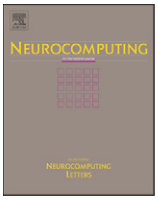
Neurocomputing 74 (2011) 3335–3342

Contents lists available at ScienceDirect

Neurocomputing

journal homepage: www.elsevier.com/locate/neucom



Application of arachnid prey localisation theory for a robot sensorimotor controller

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ARTICLE INFO

Article history:
Received 14 December 2010
Received in revised form
9 May 2011
Accepted 15 May 2011
Communicated by R. Tadeusiewicz
Available online 28 June 2011

Keywords:
Spiking neural network
Sensorimotor coordination
Robot controller
Arachnid prey localisation

ABSTRACT

We extend an existing spiking neural model of arachnid prey orientation sensing with a view to potentially using it in robotics applications. Firstly, we have added 'motor' behaviour by implementing a simulated arachnid in a physics simulation so that sensory signals from the neural model can be translated into movement to orient towards the prey. We have also created a spiking neural distance estimation model with a complementary motor model that enables walking towards the prey. Results from testing of the neural and motor aspects show that the neural models can represent actual prey angle and distance to a high degree of accuracy: an average error of approximately 7° in estimating prey angle and 1 cm in the estimation of distance to prey. The motor models consistently show the correct turning and walking responses but the overall accuracy is reduced with an average error of around 15° for angle and 1.25 cm for distance. In the case of orientation this is still in line with the error rate of between 12° and 15°, which has been observed in real arachnids.

1. Introduction

Navigation and localisation tasks in robotics generally require some sort of sensorimotor coordination. In the simplest case infrared (IR) or bump sensors can be set up to send information directly to wheel motors to steer the robot toward or away from objects in the environment. An example of this type of architecture is the Braitenberg vehicle [1], where connections between sensors and wheel motors can be set up to produce various different 'behaviours' such as attraction and avoidance. More sophisticated implementations have used evolutionary techniques to evolve more complex controllers, for example the work described in Ref. [2] attempted to mimic how adaptation occurs in natural systems by evolving for a progressively more demanding set of tasks ranging from simple forward locomotion to distinguishing between two shapes in the environment. Following experiments with simulated agents, the methods were replicated on wheeled robots and performed equally well. Another approach, described in Ref. [3], concentrated on learning sensorimotor coordination by direct interaction with the environment. Here an elegant and simple spiking neural network model including synaptic plasticity was used for obstacle avoidance. This was implemented on several versions of wheeled robot. The design of the neural network was inspired by the behaviour of the sea slug (Aplysia), which despite being a very simple organism is capable of associative and non-associative learning. In a first set of experiments the robots were equipped only with left and right bump sensors and the neural system was wired to include a reflex response to back away after bumping into an obstacle. In subsequent experiments, the neural network was rewired to include input from infrared (IR) sensors and also presynaptic facilitation was added. The results of these experiments showed that first and second order classical conditioning were possible: the robot firstly 'learned' (via synaptic changes) to associate IR sensor input with bumping into objects and thus to avoid them and subsequently it learned to associate obstacles with a second order stimulus (their shadow). An interesting approach not involving neural methods is described in Ref. [4]. Here vibration signals are used as a communication method between a group of wheeled robots to allow them to locate each other. Two signals in different frequency bands are transmitted and they are detected by a matched filter technique, which calculates the cross-correlation between the received and expected signal.

To perform more complex tasks such as localisation (enabling the robot to sense its own location in the environment) and navigation (obstacle detection and avoidance), vision systems are usually employed. An overview of robot localisation and object recognition using two popular techniques: SLAM (Simultaneous Location and Mapping) and SIFT (Scale Invariant Feature Transform) is given in Ref. [5]. Metrical SLAM approaches construct a grid-based map where each cell has a probability of containing

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0925-2312/$ - see front matter
doi:10.1016/j.neucom.2011.05.020

an object. Downsides of this method are that it is memory-hungry and very dependant on sensor robustness. Topological SLAM uses a graph-based approach where relationships between significant places are stored instead. This approach is less memory-hungry and of lower complexity than metrical SLAM but graph updating is difficult to do accurately [5]. SIFT is concerned with both the detection and recognition of objects and requires that a database of object features (SIFT descriptors) is constructed for matching with real objects. An important feature of SIFT is that it can simultaneously detect and recognise objects.

Despite the fact that the approaches previously discussed are successful it is still the case that current robot capabilities cannot match those of real organisms. The work presented here takes a slightly different approach to robot sensorimotor coordination and uses methods inspired by how a real organism solves a sensorimotor coordination problem.

The field of Computational Neuroethology encompasses the modelling of real animal behaviour grounded in biologically realistic neural models [6]. Such modelling is extremely useful in robotics research as it can provide insights into how nature has equipped animals with efficient survival strategies and moreover how fairly complex behaviours can be generated by minimal neural architectures: natural systems manage to achieve speed, fault tolerance and flexibility with low power requirements and solve problems we find very difficult to implement on machines. An important component of Computational Neuroethology is to model situations where entire animal 'behaviours' are generated from interaction with the environment: i.e. 'closing the external feedback loop from motor output and sensory input' [6]. An additional benefit in making a serious study of natural sensorimotor systems is to anticipate the future direction of robotic hardware, in particular the field of Neuromorphic Engineering. Advances in this area are now making it possible to simulate large neural networks in hardware in real time. Such 'neural chips' are massively parallel arrays of processors that can simulate thousands of neurons simultaneously in a fast, energy efficient way and compute using similar methods to the way real neurons behave. Therefore it is becoming much more feasible for researchers to actually implement biologically realistic models on board autonomous robots.

The original contribution of the current work is to extend a neural model proposed in Refs. [7,8] in two ways. Firstly, by creating a physics simulation and visualisation of a virtual arachnid and linking this to the neural model so that vibration signals result in reflexive turning behaviour to face the direction of a virtual prey. Secondly, to add a neural distance sensing mechanism and a complementary motor system to cause walking towards prey following an orientation movement. The work of Ref. [9] describes a previous implementation of localisation for a hexapod robot, which borrows from some of the orientation sensing ideas in Refs. [7,8] but does not use a neural approach. Also, finding the location of a vibration source is done using a completely separate system using radio beacons. In our work we add a prey distance estimation mechanism based upon the same biological neural network used for the orientation sensing with the aim of trying to explain/predict how the real animal might achieve distance sensing given that we know the kinds of sensors it has and its neurobiology. An integrated orientation and distance estimation method enables the future possibility of full localisation and tracking behaviour for robots using a minimal-architecture spiking neural network. The structure of this paper is as follows: Section 2 gives an overview of the biological theory behind the model of arachnid orientation behaviour and previous works which have developed computational models of it. Section 3 describes how the model in Ref. [7] has been extended by adding orientation motor behaviour in a physics simulation of an arachnid. Section 4 explains the rationale for and implementation of a distance estimation method based upon biological evidence from vibration detection experiments with real arachnids. Section 5 presents some results from testing the orientation and distance sensing behaviour of the model in response to a randomly placed prey. The final section summarises the performance of the current model and makes some suggestions for future work.

2. Modelling prey orientation detection in arachnids

The work of Brownell et al [10,11] examined the orientation behaviour of the Desert Scorpion, *Paruroctonus mesaensis*, which is nocturnal and able to locate prey purely by detection of vibrations carried by the sand substrate. The vibrations are picked up by detectors called Basitarsal Compound Slit Sensilla (BCSS), which are present on the tarsi of the scorpion's eight legs. The experiments consisted of measuring the orientation behaviour in response to artificially created mechanical vibration signals. In order to explain the neural basis of the orientation mechanism they also looked at the results of blocking the signals to one or more legs at a time and observing the degradation in turning accuracy. The mathematical model described in Refs. [7,8] was based upon the findings of this experimental work and was able to reproduce similar results to those seen in the real animal. The model is based upon a Spiking Neural Network (SNN). In contrast to traditional Artificial Neural Networks (ANNs), which are rate-based, spiking neurons compute with pulses, much like real neurons do. In the simplest form of such models the membrane voltage of a neuron increases as spikes are received from connecting neurons. Once a threshold value is exceeded, the neuron spikes and the membrane voltage is reset. Gradually, the neuron recovers during a refractory period until it is able to spike again. In Ref. [12], Maass demonstrated that SNNs are more powerful than ANNs as they can compute the same functions using less neurons. The original orientation model consists of a ring of eight sensory spiking neurons representing the basitarsal compound slit sensilla (BCSS) mechanoreceptors present on each of the arachnid's legs. In the real animal the legs are held in a 'ready' stance at specific orientations relative to the body ($\pm 18^\circ$, $\pm 54^\circ$, $\pm 90^\circ$, $\pm 140^\circ$). These sensory neurons are linked with excitatory connections to eight command neurons that represent control structures in the Sub-Oesophageal Ganglion (SOG), a major component of the nervous system in arachnids. The model assumes that the command neurons are responsible for both integration of sensory signals and executing motor commands. In reality these SOG neurons may relay sensory information to the arachnid 'brain' (located in the Supra-Oesophageal Ganglion), which then sends signals back to control the legs. Each BCSS/command neuron pair is linked to an inhibitory interneuron. Fig. 1 illustrates the arrangement and connectivity of neurons. For clarity, only connections through three legs and one interneuron are shown.

Command neurons connect in 'triads' to inhibitory interneurons (Fig. 1 illustrates one triad), which are in turn connected to a command neuron on the opposite side of the network. The placement of legs, and thus sensors at intervals around the body determines the information available to the arachnid to enable it to estimate the prey orientation: the crucial information is actually the delay between activation of the sensors of each leg as the wave signal arrives. As shown in Fig. 1, each command neuron receives both excitatory and inhibitory signals from BCSS sensory neurons. Excitatory signals come from the BCSS neuron directly linked to a command neuron and inhibitory signals come from the inhibitory triad on the opposite side of the network. The 'time window' of activation of a command neuron depends upon the delay between activation and inhibition and the number of spikes generated depends upon the length of the time window in