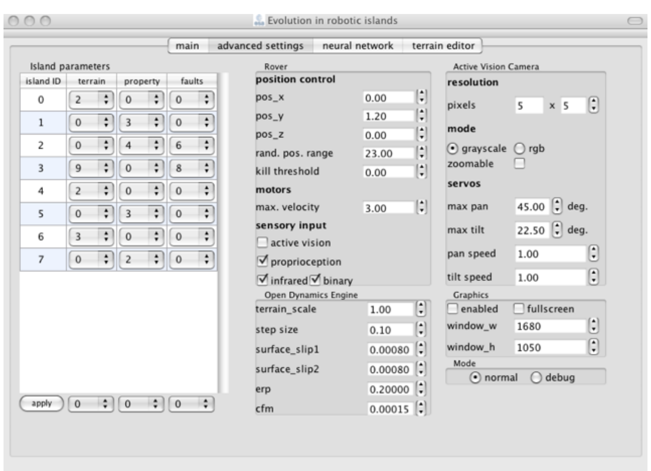

Fig. 3. Settings screen from the graphical user interface. Here it is possible to define which terrains are to be used on each island, along with their properties. It is also possible to define the sensory modality and parameters for the active vision system including retinal resolution and camera movement constraints for both axes.

The motor system of the rover model (see Fig.4) consists of six wheels where the two front and the two rear wheels are able turn up to 90° to either side. The rover is capable of overcoming obstacles that are approximately the same size as its wheels. This is possible thanks to a rocker-bogie suspension system. This advanced suspension system is designed to operate at low speeds and consists of two pivoted joints connecting two bogies with two rockers [28]. These rockers are connected together via a differential join. This means the left and right part of the rocker-bogie system can move independently while keeping the main body level.

The rover is equipped with the sensory apparatus to process 18 infrared sensors, which are used to provide information about the surrounding environment. Two different sets of sensors are used to accommodate obstacle detection. The first set consists of six lateral sensors, which provide extra safety when the robot approaches obstacles from the side. These sensors have a range of three meters and are not able to detect holes. The lateral sensors cover an area of approximately 200° around the rover, leaving the front area deliberately uncovered. These sensors return either 0 (no obstacle) or 1 (obstacle present) when activated by the presence of an object within the activation range of the sensors.

The second set consists of 12 infrared sensors with a maximum range of five and half meters. These infrared sensors, which shall be referred to as ground sensors, are positioned on the rover's camera mast and point downward at a 45° angle, reaching the ground approximately three meters in front of the rover. The twelve sensors are positioned and directed to ensure the range extends to around 400 mm beyond ground level. Ground sensors constantly scan the distance from the surface and are able to detect both rocks and holes. Each of these sensors returns a floating point value from 0 (no feedback) to 1 (strongest feedback). Holes or cliffs can be detected by the rover when it loses sensory feedback from the ground (i.e. ground sensor returns 0). The same sensors allow the robot to detect dangerous rocks or excessively rough terrain. This is achieved thanks to a particular threshold. When the activation of a sensor reaches that threshold it indicates that the robot is facing an insurmountable rock or a potentially dangerous terrain roughness. If a sensor's output goes over this threshold (a rock) or returns 0 (a hole) then its output value is changed from 0 (not active) to 1 (active). On the other hand, if the returned value stays within a certain boundary, which is given by the threshold, then the sensor returns 0. From this perspective a 0 activation can be seen as a safe zone and 1 as an obstacle. To model the lateral sensors and the ground sensors the researchers aimed to simulate the existing infrared sensors Sharp 3A003 and Sharp 0A700, respectively. In previous experiments the threshold, which can be in a range [0,1] was co-evolved with the neural network weights to a near-optimal value. In addition to the above sensors, the rover is provided with an active vision system (not used in the experiments reported in this study) and two internal sensors measuring its speed and steering angle.

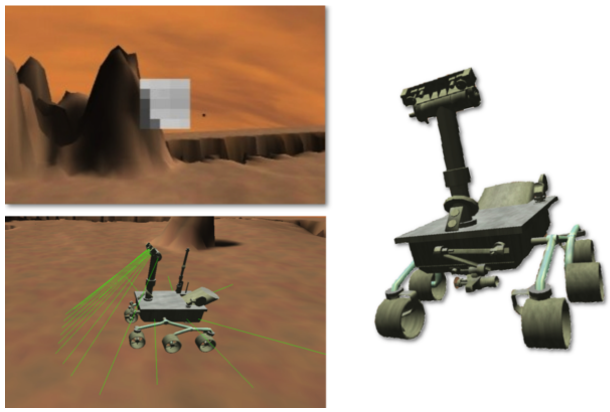

Fig. 4. 3D physics model of the rover showing the different parts of the rocker-bogie suspension system (right) as well as the vision system (top-left) and the position and orientation of the 18 infrared sensors (bottom-left). The vision system consists of a 5x5 matrix of foveal cells whose receptive fields receive input from a greyscale image of a limited area (100x100 pixels) of the whole image.

C. System Architecture

The control system is a fully-connected, discrete time, feedforward ANN (perceptron) with evolvable bias (see Fig.5). A set of 18 sensory neurons receive activation from the 18 infrared sensors of the rover, while an additional set of 2 proprioceptive neurons encode the value returned by the internal sensors, providing information about the speed and the position of the wheels. The 20 sensory neurons are fully connected to 2 motor neurons that modulate the level of the force, which is applied to the actuators, directly responsible for rover's speed and steering. Motor neurons have the sigmoid activation function:

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

in the range [0, 1], where x is the weighted sum of the inputs minus the bias. Biases are implemented as a weight from an input neuron with an activation value set to -1. The ANN does not have a hidden layer as the authors' previous experiments showed that it was redundant and did not help to achieve higher fitness. This simple architecture greatly reduces the computational demand of the control system, which is an important asset when considering a planetary rover, where the computational resources have to be kept to a functional minimum.

The rover's actions depend on the values of the synaptic weights of the ANN. Each weight must be set to an appropriate value to produce a desired output and, as mentioned previously, a genetic algorithm is used to evolve these. The free parameters that constitute the genotype of the control system and that are subject to evolution consist of: 42 synaptic weights (the 40 synaptic weights that connect the 20 sensory neurons to the 2 motors neurons, plus the 2 biases) and a single gene which encodes the threshold applied to the ground sensors. Weights and biases are encoded as floating point values in the range [-1, 1] and the threshold in the range [0, 1].

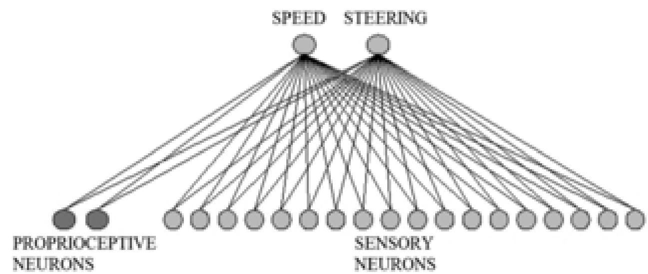

Fig. 5. Feed-forward neural network used as a control systems for the rover in the evolutionary experiments.

D. Island Model

An archipelago can be defined as a chain or cluster of islands with specific migration routes between them. In the experiments an archipelago was used consisting of 8 separate islands where each island contained 10 individuals. Every island had the same environment (see Fig.7) but unique individuals, each having been initialised with a different random seed. Therefore, the overall size of the archipelago was 80 individuals. The islands from within the archipelago were evolved independently, receiving migrants only at certain intervals, as defined by the migration rate, at which point the best individual from each island move to a different island. In this study the migration rate was set to 5, which allowed individuals to migrate between the islands every 5^{th} generation. The feasible migration paths were given by a particular topology. The island model framework supports a variety of such topologies including chain, ring, cartwheel, ladder, hypercube, lattice and broadcast topologies. For this experiment the ring topology (see Fig.6) was utilised, simply because the number of islands was not high enough to experiment with the effects of topologies in this particular task.

Each island was evolved in a separate thread and managed by a genetic algorithm. The population size of each island was set to 10 individuals. Only the best 2 individuals were allowed to produce 5 offspring each. Mutation and crossover operators subsequently acted on these offspring; a mutation occurred with the probability of 10% by adding to the original gene's value a quantity in the range [-1, 1], while crossover was exponential, happening with a probability of 95%. The best individual of the previous generation was retained unchanged and replaced the worst of the 10 offspring (often known as elitism). In this way it was possible to produce a new population of 10 individuals that inherited their genes from the best individuals of the previous generation. The whole evolutionary process lasted 100 generations. In each generation, each control system was evaluated 10

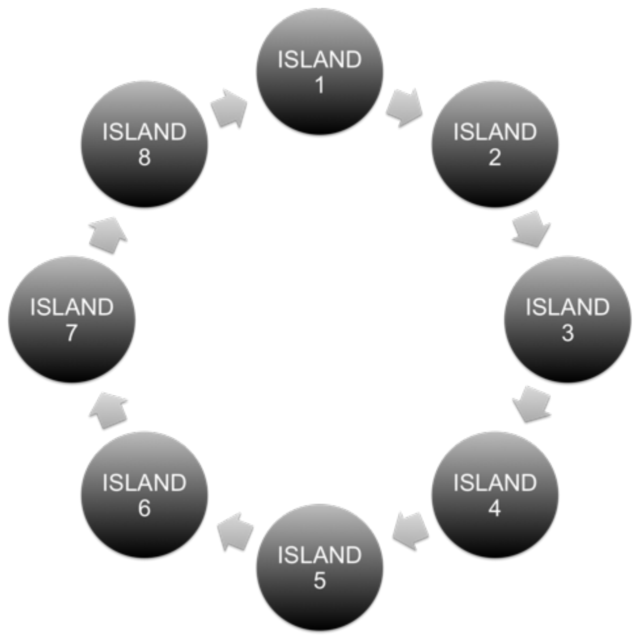

Fig. 6. Ring migration topology connecting individual islands and defining the rule sets for the exchange of genetic material between them.

times by deploying the rover in the environment (randomly positioned and rotated) and allowing it to act for up to 3000 sensory-motor cycles, that is to say, 3000 activations of the ANN. However, this was not always the case, as the evaluation of a particular genotype is terminated when a rover falls into a hole. 20 evolutionary runs were conducted, where each population was initialised with a different set of randomly generated individuals, spread across 8 separate islands.

The performance of each control system was evaluated according to the fitness function (see 2) that was carefully designed to shape the behaviour of the robot for effective and reliable exploration and obstacle avoidance behaviours:

$$F = \frac{1}{S \times T}(Sp \times St) \qquad (2)$$

where the fitness F is a function of the measured speed Sp and steering angle St, where Sp and St are in the range [0,1]. Speed Sp is 1 when the rover goes at the maximum speed and 0 when it does not move or goes backward. Steering angle St is 1 when wheels are straight and 0 when they are turned over an angle of 30° from the centre. If for example the angle was 15° then St would be 0.5. T is the number of trials (10 in these experiments) and S is the number of sensory-motor cycles per trial (3000 in these experiments). Equation 2 shows how the fitness is calculated at every sensory-motor cycle. Thus, the GA has to maximise the fitness by increasing the value of Sp and St, which implies that a rover has to move at a maximum possible speed while steering only when necessary. If a rover goes forward at the maximum speed but keeps the steering angle over 30° then its final fitness will be 0. Similarly, if a rover goes backwards or does not move at all, its fitness will also be 0 regardless the steering angle. The maximum fitness contribution at each time step is therefore $\frac{1}{S \times T}$. The final fitness of each individual is in the range [0, 1] and it is the sum of all contributions from all time steps of all trials.

In order to evolve a good controller, it was necessary to create a suitable environment to allow the robot to experience different surface conditions (see Fig.7). The environment that was modelled for this purpose is an arena of 60x60m and contains inclined and declined surfaces, three high and three small rocks, holes and rough areas. 111m^2 of the terrain is covered by obstacles and hence not traversable.

Fig. 7. Environment that was used during all evolutionary runs.

III. Results

The experimental setup involved using both the island model as well as the standard sequential approach in order to evaluate the quality of the evolved solutions produced by each model. Twenty evolutionary runs were conducted for each model and the results showed that an effective behaviour emerged throughout all the runs. In particular, due to the general behaviour optimised by the fitness function, the obtained controllers were able to navigate the environment with a certain degree of efficacy, capable of avoiding obstacles of different types and dealing with rough terrain.

The chart in Fig.8 shows the average results of the twenty evolutionary runs for each model. The graph was created by averaging values from all of the twenty runs. The black lines in the graph represent the standard approach and the grey lines the island model. The full lines show the maximum fitness obtained by the best individuals, while the dashed lines show the average fitness for all the populations. By looking at the graph it can be noticed that the island model achieved slightly higher fitness that the standard model. However, the main advantage in this particular case is the significant time reduction in completing the evolutionary process. In particular, this time decrease is proportional to the number of processors employed by the island model. In these experiments eight separate islands were running in parallel and hence the overall time necessary for finishing 100 generations (approximately 5 hours) was 8 times less than using the sequential approach (almost two days). In this

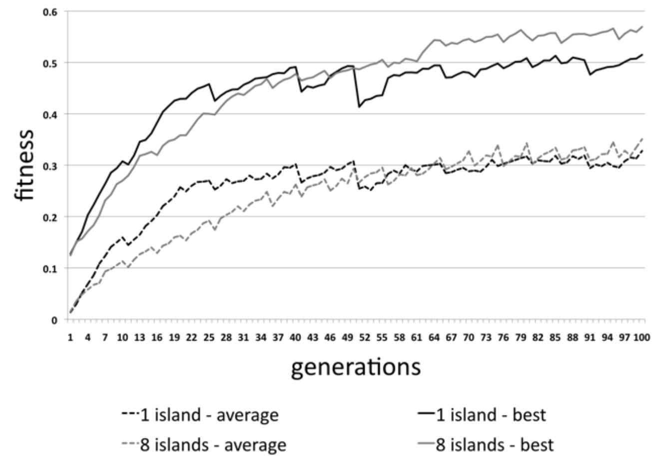

Fig. 8. Averaged fitness values from all the twenty evolutionary runs for each model. The black lines in the graph represent the standard approach and the grey lines the island model. The full lines show the maximum fitness obtained by the best individuals and the dashed lines show the average fitness for all the populations.

way it is possible to split populations across any number of processors and reduce the time significantly while not losing anything in the quality of the solutions.

Using both models the behaviour that emerged was very similar and quite simple. Since the fitness function requires the rover to go as fast as possible while keeping steering at a minimum, the rover evolves a strategy whereby it preferentially travels in straight lines, turning only when encountering obstacles. If the rover detects a rock, for example, it will immediately turn around and continue in a straight trajectory, however, the rover will only steer as much as is necessary to circumnavigate the obstacle.

IV. Conclusions

Experimental results showed that the island model produced solutions that were equally as good as those evolved using standard, sequential GAs. Splitting the populations across multiple islands resulted in a significant reduction in the time required to achieve the same results through a standard GA. Evolved neural networks were found to be able to control the rover and deal appropriately with different types of obstacles. It is worth noting that the exploration and obstacle avoidance behaviours were not obtained through a pre-specified pattern of interaction between the rover and the environment. Rather, they are the emergent product of a fitness function working at the level of the whole behaviour of the robot. These behaviours are discovered autonomously through the evolutionary process and are functional to the optimisation of the global fitness used for the evolution. This research empirically verifies that this property of evolutionary robotics can be utilised with success in the design of a robust and computationally light controller, capable of dealing with the kinds of problems that future planetary robotic missions will face. As has been shown in this work, evolved neural network controllers can be extremely simple, require only minimal processing power and yet be very robust and reliable.

It should be noted that due to the simplistic nature of this task, it was not possible to observe the island model's full potential in producing significantly superior solutions. Current and future experiments, as discussed in the following section, will assess and compare the quality of solutions produced using conventional GAs against the island model paradigm, when applied to a variety of different and more complex tasks.

V. Future Work

Current research is looking to answer the question of whether the island model can produce statistically superior results compared to a standard GA without the effects of migration. For this reason several different experiments are currently being conducted, that are also looking into other possible benefits such as evolving individuals in parallel on different terrains where each terrain is assigned to a separate island. Other tasks are focusing on the role of optimising fault tolerance, where different islands contain different populations of rovers affected by sensory failures. In this case each island provides a unique environment, each with a different number of affected sensors. In this way, it is hoped that migration with facilitate a high fault tolerance robustness. Further experiments will focus on the evolution of active vision for navigational capabilities, in conjunction with an infrared system for detecting obstacles in the rover's proximity. Active computer vision systems are inspired by biological information gathering on mammals and insects. Such systems can greatly simplify the computational complexity as they only use information from an environment that is necessary to solve a certain task, while superfluous information is ignored. Past research in this field has demonstrated that it is possible to combine an active vision system together with feature selection to acquire and integrate information from an environment in order to solve a specific task[29]. Hence, a future goal is to use both the active vision system and the current system to achieve complex, robust and reliable behaviours in a computationally inexpensive manner. In particular, future work will attempt to exploit the generalisation capabilities of ANNs and the robustness they can inherently display when used as controllers for rovers operating in unknown and potentially dynamic environments, where events such as motor or sensor failures may degrade performance but should not be deleterious to the mission's future. It is acknowledged that future planetary robotics missions will have to face many challenges, however based on this preliminary research, the authors are convinced that the evolutionary robotics approach is worth strong consideration, holding the potential to address many problems that are hard to overcome using conventional methods.

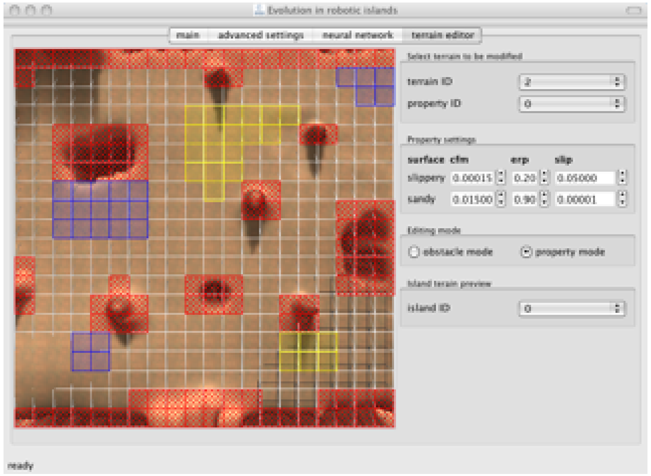

Fig. 9. Screen from the controller's graphical user interface where it is possible to define various properties for each terrain (slippage, sandiness, etc.). Every island can run an evolution on a different terrain where each terrain can have up to 10 different surface properties.

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