Adaptive Behavior

The Advantages of Evolving Perceptual Cues

Ian Macinnes, Ezequiel Di Paolo
Centre for Computational Neuroscience and Robotics, University of Sussex, UK

This paper introduces the evolvable functional circle hypothesis. This hypothesis states that if it is assumed that von Uexküll's concept of functional circles exists in robots and that the models used in evolutionary robotics are altered accordingly, then practitioners of evolutionary robotics will benefit in two ways. The first way is that by promoting the evolution of functional circles rather than sensorimotor loops, it allows evolved robots to select their own stimuli and therefore find their own meaning from environmental information. The second way is that it makes it easier for evolved robots to derive multiple meanings from the signal produced by a sensor. The paper goes on to demonstrate a method to alter our models in evolutionary robotics to promote the evolution of functional circles.

Keywords evolutionary robotics · functional circles · perceptual cues

1 Introduction

As it is most commonly practised, evolutionary robotics is a methodology by which the controllers of a population of robots are varied so the robots perform some desired behavior (Beer & Gallagher, 1992; Cliff, Harvey, & Husbands, 1993; Nolfi & Floreano, 2000). This methodology is suitable for the creation of *sensorimotor loops* (Husbands, Harvey, Cliff, & Miller, 1994) which exist when the action of a set of actuators affect, via the environment and body of the robot, a set of sensors that are in turn able to affect the actuators. By means of this feedback cycle, both the sensor and actuators influence their own future states. The concept of the sensorimotor loop is one of the main principles of evolutionary robotics. Sensorimotor loops are not evolved directly. Instead the underlying structures from which sensorimotor loops emerge are evolved.

There are a number of issues with this technique of producing behavior in a robot:

(1) *How can a robot derive meaning from input sensors?* As part of the movement within A.I. away from representation and toward the more constructivist ideas of new A.I. (Ziemke, 2000b), researchers in evolutionary robotics have designed robots to have little symbolic representation of the world (Brooks, 1991b). A robot must experience the world directly if it is to fulfil Brook's definition of embodiment (Brooks, 1991a). For a robot to meet Bourgine and Varela's definition of *autonomy* requires it to bring forth a world without being predigested in advance (Bourgine & Varela, 1992). Therefore the robots built according to these definitions generally have the signals from their sensors fed directly into their controllers so a robot can "experience the world directly" and not acquire knowledge through imposed representations. However, sensors do not usually mutate. Therefore the robot's ability to select its own stimuli over evolutionary time is constrained, and

Correspondence to: Ian Macinnes, Centre for Computational Neuroscience and Robotics, John Maynard Smith Building, University of Sussex, Falmer, Brighton, BN1 9QG, UK.
E-mail: ian.macinnes@gmail.com

(2006), Vol 14(2): 147–156.
[1059–7123(200612) 14:2; 147–156; 065744]

hence so are the relationships it can have with its environment.

(2) *How can a robot derive different meanings from the same sensor?* If a robot is to engage in complex adapted behavior, it is likely to have to select actions depending upon different input states. So that the robot "experiences the world directly", the signal from a sensor is generally passed to the controller in a non-symbolic form, often as a raw signal. It falls upon the controller to process the signal, distinguish between the different input states, and produce the appropriate action in the robot.

These issues are current lines of research. The approaches usually taken to overcome these issues are as follows:

(1) *How can a robot derive meaning from input sensors?* This is not perceived as such an issue among evolutionary roboticists as most accept the compromise of having fixed inputs as a consequence of experiencing the world directly. Work has been performed on evolving new signal primitives for sensor input (Cariani, 1993; Pask, 1958) and the philosophical implications discussed (Prem, 1997). Although it is a fascinating approach, this method requires more research before it can be implemented as an engineering method. Co-evolving the morphology alongside the controller can be currently implemented in a limited sense and this can allow the robot to gain information from the environment not directly through its sensors, but indirectly through physical alteration of the sensors or by influencing the behavior of the robot through the dynamics of its mutable morphology and its environment (Macinnes, 2001). It is an ongoing issue as to the best method of performing this (Pollack, Lipson, Funes, & Hornby, 2001).

(2) *How can a robot derive different meanings from the same sensor?* Research in pattern matching has found that different input states are distinguished more easily by using separate modules, each identifying a particular pattern, than by using one module to identify all the patterns. Research has been performed in evolutionary robotics on partitioning a CTRNN controller into modules (Floreano, 1998). However, a methodology has not yet been developed for building an evolved controller consisting of modules for general tasks, or for how the modules should be co-ordinated.

This paper intends to demonstrate that understanding adaptive behavior from a functional circle perspective allows various conclusions to be drawn that can help overcome these two limitations, and will recommend simple amendments that can be applied to current evolutionary robotic models.

2 Functional Circles and the *Umwelt*

Jakob von Uexküll developed his theory of the *Umwelt* from close inspection of the relationships between organisms and their environments. His approach was to investigate how each organism constructs its subjective world through the relationships the organism has with the objects it interacts with. He justified his work by arguing that as we are so successful at using perceptual tools such as glasses to aid our senses, and machines to augment our physical abilities, it leads us to treat animals as integrated collections of perceptual and effector tools (von Uexküll, 1934). Von Uexküll suggested that this ignores the *subject* that perceives and uses these tools. Inspired by the philosophy of Kant, von Uexküll developed his *Umwelt* theory to demonstrate how an organism constructs its own world, and as a model for how the subjective experience of an organism influences its physical environment.

Von Uexküll explained purposeful animal behavior by joining an organism's *phenomenal world* (the world as perceived) and its *effector world* (the world as enacted) into a single closed whole, the *Umwelt*. The *Umwelt* as defined by von Uexküll consists of a set of *functional circles* (Figure 1). These are abstract structures that tie together a subjective experience or perception (termed a *perceptual cue*) and the effect that the perceptual cue has on the behavior of the organism (called a *effector cue*).

Von Uexküll himself provided the example of the purposeful behavior of a female tick, in which he described three functional circles (Macinnes & Di Paolo, 2005; von Uexküll, 1934). The tick waits on a twig until an animal moves close enough for the tick to feed. The first functional circle is to fall from the twig onto the animal when the tick smells butyric acid. The second is the tick burrowing in the fur until it finds bare skin. The third produces biting motions.

These actions can all be described as reflex behaviors responding to chemical or physical stimuli. Each action has been selected by a process of natural selec-

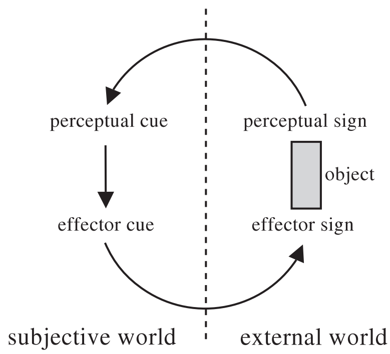

Figure 1 A functional circle describes the functional relationship between an organism and an object in its world. The perceptual sign of an object (its colour, shape, smell, or some more complex set of attributes) gives rise to a perceptual cue, the subjective experience of that object in the organism's *Umwelt*. This leads to an effector cue which drives the animal to perform some action, changing the organism's relationship to the object.

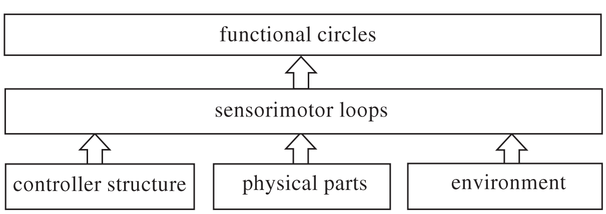

Figure 2 Normally we evolve sensorimotor loops as evolved phenomena from the underlying components making up the controller. In this paper, it is assumed that functional circles can exist as emerged phenomena from sensorimotor loops.

tion to occur in the given order. Using the model of von Uexküll's functional circles to explain them allows us to associate a perceptual cue with each action. The tick has adapted via evolution to respond to the given perceptual signs. Therefore the perceptual cues associated with each functional circle must also have evolved. It is the evolving perceptual cues that provide insight into improving our evolutionary robot models.

Organisms can often select which stimuli to react to. This means that they can choose which events will serve as perceptual signs under different conditions and so choose what they will perceive. When the tick was on the twig, the smell of butyric acid acted as a perceptual sign; when the tick was burrowing in the fur, this was no longer the case.

Functional circles are self-extinguishing (Macinnes & Di Paolo, 2005). This means that functional circles stimulate behavior in the organism that acts to remove the perceptual cue from the constructed world of the organism. Negative feedback loops can be viewed as a homeostatic process, whereby certain activations in the controller are treated as instabilities and removed by the organism by altering its own behavior.

A perceptual cue cannot be said to exist in any particular location within the organism or its environment. The existence of perceptual cues can only be surmised because of the assumption of the existence of Uexküll's functional circles. It is not necessary to know how perceptual cues are physically expressed in order to make use of and influence their evolution, as long as we use the concept of functional circles consistently.

3 Introducing Functional Circles into Evolutionary Robotics

We have assumed that we can explain the behavior of living things using functional circles. We can now apply the model of functional circles to explain robot behavior too. The idea of using functional circles to describe robot behavior has been highlighted several times before, notably by Ziemke (1999). Ziemke (2000a), described a robot in terms of functional circles that changed its behavior in response to external cues depending upon which state it was in, which itself depended upon a second external cue. The current paper asks if there is a general method we can apply to evolutionary robotics in particular that may improve its ability to retrieve information from the environment.

It is simple to decompose a phototactic Braitenberg vehicle (Braitenberg, 1984) into functional parts. The perceptual cue *bearer* is the light itself. The robot moves towards the light but may not operate properly once its light sensors are saturated. The functional circle is not complete as it is not responsible for extinguishing itself. The robot must either be picked up and turned in a different direction, or the light must be turned off if the robot is to engage in further behavior. Turning the light off once the robot moves within a specific distance enables the perceptual cue bearer, the light, to be manipulated by the robot. The functional circle is complete and the perceptual cue is extinguished by the effector cue.

We evolve sensorimotor loops by associating states between the sensors and actuators co-ordinated by the controller. The controller uses cues from the environment and internal variables to co-ordinate a series of states across parts of the robot's body and controller.

If mutational operators were altered to evolve functional circles instead of evolving sensorimotor loops, then it would be easier to evolve robots that are more adapted to their own body and their environment and therefore exhibit complex behavior. This is because there would be fewer constraints on the evolution of the perceptual cues. Therefore the robots would have more freedom to select their own meaning from cues they select over evolutionary time and to a certain extent, select their own optimal perceptual signs, even from fixed sensors.

First we will demonstrate that, applying von Uexküll's model of *functional circles*, the evolvability of a perceptual cue for a fixed sensor can be improved and hence the evolvability of the *meaning* of the signal produced by the sensor can be improved. We will then demonstrate how we can improve the evolvability of *multiple* perceptual cues using the signal produced by a single immutable sensor. This makes it easier for the robot to gain multiple meanings from the same signal produced by its sensors.

3.1 Perceptual Cues Evolve for Immutable Sensors

This section describes an example of how evolving perceptual cues, and hence the meaning a robot can ascribe to its inputs, can improve the evolvability of our models. We will use the well understood problem of evolving a robot to balance a pole fixed upon its top by a hinge (Figure 3). If the pole is subject to a strong enough force, it will become unbalanced and fall until it is lying flat across the top of the robot. The pole is subject to random forces and the robot has to move left and right to keep the pole upright. This example is not intended to demonstrate a better method of constructing pole balancing robots, but was chosen to provide a simple example of how acknowledging the existence of perceptual cues can improve evolvability generally.

The hinge has two sensors:

(1) *An angle sensor* θ_I. This sensor provides the angle in radians between the pole and the normal direction of the cart. The signal ranges from $-\frac{\pi}{2} \cdots \frac{\pi}{2}$, and is set to zero when the pole is perfectly balanced vertically.

(2) *A rate of angle change sensor* $\dot{\theta}_I$. This provides the angular velocity of the pole relative to the cart. The output of this sensor is zero if the pole position remains motionless relative to the cart.

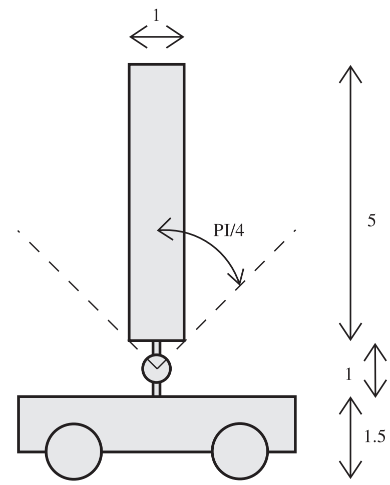

Figure 3 The robot consists of a cart and a pole attached by a hinge joint. The hinge can swing freely and the pole is balanced in the vertical position. A robot succeeds if it can maintain the pole within $\frac{\pi}{4}$ radians of the vertical. The permitted extent of the poles swing is shown by the dashed line.

A generational evolutionary algorithm using rank selection is used to vary the genotypes of a population of thirty robot controllers from an initially random population of genotypes representing robot controllers. It is desired that the robot "experiences the world directly", so both sensor signals are fed directly into the controller (Figure 4). The controller is a continuous time recurrent neural network (CTRNN) with three fully connected neurons (Beer & Gallagher, 1992).

Evolution quickly produces a population of agents able to solve the problem (Tables 1 and 2). The angle sensor produces a value of zero at the exact angle at which the pole is balanced. Therefore if the pole tips and becomes unbalanced, the angle sensor supplies a positive or negative signal depending upon whether the cart should move left or right. The *meaning* of the signal from a sensor is imposed by the designer of the experiment. If the robot is to produce a successful strategy that requires modulating the angle of the pole, it must do so by using this imposed meaning of the input

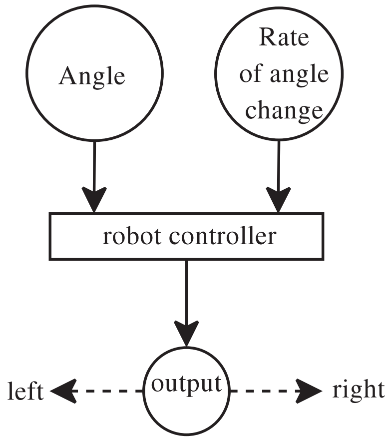

Figure 4 Two inputs are fed directly into the controller. The controller decides whether the robot should move left or right and specifies the force in order to ensure the pole remains balanced. The pole has a mass of 5 kg and the cart of 1 kg. Gravity has a force of 2 ms^{-2}.

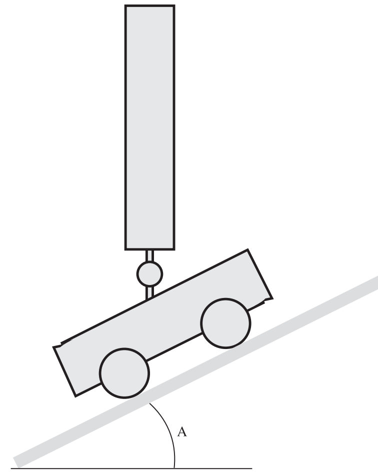

Figure 5 The robot has to balance the pole whilst on an incline of 30°. The angle sensor no longer provides a signal of zero if the pole is balanced.

Table 1 A neural network was evolved for controlling a robot to balance a pole. The weights of the links between each input and neuron are shown.

	1st hidden	2nd hidden	Motor
Angle sensor	33.307	43.184	–50.000
Rate of angle change	43.184	–9.454	49.080
1st hidden	0.789	7.973	–0.502
2nd hidden	–18.449	–17.108	1.924
Motor	–24.777	–50.000	9.980

Table 2 A robot that successfully balances a pole was evolved and the neuron attributes noted.

	1st hidden	2nd hidden	Motor
Bias	1.104	–0.775	–1.018
Time constant	21.646	13.447	2.000

signal. This is because the immutable physical sensor is not *co-evolving* along with the controller (Cariani, 1991). Therefore the ability of the robot population to evolve their own *meaning* of the signal received from the sensor is constrained.

The population is further evolved with a more difficult fitness function. The agent is no longer placed on flat ground but on ground inclined at an angle (Figure 5). It is no longer possible for the population to evolve a strategy to balance the pole using the same network architecture. Now the imposed meaning of the signal from the angle sensor is disadvantageous to solving the problem.

Now let us see what we can gain from applying the model of von Uexküll's *functional circles* to explain the behavior of the robot. The existence of a functional circle is assumed and our model changed to improve the evolvability of its perceptual cues, and therefore to allow the agent to select its own meaning from its input signals over evolutionary time. This is done by adding attributes of the sensor to the genotype. This allows the agent greater freedom to process the signal provided by its sensors.

Functional circles cannot be evolved directly because they are abstract structures. However, we can assume that a functional circle F_1 exists, ensure that all parts of it are mutable, and use evolution to produce F_1 as an emerged phenomenon from underlying sensorimotor loops (Figure 2).

Which attributes should be added to the genotype? There are many mutable attributes of the sensor that could be used. For this simple example, a genetically determined offset value is added to the signal

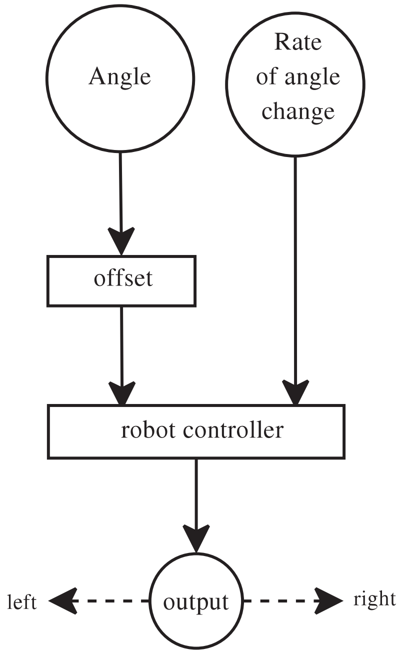

Figure 6 The controller has an added mutable offset to compensate for the angle of the pole. This is added to the signal from the angle sensor before being fed into the rest of the controller.

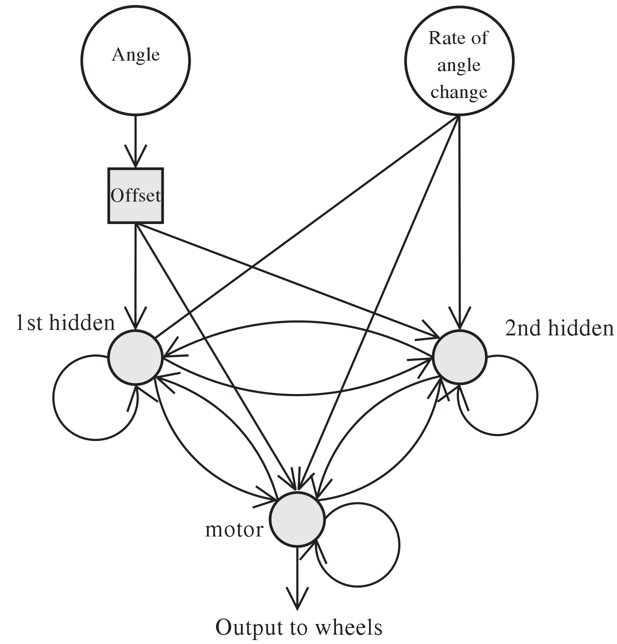

Figure 7 The topology of the neural network remains static during the evolutionary run. Initially animats are evolved without a mutable offset, then with one mutable offset, and finally with two. This diagram shows a single offset.

before the signal is presented to the controller (Figure 6). The offset means that the angle sensor would no longer produce a signal of zero if the pole is at right angles to the top of the cart. Adding the offset to the genotype facilitates the robot's ability to evolve to some extent the perceptual signs to which it responds and hence have a greater ability to select its own meaning from the angle sensor over evolutionary time. With the mutable offset added to the genotypes of the population of robots, agents can now evolve a solution to the problem of balancing the pole on a slope of 30° (Tables 3 and 4).

Allowing the perceptual cue greater freedom to evolve has allowed the robot to find a new meaning from the angle sensor that is more suitable for the task in hand. The meaning that the agent derives from the signal may be hard to decode and analyze. This is to be expected, because constraints are being removed from the manner in which the agent is coupled with its environment.

Table 3 An animat was evolved to balance a pole upon a slope of 30°. The weight values are as shown. The offset value is 0.471.

	1st hidden	2nd hidden	Motor
Angle sensor	9.667	50.000	–50.000
Rate of angle change	50.000	–48.76	–30.405
1st hidden	–50.000	1.256	–11.002
2nd hidden	–18.450	–39.368	3.642
Motor	–19.479	–21.475	12.194

Table 4 An animat was evolved to balance a pole upon a slope of 30°. The neuron attributes were noted.

	1st hidden	2nd hidden	Motor
Bias	–1.377	–0.974	0.139
Time constant	30.000	2.612	2.005

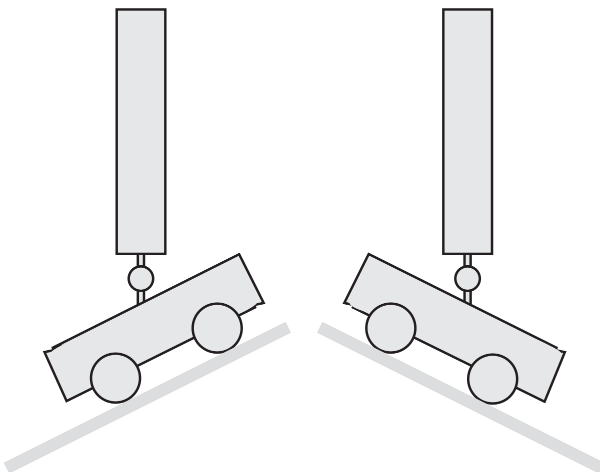

Figure 8 The robot must learn to balance the pole at two different opposing angles.

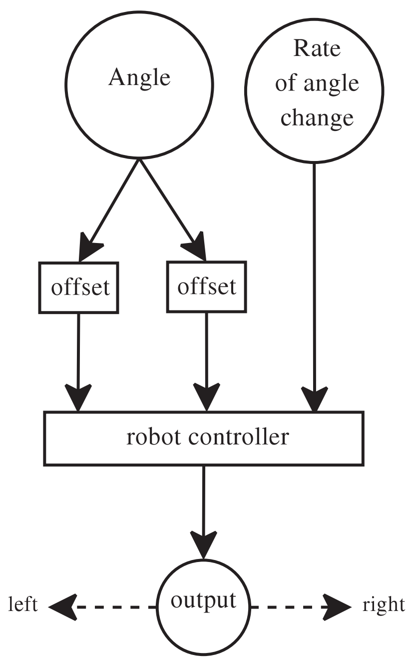

Figure 9 The controller has two mutable offsets that are added to the angle sensor output before being fed into the controller. This enables it to evolve a strategy to balance the pole at two different angles.

3.2 Immutable Sensors can Provide Multiple Perceptual Cues

The robot must now balance the pole on two inclined planes, one at a positive angle to the horizontal and one at a negative angle (Figure 8). The robots used previously that have a genetically determined offset

Table 5 The weights between the elements of a neural network that balances the pole upon two surfaces, inclined to either $\frac{\pi}{6}$ or $-\frac{\pi}{6}$. The offsets added to the input signal are –0.597 and 0.370.

	1st neuron	2nd neuron	Motor
Angle sensor	36.503	50.000	–50.000
Rate of angle change	13.625	5.627	–50.000
1st neuron	30.530	–26.293	24.138
2nd neuron	–27.640	13.354	–39.912
Motor neuron	2.059	–3.535	–7.637

Table 6 The neural parameters of a neural network that balances the pole upon two surfaces, inclined to either $\frac{\pi}{6}$ or $-\frac{\pi}{6}$.

	1st neuron	2nd neuron	Motor
Bias	–0.599	–2.593	–1.364
Time constant	18.095	13.905	3.152

cannot evolve a solution to this problem. This is because, although the robot has been provided with greater freedom to select the perceptual sign it will respond to, the sensor only provides a single meaning, whereas an optimal solution for this problem requires two.

However, a sensor can take part in more than one functional circle. We facilitate the evolution of a second functional circle F_2 by adding a second offset (Figure 9). A robot can now successfully evolve a solution to this task (Tables 5 and 6).

Allowing two mutable inputs from the same sensor allows the controller to evolve two functional circles, F_1 and F_2. It chooses which to employ depending upon the initial conditions. Each functional circle has its own perceptual cue and hence each provides a different meaning for the robot. This demonstrates that sensors can be part of a number of different functional circles and a simple robot can *choose* which function circle to employ under different circumstances. In this particular case, the dynamics of the CTRNN has evolved two attractor states. The initial input signals specify which state the network falls into.

We have seen how an animat can more easily find an optimal meaning from the signals provided by its sensors if sensor attributes are allowed greater freedom to mutate. We now see how a sensor can provide *multiple* meanings for an animat, as it allows an animat to choose multiple input values to act as different stimuli. Although the number of perceptual cues modeled here has been fixed for demonstration purposes, the number of perceptual cues can be evolved along with the other attributes.

4 Discussion

This paper does not advocate using modules to represent functional circles or perceptual cues. Explicitly modeling functional circles is probably not possible given the abstract and distributed nature of perceptual cues and functional circles. Instead we advocate assuming that perceptual cues already exist and make adjustments to our models to improve their evolvability. Although it may not be possible to accurately identify all the components through which the perceptual cue operates, by acknowledging the existence of perceptual cues and adding independently evolvable sensor attributes, the evolvability of the perceptual cues will be increased.

We predict that adding such structures to our evolutionary robotic models, and putting the number of them per sensor under genetic control, we will improve our robots' abilities to find meanings in the signals provided by its sensors.

If we are to encourage the evolution of perceptual cues, we must choose a suitable set of mutable attributes for each type of sensor. Memory is an attribute that may be applied to almost any sensor and possibly provide benefits. It is a simple task to "delay" sensor states between the sensor and the controller such that the controller receives signals that occurred in the past. Applying memory as a genetically determined attribute provides a method by which a perceptual cue can modulate its state over a longer period of time and allow an animat to vary the temporal qualities of its perceptions.

5 Conclusion

Most of the processing of the perceptions of the animat is generally expected to be performed by the varying activations of a CTRNN. Since any system can be modeled in terms of functional circles, perceptual cues can be said to operate in a CTRNN. However, the perceptual cues may not be particularly evolvable. A CTRNN with a complex enough architecture (i.e. with enough neurons and connections) would be able to solve the simple problems described in this paper, but adding mutable sensor attributes improves the evolvability of perceptual cues and allows solutions to be found without increasing the complexity of the neural network controller.

Improving the evolvability of perceptual cues eases the task of selecting the appropriate meanings of input signals. If adding separately mutable sensor attributes to the robot genotype is more likely to make perceptual cues evolvable, and improving the evolvability of perceptual cues is advantageous to evolving robots to engage in some desired behavior, then making perceptual cues explicit and evolvable is advantageous.

By assuming the existence of perceptual cues, we can improve the evolvability of our evolutionary models in two ways:

(1) We can improve the evolvability of signal processing by improving the evolvability of perceptual cues rather than relying upon the controller alone to process the input signal. This can be implemented by adding mutable attributes of the sensor to the genotype.
(2) We can facilitate the animat's ability to evolve multiple meanings from the same sensor signal by adding sets of independently evolving mutable sensor attributes. The optimal number of the sets of attributes may also be evolved.

References

Beer, R., & Gallagher, J. (1992). Evolving dynamical neural networks for adaptive behavior. *Adaptive Behavior*, *1*(1), 91–122.

Bourgine, P., & Varela, F. (1992). Toward a practice of autonomous systems. In F. J. Varela & P. Bourgine (Eds.), *Toward a practice of autonomous systems: Proceedings of* *the first European conference on artificial life* (pp. ix–xvii). Cambridge, MA: MIT Press.

Braitenberg, V. (1984). *Vehicles: Experiments in synthetic psychology*. Cambridge, MA: MIT Press.

Brooks, R. (1991a). Intelligence without reason. In J. Myopoulos & R. Reiter (Eds.), *Proceedings of the 12th international joint conference on artificial intelligence (IJCAI-91)* (pp. 569–595). Sydney, Australia: Morgan Kaufmann: San Mateo, CA.

Brooks, R. (1991b). Intelligence without representation. In A. R. Meyer, J. V. Guttag, R. L. Rivest, & P. Szolovits (Eds.), *research directions in computer science: An MIT perspective* (pp. 249–276). Cambridge, MA: MIT Press.

Cariani, P. (1991). Some epistemological implications of devices which construct their own sensors and effectors. In F. J. Varela & P. Bourgine (Eds.), *Toward a practice of autonomous systems: Proceedings of the first European conference on artificial life* (pp. 484–493). Cambridge, MA: MIT Press.

Cariani, P. (1993). To evolve an ear: Epistemological implications of Gordon Pask's electrochemical devices. *Systems Research*, *10*(3), 19–33.

Cliff, D., Harvey, I., & Husbands, P. (1993). Explorations in evolutionary robotics. *Adaptive Behavior*, *2*(1), 73–110.

Floreano, D. (1998). Evolutionary robotics in behavior engineering and artificial life. In T. Gomi (Ed.), *Evolutionary robotics: From intelligent robots to artificial life*: Applied AI systems. Evolutionary Robotics Symposium Ontario (Canada): AAI Books.

Husbands, P., Harvey, I., Cliff, D., & Miller, G. (1994). The use of genetic algorithms for the development of sensorimotor control systems. In P. Gaussier & J.-D. Nicoud (Eds.), *Proceedings of the from perception to action conference* (pp. 110–121). Los Alamitos, CA: IEEE Computer Society Press.

Macinnes, I. (2001). *An evolutionary framework for the exploration of perceptual embodiment and other aspects of embodied cognition*. Master's thesis, School of Cognitive and Computing Sciences, University of Sussex.

Macinnes, I., & Di Paolo, E. (2005). From the inside looking out: Self-extinguishing perceptual cues and the constructed world of animats. In A. Smith (Ed.), *Advances in Artificial Life – Proceedings of the 8th European conference on artificial life (ECAL)* (pp. 11–20). New York: Springer.

Nolfi, S., & Floreano, D. (2000). *Evolutionary robotics: The biology, intelligence, and technology of self-organising machines*. Cambridge, MA: MIT Press.

Pask, G. (1958). Physical analogues to the growth of a concept. In A. Uttley (Ed.), *Mechanisation of thought processes* (pp. 765–794). London: National Physical Laboratory H.M.S.O.

Pollack, J. B., Lipson, H., Funes, P., & Hornby, G. (2001). First three generations of evolved robots. In T. Gomi (Ed.), *Evolutionary robotics from intelligent robotics to artificial life: International symposium, ER 2001*, Volume 2217 of *LNCS* (pp. 62–71). London: Springer Verlag.

Prem, E. (1997). Epistemic autonomy in models of living systems. In P. Husbands & I. Harvey (Eds.), *Proceedings of the fourth European conference on artificial life* (pp. 2–9). Cambridge, MA: MIT Press.

von Uexküll, J. (1934). A stroll through the worlds of animals and men: A picture book of invisible worlds. In C. Schiller (Ed.), *Instinctive behavior: The development of a modern concept*. New York: International Universities Press. Original work published 1957.

Ziemke, T. (1999). Rethinking grounding. In M. Peschl, A. Riegler, & A. Von Stein (Eds.), *Understanding representation in the cognitive sciences* (pp. 177–190). New York: Plenum Press.

Ziemke, T. (2000a). On 'parts' and 'wholes' of adaptive behavior: Functional modularity and diachronic structure in recurrent neural robot controllers. In J. Meyer, A. Berthoz, D. Floreano, H. Roitblat, & S. Wilson (Eds.), *From animals to animats 6: Proceedings of the sixth international conference on simulation of adaptive behavior* (pp. 115–124). Cambridge, MA: MIT Press.

Ziemke, T. (2000b). *Situated neuro-robotics and interactive cognition*. PhD thesis, University of Sheffield, Department of Computer Science.

About the Authors

Ian Macinnes received his bachelor of sciences degree in artificial intelligence from the University of Westminster and is currently awaiting the viva for his D.Phil at the University of Sussex. He is a member of the Centre for Computational Neuroscience and Robotics and his interests include trying to persuade robots to evolve their morphologies.

Ezequiel Di Paolo earned his Nuclear Engineering masters degree at the Instituto Balseiro and his D.Phil at the University of Sussex. He is currently a senior lecturer within the Evolutionary and Adaptive Systems group at Sussex University. He is a member of the Centre for Research in Cognitive Science at Sussex. His research interests include adaptive behavior in natural and artificial systems, biological modeling, evolutionary robotics and enactive cognitive science. *Address*: Department of Informatics, School of Science and Technology, University of Sussex, Brighton, BN1 9QH, UK.
E-mail: ezequiel@sussex.ac.uk