

Application of Arachnid Prey Localisation Theory for a Robot Sensorimotor Controller

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Abstract

We study a neural model of arachnid prey orientation sensing with a view to potentially using the model in Robotics. The model has been implemented using the Brian spiking neural simulator and incorporates a physics simulation of the arachnid with a simple motor model that translates sensory signals from the neural model into movement to orient towards the prey. The arachnid behaviour repertoire includes the original neural orientation sensing plus prey distance sensing and also 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 degrees 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 degrees 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 degrees that has been observed in real arachnids.

Keywords: Arachnid Prey localisation; Sensorimotor coordination; Robot controller; Spiking neural network

1. Introduction

A neural model proposed in [1,2] attempted to explain the mechanism by which nocturnal desert scorpions can locate prey purely by detection of vibrations carried by the sand substrate. These works concentrate on the determination of prey orientation using a computational neural model of vibration sensitive detectors called basitarsal compound slit sensilla (BCSS) which are present on the tarsi of the scorpion's eight legs. This neural model, as described in [1] has subsequently been implemented in the Brian spiking neural network simulator and is included as a code example with the source distribution [3].

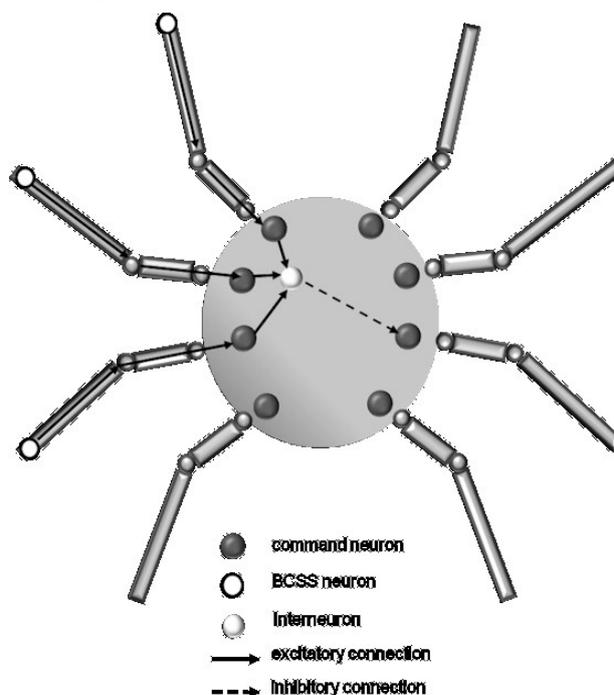
The orientation neural model generates 'an answer', i.e. a prediction of the prey angle, but it remains unclear how this information might be used in real animals to cause orientation towards the prey, or how the mechanism might be used to generate an orientation sensing behaviour for a robot. There is little or no precise information in the literature about how this happens in real animals, nor any previous work which attempts to model the motor control of arachnid prey localisation. Consequently, a main aim of the current work has been to extend the arachnid prey orientation neural model to include motor behaviour. In particular, we will demonstrate how sensory input (vibration waves caused by moving prey) can be linked to motor output (predator orients and moves towards prey) via a biologically realistic spiking neural network. This type of modelling falls under the umbrella of Computational Neuroethology which encompasses the modelling of real animal behaviour grounded in biologically realistic neural models [4]. Such models are extremely useful in robotics research as they 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. 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' [4]. In the current work, the original neural orientation model proposed in [1,2] has been extended in two ways. Firstly, by creating a physics simulation and visualisation of a virtual arachnid and then linking this to the neural model so that vibration signals result in reflexive turning behaviour to face the direction of a virtual prey. Secondly, by adding prey distance estimation to cause walking towards prey following an orientation movement. Adding the motor component has enabled the use of a standalone neural model in a practical application involving a simulated octopod robot and paves the way for future real robot applications. Adding distance estimation also enables the possibility of full localisation and tracking behaviour for robots.

The structure of this paper is as follows: Section 2 briefly describes some 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 [1] 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. Prey orientation detection in arachnids

The neural model described in [1,2] has originated from previous experimental work by Brownell and collaborators [5,6]. The experiments examined the orientation behaviour of the Desert Scorpion, *Paruroctonus Mesaensis* 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 and observing the degradation in turning accuracy. The neural model developed as a result of the findings of this work consists of a ring shaped neural network with eight sensory neurons which represent 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 ($\pm 18^\circ$, $\pm 54^\circ$, $\pm 90^\circ$, $\pm 140^\circ$). The BCSS sensory neurons are linked directly 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.

Figure 1. The arachnid neural network



Command neurons connect in 'triads' to inhibitory interneurons, which are in turn connected to a command neuron on the opposite side of the network. This arrangement of legs and BCSS sensors determines the information available to the arachnid to enable it to estimate the prey orientation: the crucial information is carried in the delay between activation of the sensors of each leg as the wave signal arrives. In [1,2] this delay is modelled by equation 1.

$$\Delta t(\gamma_k, \gamma_l | \varphi_s) = \frac{R}{v_r} [\cos(\varphi_s - \gamma_l) - \cos(\varphi_s - \gamma_k)] \quad (1)$$

Where:

Δt is the time delay

φ_s is the actual prey angle

γ_k, γ_l are the angles of legs k and l respectively

R is the scorpion radius (taken as 2.5 cm in the model)

v_r is the wave speed (approximately 50 metres per second for surface Rayleigh waves)

The Brian implementation of the model uses equation 1 to calculate an array of delays for each BCSS sensor neuron depending on its respective leg angle, and this array is used in the neuron model to apply the appropriate delay to the wave signal when calculating the voltage.

According to [5,6] the BCSS mechanoreceptors in the real animal are specifically activated by Rayleigh (surface) waves travelling through the sand. Although another type of surface wave exists (the Love wave) this was not observed to play any part in activating the BCSS sensors. Therefore, in this work we use the terms Rayleigh and surface wave interchangeably.

Using the physical characteristics of Rayleigh waves in sand from [5] both the theoretical model of [1,2] and the Brian implementation represent the wave signal mathematically as a discrete Gaussian distribution of cosine waves using equation 2.

$$y(t) = 100 * \sum_k D(f_k) \cos(2\pi f_k t + \chi_k) / \sum_k D(f_k) \quad (2)$$

Where:

$y(t)$ is the amplitude of the wave signal at time t

f_k is the wave frequency, calculated as $300 + (k - 150)$ Hz with $0 \leq k \leq 300$.

D is a Gaussian distribution with mean 300 Hz and standard deviation 50 Hz.

χ_k is a random noise variable.

In the Brian implementation, $y(t)$ is pre-calculated for each simulation time step using the range of values for f determined by the parameter k as given above. In line with the observed arachnid response time the simulation runs for 500ms at a time step interval of 0.1ms. At each time step of the simulation the wave signal at that time (minus the delay for the appropriate BCSS sensor calculated using equation 1) is applied during the calculation of the BCSS neuron voltage

Due to the arrangement of the network shown in Figure 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 which the signal is received. Command neurons at or near the prey orientation will in general receive more spikes as excitatory signals from the command neurons are not inhibited by the opposing interneuron quickly enough. Similarly, neurons on the opposite side to the prey will be inhibited more quickly by the firing command neurons on the side of the prey and so produce less spikes. The simulation output is a population vector of spike counts from the neurons corresponding to the eight legs and this information can be used to estimate the prey orientation by using a standard population vector decoding technique such as described in [7] and shown as equation 3:

$$\theta = \arg(\sum_{k=1}^N n_k e^{i\gamma_k}) \quad (3)$$

Where:

θ is the estimated direction of prey.

N is the number of command neurons (in this case 8)

n_k is the spike count from neuron k

γ_k is the angle of leg k .

It should be noted that a variant implementation of the same arachnid prey localisation model is described in [8] where a slightly different neural model is used and a sinusoidal array technique is employed to hold and process the sensory information: this is proposed to make the calculations easier and the model more robust to neuronal noise. In the current work the simpler model of [1] is adhered to.

3. Creating the arachnid simulation

3.1 Modelling software

As previously mentioned, the orientation neural model of [1] had already been implemented in the Brian spiking neuron simulator [3]. Brian is a simulation tool for spiking neural networks based on the scripting language Python¹. For initial prototyping, we used PyODE (a Python interface to the physics simulator Open Dynamics Engine)² and VPython, a Python visualisation module³ to create the full arachnid simulation. However there were issues with the performance of the motor parts of the model which were attributed to the physics simulation implementation. Although the PyODE wrapper was easy to use it transpired that ODE required careful parameter tuning to get a stable simulation. Even though some tuning was subsequently done, it was not possible to get completely satisfactory motor behaviour. The results of this initial work are described in [9]. We improved the motor model by using a different physics simulation based upon the commercial physics engine Nvidia PhysX with the JPhysx Java wrapper⁴. This had already been successfully used to create insect-like agents in [10] and showed none of the issues seen when using PyODE in the initial prototype. In the present work interfacing to the Python code is done using JPype⁵. The neural and motor simulation parts do not run concurrently: The neural model code is spawned as a separate process from the main Python program. It processes the sensory signals and returns them back to the main program which then calls the physics simulation and passes the required information.

3.2 A simplified arachnid model

In reality, the arachnid leg has several segments and joints. For the purpose of the current work it was decided that this would be simplified and only two segments and two joints would be used per leg to control the 'swing' (forward-backward) and 'stance' (up-down) phases of locomotion. These correspond approximately to the coxa-trochanter (C-TR) and trochanter-femur (TR-F) joints in real arachnids [11]. The walking gait used by real arachnids is described in [11,12] and can be approximated by a tetrapod walk where exactly four legs are on the ground and four off at any one time. This is usually an L1, L3, R2, R4 / R1, R3, L2, L4 pattern. The legs have been modelled in the physics simulation with simple 1 Degree

¹ <http://www.python.org/>

² <http://pyode.sourceforge.net/>

³ <http://vpython.org/>

⁴ <http://developer.nvidia.com/page/home.html> and <http://sourceforge.net/projects/jphysx/>

⁵ <http://jpype.sourceforge.net/>

Of-Freedom (DOF) hinge joints. Movement is controlled by sinusoidal generators which calculate the 'set point' or angle for each 1 DOF joint at each time step. These are of a form similar to that used in [13] for biologically inspired snake robots and are modelled by equation 4:

$$\theta_i(t) = A \cdot \sin(2\pi \cdot v \cdot t + 2\pi \cdot \varphi) \quad (4)$$

Where:

$\theta_i(t)$ is the set point for joint i at time t .

A is the amplitude.

v is the frequency.

φ is the phase.

Amplitude and frequency are set at suitable values to give a reasonable height of step and speed of movement. To implement the tetrapod gait pattern, the phase parameter for swing and stance joints is set so that adjacent legs cycle out of phase. Legs on the left and right sides of the body also operate out of phase. The parameters used to generate the basic arachnid gait are given in Table 1 and Figure 2 shows a diagram of the simulated arachnid body and leg arrangement.

Table 1 – Tetrapod Gait Parameters

Parameter	Coxa-Trochanter (swing)	Trochanter-Femur (stance)
Amplitude	30	30
Frequency	0.75	0.75
Relative Phases for Legs 1-4 *	1.5, 1.0, 1.5, 1.0	0.5, 0.0, 0.5, 0.0
Relative Phases for Legs 5-8 *	0.5, 0.0, 0.5, 0.0	1.5, 1.0, 1.5, 1.0

* Legs 1-4 are on the right hand side of the body and legs 5-8 are on the left hand side.

The main body consists of four spheres linked by rigid joints with a pair of legs attached to each sphere. The 'head' end of the arachnid is the sphere holding legs 1 and 8. Figure 3 shows a snapshot of the completed arachnid in the simulated world with a prey represented by a white sphere. The arachnid starts the simulation placed with its 'head' due East with respect to the world (0°) and at the centre of the world, which is (0.0,0.0). In the simulation 1 distance unit is taken to be 1 cm.

The prey is generated at a random angle up to +/- 180 degrees with respect to the initial arachnid position. Please note that 'prey angle' or 'prey orientation' in the remainder of this document refers to this angle of the prey with respect to the arachnid.

Figure 2 – The arachnid model

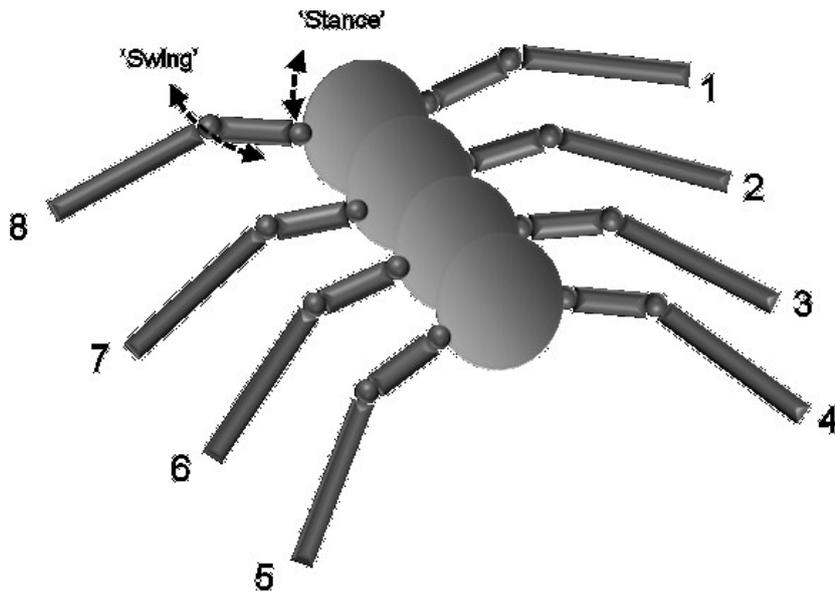
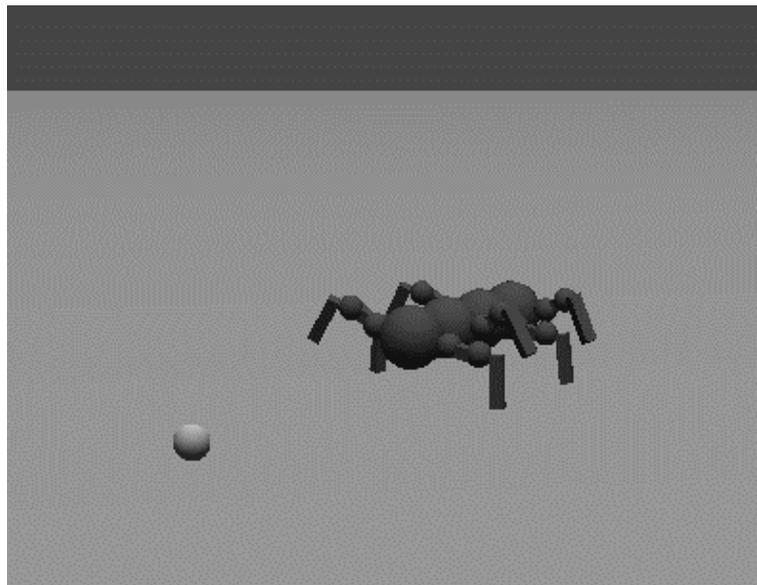


Figure 3 – The simulated world showing arachnid and prey



3.3 Translating spikes to orientation motor behaviour

Returning to the question posed earlier: how might information from the orientation neural processing be used to coordinate movement to turn towards the prey? Although a motor model was not implemented in their work, the final discussion section of [6] considers the turning behaviour of spiders and mentions the results of some previous work in [14] which examined walking and turning behaviour in jumping spiders. This work showed that turning is a simple modification of the standard walking gait. Legs that move in phase and in the

same direction on opposite sides of the body during walking (i.e. the L1, L3, R2, R4 / R1, R3, L2, L4 pattern described earlier) stay in phase but step in *opposite* directions during turning. It also confirmed that stepping frequency and amplitude on both sides remain the same during turning as for normal walking. We conclude from this that legs are probably not controlled individually. It is likely that there is a Central Pattern Generator (CPG) system, which determines the basic gait, but this can receive an overriding tonic signal that temporarily changes the pattern to produce the turning movement. Such systems are ubiquitous in nature and have been extensively studied in the field of biologically inspired robotics; for an example see [15]. Therefore this approach is used in the current work. The basic tetrapod gait described in section 3.2 is used as the default walking pattern and is modified by a 'tonic signal', i.e. the sign and magnitude of the angle calculated by the neural system. When this information is passed back from the neural processing, the sign and magnitude of the required turn angle are extracted. The sign is used directly to modulate the sign of the signal generated by the sinusoidal controllers and this causes a change in direction. The magnitude of the angle is translated into a number of time steps duration to be spent turning. This involves simply multiplying by a factor that was determined by tests with the simulator and involved running with a fixed angle to see how many time steps were needed to achieve the turn.

4. The distance estimation model

4.1 Rationale for distance sensing in arachnids

According to [2] the desert scorpion has two distinct behaviours, which involve an orientation response. These are the Defensive Orientation Response (DOR), where the animal orients only and the Predator Orientation Response (POR) that involves orientation and movement towards the prey. The latter behaviour allows scorpions to accurately catch prey in one movement if it is within 20 cm radius. We assume that distance estimation must be an important element of this behaviour in order to vary the amount of forward movement with prey distance. Although distance sensing is mentioned very briefly in some of the orientation sensing works (for example, [6]) we are not aware of any research investigating the neural mechanism in real scorpions or any theoretical or software models of such a process. Therefore, as part of the current work we present one possible mechanism, involving a simple modification of the existing orientation neural model.

A prey animal moving along on the ground produces both surface transverse travelling waves (Rayleigh waves) and longitudinal travelling waves (P waves). The P waves travel approximately three times faster than the surface waves according to [5]. In theory then, the scorpion could judge the distance of the prey by detecting the difference in arrival time for

the two waves [1,6,8]. It was also proposed in [6] that the varying amplitude of P waves across leg sensors could be used as a measure as P waves dissipate more quickly than Rayleigh waves over distance. Results from the experimental work described in [5] and [6] suggest that hairs present on the bottom of the tarsi which are directly in contact with the sand are the main mechanoreceptors for detecting P waves; the basitarsal compound slit sensilla (BCSS) appear to perform *only* surface (Rayleigh) wave detection. The orientation model of [1] used a 'time window' approach where command neuron activation is determined by the balance between excitation from BCSS sensors in the direction of prey and inhibition from BCSS sensors on the opposite side. A similar principle could be used to estimate the prey distance by using the interaction between P and Rayleigh waves reaching the BCSS and tarsal hair sensors respectively. For instance, as the P waves are fastest they arrive first and activate the tarsal hair sensors of all legs. Upon later arrival of Rayleigh waves, activation of the BCSS sensors could be used to inhibit tarsal sensors thus closing the 'window' of activity. The amount of tarsal hair sensor activity during this window would thus encode the distance to prey and govern the strength of the forward response. According to [5], the P wave sensor mechanism in scorpions is fairly short range and operates best up to about 10 cm whereas the Rayleigh waves can be detected up to 50 cm. In the current work we have chosen not to model this distinction, and both waves are assumed be detectable over the same range.

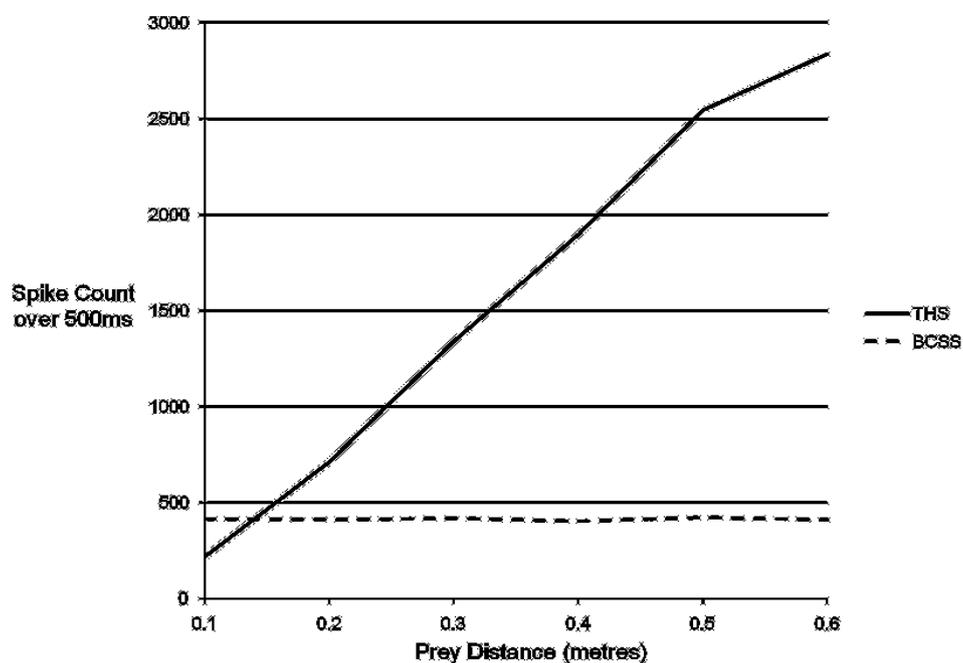
4.2 The distance estimation neural model

Following on from the ideas discussed in section 4.1, the original neural orientation model was extended to include eight tarsal hair sensor (THS) neurons and their corresponding command neurons. These have the same synapse connection structure between them as the BCSS sensory and command neurons. In addition the THS and BCSS sensory neurons in each leg are connected by strong inhibitory connections so that as soon as BCSS neurons fire they drastically reduce the activity of the THS neurons. The P wave has been modelled using the same method as the Rayleigh wave discussed in Section 2: a Gaussian distribution using information about P waves obtained from [2]. As the wave signals over time are generated by a computational model and do not actually travel, the speed difference between P and Rayleigh waves has been simulated by altering the time constant of the model equations for the tarsal hair sensors and their command neurons so the response compared to the BCSS sensors is proportionately faster dependent on the distance between arachnid and prey. It has been estimated elsewhere that the time difference is of the order of 1.3 ms per 10 cm distance [6] and so this factor is used in the current work. In contrast to the orientation sensing mechanism which uses a population

vector decoding method to estimate the prey direction, the distance neural model uses the total activity generated by the tarsal hair sensors (i.e. the sum of spikes from all legs) over the simulation time of 500 ms.

Using a standalone version of the extended neural model, test runs were done to establish the quantitative relationship between the THS activity and distance to prey so that this could be used to generate walking behaviour. The total numbers of THS and BCSS spikes generated during a 500 ms run were collected for a range of distances from 0.1-0.6 metres. Figure 4 shows a plot of activity (total spike count over 500ms) vs. distance for both BCSS and THS sensors.

Figure 4 – BCSS and THS sensor activity with prey distance



This graph shows that the total activity of BCSS sensors in this model (dashed line) is not distance sensitive (the orientation sensing relies only on differences in activity between legs). However, there is a distinct relationship between prey distance and THS activity (solid line). The greater the distance between the arachnid and prey, the bigger the time window for fast travelling P waves to activate the THS sensors and so more spikes are generated. At close distances, THS activity is almost instantaneously suppressed below the activity of BCSS sensors due to the inhibitory nature of the connections between them.

In order to turn this relationship into a quantitative model for use in determining the amount of walking required in the corresponding motor model a linear regression was performed using the THS activity test data (THS activity against prey distance) to determine the parameters for an equation using THS activity as a predictor of distance. The p value generated by the fitting process was $1.93e-05$ (well below the significance value of 0.05) and

the R^2 value was 0.9928 showing that THS activity is a very good predictor of prey distance. The generated parameters resulted in equation 5.

$$D_{\text{est}} = 0.00018 * \text{THS} + 0.06 \quad (5)$$

Where:

D_{est} is the predicted prey distance

THS is the THS total spike count

In the generation of walking behaviour, equation 5 is used to estimate the prey distance based upon the THS spike count returned from the neural processing. The distance prediction is then translated into a duration to be spent walking. This involves simply multiplying by a factor that was determined by tests in the simulation measuring how many time steps were needed to walk a fixed distance. In the extended motor model, the turning and walking behaviours are combined in a simple way. Turning behaviour is executed first to face the direction of prey and then walking behaviour is executed to walk towards it, i.e. turning/walking behaviour is not concurrent. Although this was done for simplicity, it was later realised that according to [6] that this kind of separation of the two behaviours has actually been observed in real arachnids!

5. Results

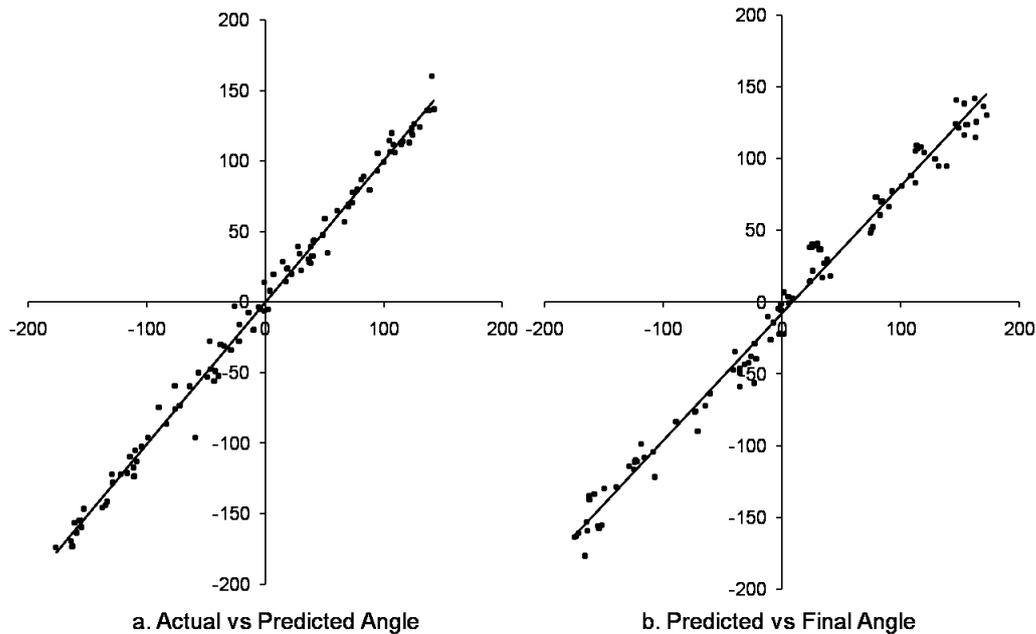
Once the orientation neural model had been extended with the distance sensing mechanism and motor behaviours added via the physics simulation, 100 trials of the software were run recording the turning and walking behaviours in response to a prey placed randomly at an angle up to +/- 180 degrees orientation and 8 – 20cm distance with respect to the arachnid starting position. The orientation and distance performance are discussed separately in the following subsections.

5.1 Orientation Performance

The actual prey angle, estimated prey angle from the neural model and final angle of the simulated arachnid were collected over 100 trials. Figure 6a shows a comparison of actual prey angle against the prediction of the neural model and 6b a comparison of the neural prediction against the final arachnid angle. Both graphs show a clear straight-line relationship with data points spread evenly across the linear regression line. In terms of the neural model alone the average absolute error (with respect to the actual prey angle) over the 100 trials is 6.52 degrees. In terms of the combined neural and motor model the absolute average error (with respect to the actual prey angle) is 15.47 degrees. Therefore, the neural

model is capable of a very accurate prediction of prey orientation but some accuracy is lost during actual movement. According to the graph in Fig 3. (a) in [1] the error in the real scorpion is in the region of +/- 12 to 15 degrees. Therefore the system behaviour is close to the performance expected of the real animal.

Figure 5 – Performance of the neural and motor orientation models

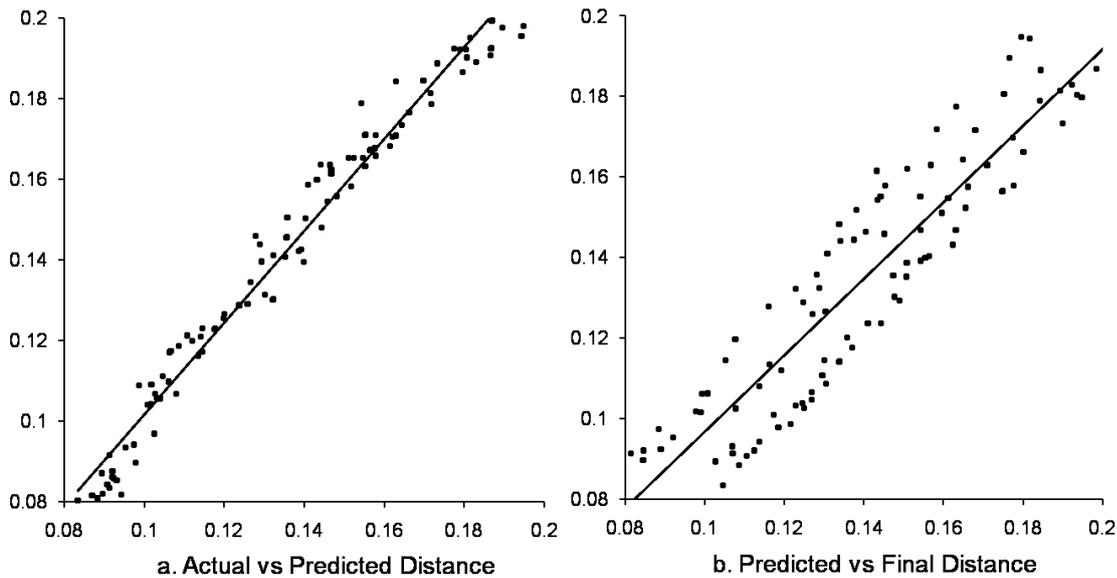


5.2 Distance Sensing Performance

The actual prey distance, estimated prey distance from the neural model and final distance travelled by the simulated arachnid were collected over 100 trials. Figure 7a shows a comparison of actual prey distance against the prediction of the neural model and 7b a comparison of the neural prediction against the final arachnid distance.

Again, both graphs show a clear straight-line relationship with data points spread evenly across the linear regression line. In terms of the neural model alone the average absolute error (with respect to the actual prey distance) over the 100 trials is 1.00 cm. In terms of the combined neural and motor model the absolute average error (with respect to the actual prey distance) is 1.25 cm. Although there are no results from a real animal to compare to in this case, this seems a reasonable level of performance given the distance over which the prey can be sensed (20 cm) and the size of the scorpion (2.5 cm).

Figure 6 – Performance of the neural and motor distance models



6. Discussion and Future Work

The results show that the neural models for orientation and distance sensing are able to predict actual prey orientation and distance to a good level of accuracy: approximately 7 degrees in the case of the orientation and 1 cm in the case of distance. Including the performance of the motor models reduces the accuracy for both orientation and distance, but the orientation results still show comparable performance to a real animal. A deficiency of the current system is that the Rayleigh and P waves are mathematically simulated following the original neural implementation of [1,2] instead of modelling the physics of the wave fronts which should have been possible in the physics simulation. The consequence of this is that the representation of the relative speeds of the two waves is somewhat artificial: the neural model response is modified to simulate difference arrival times of the waves. Future work could include incorporation of the wave fronts into the physical simulation. There are several other enhancements that the authors believe would also considerably improve the current work in terms of its applicability to robotics. In this initial implementation the neural processing and physics simulation do not operate concurrently: the neural model is run first to generate the sensory information and is then passed to the physics simulation to execute the motor operations. Making the two processes concurrent would enable re-estimation of angle and distance 'online' and allow for corrective behaviour. It would also allow the possibility of a moving prey so that the predator can orient and intercept in a reactive way. Secondly, it would be desirable to implement the motor parts of the model on an arachnid (or other) robot rather than a simulation. However some consideration would need to be given to

the appropriate sensory input, for example either using a vibration sensor or alternatively infrared or sound input.

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