

Preconditioning Electromyographic Data for an Upper Extremity Model Using Neural Networks

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Abstract:

A back propagation neural network has been employed to precondition the electromyographic signal (EMG) that drives a computational model of the human upper extremity. This model is used to determine the complex relationship between EMG and muscle activation, and generates an optimal muscle activation scheme that simulates the actual activation. While the experimental and model predicted results of the ballistic muscle movement are very similar, the activation function between the start and the finish is not. This neural network preconditions the signal in an attempt to more closely model the actual activation function over the entire course of the muscle movement.

Introduction

The EMG signal is the result of the spatiotemporal summation of the electrical depolarization through muscle which results in contraction[1]. This signal is a physiologic reflection of the individual motor unit action potentials (MUAPs) and so reflects the strength of the muscle recruitment.

The upper extremity computational model uses EMGs measured from 8 muscles, using both invasive and non invasive transducers. The model predicts joint torques, muscle forces, and joint kinematics at the elbow joint for 2 degrees of freedom for a ballistic movement [3]. The movements the model predicts are accurate for the given ballistic kinematic constraints, but are not neurophysiologically feasible.

Neural networks take their name from the networks of nerve cells that perform processing in the brain [2]. While much of the biologically specific information is lost in the development of artificial neural networks, study of these systems and their processes provides much insight into their natural predecessors.

Discussion

The upper extremity model previously preprocessed the EMG by bandpassing it, rectifying it, and then low-pass filtering it. This information was input into the model, generating an optimal activation function. The current work uses a new preconditioning method that rectifies the EMG, rank order filters it, and then implements a single hidden layer back propagation neural network that feeds directly into the muscle model (see Figure 1).

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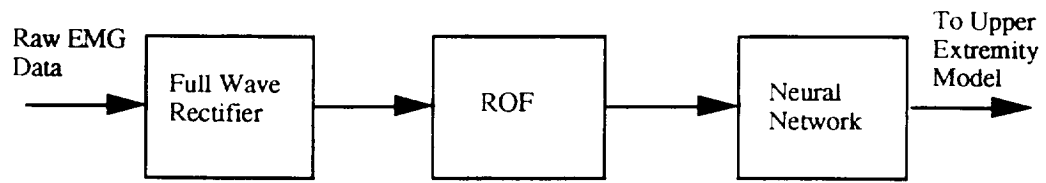


Figure 1. Filter Sequence

Rank order (RO) filtering is a recent nonlinear filtering technique [6], of which the median filter is a special case. In these filters, a single data value r of $2N+1$ from the ordered window is used as the filter output. Properties of these filters that are desirable for this work include robustness to noise, excellent edge detection, and rapid arrival at the root signal (the signal not modified by further filtering).

A single hidden layer back propagation model (see Figure 2) was trained using the rank order filtered data and angular position as input and the optimal activation output as the target output. The error function utilized when comparing the neural network output to the desired output (optimal activation) was:

$$\delta_j = (t_j - a_j)f'(S_j)$$

where t_j = target value for unit j , a_j = the output value for unit j , $f'(x)$ = the derivative of the sigmoid function f , and S_j = weighted sum of inputs to j , a standard error function for back propagation [2]. The data processed included 16 data collection protocols across multiple subjects, each involving 8 muscles and 2 degrees of freedom. A random half of the data was used in training the neural network, and the remaining half comprised the test data set.

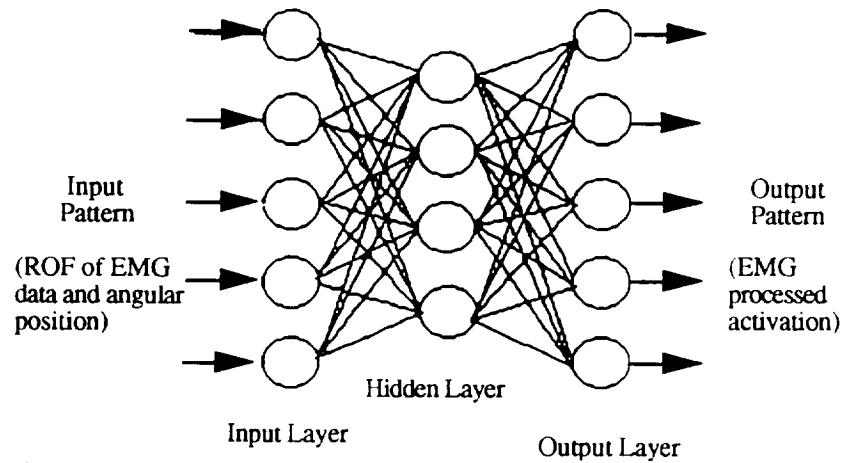


Figure 2. A typical fully connected three-layered back-propagation network

Results and Future Work

Preliminary results indicate that the neural network preprocessed EMG signal allows the model to more accurately determine the forces on the joint at any given epoch of time[5]. This model previously required almost 24 hours of dedicated processing time for each ballistic movement and that has been significantly reduced by this neural network method of preprocessing. Future work includes varying the specific rank order prefiltering of the data and varying the type and size of the artificial neural network.

References

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