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# Analysis of Evolved Sensory-Motor Controllers

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## Abstract

We present results from the concurrent evolution of visual sensing morphologies and sensory-motor controller-networks for visually guided robots. In this paper we analyse two (of many) networks which result from using incremental evolution with variable-length genotypes. The two networks come from separate populations, evolved using a common fitness function. The observable behaviours of the two robots are very similar, and close to the optimal behaviour. However, the underlying sensing morphologies and sensory-motor controllers are strikingly different. This is a case of convergent evolution at the behavioural level, coupled with divergent evolution at the morphological level.

The action of the evolved networks is described. We discuss the process of analysing evolved artificial networks, a process which bears many similarities to analysing biological nervous systems in the field of *neuroethology*.

## 1 Introduction

As part of our ongoing work in using genetic algorithms to develop ‘neural’ networks which act as controllers for visually guided robots, we have analysed the final evolved networks in order to identify how they work. This is an essential step in moving away from the treatment of artificially evolved neural networks as magical black boxes.

The mathematics of our particular style of network are such that it would be difficult or impossible to derive closed-form equations describing the action of the networks.<sup>1</sup> Instead, we analyse our networks using techniques analogous to those used in the study of biological sensory-motor neural systems. In trying to understand how our artificially evolved networks generate behaviours in the robot, we are performing a task directly analogous to the task faced by biological scientists in the field of *neuroethology*. (Neuroethology is the study of the neural mechanisms underlying the generation of a creature’s behaviour; see e.g. [7].) For further details of the link between neuroethology and artificial neural network research, see [8, 2].

We view the networks we evolve as continuous dynamical systems, rather than as computational devices transforming between representations: inputs to the system might *perturb* the trajectory of the network in state space, so it enters a different state which

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<sup>1</sup>For example, the transfer functions used in our model neurons are all nonlinear with discontinuities in the first derivative, and non-Gaussian noise is introduced at a number of points in the sensory-motor system.

might be interpreted by an external observer as a new behaviour. We find this perspective less encumbering than the traditional computational perspective, and also less amenable to the use of potentially misleading intentional language (see e.g. [3, 19, 17] for further discussion of the benefits of adopting a dynamical systems perspective).

Most of this paper deals with analysing two networks from separate populations, each evolved to perform the same task. We demonstrate that although the final observed behaviour from the two networks is very similar, the underlying mechanisms are remarkably distinct: the two populations converged at the behavioural level, while maintaining distinct sensory-motor morphologies.

The primary focus of this paper is on analysing networks resulting from the evolutionary processes.



The rear wheel is a large ball-bearing freewheel castor. The robot is equipped with tactile sensors giving a six-bit input vector: it has four radially oriented binary ‘whiskers’, and binary ‘bumper-bars’ at front and rear. For illustration, see [11]. The simulated robots are accurate models of such a vehicle, with the addition of visual sensors.

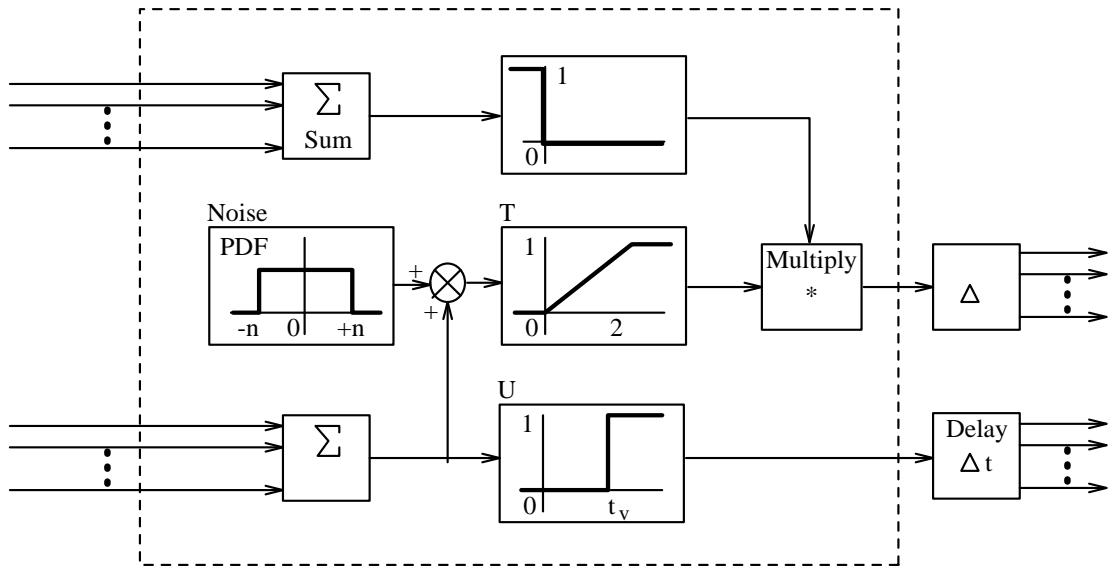
While our early tactile-only work involved the robot roving around cluttered office-like environments, all the visually-guided tasks have been set in a closed circular arena. The arena has black walls, while the floor and ceiling are white. There are no obstacles: the arena contains only the robot.

The visual input from each of the robot’s photoreceptors at any particular moment in time depends on the robot’s visual morphology, and the position and orientation of the robot in the arena. Essentially, the population of robots has to evolve to correlate the visual input with its position in the world, so as to satisfy whatever fitness evaluation we impose on the robot’s behaviours. As was demonstrated in [11], visual guidance emerges without explicit reference to vision in the evaluation process. In the early stages of evolution, the tactile sensors can be useful in helping correlate visual input with the robot’s position. However, as will be demonstrated below, later generations typically tend to rely *only* on visual information.

### 2.3 Networks and the ‘Neuron’ Model

The controller networks are continuous dynamical systems, built from model ‘neurons’ (i.e. processing units), which can have asymmetric and recurrent connectivities. Activation values (all real numbers in the range  $[0, 1]$ ) are transmitted between units along the connections, all of which have a weight of one, and impose a unit time delay in transmission. Fully asynchronous processing is simulated by fine-time-slice approximation techniques with random variation in time-cycling on each unit to counter periodic effects.

The neuron model has separate channels for excitation and inhibition. A schematic of the operations for one unit is shown in Figure 1. The inhibition channels operate as a ‘veto’ or ‘grounding’ mechanism: if a unit receives *any* inhibitory input, its excitatory output is reduced to zero (but it can still inhibit other units). Excitatory input from sensors or other units is summed:



The initial random genotypes are created to encode for networks with all the necessary input and output units, and either one or two hidden units. Because we use Harvey's







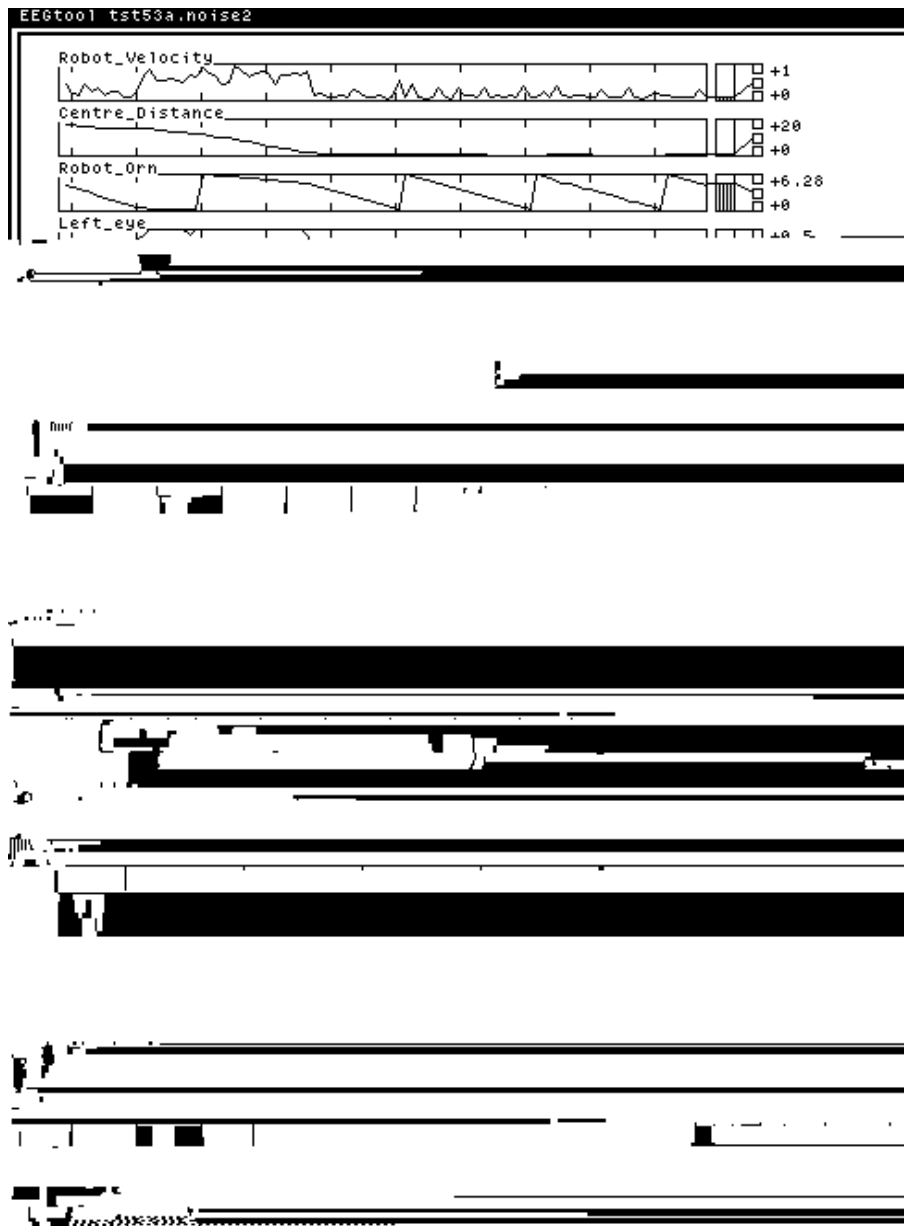
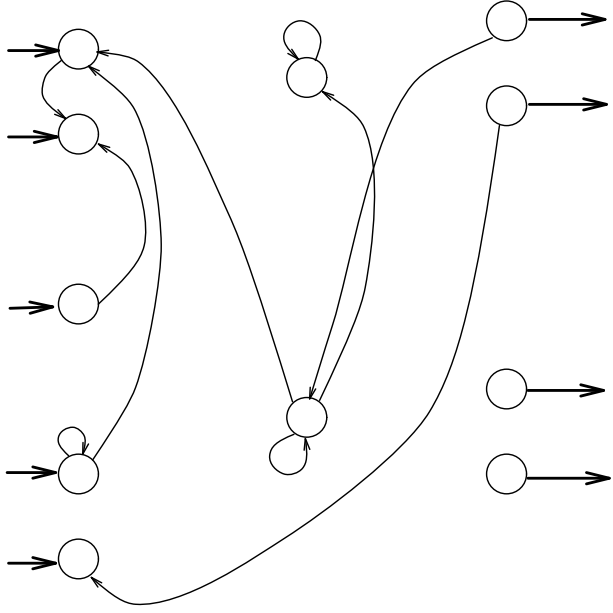


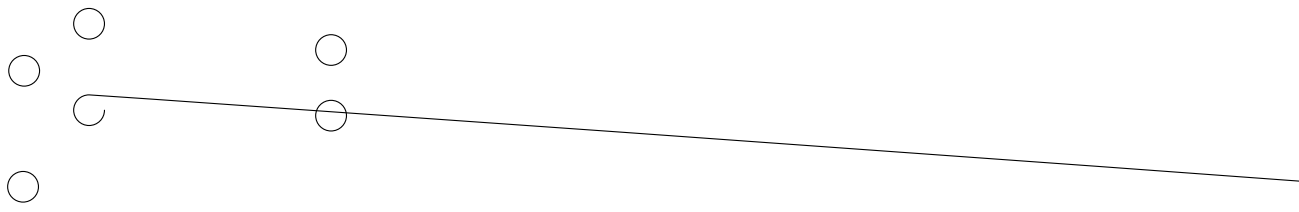
Figure 4: Record of observables and activity levels for the activity illustrated in Figure 2. Horizontal axis is time. From top: robot's velocity; robot's orientation; visual input to left photoreceptor; visual input to right photoreceptor; output of left wheel; output of right wheel; activity levels in the control network units 0 to 14.

unit) is now acting as a second-order 'interneuron'.





There follows a short explanation of the action of the network, with reference to Figures 6 to 8. All units initially have zero



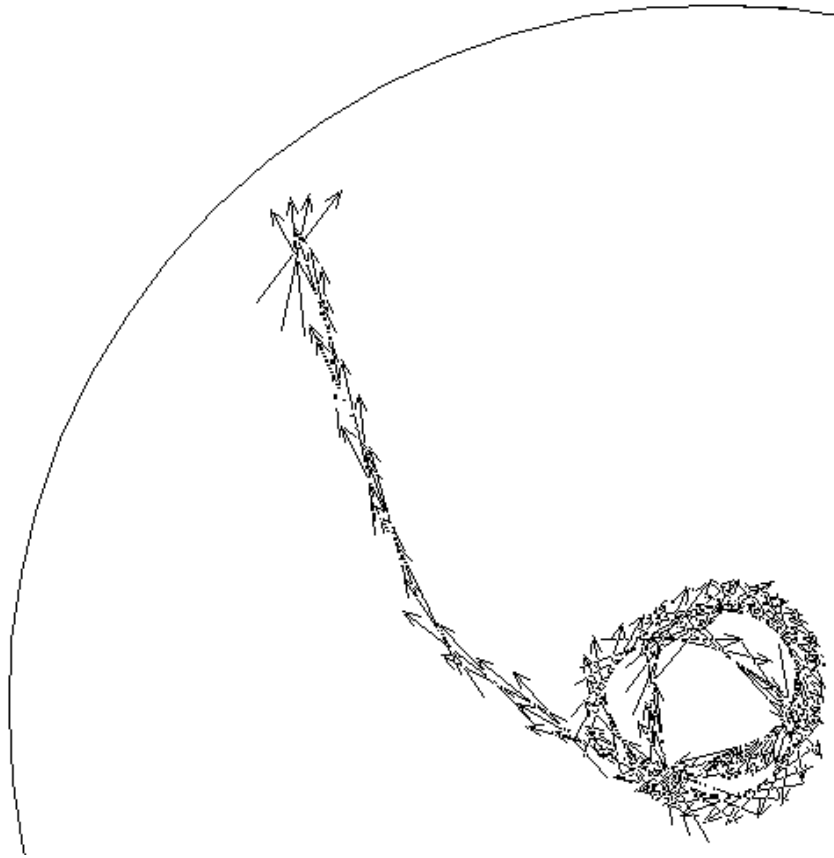


Figure 13: Typical behaviour of the C2 controller, with noise. Display format as for Figure 2. The robot starts near the edge of the arena, moves to the centre, and then spins on the spot. As can be seen, the C2 controller drives the robot in reverse (backwards).



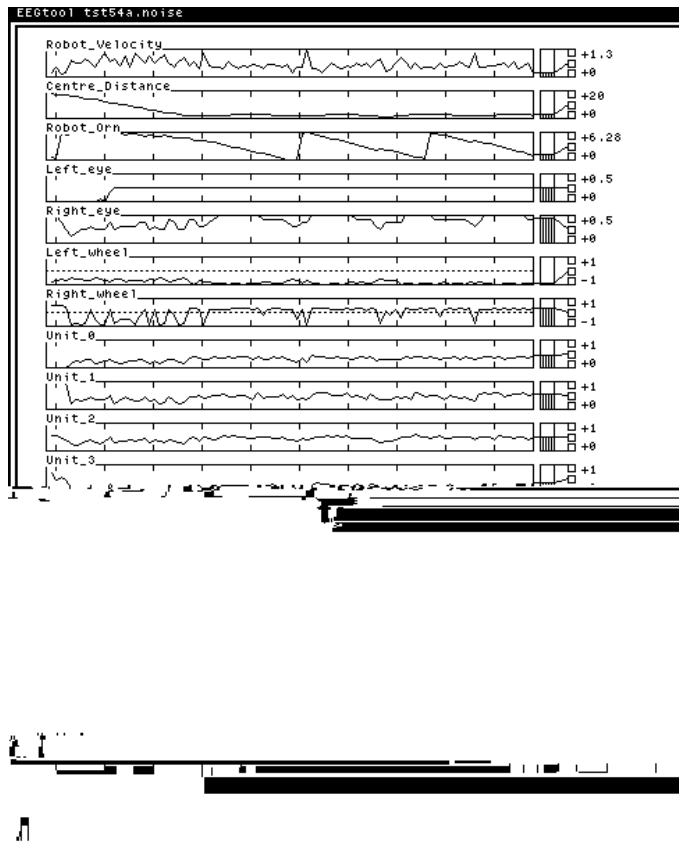


Figure 16: Record of observables and activity levels for the (with-noise) activity illustrated in Figure 13.

Examination of the activity traces (both with and without noise) allow the analysis of C2 to be taken further. First, unit 6 provides only veto outputs to other units, and it is clear from Figures 16 and 18 that the total input to unit 6 is never sufficiently high to go over the veto-output threshold, so unit 6 is effectively redundant in the context of producing the behaviours illustrated in the figures. For this reason, unit 6 can be eliminated and the C2 network re-drawn accordingly: see Figure 19. This implies that C2 is employing ‘monocular’ vision, using just the input from the right-hand photoreceptor to perform visual guidance.

To further elucidate how C2 operates, one more analysis technique can be used to improve the legibility of the network diagrams: it can be seen in Figure 19 that some units receive activation from only one unit, pass that activation through the excitationFiguract3s6



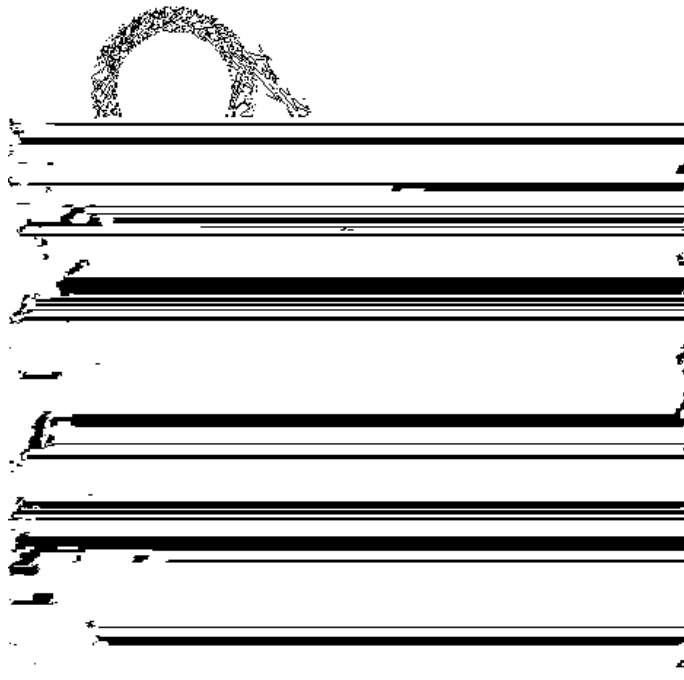


Figure 17: Typical noise-free behaviour of the C2 controller. Display format as for Figure 2.

of one and impose a unit time delay: the use of distributor units allows for “virtual connections” to evolve which have different weights or delays. Similarly, if there are  $N$  excitatory links from unit  $n$  to unit  $m$ , then they can together be considered as a single “virtual connection” with weight  $N$  and unity delay: for example, in Figure 19, the two connections from unit 10 to unit 1 form a virtual connection of weight 2.0.

Thus, distributor units and multiple connections between units can be eliminated from the network diagrams, and the network re-drawn with the various weights indicated: the final “weighted” version of C2 is shown in Figure 20. The “weighted” forms of the networks are useful analytic tools: from Figure 20 it is fairly clear that the operation of C2 depends crucially on unit 1: if there is sufficient visual input to the right photoreceptor (through unit 7), unit 1 inhibits unit 15, and the robot enters a low-radius turn: the turn is only sustainable when the robot is within the central isoluminance zone; at other locations the turn will reduce visual input, thereby preventing continued inhibition of unit 15, so the robot’s path to the centre is a straight line punctuated by brief bursts of low-radius turns as unit 15 is intermittently inhibited.

From the above analysis, it is clear that while C2 produces similar observable behaviour to C1, the internal mechanisms responsible for generating these behaviours operate on markedly different principles. This is discussed further below.

### 3.3 Discussion

The primary factor of note in comparing controllers C1 and C2 is that, although they were evolved separately, they had indistinguishable initial populations (i.e. both populations

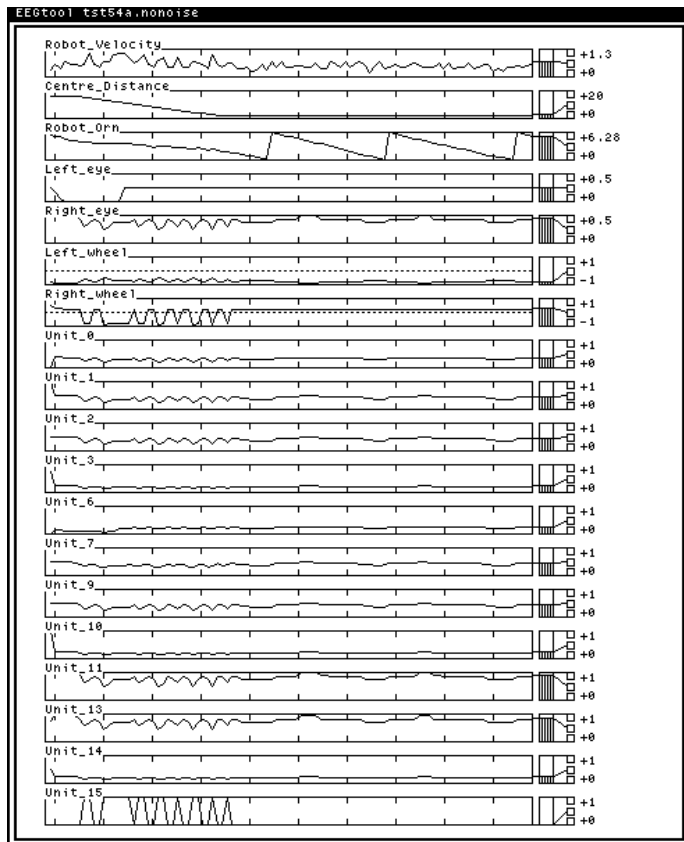


Figure 18:

the same task. This is an accordance with the principles underlying the SAGA genetic algorithm we used [14].

Such networks exhibited graceful degradation in the presence of increased noise. During evolution, an internal noise distribution of  $\pm 0.1$  was used; we found the robots could still approach the centre with noise distributions as high as (in the case of C1)  $\pm 0.8$ : see [10].

In almost all of the networks we have analysed, there has been no clearly identifiable structure. C2 is a clear example. Nevertheless, we find the structure of C1 intriguing: the role of unit 2, which can disable unit 12 (and, in doing so, also disables unit 14) seems vaguely reminiscent of a two-layer subsumption architecture, in that units 12 and 14 are responsible for generating the ‘spin’ behaviour; a behaviour ‘subsumed’ by the approaching behaviour. See [4, 5] for details of subsumption architectures, and e.g. [12] for an example of a two-layer subsumption visually guided robot. Clearly, it is too early to make strong claims, but we suspect that it is not infeasible that subsumption-style architectures could evolve within our scheme: because we use *truly* incremental evolution, it is possible that mechanisms generating elementary low-level behaviours evolve first, with structures responsible for generating higher-level behaviours coming later. Such an evolutionary trajectory would make sense, given the need for satisfying intermediate viability (i.e. good controllers have to be built from minor changes to earlier slightly-less-good controllers – there is no opportunity for a total re-design from scratch). This may go some way toward explaining why subsumption-style controllers (i.e. behavioural decomposition) have been identified in biological creatures [1, 9].

It is important to note that both the C1 and C2 controllers were evolved in a fixed-size arena, and hence are dependent on the ratio of the height of the arena’s walls to the diameter of the floor. It is this ratio, combined with the controller’s particular visual morphology, that determines the brightness values in the central isoluminance zone discussed in Section 3.1. Work is currently underway on varying the arena dimensions on each evaluation, in order to evolve truly general-purpose controllers which should operate in *any* circular arena.

### 3.4 Conclusion

We have examined two controller networks evolved using incremental genetic algorithms, and found a form of speciation, in that two controllers evolved in separate populations produce convergent behaviours while employing divergent mechanisms for generating those behaviours. Nevertheless, both controllers perform in a close-to-optimal manner, and are robust in the presence of noise. While both the robot’s world and behaviours are relatively trivial, we can see no reason why our methods, suitable extended beyond the specifics described here, should not prove successful in increasingly complex domains.

The important achievement in this paper is not that we got a simulated robot to perform a particular visually guided behaviour, nor that the behaviours were generated by evolved neural networks. What matters is that we haven’t treated the evolved networks as magic black boxes. We specified *what* the robots should do, but not *how* the controllers work. Nevertheless, analysis lets us know what’s going on inside the box. And, for the record, we don’t think that it’s computation (at least, not in the conventional sense).

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