EVOLVING ROBUST ROBOT CONTROLLERS FOR CORRIDOR FOLLOWING USING GENETIC PROGRAMMING

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Abstract: Designing robots and robot controllers is a highly complex and often expensive task. However, genetic programming provides an automated design strategy to evolve complex controllers based on evolution in nature. We show that, even with limited computational resources, genetic programming is able to evolve efficient robot controllers for corridor following in a simulation environment. Therefore, a mixed and gradual form of layered learning is used, resulting in very robust and efficient controllers. Furthermore, the controller is successfully applied to real environments as well.

1 INTRODUCTION

Many interesting and realistic applications where robots can be used are too difficult for the current state-of-the-art. Robots are mainly used for relatively easy and repetitive tasks. Fully autonomous robots in realistic applications are exceptions (Pollack et al., 2000). This is mainly caused by the highly complex design of such systems. More specifically, the development of robust controllers for real mobile robots is challenging.

The main objective of this contribution is developing robust controllers for corridor following using genetic programming (GP), an evolutionary method based on program induction. The robot must navigate in a corridor system from start to end as efficiently as possible and without collisions. The evolved mobile robot controllers must be robust enough to navigate successfully in corridor systems on which the robot was trained during the evolutionary process as well as new and unseen environments. Furthermore, the controller evolved in simulation must be transferable to the real robot preserving its behaviour learned in simulation.

An example of using GP in a basic simulation environment is found in (Lazarus and Hu, 2001). GP is used for evolving wall following-behaviour, which is part of many higher level robot skills. Similar experiments provide some basic proof for using GP in robotics but their practical use is questionable. In (Reynolds, 1994) a simplified but noisy simulation environment for evolving corridor following behaviour with steady-state GP was used. In (Dupuis and Parizeau, 2006), a vision-based line-following controller was evolved in simulation by incrementally improving the visual model in the simulation. Mainly caused by some oversimplifications in the simulator, the authors were not able to successfully transfer this behaviour to the physical robot. Some experiments were conducted directly on real robots. An example is in (Nordin and Banzhaf, 1995), where an obstacle avoidance controller for the *Khepera*-robot is evolved, using steady-state GP. The resulting program was robust, as it was successful in other environments as well.

The remainder of this paper is composed as follows. Section 2 provides a short introduction to the GP specifics used in the experiments. After that, in Section 3 the experimental setup is set out, including the simulation environment and the robot platform. Finally, Section 4 discusses the evolution of robot controllers in simulation and the transfer to reality.

2 GENETIC PROGRAMMING

Due to page restrictions this section will only describe the various parameter settings used in this study. A more detailed overview of the GP evolutionary cycle is given in (Nordin and Banzhaf, 1995). 300 individu-

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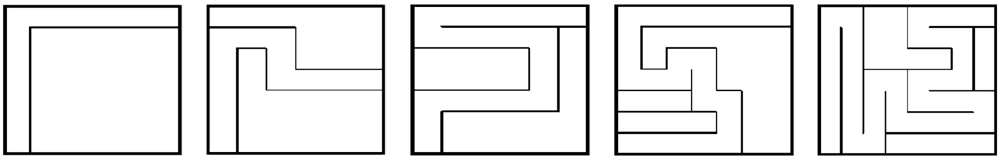


Figure 1: A representative environment for each of the five categories, as used in the standard approach. Each category consists of increasingly difficult environments in terms of the number and type of turns and the length of the optimal path.

als were initially created by the ramped half-and-half method with depth ramps between 2 and 6 and were allowed to evolve during 50 generations. Crossover (90%) and reproduction (10%) were used in combination with tournament selection with seven individuals. The function set contains two functions: *IfLess* (arity 4), and *PROGN2* (arity 2), both well known. Terminals to move forward and backward over a distance of 10 cm are also included. Whereas in the first experiments (Sections 4.1 and 4.2), turn left and right makes the robot turn 90 degrees in place, further experiments (Section 4.3) employ 15 degree turns. Three infrared distance sensors are used: front, left and right, each perpendicular on the robot. The frontal sensor is placed left of the center of the robot. Finally, three threshold values are available: low, medium and high, respectively 75, 150 and 300 mm.

Each generation all individuals are tested in three environments and can perform 500 movements in each environment. The fitness function is averaged over all three tested environments and consists of three components. A first, basic, component measures the distance in bird's eye perspective the robot has covered so far. This component mainly differentiates between controllers in initial generations. The second component punishes every collision detected using either sensor on each side of the robot. The penalty consists of adding a fixed value to the number of movements so far. Thirdly, a bonus component is added when the robot reaches the end of the corridor system. This consists of a fixed part and a variable part. The variable part is relative to the number of spare movements and thus rewards efficient controllers.

While evaluating fitness on a single environment most likely leads to brittle strategies, averaging over multiple fitness cases results in more general solutions. Therefore, we use a variant of the layered learning approach (Gustafson and Hsu, 2001). Categories of environments with increasing level of difficulty (see Figure 1) are interchanged every number of generations. In a *standard* setting, each of the five categories consists of three equally difficult environments. We also construct a *mixed* setting. Here, two environments from one category and one from a clearly more difficult or easier category are selected, however maintaining the overall increase in difficulty towards the end of a GP run. The *gradual* approach does just the same, but the number of generations that is used to train on increases, leaving more time for the evolutionary process to learn more difficult behaviour.

3 EXPERIMENTAL SETUP

We use the *EyeBot*-platform for our experiments (Bräunl, 2006). The evolutionary process is carried out in the EyeSim, the simulation environment of the platform because analysis of robot behaviour in software is straightforward whereas in reality image processing would be required. Main advantage is that programs for the EyeSim can be transferred immediately for execution on the real EyeBot.

Gaussian distributed noise is a good option to model realistic errors. The standard deviation we use is 3 for sensor noise and 2 for motor noise. Combined with this noise, the simulation environment facilitates the evolution of controllers for real applications, which is impracticable in simplified and naive simulation environments.

The GP process was handled by ECJ [1]. ECJ constructs controllers of which the fitness is evaluated in the EyeSim and returned back to ECJ, which performs all evolutionary computations. Since GP is a probabilistic method, we consider three different runs of each experiment. This relatively low number is justified because we are interested in the best controller, not some mean value. Moreover, when considering too many runs, the computational cost becomes too high. Finally, the standard deviations for all successful runs turn out to be small.

4 EVOLVING ROBOT CONTROLLERS

We start with evolving robot controllers in simulation under relatively simple conditions (Section 4.1). To increase realism we then add noise. Firstly, noise is added to the sensory equipment. Secondly, noise is

[1] http://www.cs.gmu.edu/ eclab/projects/ecj/

also added to the steering mechanism (Section 4.2). To allow adjusting for incomplete turns, we also refine the terminal set with 15 degree turns instead of 90 degree turns. Eventually in Section 4.3 the evolved controller is transfered to the real Eyebot.

4.1 Evolution in Simulation

Table 1 lists the results of the experiments in simulation. The best controller of every experiment is able to navigate through all corridor systems, except in experiments 4 and 6, where the controller solves 14 out of 15.

Next to the more classic approach of changing the number of generations and population size, we will focus mainly on combining different fitness cases. More precisely, we investigate if and how we can improve the resulting controllers and reduce the computation time by constructing well-considered categories of training environments.

Columns 7 and 8 display the results from the evolutionary process. From all three runs, the best performing controllers' fitness on the last category is listed. Remark that the differences in absolute numbers are small however significant, since a difference of 0.001 can still be noticed by observation of the controllers behaviour. Furthermore, the best controllers' fitness of each run is averaged in the column *mean*. Columns 9–12 contains results of verification tests. Conclusions concerning the robustness and generality of the best controller require verification in new environments which were not used during evolution. We considered five environments with the same difficulty level of the environments in the last category of fitness cases. The number of collisions (too close to the wall) and the number of moves aggregated over all five environments are listed. The number of environments (out of five) in which the robot reaches the end in less than 500 moves is indicated as well. Finally the fitness averaged over all 5 verification environments is found in the last column. Note that this was calculated in order to make them comparable over all penalty values.

For the noiseless simulations, experiment 1 using the mixed approach clearly yields the best results. Even with significant time reduction compared to experiments 2 and 3, this setup results in a more robust (all verification environments are successfully completed) and efficient (small number of movements) controller. Therefore it is very beneficial using mixed categories containing enough diversity and increasingly difficult fitness cases. This diversity enables the evolutionary process to build further on more general controllers.

4.2 Preparing for Reality

As stated in literature, noise can improve simulation results and lead to more robust controllers (Jakobi et al., 1995; Bräunl, 2006; Reynolds, 1994). Main argument is that with noise, evolution is no longer able to exploit coincidences in fitness cases only valid in simulation and therefore leads to more robust controllers. Indeed, in the second series of experiments, with noise added to the sensor values, results improved significantly.

Experiment 5 in Table 1 leads to a reasonable controller without collisions, though two verification environments were not solved successfully. However, since entropy is still fairly high, further improvements can be expected. To verify this, in experiment 6 the best run from experiment 5 was allowed to evolve for some more generations resulting in a successful controller which navigates very robustly and efficiently in all verification environments. Important remark is that the mean fitness value from experiment 5 is extremely high, even better than the best results in all other experiments. Therefore the gradual approach is very interesting for this problem domain since most runs will lead to excellent controllers.

This intermediary setup thus provides sufficient knowledge to move on for a more realistic simulation. Next to the noisy sensor values, noise is added to the steering mechanism as well. Furthermore, turns of 15 degrees are used instead of 90. This way, the controller will be able to navigate smoother and adjust for incomplete turns, which are very common in reality. This clearly is a scaled up version of the previous problem. Though, by using exactly the same setup of experiment 5 and augmenting the population size and the number of generations, a very efficient and robust solution was evolved. This solution is able to fulfil, with 4 collisions in total, all tested environments, whether they were used during evolution or not. An example trail of this controller is depicted in Figure 2(a).

An interesting remark is that the underlying strategy of nearly all successful controllers of the experiments is wall following. Mostly, the left wall is followed, navigating to the end of the corridor system without turning and proceeding in the wrong direction. This general strategy is a nice example of evolutionary processes to come up with simple yet general and efficient solutions.

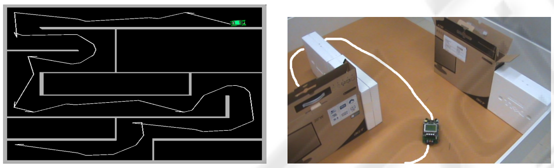
4.3 Transfer to Real World

When transferring the best controller thus far to reality, performance slightly decreased. This was mainly

Table 1: Results of the first series of experiments. The number of generations and the population size are denoted by G respectively P, the penalty is referenced by Pen, and collisions is abbreviated to Coll. Experiments 1–4 don't use the *medium* constant. Experiment 6 is a continued evolution of the best controller from experiment 5 and hence has no mean fitness.

		Parameters				**Evolution**		**Verification**			
	Nr	G	P	Pen.	Fitness c.	Best	Mean	Coll.	Moves	/5	Fitness
no noise	1	50	300	1	Mixed	0.90769	0.86914	25	1087	5	0.91402
no noise	2	50	500	1	Standard	0.90933	0.85658	31	1667	3	0.88443
no noise	3	100	200	1	Standard	0.90341	0.85866	126	1356	5	0.89780
noisy	4	50	300	3	Mixed	0.90922	0.86332	25	1777	2	0.85497
noisy	5	50	300	3	Gradual	0.91174	0.91077	0	1575	3	0.88553
noisy	6	68	300	3	Gradual	0.91234		2	871	5	0.91711

caused by the fact that the real PSD sensors return increasing values when approaching a wall from a certain distance. After increasing the lowest threshold from 75 to 100 (the distance under which the sensor values become unreliable), this problem was solved. The robot was able to navigate efficiently through previously unseen environments. The robot successfully drives straight ahead, adjusts where necessary and most curves are taken smoothly. Nevertheless we noted slightly more collisions than in simulation. Figure 2(b) shows the real robot in a test environment. Remark that the left wall following is illustrated by omitting some right walls, yet resulting in a successful navigation.



(a) (b)

Figure 2: Best controllor found. (a) The robot trail in simulation. (b) The real EyeBot in a test environment. The white line denotes the robot trajectory.

5 CONCLUSIONS

We demonstrated that, even with a basic PC and limited computation time, GP is able to evolve controllers for corridor following in a simulation environment by using a gradual form of layered learning. Moreover, this controller was transferred successfully to reality.

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