Artificial Neural Network Models of Intersegmental Reflexes

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Keywords: Reflex, Artificial Neural Network, ANNs, Time Delay Neural Network, Metaheuristic Algorithm, Evolutionary Programming, Particle Swarm Optimisation, Chordotonal Organ, Locust.

Abstract: In many animals intersegmental reflexes are important for postural control and movement making them ideal candidates for the bio-inspired design of medical treatment for neuromuscular injuries in cases such as drop foot and possibly in robot design. In this paper we study an intersegmental reflex of the foot (tarsus) of the locust hind leg, which is a reflex that raises the tarsus when the tibia is flexed and depresses it when the tibia is extended. A novel method is described to quantify the intersegmental responses in which an Artificial Neural Network, the Time Delay Neural Network, is applied. The architecture of the network is optimised through a metaheuristic algorithm to produce accurate predictions with short computational time and complexity and high generalisation to different individual responses. The results show that ANNs provide accurate predictions when trained with an average reflex response to Gaussian White Noise stimulation compared to autoregressive models. Furthermore, the network model can calculate the individual responses from each of the animals and responses to another input such as a sinusoid. A detailed understanding of such a reflex response could be included in the design of orthoses or functional electrical stimulation treatments to improve walking in patients with neuromuscular disorders.

1 INTRODUCTION

Intersegmental reflexes are key elements in postural control and locomotion in many animals. One of their roles is to provide stability and agility to movements (Prochazka, Clarac et al. 2000). A reflex response is a neurally mediated reproducible movement graded with respect to stimulus intensity that is not controlled voluntarily. Understanding such types of reflexes might improve current medical treatments for neuromuscular injuries such as drop foot. It can also be applied to the design of prosthesis or active prosthesis for amputees (Herr and Grabowski 2011).

Intersegmental reflexes have been observed in many vertebrates and invertebrates, such as cats, crustaceans and insects (Burrows and Horridge 1974, Bush, Vedel et al. 1978, Field and Rind 1981, Smith, Hoy et al. 1985). Vertebrates and invertebrates have many similarities in motor control (Pearson 1993) and by studying intersegmental reflexes in insects, the complexity of the motor system and reflex responses is reduced, aiding its understanding. In locusts, the tarsus is moved by only three motor neurons (Burrows 1996). The tarsal intersegmental reflex elevates the tarsus when the tibia is extended and depresses it when the tibia is flexed (Figure 1). The response is therefore initiated by knee joint kinetics, which are monitored by a sensory organ in the femur, the femoral chordotonal organ (FeCO).

Figure 1: Tarsal intersegmental reflex when the tibia is fully flexed, in 60° and fully extended.

The chordotonal organ is connected to the tibia by a strand, an apodeme, which pulls on the FCO when the tibia is flexed and reduces the tension on the FCO when the tibia is extended (Shelton, Stepehn et al. 1992, Field and Matheson 1998).

Mathematical models have been used for many years to understand and describe similar reflexes. Linear and nonlinear models, such as Wiener

Costalago Meruelo A., M. Simpson D., Veres S. and L. Newland P..
Artificial Neural Network Models of Intersegmental Reflexes.
DOI: 10.5220/0005029000240031
In *Proceedings of the International Conference on Neural Computation Theory and Applications* (NCTA-2014), pages 24-31
ISBN: 978-989-758-054-3

methods, have been used in many studies (Newland and Kondoh 1997, Dewhirst, Simpson et al. 2009). Although these methods provide a quantitative description of the dynamic transfer characteristics of the system, they can contain different types of estimation errors (Korenberg and Hunter 1990). Artificial Neural Networks (ANNs) are considered to be able to approximate any continuous function (Haykin 1999), including non-linear systems (Hunt, Sbarbaro et al. 1992), they can adapt and generalise better than other mathematical methods (Benardos and Vosniakos 2007) and can be easily implemented in software and hardware devices (Hunt, Sbarbaro et al. 1992, Twickel, Büschges et al. 2011). Another issue is that, to date, mathematical models of biological systems have only been fitted to individual responses, i.e. the parameters are fitted to the response of one individual, which can be a poor representation of a population (Marder and Taylor 2011).

This paper describes novel methods to quantify intersegmental responses in the locust hind leg tarsus, describes a new mathematical approach to model and predict the tarsal reflexes using ANNs and asks whether individual responses or the average response should be used to model and study the system.

2 METHODS

2.1 Experimental Methods

Adult male and female locusts (*Schistocerca gregaria*) were fixed in modelling clay ventral side up, with the femur fixed at 60° from the abdomen and with the tibia fixed at an angle of 60° to the femur, an angle which represents the middle of the linear range movement of the FeCO apodeme (Figure 2). The FeCO was exposed by removing a small piece of cuticle at the distal end of the femur, and the cavity was perfused with locust saline. The FeCO apodeme was grasped with a pair of fine forceps tip attached to a shaker (permanent magnet shaker LDS V101). The shaker was driven by a signal generated in Matlab®, which was amplified and converted to analogue via a digital-to-analogue (DA) converter (USB 2527 data acquisition card (DAC), Measure Computing Norton, MA, USA). The movement response in the locust tarsus was recorded with a Keyence laser displacement sensor (LK G3001V controller, LK G32 Head, Keyence) aimed at the last segment of the tarsus.
The stimulus signals were designed and applied through Matlab®. Locusts walk at a step frequency of approximately 3 Hz (Burrows and Horridge 1974) and for this reason, Gaussian White Noise (GWN) was produced band-limited between 0 - 5 Hz, and a sinusoidal input simulating walking was applied at 1 Hz. GWN was chosen since it contains all the frequencies within that band and all the amplitudes within a range. The maximum peak-to-peak amplitude of the input signals was approximately 1 mm, which represents a femoro-tibial displacement of 90° (Field and Burrows 1982, Dewhirst, Angarita-Jaimes et al. 2012). The signals were scaled so that approximately 99.7 % of their values fall in the femoro-tibial joint angle between 20° and 100° (0.9 mm of displacement of the FeCO apodeme). The frequency and phase response of the equiment was linear between 0 and 200 Hz.

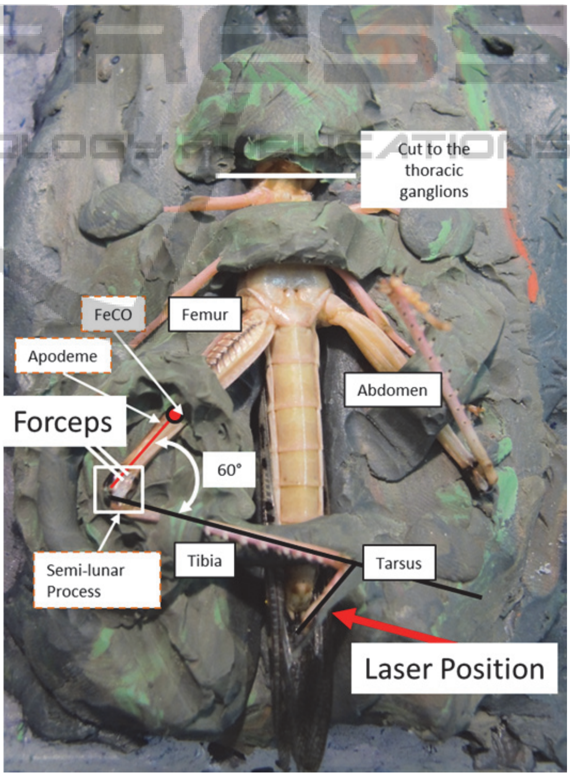

Figure 2: Image of a locust showing the set up for analysis. The forceps were attached to the apodeme in the distal part of the femur and a laser was aimed at the tarsus to monitor its movements.

2.2 Mathematical Methods

2.2.1 Data Post-Processing

Recordings of tarsal movement from eight locusts were made following the procedure described and recorded at a sampling frequency of 10,000 Hz. The mean value was subtracted from the recordings to eliminate any effect of laser position. To eliminate low frequency noise and spontaneous movements not related to the applied stimulus a third order high-pass Butterworth filter was applied with a cut off frequency of 0.2 Hz. The data was then resampled to 500 Hz after applying an anti-alias filter, a third order Butterworth with cut off frequency of 200 Hz, thereby reducing file size and processing time. Both Butterworth filters were applied in the forward and reverse directions to avoid introducing any phase delay. An average reflex response was calculated using the responses from the eight individuals to test whether the average is representative of the system or is if it is better to use individual responses

2.2.2 Artificial Neural Networks

To model the intersegmental reflex responses of the tarsus a dynamical artificial neural network is proposed, a Time Delay Neural Network (TDNN) (Waibel, Hanazawa et al. 1989). This network uses delayed versions of the input to estimate the output, turning the static Feed-Forward Network into a dynamic network (Haykin 1999). Using this, we assumed the reflex responses to be a combination of current and past input samples. The network is formed by an input node, an output node, and a number of hidden layers and with hidden nodes. The activation function for each hidden node is the sigmoid. The output node has a linear function, so all the non-linear calculations are performed inside the network. The training algorithm for the network is the Levenberg - Marquadt back-propagation algorithm, that has higher accuracy and faster convergence time compared to classical back-propagation algorithms (Bishop 1995). The number of delayed samples used in the input is set to 100 samples, which is based on preliminary work (optimisation of decrease in NMSE as the delay increases for a set architecture). The architecture of the network is optimised using a metaheuristic algorithm presented in the next section.

2.2.3 Metaheuristic Algorithm

The choice of the architecture of a neural network affects the performance of such network. In this case, the optimal networks should have high accuracy and low complexity to reduce computational time, and should be able to generalise, i.e. it should not over-fit the training data. To choose a performance optimal for the task an algorithm is proposed (Figure 3) based on a combination of Evolutionary Programming and Particle Swarm Optimisation (PSO) (Kennedy and Eberhart 1995, Eiben and Smith 2003). Similar algorithms have been successfully applied previously to design artificial neural network architectures (Benardos and Vosniakos 2007, Suraweera and Ranasinghe 2008). The algorithm creates a population of possible TDNN solutions, composed of random individuals. Each individual denotes the architecture of a neural network in a vector representation, with architectures limited to 5 hidden layers and 32 nodes per layer (Carvalho, Ramos et al. 2011), which provide a wide range to determine the optimal architecture. An individual has the form:

$$\eta = [n_1\ n_2\ n_3\ n_4\ n_5] \tag{1}$$

Where η is the individual or candidate TDNN architecture, and n_i the number of nodes in the layer i.

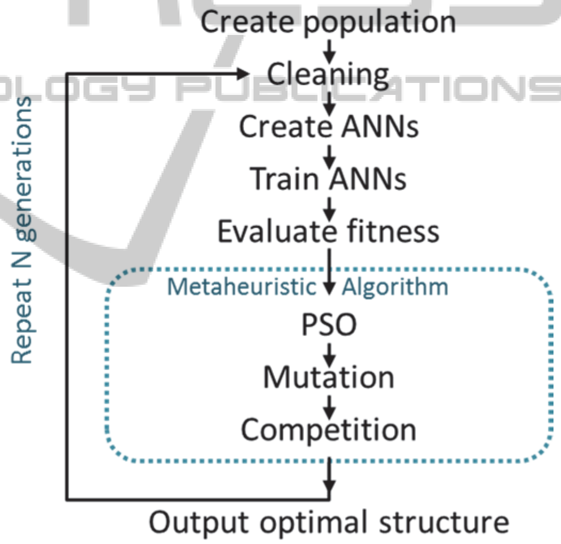

Figure 3: Metaheuristic algorithm for the design of the TDNN architecture.

A cleaning function is applied to the population of randomly initiated individuals $\boldsymbol{\eta}_j$, so that no network contains 0 hidden layers. Subsequently, the networks are created and trained with two thirds of the GWN average response calculated across individuals. The networks are then tested with the third GWN not used on the training and their performance and fitness is evaluated. The performance is calculated as the Normalised Mean Square Error (NMSE) between the predicted output $\hat{y}$ and the recorded output y.

$$NMSE(\%) = 100 \cdot \frac{\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{N}\left(y_i\right)^2} \tag{2}$$

The fitness function designed (Equation 3) evaluates the performance of the network, its size, and indirectly, the computational time. Since the networks are set to train for a limited amount of iterations, poor performance is obtained if they are not fully trained by then.

$$fit(\eta) = e^{\left(\frac{100}{NMSE(\%)} - a \cdot \sum \eta_i\right)} \tag{3}$$

Where a is a constant set to 0.002 (based on preliminary trial an error experiments) and $\sum \eta_i$ is the number of nodes in the network. The fitness evaluates the accuracy of the network and uses a penalty factor dependant on the network size. Using the fitness function, the architectures are modified using PSO and mutation. PSO uses a population approach where all individuals work together in the search space to find the optimum. The mutation rate adds random jumps in the search space to avoid local maxima. For PSO the architecture of the network represents its "position", $x_\eta(t)$. Its "velocity", $v_\eta(t)$, is the difference between the actual position and its previous position.

$$v_\eta(t+1) = i \cdot v_\eta(t) + 2 \cdot R_1 \cdot \left(p_\eta - x_\eta(t)\right) + 2 \cdot R_2 \cdot \left(p_g - x_\eta(t)\right) \tag{4a}$$

$$x_\eta(t+1) = x_\eta(t) + v_\eta(t+1) \tag{4b}$$

Where $i = 1.05$ is the inertia weight (Shi and Eberhart 1998), R_1 and R_2 are random numbers that evaluate the contribution from the personal best of the individual p_η and the global best of the population p_g over the generations. The mutation algorithm uses a dynamical mutation rate $R(\eta)$ (Equation 5) like the one used by Angeline, Saunders et al. (1994).

$$R(\eta) = 1 - \frac{fit(\eta)}{fit_{max}} \tag{5}$$

Where $fit(\eta)$ is the fitness of an individual and fit_{max} is the fitness of the best performing individual. The mutation rate is larger if the network is performing poorly and smaller if the fitness is high, fine tuning in the optimal architecture. Once the individuals have been modified, a competition algorithm ensures that the fittest of the pair parent-offspring passes to the next generation.

The algorithm is repeated over a number of generations, in this particular case for 50 generations, or until an optimal network is found.

2.2.4 Autoregressive Model

To compare the results of the TDNN, an auto-regressive (AR) model of the tarsal movements is developed. As with the TDNN, the model assumes that the tarsal response is a combination of current and past input samples. Considering the discrete form, the response of the system can be characterised as:

$$z(t) = \sum_{\tau=0}^{T-1} h(\tau) \cdot u(t-\tau) + v(t) \tag{6}$$

Where $z(t)$ is the response, $h(\tau)$ is the transfer function of the system, $u(t-\tau)$ is the stimulus and $v(t)$ is the noise. To calculate de parameters of $h(\tau)$ the least square method is used. The equation of the Minimum Mean Square Error cost function (Haykin 2002) is rearranged and it is assumed that the prediction is a linear function of the impulse response function. Combining the cost function with the system response, the least square estimate of the AR parameters is:

$$\hat{\boldsymbol{h}} = (\boldsymbol{U}^T \boldsymbol{U})^{-1} \boldsymbol{U}^T \boldsymbol{z} \tag{7}$$

Where $\boldsymbol{z}$ is the output, $\boldsymbol{U}$ is the pre-windowed matrix (Ljung 1999) and $\hat{\boldsymbol{h}}$ the estimated model parameters. For a full derivation see Dewhirst (2013).

To compare the results from both mathematical models, the NMSE (Equation 2) is going to be used, when the model is tested with the same data not used in training.

3 RESULTS

3.1 Intersegmental Reflex Responses

The movements of the tarsus recorded and post-processed show that as the tibia is extended the tarsus is depressed and when the tibia flexes the tarsus is levated (Figure 4) which corroborates the

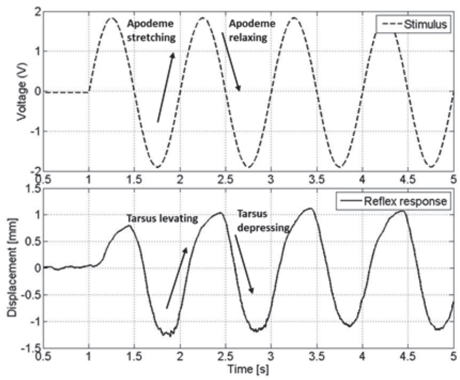

Figure 4: Tarsal intersegmental average response recorded with shaker stimulus applied for the input at 1 Hz.

results described by Burrows and Horridge (1974). There is also an observable delay between the input to the FCO and the response in the tarsus of 0.1 s, resulting from known neural conduction times and synaptic delays (Burrows, 1996).

3.2 Metaheuristic Algorithm TDNN Architecture

Using the responses from the eight animals and the average response to band-limited GWN the algorithm was run until the optimal architectures for each response were obtained (Table 1), a total of 9 models. While the algorithm was set to a maximum of five layers and 32 nodes per layer, the optimal architectures are limited to two layers and a maximum of five nodes per layer. The algorithm was set to run over 50 iterations or generations, however, the ANN architectures converge and the best or optimal network was obtained after the 35^{th} generation for all the individual responses, including the average response. Therefore, we can assume it has reached the maximum fitness within 35 generations.

Table 1: Number of nodes per layer for the TDNN designed using the metaheuristic algorithm.

	Layer 1	Layer 2
Average response	4	-
Animal 1	3	-
Animal 2	5	-
Animal 3	5	1
Animal 4	2	1
Animal 5	3	1
Animal 6	3	-
Animal 7	4	-
Animal 8	3	-

3.3 TDNN and AR Performance of the Average Response

The TDNN and AR optimised for the average response across animals were tested using unseen GWN data and a sinusoidal input not used in the training or the algorithm. The TDNN was able to predict the averaged responses to both stimuli with a high accuracy. The NMSE (%) between the predicted response and the average GWN response recorded was 13.85 % for the TDNN (Figure 4) and 27.18 % for the AR model. This same network was tested with a 1 Hz input to study its generalisation to a different input (Figure 5). The performance of the network with the 1 Hz data is NMSE = 4.3 %, while the AR model was 4.6 %, suggesting that both models were able to generalise to at least one other input when trained with GWN.

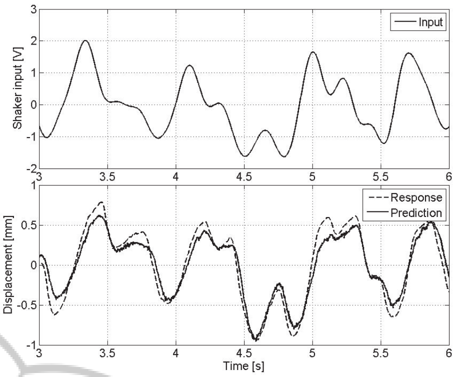

Figure 5: Prediction of the TDNN of the average reflex response to a GWN stimulus. The NMSE = 13.85 %.

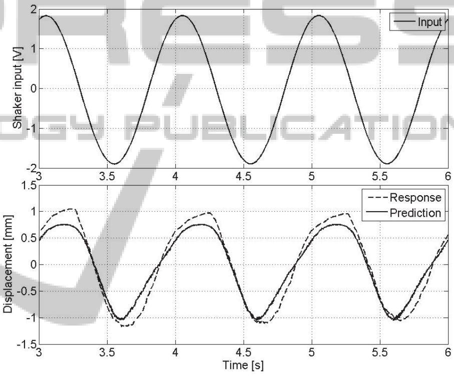

Figure 6: Prediction of the TDNN of the average reflex response to a 1 Hz stimulus, with NMSE = 4.3 %.

3.4 TDNN and AR Performance of the Individual Responses

The models designed for the individual responses, TDNNs and AR models, were also tested with unseen data, both from GWN and 1 Hz sinusoidal stimulation to the FCO. This section studies the accuracy of the models trained with GWN responses from an individual and tested with responses from the same individual as training, but not the same data. The mean NMSE for all the TDNN with GWN was μ = 26.1 % (standard deviation σ = 9.2) (Table 2), where some of the models perform better than others. In the case of the AR models, the mean was μ = 53.5 % (standard deviation σ = 21.7). When tested with 1 Hz sinusoids, some of the TDNN performed poorly (μ = 97.5 %, σ = 128.9, due to two NMSE higher than 100 %), while others had low prediction errors. In the case of the AR models, the predictions were better on average (μ = 43.8 %, σ = 41.1), with only one with a high error. A statistical analysis was performed to compare the TDNN and the AR models. The results show that, when tested with GWN, they are statistically different ($t(7) = -3.02$, $p = 0.009$), however, with a 1 Hz sinusoid although there is a large difference in the mean values, the models are not significantly different ($t(7) = 1.14$, $p = 0.14$).

Visual inspection of the poor performance of the models with some of the 1 Hz responses shows that the models overestimate the amplitude of the actual response. Such differences in amplitude are due to measurement noise, variability across individuals, and the motor neuron responses to a stimulus (Schneidman, Brenner et al. 2000, Marder and Taylor 2011). These results emphasized the differences across individual responses and the problems of choosing only one individual to model a system and use this as a generic model for all animals.

Table 2: NMSE of the individual models when tested with unseen GWN and 1 Hz sinusoidal inputs from the same individual as training, but not the same response as used in the training.

	TDNN		AR	
	GWN	1 Hz	GWN	1 Hz
Animal 1	15.4	10.9	27.2	4.6
Animal 2	28.6	11.0	81.3	11.8
Animal 3	20.8	> 100	41.5	13.0
Animal 4	17.1	26.8	49.9	80.4
Animal 5	28.0	55.9	71.1	61.4
Animal 6	28.7	99.5	82.6	33.2
Animal 7	39.5	20.0	38.2	<100
Animal 8	42.7	> 100	33.9	13.7
Mean	26.1	97.5	53.5	43.8

3.5 Performance of the Average Response TDNN and AR Models with Individual Responses

We then analysed the accuracy of the TDNN and the AR models trained with the average response when predicting individual responses to GWN and 1 Hz inputs, and evaluate if the average response is representative of the population.

The NMSE values obtained for the TDNN showed that the network trained with the average response is able to predict responses in all individuals to GWN ($\mu = 34.5$ %, $\sigma = 7.0$) and to 1 Hz sinusoid, with the exception of Animal 3 and 6 ($\mu = 45.1$ %, $\sigma = 56.0$). The AR model has poorer performance with GWN ($\mu = 70.8$ %, $\sigma = 53.9$), although its performance is similar with 1 Hz ($\mu = 43.8$ %, $\sigma = 41.1$), including the poor performance with the same individuals. The TDNN provides a significantly better performance than the AR model for GWN inputs ($t(7) = -2.08$, $p = 0.03$), however, for 1 Hz inputs, they are not significantly different ($t(7) = 0.15$, $p = 0.44$).

The differences between the NMSE of the individual TDNNs and the NMSE of the TDNN trained with the average response and tested with the individuals are not significantly different ($t(7) = 1.4$, $p = 0.2$), suggesting that the TDNN trained with the average response across the eight individuals is a good representation of the system.

Table 3: NMSE of the TDNN trained with the average response when predicting individual responses to GWN and 1 Hz inputs.

	TDNN		AR	
	GWN	1 Hz	GWN	1 Hz
Animal 1	34.4	7.7	>100	11.8
Animal 2	27.3	14.1	41.5	13.0
Animal 3	34.1	> 100	55.7	80.4
Animal 4	36.7	12.7	65.0	61.4
Animal 5	46.5	33.4	>100	33.2
Animal 6	34.6	> 100	32.8	>100
Animal 7	38.6	19.3	35.3	13.7
Animal 8	23.4	9.0	29.8	13.5
Mean	34.5	45.1	70.8	43.8

4 CONCLUSIONS

The methods described here were used to model the reflex responses of the tarsus of the hind leg of the locust. The intersegmental reflex responses recorded were similar to those described by Burrows and Horridge (1974): raising the foot when the tibia was flexed and lowering the foot when the tibia was extended, matching the natural movement of the foot when walking in locusts and humans. Such movement has been speculated to be related to postural stability and agility (Burrows, Laurent et al. 1988, Büschges 2005).

The results have also shown that such responses can be modelled using AR models and optimised ANNs. The metaheuristic algorithm developed was able to find an optimal and relatively parsimonious network based on the specifications given. The combination of PSO and dynamic mutation provided a fast convergence in the design of ANNs, although the data cannot be directly compared to other publications, since, based on the authors knowledge, no similar modelling has been done.

The TDNN optimised and trained with the responses to band-limited GWN predicts the responses accurately for unseen band-limited GWN and sinusoidal inputs, significantly better than the AR model in the case of GWN stimuli. Furthermore, the TDNN trained with the average response is also able to predict responses in different individuals, although with limited accuracy. The accuracy of the average response TDNN model was not statistically different to that of the individual models, which suggests that, in this case, the average response is a good representation of the system. Furthermore, the NMSE values are similar to those obtained with Wiener methods in locusts electrophysiological responses of tibial motor neurons (Dewhirst, Simpson et al. 2009), which suggests that ANNs could be a good approach to model nervous systems.

The errors in the predictions are related to the levels of measurement noise, background spontaneous activity and individual differences in the responses (Schneidman, Brenner et al. 2000, Faisal, Selen et al. 2008, Marder and Taylor 2011). There is, however, an underlying response common to all individuals that the TDNN is able to model and predict accurately, but the noise and the inherent response from each animal cannot be predicted with a generic model.

Therefore, the TDNN model of the average reflex response exceeds the performance of the AR model and is a good candidate model to be considered towards the understanding of nervous systems and motor control. It could also be used in the design of treatment for neuromuscular injuries, such as drop foot. Similar reflexes could also be applied in the design of active prosthesis or autonomous robots.

ACKNOWLEDGEMENTS

Alicia Costalago Meruelo was supported by a studentship from The Institute for Complex Systems Simulation (ICSS), funded by the Engineering and Physical Sciences Research Council (UK) and the University of Southampton.

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