Available online at www.sciencedirect.com
SciVerse ScienceDirect
ELSEVIER
Physics Procedia 25 (2012) 814 – 821
Physics Procedia

2012 International Conference on Solid State Devices and Materials Science

Vehicle Study with Neural Networks

Xiaogang Ruan, Lizhen Dai

Institute of Artificial Intelligence and Robots
BJUT
Beijing, China

Abstract

The biology is characteristic of biologic phototaxis and negative phototaxis. Can a machine be endowed with such a characteristic? This is the question we study in this paper, so a method of realizing vehicle's phototaxis and negative phototaxis through a neural network is presented. A randomly generated network is used as the main computational unit. Only the weights of the output units of this network are changed during training. It will be shown that this simple type of a biological realistic neural network is able to simulate robot controllers like that incorporated in Braitenberg vehicles. Two experiments are presented illustrating the stage-like study emerging with this neural network.

*Keywords:*neural network; vehicle; study; moving

1. Introduction

All humans develop in an autonomous open-ended manner through lifelong learning. So far, no robot has this capacity. Building such a robot is one of the greatest challenges to robotics today, and is the long-term goal of the growing field of developmental robotics [1], [2]. This paper explores a possible route towards such a goal.

Living and moving creatures most perfectly exhibit abilities that are the focus of many research areas. Some of them will be discussed in parts in this article: information processing of real-world sensors in real-time, learning of complex tasks on a variety of time scales and controlling actuators to move around in the habitat. The idea of creating artificial creatures that can move autonomously and exhibit a certain learning behaviour is not new. Many successful approaches have been found to accomplish some tasks that involve the areas mentioned above [3], [4], [5]. Often combinations of these techniques are used. Some of them will be briefly discussed in this introduction. One of the most fascinating approaches seems to be the last

1875-3892 © 2012 Published by Elsevier B.V. Selection and/or peer-review under responsibility of Garry Lee
Open access under CC BY-NC-ND license. doi:10.1016/j.phpro.2012.03.162

one, since advances in the research would include enabling us to understand parts of the biological processes that occur in every one of us. Furthermore, neural networks are proven to be computationally powerful [6]. The common view of a neural network is that of a set of neurons plus a set of weighted connections (synapses in the biological context) between the neurons. Each neuron comes with a transfer function computing an output from its set of inputs. In multi-layer networks these outputs can again be used as an input to the next layer of neurons, weighted by the relevant synaptic "strength". Feed-forward networks have only connections starting from external input nodes, possibly via one or more intermediate hidden node processing layers, to output nodes. Recurrent networks may have connections feeding back to earlier layers or may have lateral connections (i.e. to neighboring neurons on the same layer). With this recurrence, activity can be retained by the network over time. This provides a sort of memory within the network, enabling them to compute functions that are more complex than just simple reactive input/output mappings. This is a very important feature for networks that will be used for generating adaptive behaviour in robotics, because in most cases the current behaviour of the robot is not solely a function of the current sensory input, but a function of the current and previous sensory inputs and also of the current and previous internal network states. This allows a system to incorporate a much richer range of dynamical behaviours. Many approaches have been elaborated on recurrent artificial neural networks. Some of them are dynamic recurrent neural networks [7], radial basis function networks [8], Elman networks [9], self-organizing maps [10], Hopfield nets [11] and the "echo state" approach from Jäger [12] .Therefore, we use neural networks to realize the learning process of Braitenberg vehicle simulating biologic phototaxis and negative phototaxis.

2. Biologic Phototaxis

Phototaxis is a kind of taxis, or locomotory movement that occurs when a whole organism moves in response to the stimulus of light. This is advantageous for phototrophic organisms as they can orient themselves most efficiently to receive light for photosynthesis. Phototaxis is called positive if the movement is in the direction of increasing light intensity and negative if the direction is opposite.

Two types of positive phototaxis are observed in prokaryotes. The first is called scotophobotaxis (from the word "scotophobia"), which is observed only under a microscope. This occurs when a bacterium swims by chance out of the area illuminated by the microscope. Entering darkness signals the cell to reverse flagella rotation direction and reenter the light. The second type of phototaxis is true phototaxis, which is a directed movement up a gradient to an increasing amount of light. This is analogous to positive chemotaxis except that the attractant is light rather than a chemical.

Phototactic responses are observed in many organisms such as Serratia marcescens, Tetrahymena, and Euglena. Each organism has its own specific biological cause for phototactic responses, many of which are unintended and serve no end purpose.

3. Experimental Setup

A framework consisting of the neural network, assessor and a standard miniature robot called Braitenberg vehicle was used to implement "vehicle study". Its structure is shown in Figure 1. The robot Braitenberg vehicle is well known in the robot community and has been used in a variety of experiments. In this setup a Braitenberg vehicle is first steered by a programmed controller in a precisely defined environment. All photosensitive sensor and motor speed data are recorded. These data are presented to a neural network. The goal is to imitate and generalize the behaviour by a controller now consisting of a trained neural network. The difficulty is that the original predefined behaviour is only available in the form of the previously recorded data and not in form of any rules that could be extracted out of the controller that was used before.

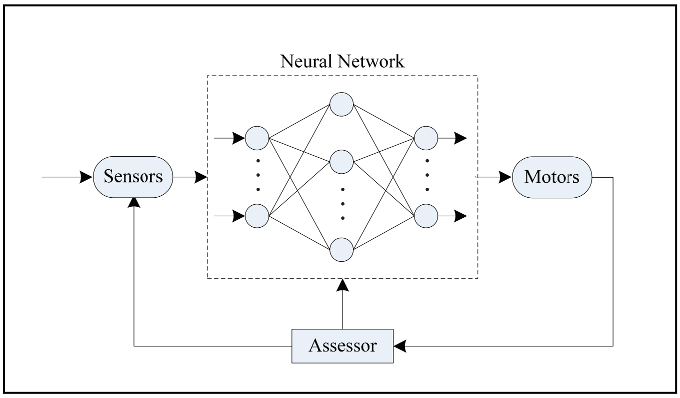

Figure 1. The architecture of learning system.

3.1 Braitenberg Vehicle

Braitenberg vehicles are small robots that can exhibit complex behaviors with very simple circuitry. The vehicles typically have small box-shaped bodies with one wheel on each side. At the front of the vehicle are sensors, which detect different types of stimuli (for example, light) from the environment. These sensors are connected directly to the vehicle's wheels so that the wheels turn when the sensors are activated. Two simple Braitenberg vehicles are shown in Figure 2. The concept is simple, but Braitenberg showed that these vehicles could appear to exhibit interesting and complex behaviors such as "love" or "hate", depending on how the sensors were connected to the wheels. This paper describes how to create simulated Braitenberg vehicles in breve.

3.2 Configuration: Two sensors (one on each side) and two motors (left and right). Two types of vehicles:.

- Each sensor is connected to the motor on the same side.
- Each sensor is connected to the motor on the opposite side.

The greater the sensor input, the faster the motor goes. Suppose light source and Braitenberg vehicle are in the same plane. So, the light intensity E that the sensor has received from environment is equal to the distance between the light source and the sensor of Braitenberg vehicle denoted by d. It is expressed by the formula

$$E\left(t\right)=D\left(t\right). \tag{1}$$

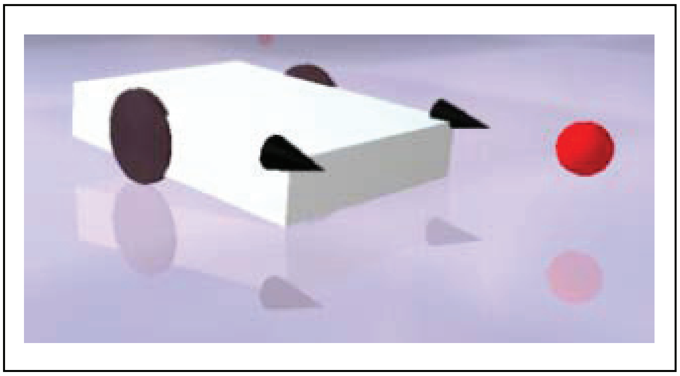

Figure 2. Braitenberg vehicle .

3.3 Motor Control

The robot is a box with two wheels (see Figure. 1). Each wheel can be controlled by setting its speed (real number is 0 or 1). The robot can be also photosensitive. The action space is three-dimensional and continuous, and deciding for an action consists in setting the values of the motor vector *M(t)*

$$M(t) = (l,r,E)\,. \tag{2}$$

Where l is the speed of the motor on the left, r the speed of the motor on the right, and E the light intensity of the emitted light. The robot moves in a plane. There is a light source in this plane that can be luminescent. This robot moves randomly at the beginning, and it can move toward or forward the light source as the process of learning.

3.4 Perception

The robot perceives the distance to the light source with photosensitive sensors, so its sensory vector *S(t)* is one-dimensional

$$S(t) = (d)\,. \tag{3}$$

Where d is the distance between the robot and the light source at time t.

3.5 Action Perception Loop

As a consequence, the mapping that the robot is trying to learn is

$$\eta : SM(t) = (l,r,E,d) \mapsto S(t+1) = (\tilde{d})\,. \tag{4}$$

Using the neural network and assessor, the robot will thus act in order to maximize its learning progress. The robot has no prior knowledge and, in particular, it does not know that there is a qualitative difference between setting the speed of the wheels and setting the light intensity (for the robot, these are unlabeled motor channels). However, we will now show that the robot manages to autonomously move toward or forward the light source, evaluate their relative complexity, and exploit this information for organizing its own behavior.

3.6 Creation of Training and Test Data

All experiments are carried out in the same way. In a first phase, sensor and motor data are collected while the robot is controlled with the controllers. The collected data is then partitioned into segments with a single occurrence of an obstacle.

4. Parameter Settings

Before you begin to our experiments, first set the parameters of the learning system. Figure 1 shows a typical architecture of learning system. The neural network has two inputs and two outputs. The inputs are light intensity coming from the photosensitive sensor, and the outputs are drive for motor of vehicle's wheels. For the experiments the values of the two photosensitive sensors have to be fed continuously into the neural network. Therefore, two linear input neurons with the ability to receive external input in real-time were used. Giving 100 learning samples randomly and 100 test samples. Neural network randomly generated weights firstly. As the learning process, assessor gives reward or punishment to the vehicle so as to make the weights of the neural network change according to the behaviour of the vehicle at the last time. The parameters determine the dynamical behavior of the neural network.

5. Results

First of all, one can study the behavior of the robot during a simulation from an external point of view. A way to do that is to use our knowledge of the structure of the environment in which the robot lives and build corresponding relevant measures characterizing the behavior of the robot within a given period of time: 1) each sensor is connected to the motor on the same side, if the sensor input source is directly ahead, the vehicle may hit it. If the source is to one side, the vehicle will turn towards the source and may eventually hit it. 2) crossed connections in which the left sensor is connected to the right motor, and the right sensor is connected to the left motor. When the detected quality is dead ahead, this vehicle is like the previous one, and moves straight into it. However, when the signal source is to the side, this vehicle will turn towards it. Indeed, given enough time, the vehicle is guaranteed to hit the source of the signal, provided that it stays in the vicinity of the source.

The basic task in the experiments was to learn phototaxis and negative phototaxis described in the previous chapters to imitate behaviours that were demonstrated and recorded by the controller architectures introduced in the previous section. During the test phase both readout neurons are simply modeled as linear gates, with their weight vectors applied to the input states. The weight vectors are fixed after training and remain constant during the whole test run and later on. Finally, when running in real-time mode, the outputs of both readout neurons are directly communicated as the motor commands.

The training results of the first type of the vehicle are shown in Figure 3 and 4.And Figure 5 shows training error. It illustrates that the vehicle can move away from the light source. As the same, the second type, crossed connection indicates the vehicle can move towards to the light source. Its training error is shown in Figure 6.

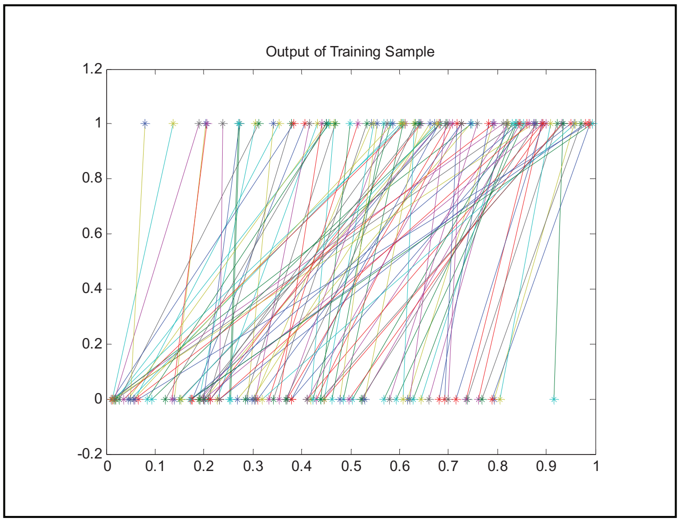

Figure 3. Output of training sample of the type 1.

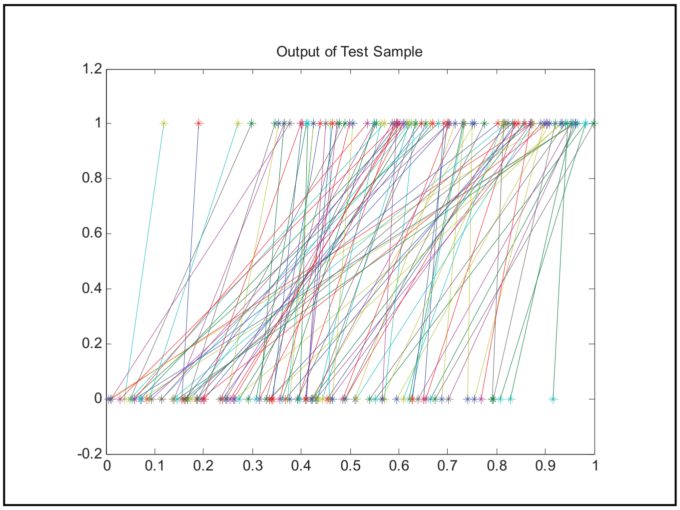

Figure 4. Output of test sample of the type 1.

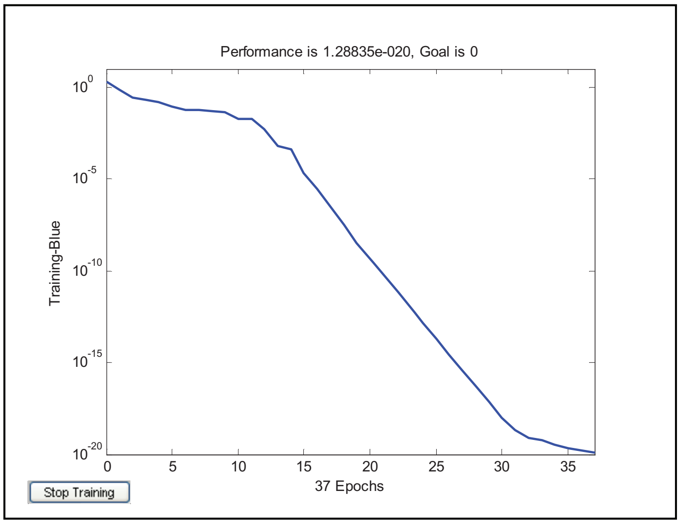

Figure 5. Training error of the type 1.

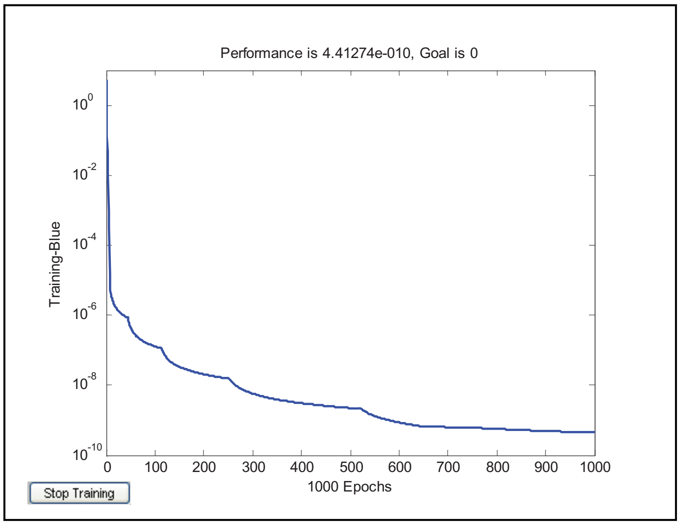

Figure 6. Training error of the type 2.

6. Conclusion

A type of orientation, based upon directional information, in which the animal heads directly towards or away from the source of stimulation. This may be achieved by means of simple sensory receptors and successive comparison of stimulus intensity in different locations, achieved by turning movements. This paper has used a neural network realizing vehicle's phototaxis and negative phototaxis. A randomly generated network is used as the main computational unit. Only the weights of the output units of this network are changed during training. It is showing that this simple type of a biological realistic neural network is able to simulate robot controllers like that incorporated in Braitenberg vehicles. Two experiments are presented illustrating the stage-like study emerging with the neural network. A biological similar characteristic is reflected in robots. Can it produce complicated behavior? Such as ,add additional lights to make the vehicle move in a specific pattern, like a figure-eight or a circle, modify the weights, wheel positions and velocities to create new behaviors, add a second vehicle with a different behavior. These are what we research in the future.

Acknowledgment

This work is supported by NSFC (60774077), 863 programs of China (2007AA04Z226), BMEC and BMSF (KZ200810005002), BNSF (4102011) and NSFC (61075110).

References

[1] J. Weng, J. McClelland, A. Pentland, O. Sporns, I. Stockman, M. Sur, and E. Thelen, “Autonomous mental development by robots and animals,” Science, vol. 291, 2001, pp. 599–600.

[2] M. Lungarella, G. Metta, R. Pfeifer, and G. Sandini, “Developmental robotics: A survey,” Connection Sci., vol. 15, no. 4, 2003, pp. 151–190.

[3] H.Burgsteiner, “Imitation learning with spiking neural networks and real-world devices,” Engineering Applications of Artificial Intelligence, 2006, 19(7), pp. 741-52.

[4] J.M.Cuadra Troncoso, J.R. Alvarez Sanchez and F. de la Paz Lopez, “Discretized ISO-learning neural network for obstacle avoidance in reactive robot controllers,” Neurocomputing, 2009. 72(4-6): pp. 861-870.

[5] R.Salomon, “The evolution of different neuronal control structures for autonomous agents,” Robotics and Autonomous Systems, 1997. 22(3-4): pp. 199-213.

[6] W. Maass, “Networks of spiking neurons: the third generation of neural network models,” Neural Networks, 1997, 10, pp. 1659–1671.

[7] B. Pearlmutter, “Gradient calculation for dynamic recurrent neural networks: a survey,” IEEE Transactions on Neural Networks, 1995, 6 (5), pp.1212–1228.

[8] C. Bishop, “Neural Networks for Pattern Recognition,”. Oxford, UK: Oxford University Press, 1995.

[9] J. Elman, “Finding structure in time,”.Cognitive Science, 1990, 14, pp. 179–211.

[10] T. Kohonen, “Self-Organizing Maps,” 3rd Edition. Springer-Verlag, 2001.

[11] J. Hopfield, “Neural networks and physical systems with emergent collective computational abilities,” In: Proceedings of the National Academy of Science. 1982, Vol. 79. pp. 2554–2558.

[12] H. Jäger, “The echo state approach to analysing and training recurrent neural networks,”. Tech. Rep. GMD Report 148, German National Research Center for Information Technology, 2001.