ACTIVE VISION FOR NAVIGATING UNKNOWN ENVIRONMENTS: AN EVOLUTIONARY ROBOTICS APPROACH FOR SPACE RESEARCH

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ABSTRACT

Evolved active vision control systems have the ability to extract relevant information from an environment in order to solve a specific task [1]. This work has the objective to investigate an obstacle avoidance and navigation systems for space exploration rovers capable of performing autonomous tasks in challenging planetary terrains. The paper presents an evolutionary robotics approach applied to a Mars rover model that is equipped with an active vision camera and a neural network control system. Preliminary experimental results suggest that such an active vision system provides a powerful and yet computationally cheap way of developing important visual processing strategies to navigate in the environment.

1. INTRODUCTION

In the near future, autonomous robots are expected to be the principal actors in the exploration of Solar System planets. The difficulties of planning a human mission and the distances that separate the Earth from the other planets require the design of robots capable of operating autonomously for the majority of the time. Nowadays, the time delay that affects the communication between the Earth and other Solar System planets makes autonomous robot exploration the only feasible way to shed light on the mysteries of deep space planets.

After the successful mission of the Mars Pathfinder in which the first semi-autonomous vehicle explored the Martian surface, other missions to Mars have been programmed and lunched. In 2004 rovers Spirit and Opportunity landed on Mars and, besides the planned operation time of 90 days, they are still exploring the Martian surface after five years [2]. In the light of Spirit and Opportunity's successes, other robotics missions are planned both from NASA and ESA. NASA MSL (Mars Science Laboratory) and ESA ExoMars projects are based on rovers able to navigate autonomously on the surface and provided with scientific instruments that allow a number of analyses on Martian terrain and atmosphere.

Navigation and obstacle avoidance behaviors in Spirit and Opportunity are accomplished through a set of stereo cameras. In particular, the robots are equipped with three sets of stereo camera pairs. One pair is looking forward, below the solar panel in front. Another pair is looking backward, below the solar panel in the back, and the last pair is placed on the mast. With the images taken by the cameras, a stereo algorithm calculates the 3D representation of the terrain in front of the robot and other algorithms are used to calculate a "traversability" map [3]. Information from the cameras is used to create a grid-type traversability map based on the terrain around the robot. This map, in turn, is used to plan the next action of the robot.

Besides the techniques actually used on Spirit and Opportunity, there is plenty of research on navigation and obstacle avoidance for autonomous robots that relies on visual information and that can be relevant for spatial exploration. For instance, a well studied method is the "arcs approach" [4][5]. In the arcs approach, after the construction of the 3D representations from the cameras, an algorithm is devoted to generate several candidate arcs for steering the robots on the terrain. After a comparison between different arcs, one of the arcs is chosen on the basis of specific criteria (i.e. the arc with the largest clearance or, after calculating the costs along each arc, the one with the lowest cost is selected) and the robot is finally steered along the winning arc.

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2. FEATURE SELECTION AND ACTIVE VISION

The methodologies described above rely on a 3D representation of the entire scene captured by the stereo cameras. The construction of the 3D scene requires extremely demanding computation. Given the limited energy supply and computational power that is often available to robots devoted to planetary exploration, the process of creating the entire 3D representation of the environment is one of the factors that significantly affect the navigation performance of the robot.

At the basis of this approach there is the idea that perception mainly consists in the internal construction of a detailed representation of the external world, e.g. [6]. According to this view, the main challenge is to transform egocentric, incomplete, and noisy sensory information into allocentric, complete, and precise representations of the external environment. To achieve this goal in vision, for example we face the problem of inferring the 3D arrangement of the scene from 2D images. This explains the importance of relying on stereo cameras. Motor behavior (i.e. the interaction with the external world) is not viewed as a resource for the robot, but rather as a problem to be controlled. The result of the perceptual process, in fact, should be as independent as possible from the behavior displayed by the robot during the collection of sensory data.

Starting from a different perspective, the *active perception* approach [7][8] assumes that the world can be viewed as its own external representation, and perception consists in mastering the regularities arising from sensory-motor interactions. From this point of view, perception is a way of acting, as pointed out by O'Reagan [9]. Active vision, i.e. the application of the active perception approach to vision, consists in the process of sequentially analyzing only parts of the visual scene, rather than the entire scene [10][11]. This approach can simplify the computation involved in vision processing, by reducing the information load and by selecting only characteristics of the visual scene that are relevant for a given task [1][12][13].

In the same vein, visual processes implied in vision-based navigation can be significantly simplified by creating a system which is able to select and pay attention only to a reduced set of relevant environmental features. However, the combination of active vision and feature selection is a field still largely unexplored. The dominant approach in computer vision generally consists of a defining set of predefined features which are exploited by an active vision system [14][15]. It is interesting to note that the majority of these models do not take into account that the types of visual features depend also on the sensory-motor and behavioural characteristics of the organism in its environment [16].

The co-development of active vision and feature selection has been especially explored by the Evolutionary Robotics approach, which consists of encoding the parameters of a neural system (architecture, connection weights, time constants, sensor position, etc.) of a robot into an artificial genome, and evolve a population of such genomes according to a fitness function [17]. For example, Harvey et al. evolved an evolutionary active vision system in which sensory and neural morphology for a robot have been evolved for discriminating a triangle and a square [18]. More recently, Floreano et al. described a set of experiments in which the same neural architecture has been implemented on different active vision systems (an artificial retina, a wheeled robot and a virtual car) [13]. These experiments showed that such a system was able to exploit active vision for selecting the relevant features in the environment in order to accomplish an adaptive task.

In this paper we will use an evolutionary active vision system for a rover navigation task in unknown environments. The architecture of the control system described here is based upon the work initially explored in Floreano et al. [13].

3. METHOD

As we have mentioned before, our approach is based on evolutionary robotics (ER). The ER approach emphasizes agent's embodiment, which means that an emerging behavior is not only dependent on various properties of the actual robot such as its size, speed, degrees of freedom, sensors and actuators, but also on the environment with which a robot interacts [19]. ER is an excellent technique that allows us to create artificial control systems that autonomously develop their skills in close interaction with the environment and that exploit very simple, but extremely powerful sensory-motor coordination [20].

3.1. The rover

The robot used in this experiment is a 3D simulated model of the MSL rover. The model cannot be considered as a trustful and 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, weights and sizes of different parts, as well as of many other design details. According to Centre National d'Etudes Spatiales [21], the dimensions of the real rover are 2900Lx2700Wx2200H mm and its weight is about 775 kg. The physical rover model was therefore built considering these details and several diagrams and pictures that were available. These limitations are not crucial in this study, as at this stage we want to demonstrate that it is possible to use an ER approach and a simple sensory setup to develop a suitable active vision controller able to handle complex obstacle avoidance tasks in unknown rough terrains.

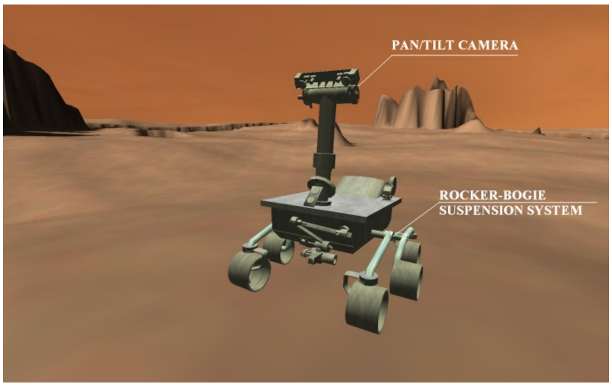


Figure 1. 3D physics model of the rover highlighting different parts of the rocker-bogie suspension system.

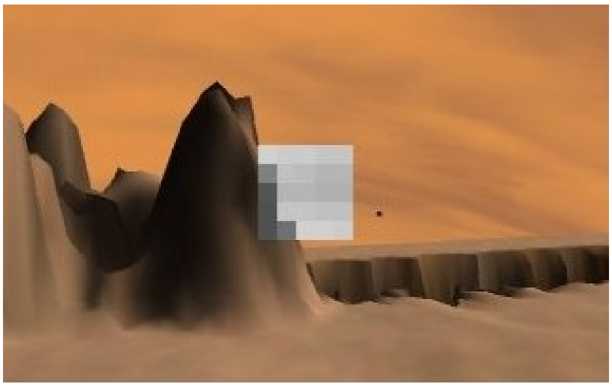


Figure 2. Example of the vision system of the robots, which consists in a 5x5 matrix of foveal cells whose receptive fields receive input from a gray level image of a limited area (100x100 pixels) of the whole image. The entire image is 640x480 pixels.

The motor system of the rover model (see Fig. 1a) consists of six wheels, where two front and two rear wheels are able to turn up to 90° to either side. The rover is capable of overcoming obstacles that are approximately of the size of its wheels. This is possible thanks to a rocker-bogie suspension system. This advanced suspension system is designed to be operated at low speed, and consists of two pivotal joints connecting two bogies with two rockers [22]. The 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 levelled.

The rover is equipped with an active vision camera that has two degrees of freedom (pan and tilt). This camera was positioned at the top of the rover, approximately 2.2 metres above ground, and is able to turn within 45° on the vertical and 22.5° on the horizontal axis.

3.2 System architecture and parameters

The active vision system is based on a discrete-time recurrent artificial neural network (ANN) (Fig. 3). The recurrent connections are implemented using 4 memory units that maintain a copy of the activations of output units at the previous sensory-motor cycle [23]. A set of 25 visual neurons receive the activation from an artificial retina composed of a 5x5 matrix of visual (foveal) cells whose receptive fields receive input from a gray level image of a limited area (100x100 pixels) of the whole image (640x480 pixels) (Fig. 2). Foveal activations together with the proprioceptive information (motor speed, steering and pan/tilt positions) are fed into the neural network. Both visual and proprioceptive neurons are fully connected to 4 output neurons that modulate the level of force which is applied to the actuators directly being responsible for the rover's speed, steering and direction of the camera. The output neurons have a sigmoid activation function with [0, 1]. Biases are implemented as weights from input neurons with activation values set to -1. The ANN does not have a hidden layer, as our previous experiments showed that it was redundant and did not help to achieve higher fitness [24]. This simple architecture greatly reduces the computational demand of the control system, which is one of the most important requirements for designing a planetary rover.

The rover's motor actions depend on the value of the synaptic weights of the ANN. A genetic algorithm was used to evolve the weights. The free parameters that constitute the genotype of the control system, and that are subject to evolution, consist of: 136 synaptic weights (100 synaptic weights that connect the 25 retinal neurons to the 4 motors neurons, 4 proprioceptive and 4 memory neurons that connect to the output neurons, plus 4 biases). Weights and biases are encoded as floating point values in the range [-5, 5].

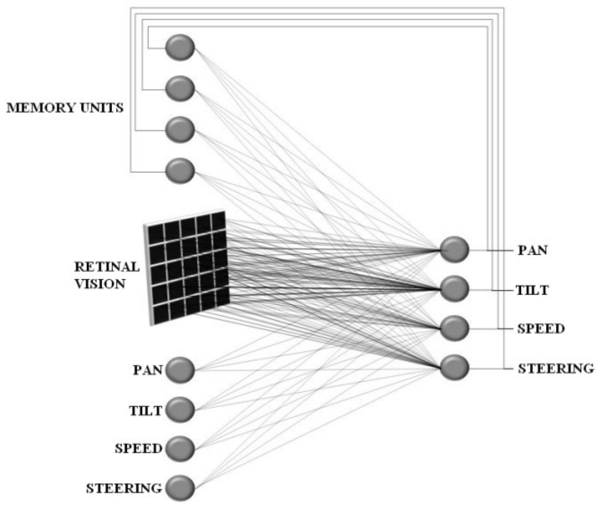


Figure 3. Neural architecture of the active vision system.

In our experiments we used a population size of 100 individuals, where the best 20 individuals were allowed to produce 5 offspring each with a mutation probability of 10% (a mutation occurs by adding to the original gene's value a quantity in the range [-3, 3]). The only exception was the first offspring of the best individual, which was copied to the next generation without mutation (elitism). This produced a new generation of 100 individuals that inherit their genes from the best individuals of the previous generation. The whole evolutionary process lasted 100 generations. At every generation, each control system was tested 5 times by deploying the ANN in the rover (randomly positioned and rotated) and allowing it to act in the environment for up to 10000 sensory-motor cycles (i.e. 10000 activations of the ANN). The evaluation of a particular genotype was terminated when a rover fell into a hole or crashed into an obstacle. Five evolutionary runs were conducted starting from different randomly initialized populations.

The performance of every single control system was evaluated according to the fitness function (1) that was carefully designed to shape the behavior of the robot for effective and reliable exploration and obstacle avoidance:

$$F=\frac{0.5}{S \cdot T}(Sp \cdot St)+Bs \qquad (1)$$

where the fitness F is a function of the measured speed *Sp*, steering angle *St* and steering bonus *Bs* , with each of these parameters is 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 (5 in these experiments) and *S* is the number of sensory-motor cycles per trial (10000). The steering bonus *Bs* is 1 if the steering position changed since the last time step and 0 if not. The GA has to maximize the fitness by increasing the value of *Sp*, *St* and *Bs*, 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 keeping 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 $1/(S*T)$. The final fitness of each individual is in a range [0, 1] and it is the sum of all contributions from all time steps of all trials.

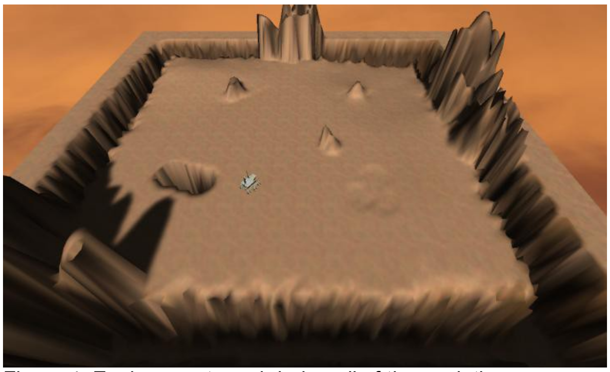


Figure 4. Environment used during all of the evolutionary runs

In order to evolve a good controller, it was necessary to create a suitable environment to allow the robot to experience different conditions (see Fig. 4). The environment is an arena of 60x60m and contains inclined and declined surface, three high and three small rocks, holes and rough areas. 111 m^2 of the terrain is covered by obstacles and hence not traversable.

4. EXPERIMENT RESULTS

The results obtained from all five evolutionary experiments show that an effective behavior emerged in all replications. Evolved robots can navigate the environment with a certain degree of efficacy and are able to avoid obstacles of different types by relying on the active vision system. The chart in Fig. 5 shows the averaged results for the five evolutionary runs. The dark grey line shows the maximum fitness reached by the best robots for every generation and the light grey line shows the average fitness of the population.

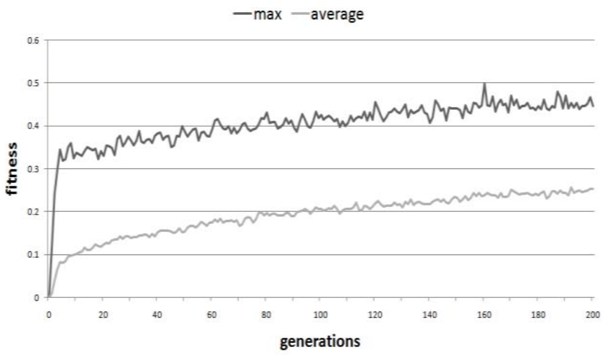
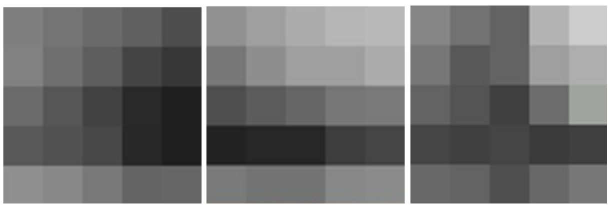


Figure 5. Maximum and average fitness obtained by the robots during the evolution (average of 5 replications). Note that, according to equation (1), the fitness can never reach 1.0 as the rover needs to turn and decrease its speed to avoid obstacles.

In order to understand the evolved behavior, analyses focused on the vision and camera movements, taking into account their mutual integration and their interaction with the robot's steering. The analyses were performed to verify the hypothesis that the evolved active vision system is able to respond to particular features that are common in the environment. The best individual of all the five repetitions were used in all tests. Two different types of analysis were carried out: *Original Environment Test*, using the same environment of the evolution experiments, and the *Artificial Environment Test* using two new environments specifically configured to better highlight certain properties of the behaviour and to quantitatively confirm the observations made during the first test.



(a) (b) (c)

Figure 6. Shows the three accumulated patters, i.e. the average of the recorded images, which affect (a) pan, (b) tilt and (c) steering, respectively.

4.1 Original Environment Test

(a) In this test, each best evolved individual was left free to move in the environment for 10^6 (one million) time steps, during which the visual input was recorded and then analysed. The three images above (Fig. 6 (a), (b) and (c)) are the result of accumulation of retinal inputs saved every time the rover used the camera pan, the tilt or when it significantly steered. This was done by comparing previous join positions with current positions and if the difference was over 3° the image was saved.

(b) *Camera Pan*
In the case of camera pan, as can be seen in Fig. 6a, the receptive pixels that affect the camera seem to form a triangular pattern with the highest sensitivity in the bottom right corner, and gradually decreasing in intensity towards the top left corner. This pattern is mostly present when the rover moves the camera horizontally, in the presence of rocks in its field of view.

(c) *Camera Tilt*
In the case of camera tilt, the image in Fig.(6b) shows two interesting features. The first is again a triangular gradient spreading from the bottom left corner and reaching the top right corner. The second feature, which is also the most apparent, shows a clear horizontal orientation which is noticeable from the three bottom lines with the strongest intensity in the middle. The rover appears to be using the vertical camera movements mostly when it detects holes. From the observation of the behaviour, the rover uses the tilt for at least two reasons. One is to fixate the camera on a feature and keep it in the field of view so that it can later avoid it. The other is to use tilt for distance estimation as the analysis showed that even when the retinal input remained approximately the same, changes in steering occurred. The tilt and the memory integration were the only factors that could influence the steering in this scenario. Further details on this topic will be given in the next section.

(d) *Steering*
The image in Fig. 6c, recorded when the robot steers, displays horizontal and vertical lines suggesting that the retina is sensitive to different features in the environment as none of the obstacles seem to have this type of shape. This image appears to be an accumulation of at least two different features over time. One is the hole, which is reflected by the horizontal line. The other seems to be an edge of a rock or a cliff, shown as a vertical line. By considering that the steering is the

behaviour that actually allows the rover to avoid an obstacle, it is probable that the recorded accumulation pattern is the results of a mixture of the pan and tilt activation pattern.

In addition to these analyses, the trajectory and the visual input were analysed for a period of 50000 time steps. Figure 7 shows the results of a qualitative analysis which examined the association between visual input and changes in steering, where the superimposed retinal images correspond to critical points in obstacle avoidance. As we can clearly see from the figure, different visual patters are produced by different obstacles. The first and second images on the right of the picture show the pattern related to a hole, at the moment in which the rover is about to avoid it.

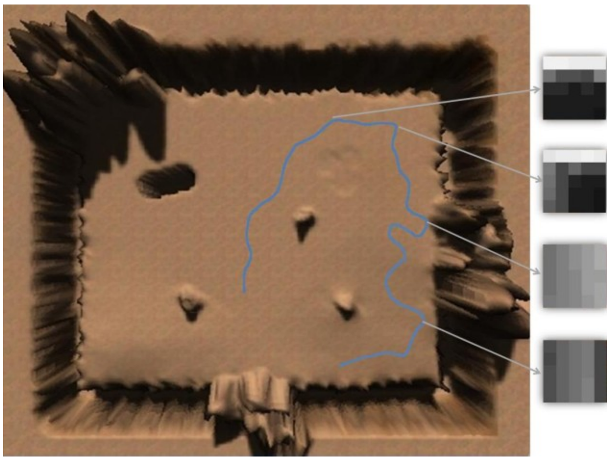


Figure 7. Trajectory and visual inputs from crucial obstacle avoidance manoeuvres.

The pattern is horizontally oriented and the boundaries between the ground and the hole are clearly visible. The third and the fourth images are related to rocks. In this case the visual pattern is rather uniform all over the retina and no clear boundaries are present. In the fourth image it is possible to notice the vertical orientation of the pattern, in contrast with the horizontal one produced by the hole.

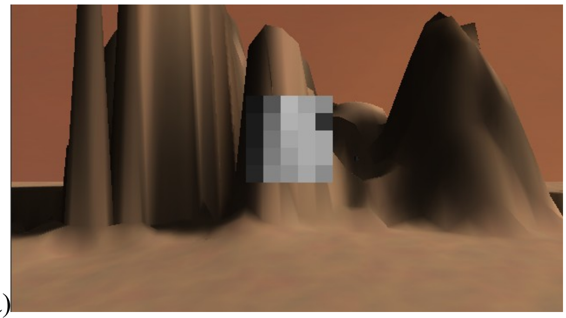
4.2 Artificial environment test

In the following test the ability of the robot to use vision for avoiding obstacle has been tested in relation to the active movement of the camera. Two different types of test scenarios were designed for this test (Fig. 8):

- *Rock-type obstacle test scenario*. The individual is located in front of a rock obstacle placed at the center of the environment.
- *Hole-type obstacle test scenario*. The individual is set in front of a hole obstacle.

In both cases the number of times the robot was able to correctly avoid the obstacles were recorded. For each of these scenarios, two features of the camera's movement were used independently, in order to further understand the contribution of each of them in the avoiding behaviour. In particular, tests were run with the robot using only tilt, only pan, or both of these features. Each test consisted of 200 steps.

(a)



(b)

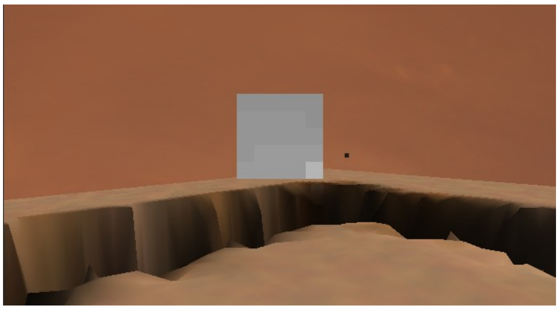


Figure 8. (a) Rock-type and (b) Hole-type obstacle starting conditions used for the testing the usage of camera pan and tilt.

The chart in Figure 9 shows the percentages of successful trials in which the robot was able to avoid the obstacle, out of the allowed 200 trials. From this test we can draw the following conclusions: (i) the robot is able to avoid holes better than rocks and (ii) the tilt feature in the active vision strategy makes a larger contribution to the successful avoidance of obstacles than the pan. Tilt-only condition shows a higher percentage of success than the pan-only condition in both the scenarios considered. Moreover, qualitative comparisons of the tilt-only and pan-only conditions indicate that pan movements are more related to rocks detection than holes (see section 4.1), as the performance decay in avoiding rock obstacles is greater than the performance decay in holes obstacle.

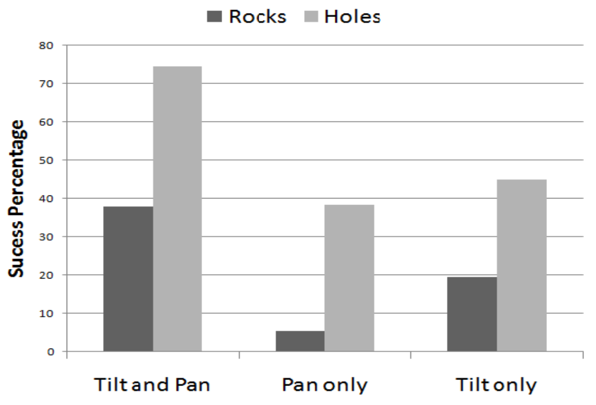


Figure 9. Percentages of successful trials in which the robot was able to avoid the obstacle in case of rock-type and hole-type obstacle and for each of the 3 conditions considered.

5. DISCUSSION

Although further analysis and tests would provide a clearer picture of the active vision strategy used by the evolved agents, from the behavioural analysis and test presented here we can try to draw a general description of the sensory-motor strategy involved.

The evolved individuals tested are able to locate and track hole-type obstacles better than rocks. This fact, however, should be considered in the light of the whole evolutionary process. Given that the majority of obstacles surrounding the environment are holes, it is plausible that a large amount of adaptive pressure during the evolution has produced robots more capable of avoiding holes, given the higher probability of encountering holes than rocks.

The strategy followed by the rover toward a hole-type obstacle is to steer until a low input (black pixels) is in the central part of the visual field. This seems to activate the tilt of the camera down and the activation of the motors for moving forward. Analysis showed that the tilting down and moving forward movements were very often actuated together when a low input was in the central lower part of the visual. This produced an ability of the robot to move in parallel to the edges of the holes.

When the pan movement is inhibited, the rover shows a similar behaviour. Even though the robot does not use pan very often, this condition prevents the robot from achieving a high rate of success in avoiding holes (Fig. 9). Panning to the right is the most common position of the camera. Thus, with the inhibition of the pan movement the robot seems not properly 'adjusted' to the situation and makes miscalculations of the hole position. This could be explained by the fact that that evolution has produced robots that preferably use the steering to do panning, instead of the actual camera panning. This might be due to the evolution of a simpler vision field control.

Differently than pan, tilt is crucial for the avoidance of holes and for the more general navigation ability. Tilt is used as a means of determining the distance of holes. When the rover tilts the camera down a low output to the motors' power is produced, so as to reduce the speed. On the other hand, when the tilt is sufficient to make the camera point to the horizon or above it, the rover increases the speed, by making the robot move straight.

In the case of rock-type obstacles, it was evident that the rover evolved a better control of the visual field by steering, rather than by using the camera's pan. Steering was used extensively in the process of avoiding rocks. In this respect, it is particularly interesting the way in which the rover appears to distinguish between rocks and holes. The general strategy is as follows: once a low value input is detected in the high part of the visual field, steering is activated along with tilting down the camera. If these actions do not produce a consequent low value activation of the input in the middle of the vision field, then the obstacle is treated as a rock instead of a hole, and the action taken is to increase the steering angle. This behaviour is in contrast with the distance-estimation behaviour in the case of hole-type obstacles. In such a case, the tilt down movement maintains low value input in the middle of the visual field. This indicates a movement towards the hole.

This type of behaviour closely resembles the action-perception loop of the sensory-motor strategies described in the literature, such as in [8][20][25]. These studies were based on different robots, namely a khepera wheeled robot, a robotic arm, and a robotic hand, respectively. In these cases the robots show a sensory-motor behaviour that allows agents to disambiguate specific input patterns among a very noisy input activation state. This is achieved by acting in the environment in such a way to produce a defined sequence of input patterns that solely pertains to a specific category. The only category that allows the robot to produce a given motor sequence is to start from the interaction schema actively produced by the robot itself (see [9] for a discussion).

CONCLUSION

In this paper we have shown that evolutionary robotics techniques are feasible for creating effective control system for autonomous robots that use active vision for navigation purposes. In particular, we showed that evolved robots are able to perform a navigation task in a complex environment by using active vision for distinguishing between different types of obstacles. The behavioural strategies displayed by the robots are also interesting and make use of a complex action-perception loop, despite the simplicity of the neural controller. Given the preliminary, yet encouraging results of the experiments presented here, we intend to proceed toward a better understanding of the active vision systems and the evolution of better and robust control systems for autonomous rover devoted to spatial explorations.

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