

A Method for Isolating Morphological Effects on Evolved Behaviour

Josh C. Bongard Rolf Pfeifer

Artificial Intelligence Laboratory

Department of Information Technology

University of Zürich

Winterthurerstrasse 190, Zürich, Switzerland

{bongard|pfeifer}@ifi.unizh.ch

Abstract

As the field of embodied cognitive science begins to mature, it is imperative to develop methods for identifying and quantifying the constraints and opportunities an agent's body places on its possible behaviours. In this paper we present results from a set of experiments conducted on 10 different legged agents, in which we evolve neural controllers for locomotion. The genetic algorithm and neural network architecture were kept constant across the agent set, but the agents had different sizes, masses and body plans. It was found that increased mass has a negative effect on the evolution of locomotion, but that this does not hold for all of the agents tested. Also, the number of legs has an effect on evolved behaviours, with hexapedal agents being the easiest for which to evolve locomotion, and wormlike agents being the most difficult. Moreover, it was found that repeating the experiments with a larger neural network increased the evolutionary potential of some of the agents, but not for all of them. The results suggest that by employing this methodology we can test hypotheses about the behavioural effect of specific morphological features, which has to date eluded precise quantitative analysis.

1. Introduction

It has been over a decade since the idea of embodied AI was first introduced (for a review, see (Brooks, 1991)). Since that time, the belief that choices regarding an agent's or robot's body greatly affect its possible behaviours has come to be widely accepted, but relatively little quantitative data has been collected to support this view. One of the reasons for this is that embodied AI relies heavily on the synthetic methodology. That is, all aspects of agent design are interdependent, so building and then analyzing the behaviour of complete agents is the best way to generate autonomous, intelligent agents (Pfeifer and Scheier, 1999). However, it is then difficult to attribute the effect, if any, a part of an agent has on its resulting behaviour. This is complicated by the fact that designing,

constructing and analyzing an autonomous, embodied agent takes a long time, even if computer simulation is employed.

Yet, with the recent advent and maturation of physical simulation, it has become possible to rapidly build and test the behaviours of embodied, situated agents. Such simulations are often coupled with artificial evolution. Some experiments focus on the evolution of controllers for a fixed agent design (Ijspeert and Arbib, 2000, Reil and Massey, 2001) or slight modification of a generic body plan (Bongard and Paul, 2001), or on the combined evolution of both the morphology and controller of the agent (Sims, 1996, Ventrella, 1996, Kikuchi and Hara, 1998, Lipson and Pollack, 2000, Komosinski, 2000, Bongard and Pfeifer, 2001, Taylor and Massey, 2001).

In the latter case, it has been demonstrated that agents with widely differing morphologies can accomplish the same task. However, little work has focussed on which properties of an agent's morphology make it suitable for a given task. An exception is the work by Lund *et al* (Lund *et al.*, 1997), in which it was shown that for wheeled robots, a correlation between body size, wheel base and sensor range exists.

This paper investigates the behavioural effect of morphology by comparing a set of legged agents with the same number of sensors, actuated joints and neural network architectures, but differing body plans. Most papers published in the artificial life and adaptive behaviour literature study a single agent or robot, and attempt to draw conclusions from the resulting behaviour. However, Terzopoulos *et al* described learned controllers for three different fish morphologies in (Terzopoulos *et al.*, 1996); Cruse *et al* described the commonalities and difference between locomotion strategies in real animals based on their biomechanical properties and environment (Cruse, 1991); and Cecconi *et al* (Cecconi and Parisi, 1991) evolved controllers for two grasping robots with different morphologies, but the second agent had a more complex neural network architecture.

The change in behaviour caused by different morphologies has been made clear by experiments in which evolved controllers are transferred from one type of robot to another (Floreano and Mondada, 1998), and from simulated

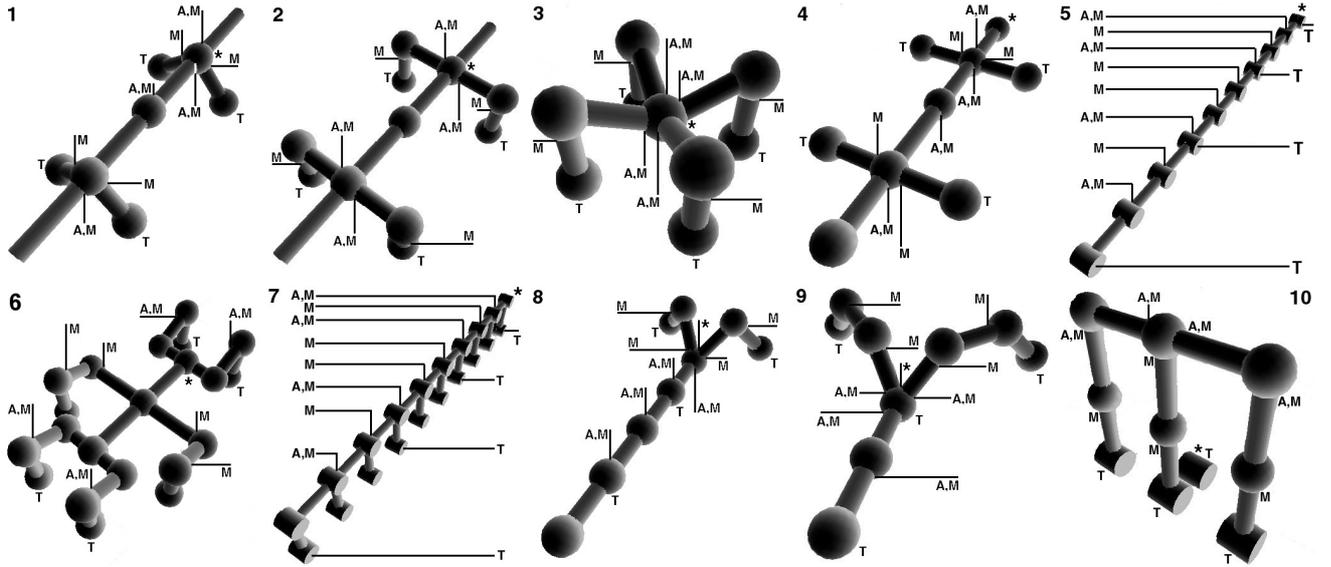


Figure 1: **The agents used for comparison.** Each agent contains four touch sensors (T), four angle sensors (A), and eight motors (M) actuating eight one degree-of-freedom joints. Fitness is based on the forward displacement of one of the body parts (indicated by *) contained in the agent over a fixed period of time.

agents to real robots (Miglino et al., 1995, Jakobi, 1997, Tokura et al., 2001). However, specific claims as to which aspects of the morphology cause the observed behavioural changes are not provided. Also, work has been done on heterogeneous robot groups (Parker, 1994), in which the actual morphologies of the robots differ, but there has been little or no mention of how particular aspects of the different robot morphologies affected the overall group task performance. Balch (Balch, 2000) has formulated a measure for determining the heterogeneity between robot groups, but this measure does not rely on, or clarify correlations between individual robot morphology differences, and differences in behaviour competencies.

In what follows, we introduce a methodology that can be used to isolate the effect of particular morphological properties—such as total mass, mass distribution (Paul and Bongard, 2001), size or stability—have on the evolution of agent behaviour. In the next section, this methodology is described in detail. In section 3, results are presented using this methodology. In section 4 the implications of this work for generalizing adaptive behaviour results to entire classes of agents are discussed. The final section provides some concluding comments and directions of future research.

2. Methods

In order to compare morphological effect on behaviour, 10 legged agents were constructed and tested in a physics-based, three-dimensional simulation toolkit developed by MathEngine PLC¹. The morphologies of the ten agents are shown in Fig. 1. Each of the connecting cylinders has a radius of

10cm and a length of 50cm. Each of the spheres has a radius of 20cm. Each of the small cylinders contained in the two segmented agents and the tripod (agents 5, 7 and 10 in Fig. 1) has a radius of 20 cm and a length of 40cm. All body parts have a mass of 1kg.

Each agent contains a total of four touch sensors, four angle sensors, and eight actuated, one degree-of-freedom joints, irrespective of its number of legs or body plan.

The touch sensors return a maximum positive signal if the body part in which they are contained is in the contact with the ground plane, and return a maximum negative signal otherwise. The angle sensors return a signal commensurate with the joint’s current angle. For example, the sensors emit a maximum negative signal when the joint to which they are attached is at maximum flex, a zero value when the joint angle is equal to the original setting (shown in Fig. 1), and a maximum positive signal when the joint is at maximum extension.

The joints can rotate between $-\frac{\pi}{4}$ and $\frac{\pi}{4}$ radians of their original setting. Each of these joints is actuated by a torsional motor, which receives desired angle settings from the neural controller, and exerts torque proportional to the difference between the current joint angle and the desired angle using

$$\tau_{t+1} = \max(I(\omega_t - k(\theta - \theta_d)), \tau_{max}),$$

where θ is the actual joint angle, θ_d is the desired joint angle, τ_{max} is the maximum torque ceiling, $\omega = \dot{\theta}$, and I is the inertia matrix.

All motors in all the agents have the same maximum torque ceiling, as well as the same damping properties, which were tuned by hand to disallow extreme actions such as jumping or hopping in all 10 agents. However, combined motor ac-

¹Final beta release of MathEngine SDK; www.cm-labs.com

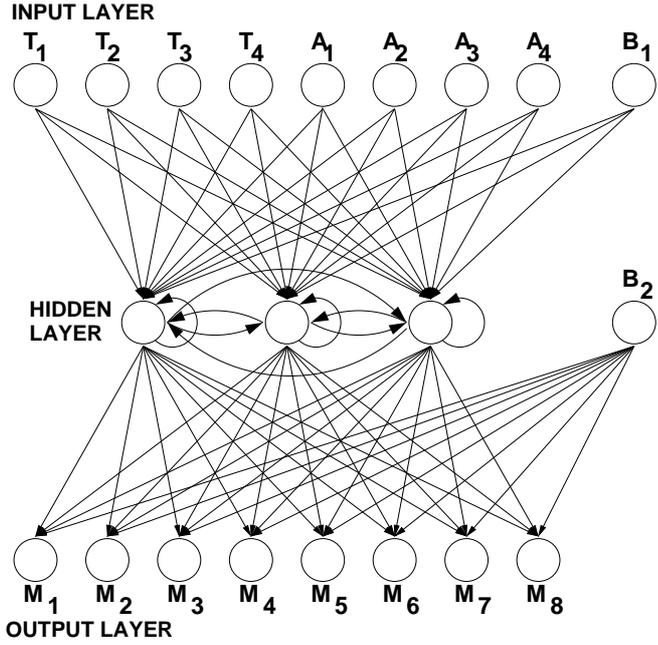


Figure 2: **The neural network architecture.** The four touch sensor signals are scaled and passed to input neurons T1–T4, and the angle sensors are scaled and passed to input neurons A1–A4. The output neuron values (M1–M8) are translated from desired angles into torque by the eight motors of the agent.

tion was sufficient for walking, and in some cases dynamic gaits in which the agent’s centre of mass passed outside of the support polygon created by its contacts with the ground plane emerged.

The four motors actuating agent 1’s four legs rotate through the transverse plane, while its four spinal motors rotate through the frontal plane. In agent 2, the four knee joints rotate through the transverse plane, and the four shoulder joints rotate through the frontal plane. The two joints on each leg of agent 3 rotate through the plane defined by that leg. The four shoulder joints in agent 4 rotate through the transverse plane, and the four spinal joints rotate through the frontal plane. The eight spinal joints in agents 5 and 7 rotate through the sagittal plane. All eight joints on the hexapedal agent (agent 6) rotate through the sagittal plane. The joints on the arms of agents 8 and 9 rotate through the plane defined by those arms; the spinal joints rotate through the sagittal plane.

The knee and hip joints on each of the three legs of agent 10 rotate through the sagittal plane, and the two pelvic joints rotate through the transverse plane.

All of the agents are controlled by a partially recurrent neural network, the architecture of which is shown in Fig. 2. The input and output layers correspond to the sensor and motor array, respectively. There is an additional bias neuron at the input and hidden layers that outputs a constant signal of 1. The input layer is fully connected to the hidden layer, and the hidden layer is fully connected to the output layer. In addition, the hidden layer is fully, recurrently connected.

At each time step of the simulation of an agent’s behaviour, the eight sensor signals are scaled to floating-point values in $[-1.0, 1.0]$, and supplied to the input layer. The values are propagated to the hidden and output neurons. The hidden and output neurons scale their incoming values using the activation function

$$O = \frac{2}{1 + e^{-a}} - 1,$$

where a is the summed input to the neuron.

A fixed length, generational genetic algorithm is used to evolve locomotion for the 10 agents. Genomes encode the 68 synaptic weights for the neural network as floating-point values, which can range between -1.00 and 1.00 . For the experiments reported in the next section, each evolutionary run was conducted using a population size of 300, and was run for 200 generations. At the end of each generation, strong elitism was employed: the 150 fittest genomes were copied into the next generation. Tournament selection, with a tournament size of 3, is employed to select genomes from among this group to participate in mutation and crossover. 38 pairwise one-point crossings produce 76 new genomes. The remaining 74 new genomes are mutated copies of genomes selected from the previous generation: an average of three point mutations are introduced into each of these new genomes, using random replacement.

In the second set of experiments, the hidden layer was expanded to include five, instead of three hidden nodes. This increases the synapse count from 68 to 118, and thus the genome length from 68 to 118. However, except for the increase in genome length, no other genetic algorithm parameters were altered during this second set of experiments.

3. Results

For each of the 10 agents, 30 evolutionary runs were performed, in which fitness was set to the forward displacement of the selected body part (see Fig. 1) in the agent after 500 time steps of the physical simulation. During each time step of the evaluation, sensor readings are taken, the neural network is updated, the motor commands are translated into the torques. Also the body parts’ positions, velocities and orientations are updated based on these torques as well as on external forces such as gravity, inertia, friction and collision or contact with the ground plane.

The highest fitness obtained in each generation was recorded, as well as the corresponding genome. For each agent, these fitness values from the 30 runs were averaged together, and are shown in Fig. 3.

Within each set of 30 evolutionary runs, the run which produced the fittest agent was found, and the time steps for which the agent’s body parts were in contact with the ground plane were recorded. The footprint graphs for these agents from each agent type are shown in Fig. 4.

In order to account for the performance differences indicated in Fig. 3, various morphological aspects of the agents were compared against their average evolutionary perfor-

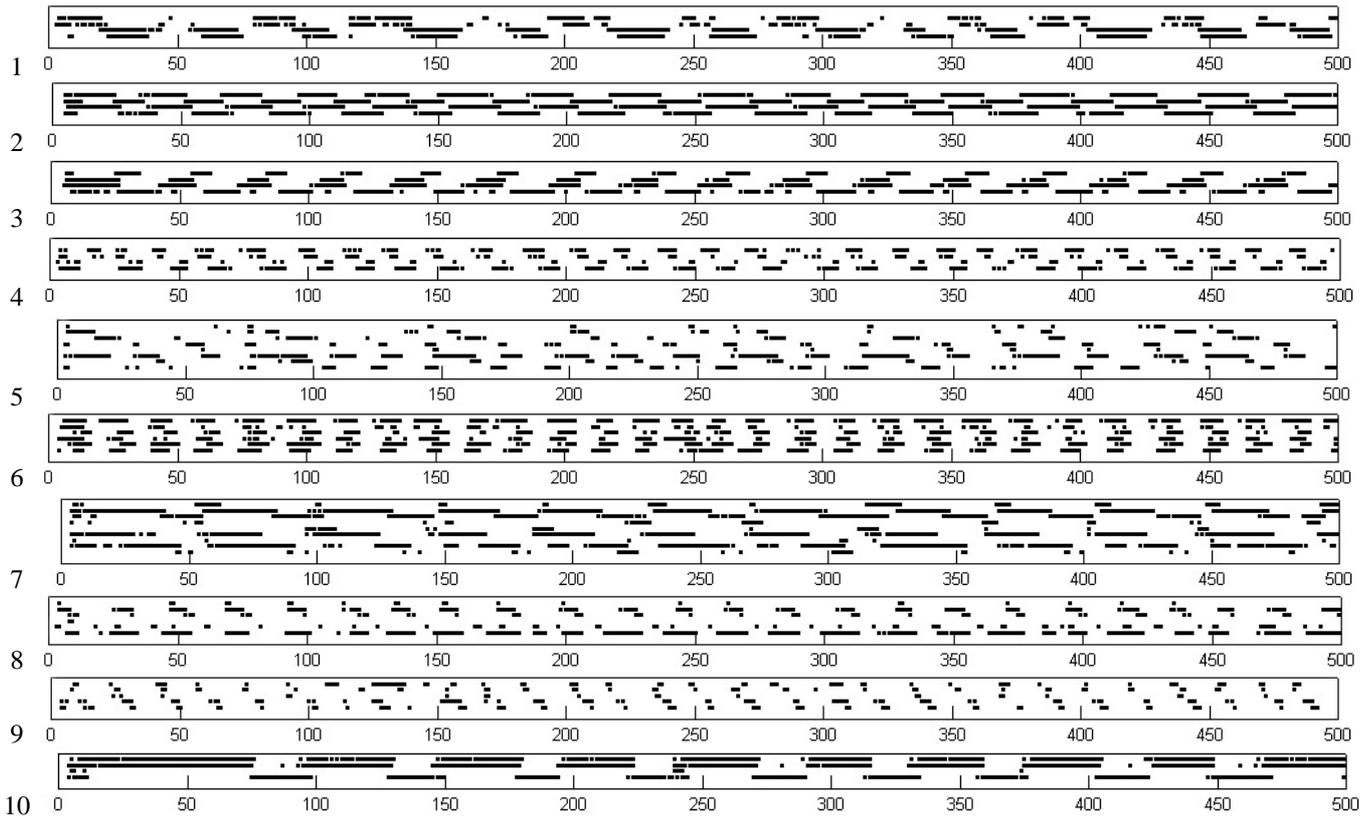


Figure 4: **Footprint graphs produced by the most fit agent of each type.** Numbers indicate agent index as given in Fig. 1. The horizontal axis indicates time; the rows arranged along the vertical axis correspond to one of the body parts comprising the agent that comes in contact with the ground plane for at least one time step during evaluation. Black bars indicate time periods for which the body part is in contact; the white gaps indicate periods in which it is not in contact with the ground plane.

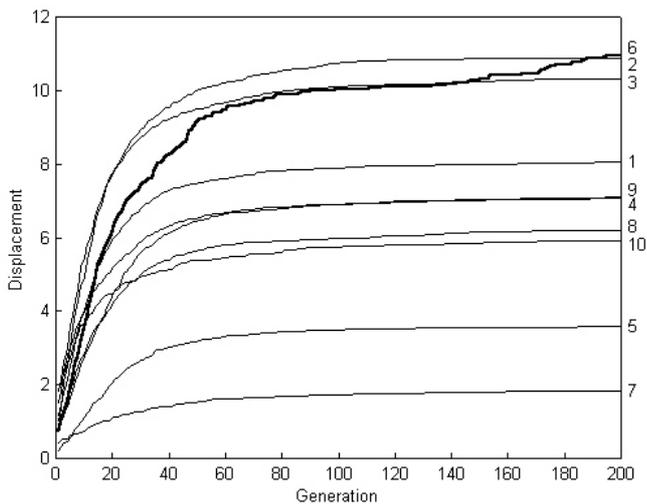


Figure 3: **Average evolutionary performance of the 10 agents.** The curves are averages of the best fitness curves taken over the 30 evolutionary runs for each agent. The numbers to the right indicate to which agent that curve belongs (i.e., agents 6 and 2 performed the best). Displacement is in meters.

mance. Average evolutionary performance was computed by collecting the best fitness values achieved at the end of each of the 30 evolutionary runs, and averaging them. Fig. 5 plots the agent’s total mass against average evolutionary performance. Fig. 6 plots the number of points of contact of the agent with the ground plane against average evolutionary performance.

Finally, a second set of experiments was conducted in which the hidden layer was expanded from three neurons to five neurons. Thirty evolutionary runs were again performed for each agent type, and the fittest genome was retained, and its fitness recorded, after each generation. The best fitness achieved at the end of each run was recorded and averaged within the set of 30 runs, for each agent. Fig. 7 plots the performance increase (or decrease) for each agent type realized by the increase in neural network size.

4. Discussion

Fig. 4 shows that most of the agents achieve a relatively rhythmic gait during evolution, with the exception of the segmented agent 5. For example, the tripedal agent (agent 10) keeps its left and right feet on the ground plane while its central leg swings into the air, and with the aid of the momentum

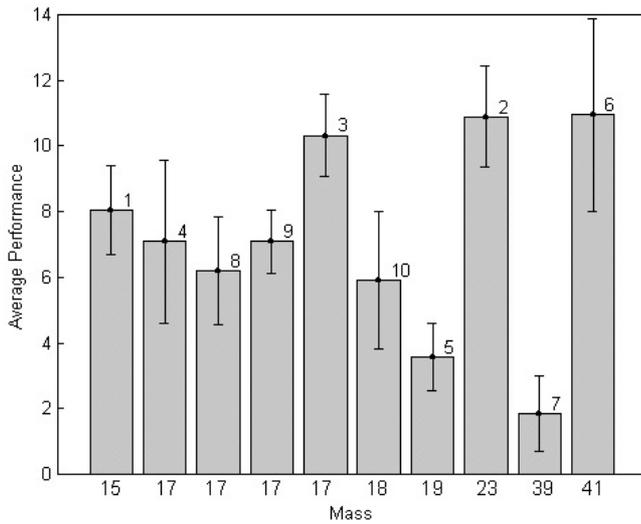


Figure 5: **Mass versus evolutionary performance.** The horizontal axis indicates the total mass of the agent, in kilograms. The vertical axis indicates the average displacement of the targetted body part for each agent type, in meters. The numbers above the bars indicate the agent index as given in Fig. 1. The error bars are two standard deviation units in length.

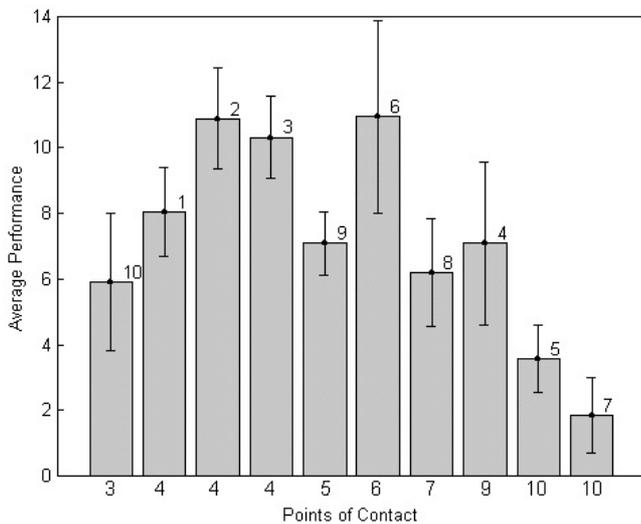


Figure 6: **Points of contact versus evolutionary performance.** The horizontal axis indicates how many body parts of the agent can contact the ground plane. The vertical axis indicates the average displacement of the targetted body part for each agent type, in meters. The numbers above the bars indicate the agent index as given in Fig. 1. The error bars are two standard deviation units in length.

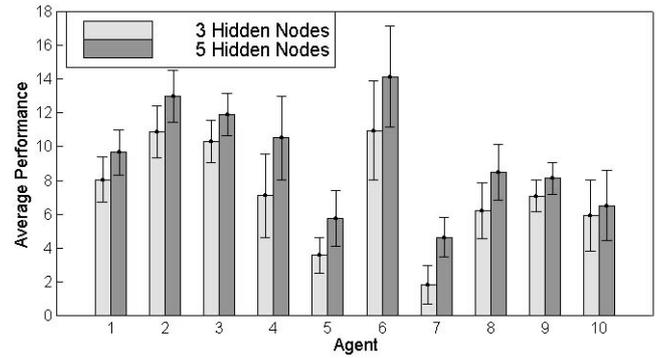


Figure 7: **Change in performance based on addition of hidden neurons.** The light coloured bars indicate the average evolutionary performance for that agent using three hidden neurons. The dark coloured bars indicate average performance for that agent using five hidden neurons. Numbers along the horizontal axis denote the agent's index number, as denoted in Fig. 1. The error bars are two standard deviation units in length.

of the return stroke falls into a regular gait where the left and right legs move in almost perfect synchrony (lowest panel, Fig. 4).

As can be seen from Fig. 3, it is much easier to evolve locomotion for two of the quadrupedal agents (agents 2 and 3) and the hexapedal agent (agent 6) using the genetic algorithm and neural network architecture reported here, than is the evolution of locomotion for the segmented agents (agents 5 and 7). Because the evolutionary method and neural controllers were kept constant for all agents, a morphological explanation must be found to account for this performance discrepancy.

One hypothesis is that the greater the number of legs an agent has, the more difficult it is to evolve a neural controller to coordinate them, or they generate more friction with the ground, and thus make locomotion more difficult.

However, Fig. 6 seems to refute this hypothesis, as there seems to be an inverse U-shape relationship between performance and leg number: performance increases from the tripedal agent (agent 10) up to the hexapedal agent, and then decreases again as the number of points of contact increases. This may be a general trend, and needs to be tested by including more agents in the group, such as bipedal and octapedal agents.

An alternative hypothesis is that the segmented agents have larger masses, and because the number of motors and the torque ceiling is kept constant across agents, it may simply be more difficult for the heavier agents to locomote. This hypothesis seems to be supported by the data reported in Fig. 5, because there is a partial negative correlation between mass and evolutionary performance. However, the three best agents (agents 2, 3 and 6) run against this apparent correlation, suggesting that mass is a necessary, but not a sufficient morphological explanation for the observed performance differences, and that six legs may be an optimal configuration

for this experimental setup. We can envisage several other morphological explanations that could be tested using this method: static stability, dynamic stability, and orientation of joints are just a few possibilities.

Aside from isolating and testing hypotheses about specific morphological characteristics, by experimenting with sets of agents instead of just a single agent, we can measure the general effect of controller and evolutionary method choices, not just how they affect a particular agent. For example, Fig. 7 shows that by increasing the size of the neural network by adding hidden neurons is a great advantage for the segmented agents with many similar parts, helps somewhat with the other agents, but has no significant advantage for the tripedal agent. The advantage for the segmented agents is made more clear in Fig. 8, where the best evolved gait for agent 5 using three hidden neurons is contrasted against the best evolved gait using five hidden neurons. The first gait allowed the agent to travel 2.45 meters in 500 time steps; the second gait allowed the agent to travel 7.58 meters. It can be seen that in the first case the best gait has not yet achieved rhythmicity, whereas the second gait is much more rhythmic. Note also that despite hand-tuning the maximum motor torques, the second gait has achieved jumping: there are periods of time for which no part of the agent is in contact with the ground plane.

The large performance increase observed for the segmented agents lends support to the hypothesis that segmented animals require multiple, modular neural components in order to achieve travelling waves of muscular contraction in order to move (Ijspeert and Arbib, 2000). Our result also agrees with that of Gruau (Gruau and Quatramaran, 1997), who reported that a neural network with 16 hidden nodes was required, in his experimental setup, to evolve locomotion for an eight-legged robot.

By comparing new evolutionary techniques and controller architectures on different agents, it is possible to determine whether any observed gain in performance is general, or is useful only for particular agents. For example in this paper we have demonstrated that increasing network size is useful for segmented agents, but not for the tripedal agent. We hypothesize that if the tripod, which is inherently unstable, were equipped with tilt sensors it may be possible to exploit the extra neural connections for balanced locomotion.

5. Conclusions

In this paper we have introduced a comparative methodology that serves two purposes. First, it can be used to measure how much a particular morphological characteristic will facilitate or hamper the evolution of behaviours for simulated agents. Moreover, because the methodology encompasses a group of agents, it could allow for predictions as to how easy or difficult it will be to evolve the behaviours for new agents, if the new agent shares one of the morphological characteristics with an agent from the original group. For example, because we have found that quadrupeds and hexapods are particularly

good candidates for which to evolve locomotion, given our choice of neural network and evolutionary scheme, we predict that it would be relatively easy to evolve locomotion for new agents with quadrapedal or hexapedal body plans.

Second, by modifying the evolutionary scheme or controller, re-evolving the agents in the set for the same behaviour, and then measuring performance changes, we can begin to understand how particular controller architectures or evolutionary schemes are appropriate—or inappropriate—for particular agents.

As physical simulation becomes more sophisticated and computational power continues to increase, it has become feasible to test hypotheses about adaptive behaviour on a whole class of agents, not just a single instantiation. Moreover, by gaining more specific insights into morphological effects on behaviour, it may become easier to transfer evolved agents from physical simulation to real world robots.

References

- Balch, T. (2000). Hierarchic social entropy: An information theoretic measure of robot group diversity. *Autonomous Robots*, 8(3).
- Bongard, J. C. and Paul, C. (2001). Making evolution an offer it can't refuse: Morphology and the extradimensional bypass. In Kelemen, J. and Sosik, P., (Eds.), *Sixth European Conference on Artificial Life*, pages 401–412.
- Bongard, J. C. and Pfeifer, R. (2001). Repeated structure and dissociation of genotypic and phenotypic complexity in artificial ontogeny. In Spector, L. and Goodman, E. D., (Eds.), *Proceedings of The Genetic and Evolutionary Computation Conference, GECCO-2001*, pages 829–836.
- Brooks, R. A. (1991). New approaches to robotics. *Science*, 253:1227–1232.
- Cecconi, F. and Parisi, D. (1991). Evolving organisms that can reach for objects. In Meyer, J. A. and Wilson, S. W., (Eds.), *Proceedings, From Animals to Animats*, pages 391–399.
- Cruse, H. (1991). Coordination of leg movement in walking animals. In Meyer, J. A. and Wilson, S. W., (Eds.), *Proceedings, From Animals to Animats*, pages 105–119.
- Floreano, D. and Mondada, F. (1998). Evolutionary neuro-controllers for autonomous mobile robots. *Neural Networks*, 11:1461–1478.
- Gruau, F. and Quatramaran, K. (1997). Cellular encoding for interactive evolutionary robotics. In Husbands, P. and Harvey, I., (Eds.), *Fourth European Conference on Artificial Life*, pages 368–377.
- Ijspeert, A. J. and Arbib, M. (2000). Visual tracking in simulated salamander locomotion. In Meyer, J. A. and

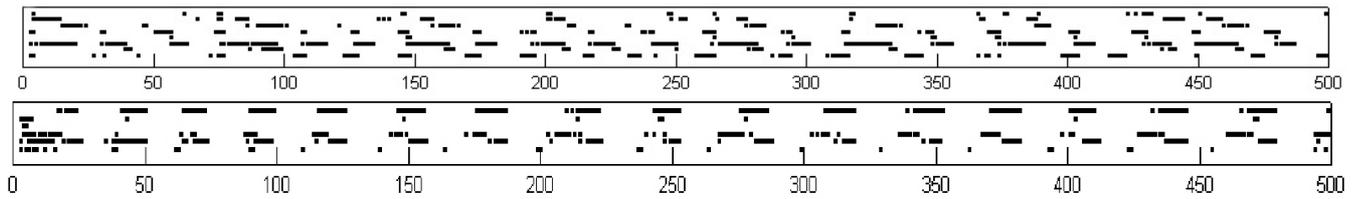


Figure 8: **The best evolved gaits using two different neural networks.** The upper panel shows the best evolved gait for agent 5 using a hidden layer with three neurons. The lower panel shows the best evolved gait for the same agent using a hidden layer with five neurons.

- Berthoz, A., (Eds.), *Proceedings, From Animals to Animats 6*, pages 88–97.
- Jakobi, N. (1997). Evolutionary robotics and the radical envelope of noise hypothesis. *Adaptive Behavior*, 6(1):131–174.
- Kikuchi, K. and Hara, F. (1998). Evolutionary design of morphology and intelligence in robotic system using genetic programming. In Pfeifer, R. and Blumberg, B., (Eds.), *Proceedings, From Animals to Animats 5*, pages 540–545.
- Komosinski, M. (2000). The world of Framsticks: Simulation, evolution, interaction. In *Proceedings, Second Intl. Conf. on Virtual Worlds (VW2000)*, pages 214–224.
- Lipson, H. and Pollack, J. (2000). Automatic design and manufacture of artificial lifeforms. *Nature*, 406:974–978.
- Lund, H. H., Hallam, J., and Lee, W. P. (1997). Evolving robot morphology. In *Proceedings of the Fourth International Conference on Evolutionary Computation*.
- Miglino, O., Lund, H., and Nolfi, S. (1995). Evolving mobile robots in simulated and real environments. *Artificial Life*, 2:417–434.
- Parker, L. E. (1994). Alliance: An architecture for fault tolerant, cooperative control of heterogeneous mobile robots. In *Proceedings of the IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems (IROS)*, pages 776–783.
- Paul, C. and Bongard, J. C. (2001). The road less travelled: Morphology in the optimization of biped robot locomotion. In *Proceedings of The IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS2001)*.
- Pfeifer, R. and Scheier, C. (1999). *Understanding Intelligence*. MIT Press.
- Reil, T. and Massey, C. (2001). Biologically inspired control of physically simulated bipeds. *Theory in Biosciences*, 120:1–13.
- Sims, K. (1996). Evolving 3d morphology and behavior by competition. In Brooks, R. A. and Maes, P., (Eds.), *Proceedings, Artificial Life IV*, pages 28–39.
- Taylor, T. and Massey, C. (2001). Recent developments in the evolution of morphologies and controllers for physically simulated creatures. *Artificial Life*, 7(1):77–88.
- Terzopoulos, D., Tu, X., and Grzeszczuk, R. (1996). Artificial fishes with autonomous locomotion, perception, behaviour, and learning in a simulated physical world. In Brooks, R. A. and Maes, P., (Eds.), *Proceedings, Artificial Life IV*, pages 17–27.
- Tokura, S., Ishiguro, A., Kawai, H., and Eggenberger, P. (2001). The effect of neuromodulations on the adaptability of evolved neurocontrollers. In Kelemen, J. and Sosik, P., (Eds.), *Sixth European Conference on Artificial Life*, pages 292–295.
- Ventrella, J. (1996). Explorations in the emergence of morphology and locomotion behavior in animated characters. In Brooks, R. A. and Maes, P., (Eds.), *Proceedings, Artificial Life IV*, pages 436–441.