AN ARTIFICIAL NEURAL NETWORK THAT EXPLORES THE ROLE OF SENSORY INFORMATION FOR LEARNING THE NEURAL CONNECTIONS FOR LOCOMOTION

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INTRODUCTION

Human and animal research has indicated that the spinal locomotive neural network wiring is depended on appropriate sensory information. Previous studies have indicated that the loading of the stance limb and the stretch of the hip musculature during the terminal portion of the stance phase are important sensory variables for establishing the spine's neural network connections [1]. However, it is currently not clear which sensory information has a greater influence on the neural wiring. Such difficulties may lie in the fact that it is difficult to completely separate the sensory variables in humans and animals [1].

Artificial neural networks (ANN) are composed of biologically inspired neuron like elements that can be use to model the behaviors of spinal neural networks [2]. ANN are unique because they can be used to simulate the influence of isolated sensory inputs on the wiring of the network's neural connections. Here we use ANN models to further elucidate the effect of limb loading and hip joint sensory information on the development of the neural connections for locomotion.

METHODS

Two feed-forward ANN models that each had six input neurons, three hidden neurons and one output neuron were developed. Neurons between each layer were connected via a series of weighted edges (w_{ij}). Each *i*th neuron had an input value x_i and an output value $y_i = g(x)$. A sigmoid function $g(x) = (1+ e^x)^{-1}$ was used to determine the excitation of the neuron where the value of x was given by $x_i = \sum w_{ij}y_{j.}$ Through training, the two ANNs learned the proper neural connections to supply a toe-off impulse that actively powered a passive dynamic bipedal model [3] (Figure 1). The simple bipedal model consisted of two rigid legs connected by a torsional spring at the hip. The potential energy of the spring (PE) at the terminal portion of each step was used to model the hip joint sensory information (Eq 1).

$$\text{PE} = \tfrac{1}{2}\, k\, (\phi-\theta)^{2=} \qquad \text{Equation 1.}$$

Where k was the stiffness of the hip spring, θ was the stance leg angle, and ϕ was the swing leg angle. k was constant in the bipedal model and was set at 0.01 s^{-2}. The loading force (LF) of the new stance leg was modeled by geometrically calculating the force that occurred at heel-contact (Eq 2).

$$\text{LF} = \text{Cos}\,(90-2\theta) * \ddot{\theta} \qquad \text{Equation 2.}$$

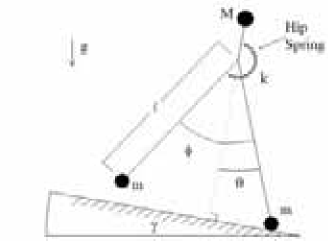

Figure 1. The passive dynamic bipedal walking model [3] that the ANN learned to actively power with a toe-off impulse.

The six sensory inputs for each ANN model were as follows: θ, $\dot{\theta}$, ϕ, $\dot{\phi}$, PE and LF. The first ANN model was not provided with LF, but was provided with PE. The second ANN model was not provided PE, but was provide LF. The initial edge weights for the neurons that were common between the two ANN models were the same. Sensory nodes that were not used in the respective ANN models were set to null. A total of 120,000 training epochs were used in this investigation. The ANN model with the largest mean square error at the respective epochs had a worse learning curve.

RESULTS AND DISCUSSION

Our simulations indicate that the PE and LF played different roles for learning the locomotive neural connections. The ANN trained with LF had a faster initial learning rate. However, as the training exceeded 3000 epochs, the amount of learning that occurred with the LF did not substantially change. Sensory information provided by the PE resulted in a more gradual learning curve and did not influence the neural connections as drastically during the early learning stages. However, as the number of epochs increased, the learning curve from the ANN trained with EPE eventually surpassed the performance of the ANN model trained with LF. These simulations suggest that during the early portions of locomotor training, sensory information from the loading forces may be vital to accelerate the learning process. However, as training progresses, hip joint sensory information may provide more meaningful information for the establishment the neural connections for stable locomotion. These simulations provide insight on the interactive role of these two sensory variables for learning the locomotive neural connections.

REFERENCES

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