

# A Sensory-Motor Model of Arachnid Prey Localisation

S. V. Adams, P.F. Culverhouse, T. Wennekers, G. Bugmann and S. Denham

**Abstract**— The basis of the current work is a neural model of arachnid prey orientation sensing originally formulated by [1]. With a view to potentially using the model in Robotics work, it has been extended to incorporate a physical simulation of the arachnid with a simple motor model that translates information from the neural model into movement to orient towards the prey. The arachnid behaviour repertoire has also been extended to include prey distance sensing in the neural model and a complementary motor model that causes walking towards the prey. Results from testing of the neural and motor models show that the neural models can represent actual prey angle and distance to a fairly high degree of accuracy:  $\pm 10$  degrees in the case of angle and  $\pm 1$ cm in the case of distance. Although the motor models show the correct responses the accuracy of the neural prediction is somewhat reduced in translating the neural signals to movement. Most of this is due to difficulties in tuning physics simulation parameters and can be improved with more work.

## I. 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 the orientation relative to the arachnid of a prey animal 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 has previously 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 enables the generation of 'an answer', i.e. the angle of the prey in relation to the arachnid, but how might this information be used in real animals to cause orientation towards the prey? As far as the authors are aware there is no precise information in the literature about

Manuscript received April 29, 2010.

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how this happens in real animals, nor any previous work that attempts to model the motor control of arachnid prey localisation. Consequently, a main aim of the current work was to extend the arachnid prey orientation neural model to include motor behaviour. In particular, to 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 plausible spiking neural network. Such a model 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 aspect 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 first step was to create a physics simulation and visualisation of the virtual arachnid and then link this to the orientation neural model so that vibration signals resulted in turning behaviour to face the direction of the prey. The neural model was then extended by adding distance estimation to enable movement towards prey following orientation. The structure of this paper is as follows: Section II. briefly describes some of the biological theory behind the neural model of arachnid orientation. Section III. describes how the model in [1] has been extended by adding orientation motor behaviour using a physics simulation of an arachnid and also a distance estimation method based upon biological evidence from vibration detection experiments with real arachnids. Section IV. presents some results from testing the orientation and distance sensing ability of the model in response to a randomly placed prey. The final section discusses the performance and limitations of the current model and some suggestions for future work.

## II. PREY ORIENTATION DETECTION IN ARACHNIDS

The neural model described in [1], [2] has originated from several previous works which describe findings from experiments with the Desert Scorpion, *Paruroctonus Mesaensis* ([5], [6]). The neural model consists of a ring network of eight sensory neurons which represent the basitarsal compound slit sensilla (BCSS) mechanoreceptors in the legs which are held at specific orientations relative to the body ( $\pm 18^\circ$ ,  $\pm 54^\circ$ ,  $\pm 90^\circ$ ,  $\pm 140^\circ$ ). These

‘receptor’ neurons are linked directly to eight ‘command’ neurons which represent control structures in the Sub-Oesophageal Ganglion (SOG), a major component of the nervous system in real arachnids. These command neurons are responsible for integrating sensory signals and executing motor commands. Each BCSS / command neuron is also associated with an inhibitory interneuron. Fig. 1. illustrates the arrangement and connectivity of neurons, where command neurons are shown as filled black circles and inhibitory interneurons are grey (for clarity, only two of the eight interneurons are shown).

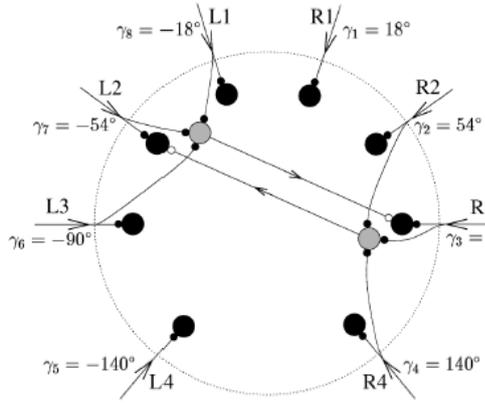


Fig. 1. The arachnid neural network model. Taken from Fig. 2. in [1]

Thus each command neuron is connected to an ‘inhibitory triad’ on the opposing side of the network. The BCSS mechanoreceptors are activated by Rayleigh (surface) waves travelling through the sand and the model represents these by a Gaussian distribution of wave signals:

$$100 * \sum_k D(f_k) \cos(2\pi f_k t + \chi_k) / \sum_k D(f_k) \quad (1)$$

Where:

$f_k = 300 + (k - 150)$  Hz with  $0 \leq k \leq 300$ .

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

$\chi_k$  is a random noise variable.

The orientation sensing model relies on time differences in arrival of vibrations to the eight legs. At distances greater than 8cm from the arachnid the signals are assumed to be plane waves and the time delay between two legs,  $k$  and  $l$  can be calculated as follows:

$$\Delta t(\gamma_k, \gamma_l | \varphi_s) = \frac{R}{v_r} [\cos(\varphi_s - \gamma_l) - \cos(\varphi_s - \gamma_k)] \quad (2)$$

Where:

$\varphi_s$  is the prey angle

$\gamma_k, \gamma_l$  are the angles of tarsi  $k$  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 Rayleigh waves)

According to [5], when the original work was done looking at the wave sensing ability of the desert scorpion only surface waves with the characteristics of the Rayleigh wave were detected and not the other type, the Love wave.

Therefore, the parameters used in equations 1 and 2 reflect this and in this work we use the terms Rayleigh and surface wave interchangeably.

The model simulation duration is set to be 500 ms which is approximately the real arachnid response time. When a wave signal is received, each command neuron receives excitatory and inhibitory signals from BCSS neurons. Excitatory signals come from the BCSS neuron directly linked to a command neuron and inhibitory signals come from the inhibitory triad. The number of spikes subsequently generated by a command neuron corresponds to the length of the time window in which the signal is received. Command neurons at or near the prey direction in general will 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 output of the model is a population vector of spike counts from the eight legs which is converted to an estimated prey orientation. This is done using a standard population vector decoding technique such as described in [7] and uses the following calculation:

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

Where:

$\phi$  is the estimated direction of prey.

$N$  is the number of command neurons (in this case eight).

$n_k$  is the spike count from neuron  $k$ .

$\gamma_k$  is the angle of leg  $k$ .

A variant implementation of arachnid prey localisation is described in [8] where a slightly different neural model to that of [1] 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. However, in the current work the simpler model of [1] is adhered to.

### III. CREATING A SIMULATED ARACHNID

#### A. A Simplified Arachnid Model

Arachnid legs have several segments and joints but in the current work we have chosen to simplify this with only two segments and two joints 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 [9]. The walking gait used by real arachnids is described in [9], [10]. Although the ‘footprint’ diagrams show quite a complicated walking sequence (it is actually a ‘rolling

tetrapod’) it can be approximated by an ideal 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-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 [11] for biologically inspired snake robots and are modelled by the following equation:

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

Where:

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

$A$  is the amplitude.

$v$  is the frequency.

$\varphi$  is the phase.

Amplitude and frequency need to be set at suitable values to give height of step and speed of movement. Phase values for swing and stance need to be out of phase and also different between adjacent legs. 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. The physics simulation and visualisation was implemented using PyODE (a Python wrapper for the ODE physics simulator) and VPython. Fig. 2 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 simulated world and this is taken to be zero degrees. The prey is generated at a random angle up to  $\pm 180$  degrees with respect to the initial arachnid position. When we refer to ‘prey angle’ or ‘prey orientation’ in the remainder of this document we are referring to this angle of the prey with respect to the arachnid.

### B. Translating Spikes to Motor Orientation Behaviour

We return to the question posed in the introduction. 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 [12] 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 on opposite sides of the body (i.e. the L1, L3, R2, R4 / R1, R3, L2, L4 pattern mentioned earlier) step in *opposite* directions rather than the same direction. This work 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 by neural signals 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 from a control centre which temporarily changes

TABLE 1  
TETRAPOD GAIT PARAMETERS

Parameter	Coxa-Trochanter (swing)	Trochanter-Femur (stance)
Amplitude	60	60
Frequency	0.25	0.25
Phases for Legs 1-4 *	0.5, 0.0, 0.5, 0.0	0.0, 0.5, 0.0, 0.5
Phases for Legs 5-8 *	1.5, 1.0, 1.5, 1.0	1.0, 1.5, 1.0, 1.5

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

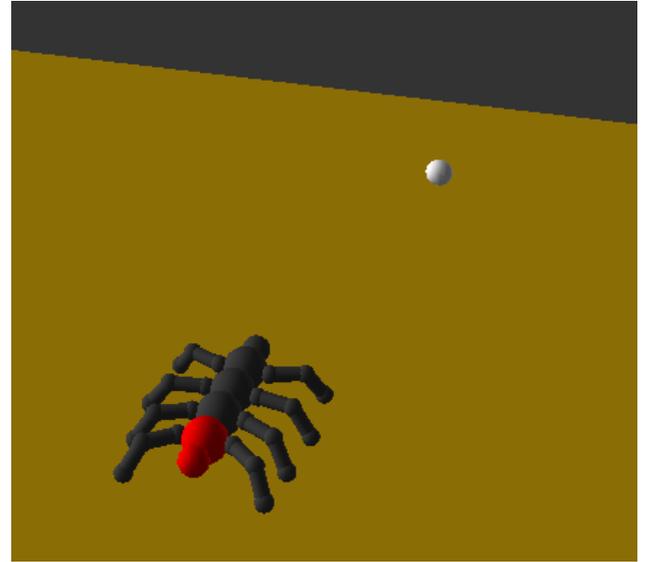


Fig. 2. The simulated arachnid and prey

the gait pattern to make 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 [13]. Therefore this approach is followed in the current work. The basic tetrapod gait described previously is used as the default walking pattern and is modified by the characteristics of the ‘tonic signal’, i.e. the angle calculated by the neural system. In the current work, the neural simulation is run first to generate the angle which is passed to the motor simulation which extracts the sign and magnitude. The sign of the angle controls the direction of turn by applying a change of sign to the values generated by the sinusoidal controllers and the magnitude of the angle is used to calculate the number of timesteps duration to be spent turning.

### C. A Simple Distance Estimation Model

According to [2] the desert scorpion has two distinct behaviours which involve the aforementioned orientation response. The Defensive Orientation Response (DOR) where the animal orients only and the Predator Orientation Response (POR) which involves orientation and movement towards the prey. The latter behaviour allows scorpions to accurately catch prey in one movement if it is within 20cm 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. However, the authors are not aware of any research investigating this in real scorpions or any neural models which reproduce it.

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 transverse waves [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 is also possible that varying amplitude of the P wave across leg sensors could be used as P waves dissipate more quickly than Rayleigh waves over distance [6]. Results from [5], [6] suggest that hairs present on the bottom of the tarsi and which are directly in contact with the sand are the main mechanoreceptors for detecting P waves; the basitarsal compound slit sensilla (BCSS) perform *only* surface (Rayleigh) wave detection.

The orientation model of [1] uses a ‘time window’ approach where activation is determined by the balance between excitation from BCSS sensors in the direction of prey and inhibition from opposing BCSS sensors. A similar principle can be used to estimate the time difference between P and Rayleigh waves reaching the BCSS and tarsal hair sensors respectively. The P waves arrive first and activate the tarsal hair sensors of all legs. Upon later arrival of Rayleigh waves, activity from the tarsal sensors is inhibited thus closing the ‘window’ of activity. The amount of activity during this window encodes the distance to prey and governs the strength of the forward response. In reality, the P wave sensor mechanism in scorpions is fairly short range and operates best up to about 10cm whereas the Rayleigh waves can be detected up to 50cm [5]. In the current work we have not chosen to model this and both waves are assumed be detected over the same range.

The original neural orientation model has been extended to include eight tarsal hair (THS) sensory 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 II: A Gaussian distribution using information about the P wave speed and frequency 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 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 1.3ms per 10 cm distance

[6] and so this factor is used in the current work. The orientation neural model uses the population vector decode method to estimate the direction of prey as the contribution of spikes from a population of legs needs to be resolved. In contrast, the direction neural model uses the total activity generated by the tarsal hair sensors (i.e. the sum of spikes from all legs). The simulation time is again 500 ms in line with the original model.

#### D. Translating Spikes to Walking Motor Behaviour

Using a standalone version of the extended neural model described in the previous subsection test runs were done to collect data in order to make a quantitative model of the relationship between the total THS activity and distance to prey for use in determining the amount of walking required. The total number of THS spikes generated during a 500 ms run were collected for a range of distances from 0.1-0.6 metres. A linear regression was performed to determine how effective THS activity was as a predictor of distance and the results showed an extremely good fit to a straight line relationship: 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 an almost perfect fit. Fig. 3. shows a plot of THS Activity (total spike count over 500ms) vs. prey distance predicted by the model.

This graph shows that the total activity of THS sensors is very distance sensitive. The greater the distance between the arachnid and prey, the bigger the time window for fast travelling P waves to activate the THS sensors. At close distances, THS activity is almost instantaneously suppressed by the activity of BCSS sensors due to the inhibitory nature of the connections between them.

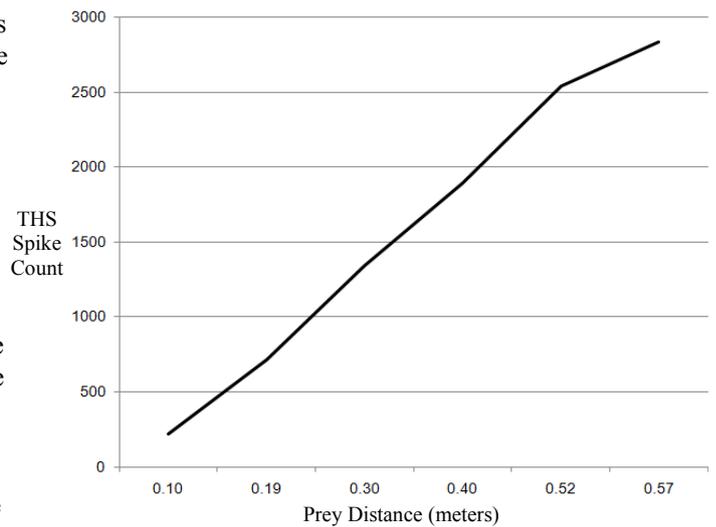


Fig. 3. Linear variation of THS sensor activity with prey distance

After the neural model has run, the THS spike activity value is passed to the physics simulation and converted into a prediction of prey distance using the above relationship. This is then used to estimate the number of timesteps duration of forward walking. In the extended model 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. It is mentioned in [6] that this kind of separation of the two behaviours has actually been observed in real arachnids.

#### IV. RESULTS

##### A. Orientation Performance

Once the original neural model had been extended with physics simulation, 100 trials of the software were run and the actual prey angle, estimated prey angle by the neural model and final angle of the simulated arachnid were collected to an accuracy of two decimal places. The neural model appeared to be very good at estimating the prey angle with errors in the region of  $\pm 10$  degrees. According to data from Fig 3. (a) in [1] the error in the real scorpion is somewhere in the region of  $\pm 12$  to 15 degrees. The motor model had comparable accuracy for small turn angles (up to  $\pm 75$  degrees) but at the extremes the model overestimated the required turn for positive angles and underestimated (to a lesser degree) for negative turn angles. This indicated that the motor orientation model required some adjustment. Initially, it was found that the friction value set in the physics simulation could be reduced and resulted in smoother turns. It was also found that the turning speed was not always the same for clockwise and counter-clockwise moves despite the leg arrangement and gait being set up to be symmetric. The reason for this was not clear and needs further investigation. A crude fix was put in place to the code that translates the angle magnitude into turn steps and used a different scaling value for clockwise and counter-clockwise turns. Following these amendments, another set of 100 trials were run, again collecting actual prey angle, estimated prey angle by the neural model and final angle of the simulated arachnid after the turn. In this version of the software the distance sensing behaviour had also been enabled, so in addition the actual prey distance, estimated prey distance and final arachnid distance were collected, also to an accuracy of two decimal places. As walking towards the prey happens after turning this does not affect initial turning behaviour. However, we considered that during walking the angle of the arachnid might be affected so in order to find out if this was the case the arachnid angle was measured both after the turn and after walking. Fig. 4. (a) shows a comparison of the actual prey angle with the prediction from the neural model (stars) and also the predicted prey angle against the arachnid angle after turning (circles). Linear regression lines have been added to make the relationships between the datasets more obvious. Firstly, we note the success of the neural model in predicting the actual prey angle generally to within about  $\pm 10$  degrees. Also amendments to the orientation motor model have eliminated some of the biases seen initially for larger positive and negative angles: the points for the Predicted vs. Final plot line are mostly evenly distributed either side of the regression line. However, it can be seen that the motor model is not executing the turn accurately enough to

maintain the predicted angle, in particular for larger negative angles.

Fig. 4. (b) compares the predicted prey angle against the arachnid angle after turning (circles) and the arachnid angle after walking against the arachnid angle after turning (crosses). This data shows that the walking behaviour is indeed disrupting the orientation of the arachnid set up by the turn: positive angles are reduced and negative angles are also increased in magnitude (made more negative). The effect is more noticeable for larger negative angles.

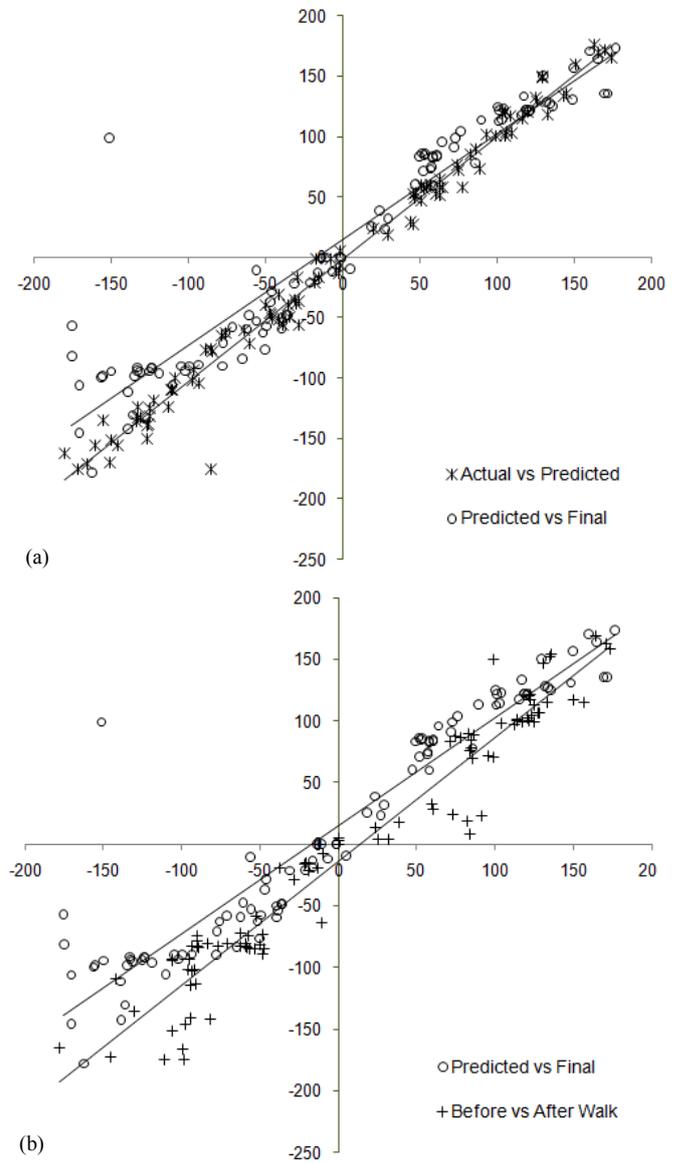


Fig. 4. Performance of the neural and motor orientation models (measurements are in decimal degrees)

##### B. Distance Sensing Performance

Fig. 5. shows a plot comparing actual prey distance against the estimation of the neural model (crosses) and the estimated distance against the final arachnid distance travelled (triangles). The Actual vs Predicted data (crosses) shows a consistent performance over the full range of

distances: there are no biases for any particular distance and the error is of the order of  $\pm 1$  cm. The Predicted vs Final data (triangles) shows a consistent underestimation in the motor model compared to the actual/predicted data of between 1 and 1.5 cm. Hence, there is a similar situation to the orientation model: the neural component is very successful at estimating prey distance but the motor model is not as successful in executing this and needs some tuning.

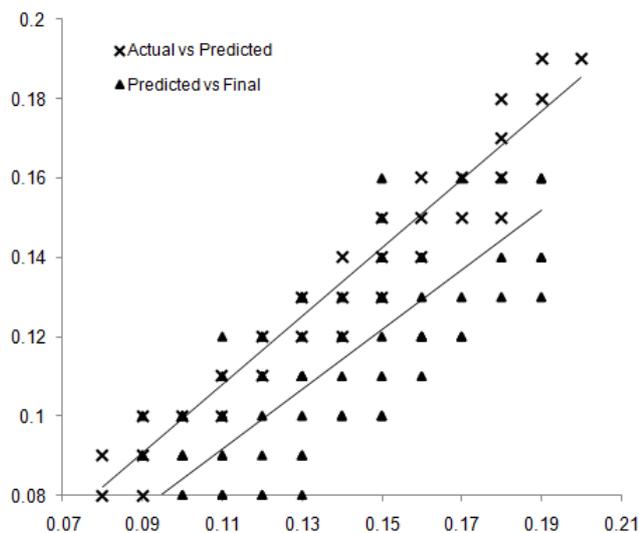


Fig. 5. Performance of the neural and motor distance models (measurements are in metres)

## V. CONCLUSIONS

The results of the previous section show that the neural models for orientation and distance sensing are able to predict actual prey orientation and distance to a reasonable level of accuracy:  $\pm 10$  degrees in the case of the orientation and  $\pm 1$  cm in the case of distance. Both motor models show various kinds of bias and variable behaviour which we believe are due mainly to tuning issues in the physics simulation. The main results showed that the motor orientation performance was affected by the magnitude of the turn angle. Following some investigation with fixed angles of  $\pm 60$  degrees and  $\pm 120$  degrees we noted that for the smaller angle we did not require the fix to correct turning behavior: the clockwise and counter-clockwise turns were performed correctly. For the larger angle the discrepancy became more obvious. Also, there were two particular simulation aspects that had a significant effect on locomotion. Firstly, the surface friction setting needed to be set high enough for legs to grip the ground surface without slipping but too high a value disrupted walking and turning severely. Secondly, the simulation timestep needed to be set small enough to avoid accumulation of errors in the simulation, but high enough for the simulation to run at a reasonable pace. The conclusion of this work is that it is most likely the simulation aspects, in particular friction, which are affecting performance when a large amount of turning is required.

As well improvements for the above problems, there are several enhancements which the authors believe would considerably improve the current work. Firstly, to make the neural processing and physics simulation concurrent. This 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 a real arachnid robot rather than a simulation. However some consideration would need to be given to the appropriate sensory input, for example using infrared or sound input instead of vibration.

## ACKNOWLEDGMENT

The authors wish to thank the two anonymous reviewers for their helpful suggestions for improvements to this paper.

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