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From Neuromuscular Activation to End-point Locomotion: An Artificial Neural Network-based Technique for Neural Prostheses

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Abstract

Neuroprostheses, implantable or non-invasive ones, are promising techniques to enable paralyzed individuals with conditions, such as spinal cord injury or spina bifida (SB), to control their limbs voluntarily. Direct cortical control of invasive neuroprosthetic devices and robotic arms have recently become feasible for primates. However, little is known about designing non-invasive, closed-loop neuromuscular control strategies for neural prostheses. Our goal was to investigate if an Artificial Neural Network-based (ANN-based) model for closed-loop controlled neural prostheses could use neuromuscular activation recorded from individuals with impaired spinal cord to predict their end-point gait parameters (such as stride length and step width). We recruited 12 persons with SB (5 females and 7 males) and collected their neuromuscular activation and end-point gait parameters during overground walking. Our results show that the proposed ANN-based technique can achieve a highly accurate prediction (e.g., R-values of 0.92 – 0.97, ANN (tansig+tansig) for single composition of data sets) for altered end-point locomotion. Compared to traditional robust regression, this technique can provide up to 80% more accurate prediction. Our results suggest that more precise control of complex neural prostheses during locomotion can be achieved by engaging neuromuscular activity as intrinsic feedback to generate end-point leg movement. This ANN-based model allows a seamless incorporation of neuromuscular activity, detected from paralyzed individuals, to adaptively predict their altered gait patterns, which can be employed to provide closed-loop feedback information for neural prostheses.

Keywords

Electromyography (EMG); Spina bifida; Neural prosthesis; Gait; Implant; Artificial neural network

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Conflict of interest statement

There is no conflict of interest.

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1. Introduction

Implantable and non-invasive neuroprostheses, such as functional electrical stimulation (FES), neural implants, and robotic limbs, hold the promise to improve functional movement and to obtain quality of life for paralyzed individuals, including people with spinal cord injury, spina bifida, and other disabilities. Direct cortical control of invasive neuroprosthetic devices and robotic arms have recently become feasible for primates (Wessberg et al., 2000; Taylor et al., 2002); however, the technique in its current form can risk damaging the central nervous system due to adverse effects, such as infection, associated with drilling holes into the human skull. Additionally, most commercially available solutions, such as the NESS FES system (Snoek et al., 2000), are based on open-loop control, which suffer the drawbacks of little adaptability and crude user interface that can prevent the users from incorporating them into natural daily functions. Thus, we propose to use neuromuscular activity to provide closed-loop feedback information for neuroprostheses with adaptability to impaired intrinsic neurophysiological systems and extrinsic environments. Specifically, we investigated whether neuromuscular activity detected from paralyzed individuals can be used to predict and reproduce their altered gait patterns. Instead of monitoring continuous thigh, shank, and foot segmental trajectories, we propose to monitor discrete end-point gait parameters, such as step length and width. Compared to traditional continuous trajectory-based control, end-point control, which focuses on intended targets of limb movements, can be more precisely and accurately performed by neuroprostheses and brain-computer interfaces (Santhanam et al., 2006). Thus, we focus on developing an end-point control algorithm.

Spina bifida (SB) is a form of neural tube defect, usually occurring at the lumbar or sacral levels of the spine. Because of spinal cord impairment, muscle weakness and sensory deficits in people with SB make their walking control a greater challenge (Chang and Ulrich, 2008). Approximately 70,000 individuals in the United States today have SB (0.4 to 1 out of 1,000 live births) (Lary and Edmonds, 1996). The total annual medical costs in the United States for people with SB are estimated to exceed US\$200 million (Lary and Edmonds, 1996). Most of these health care costs are for surgeries, assistive technologies, and rehabilitation to enhance their mobility. As independent walking is essential for people with SB to obtain quality of life, we propose to improve their locomotion by designing the next-generation neural prostheses with closed-loop control that uses neuromuscular activity as intrinsic feedback (Figure 1).

Artificial neural network (ANN) is one of the most established machine-learning techniques to synthesize a self-adaptable system (Becker and Hinton, 1992; Sepulveda et al., 1993; Principe et al., 1994; Cheron et al., 2003; Popovic et al., 2003; Lin et al., 2004; Hahn et al., 2005; Chang et al., 2008; Krogh, 2008). Its ability to “learn” to recognize complex, unforeseen patterns has been proven effective in the domain of cortical-related hand trajectory prediction (Wessberg et al., 2000) and autonomous robotic motion planning (Yang and Meng, 2000). Given ANN’s prior successes to allow a machine to adaptively learn to recognize complex, unforeseen patterns, the goal of this study is to investigate the feasibility and practical implementation issues of applying ANN theories to develop an Artificial Neural Network-based (ANN-based) technique for neuroprostheses.

The contributions of this study are tri-fold: (a) we developed and tested the viability of applying ANN-based technique for predicting end-point limb motions that could be the groundwork for closed-loop controlled neuroprostheses with neuromuscular activity feedback; (b) in contrast to testing on primates or healthy people, we examined humans with impaired and altered motions due to the interrupted spinal cord; (c) instead of investigating upper limb movement, we focused on a less explored functional lower limb movement required for daily life activity that could be a challenging task for cortical control neural prostheses due to the limitations of cortical signal recordings.

2. Methods

2.1. Participants

We recruited 12 individuals with lumbar or sacral level SB (5 females, 7 males; age = 14.17 ± 6.07 years; height = 1.46 ± 0.21 m; weight = 56.31 ± 28.85 kg; body mass index = 24.64 ± 6.47 kg/m²) from University of Michigan Medical Center. All participants could walk independently for at least 4 to 6 steps. They did not show any warning sign of neurological progression. Participants and their parents signed assent and consent forms approved by the Institutional Review Board of the University of Michigan Medical School (IRBMED).

2.2. Equipment and procedures

The experiments were performed in the Developmental Neuromotor Control Laboratory at the University of Michigan. We placed surface preamplified bipolar electromyographic (EMG) electrodes on both legs over the following muscle bellies: tibialis anterior (T), gastrocnemius (medial head) (G), soleus (S), quadriceps (rectus femoris, QR; vastus lateralis, QV), and hamstrings (biceps femoris, H). Participants walked at their preferred speed (without any shoes or assistive devices) for 12 trials over a 4.57 meter-long GAITRite mat which captured end-point locomotion data. Each participant had a 30-second resting period between two consecutive trials. Participants' EMG baseline activity for each leg was recorded during sitting for 30 seconds. We used a 6-camera Peak Motus™ real-time system to collect reflective marker position data at 60 Hz and a video camera to record gait patterns (Figure 2). We recorded neuromuscular activity at 1200 Hz by using the Therapeutics Unlimited EMG equipment.

2.3. Data reduction

Raw kinematic data were converted to 3D data via the Peak Motus system software and filtered with a second order Butterworth filter at a cut-off frequency of 6 Hz (Chang et al., 2006). The gait events, touchdown and toe-off, were determined via behavior coding. The time of touchdown was at the frame in which any part of the foot contacted the ground at the beginning of the stance phase. The time of toe-off was identified when the foot was off the ground at the beginning of the swing phase. We used touchdown to identify onset of each stride cycle. We collected a total of 144 trials (12 trials for each of 12 participants). Trials with missing markers or without at least two complete steps were excluded from the data analysis; thus, we analyzed a total of 127 trials (5 to 12 trials per participant) of leg neuromuscular activity and end-point parameters.

Raw EMG data were high-pass filtered at 20 Hz to remove movement artifacts, full wave rectified, and low-pass filtered at 6 Hz to smooth the signals (Ferris et al., 2007; Chang and Ulrich, 2008). To determine on-off activity, a threshold value of 3 standard deviations (for 50 ms) beyond the mean of the muscle's baseline activity was used (Hodges and Bui, 1996). Due to the differences in stride cycle duration among individuals, we normalized the burst duration by the stride cycle duration. We calculated the co-activation indexes (Falconer and Winter, 1985) for each muscle pair, T and G, T and S, QR and H, QV and H, G and QR, G and QV, S and QR, as well as S and QV.

The input variables included each normalized muscle burst duration and muscle co-activation ratio. The output variables were normalized end-point locomotion parameters (stride length, step width, stance phase ratio, double support phase ratio, step cadence (steps per minute), and stride velocity). Due to the differences in leg length among individuals, the gait parameters related to this factor needed to be normalized by leg length (Pierrynowski and Galea, 2001; Chang et al., 2006; Chang and Ulrich, 2008).

2.4. Data analysis via ANN-based model

We proposed to implement a multilayer ANN-based model to explore the inherent correlation between the intrinsic impaired neuromuscular activities of people with SB and their extrinsic gait behaviors. Figure 3 illustrates the general workflow of using ANN-based model. Specifically, we adopt a three-layer (input, hidden, and output layers) feed-forward network topology as it is one of the most popular schemes that have been shown to offer a balanced trade-off between prediction accuracy and network complexity. We employed Levenberg-Marquardt algorithm (Jonic et al., 1999) as the learning algorithm for our ANN-based model, which is a backpropagation-based algorithm (Haykin and Deng, 1991; Nussbaum et al., 1995) that has been shown to be very effective due to its better time efficiency and higher prediction accuracy (Hagan et al., 1996). We analyzed data using Matlab version R2007b and ran statistical regression models for comparison using the Matlab's Statistics Toolbox 6.2.

2.5. Exploration of the ANN Hidden Layer

In order to identify the most appropriate neural network structure for optimizing its prediction performance, we investigated the fitting accuracy of 10 neural networks, which differed only in the number of hidden neurons (5, 10, 15, 20, 25, 30, 35, 40, 45, 50). Since the hidden layer was where significant portion of ANN learning and the solution processing took place, it was one of the most important parameters that directed the process of the network training and impacted the final fitting accuracy. Thus, we investigated the effect of the number of hidden neurons on prediction performance. To increase the generalizability of this investigation and to avoid the pitfall of drawing conclusions based only on one particular training/validation/testing data set assignment, we independently constructed 50 randomly composed data sets from the sample pool of 127 trails by randomly assigning 2/3 of sample pool to the training set, 1/6 to the validation set, and 1/6 to the testing set. This training/validation/testing set assignment is exclusive: the same trail cannot belong to more than one group. We ran each of the 50 composed data sets on all 10 neural networks and compared their respective fitting results.

2.6. Comparing the ANN-based Model with Statistical Regression Techniques

To demonstrate the efficacy of the proposed ANN-based approach, we compared our ANN-based model with two statistical regression techniques: 1) Multiple Linear Regression and 2) Robust Regression. Multiple Linear Regression is widely used in statistical analysis, in which the trend exhibited by the observational data is modeled by a linear function that can obtain the best data fitting result. Robust Regression is another linear-like regression technique, which considers the weights of data points and is less sensitive to large changes in small parts of the data. In this comparison, we also evaluated another very important ANN parameter: activation function. Hence, there were two different ANN schemes: 1) ANN(tansig+purelin) that used "tansig" in the hidden layer and "purelin" in the output layer, and 2) ANN(tansig+tansig) that used "tansig" activation function in both the hidden layer and the output layer.

To evaluate the fitting performance of all 4 schemes above, we randomly constructed one composition of data set from the sample pool following the procedure described in section 2.5 and designated it as the target composition. Based on the characteristics of the target composition, we trained, optimized, and tested all 4 schemes and obtain their R-values. To evaluate the generalizability of all 4 schemes, we ran them with additional 500 different compositions of data sets randomly generated from the sample pool and obtained the average R-value for each scheme.

2.7. Comparing Predicted and Actual End-Point Locomotion Parameters

To evaluate ANN's prediction accuracy, we compared the predicted values with the actual values for all 6 end-point locomotion parameters, observed from all 12 individuals with SB. We made the comparisons both individually as well as for the group. For group comparison, we trained, validated, and tested ANN-based model using all 127 trails collected from all 12 subjects. For individual comparison, we trained, validated, and tested ANN-based model using the established Leave-One-Out Cross-Validation (LOOCV) method to address the issue of smaller data sets (Ney et al., 1995; Sebelius et al., 2005).

3. Results

3.1. Optimizing the Hidden Layer of ANN-based model

We present the fitting performance of all 500 data points (50 compositions of data and 10 neural networks) in terms of the R-values in Figure 4. Our results show that as the number of hidden neurons increased from 5 to 20, the R-values increased substantially; however, as the number of hidden neurons exceeds 30, the R-values gradually decreased. The best fitting results were obtained when the number of hidden neurons was in the range of 20 to 30. Thus, we adopted 25 hidden neurons for our ANN-based model.

3.2. Examining Fitting Performance of ANN-based model and Statistical Regression Techniques

We show the fitting performance of the ANN-based and regression-based techniques in Table 1. For single composition of data set, both ANN-based approaches significantly outperformed regression-based approaches in both training and testing phases. For instance, the R-values of ANN(tansig+tansig) were 0.9721 in training and 0.9178 in testing, whereas the highest R-value from both regression-based techniques is no more than 0.6516. Similar conclusions can also apply when the number of data sets was increased to 500 compositions. For instance, the R-values of ANN(tansig+purelin) were 0.9047 in training and 0.7090 in testing, whereas the highest R-value from both regression-based techniques were 0.6601 in training and 0.5385 in testing. We also observed that ANN(tansig+tansig) outperformed ANN(tansig+purelin) for single composition of data sets; and ANN(tansig+purelin) outperformed ANN(tansig+tansig) for 500 compositions of data sets.

3.3. Examining End-Point Prediction Performance of ANN-based model

We evaluated ANN's prediction power on all 6 end-point locomotion parameters and presented the results in Figure 5. We found that the predicted end-point locomotion parameters were closely matched with their actual observed values. The prediction performance was satisfactory across all 12 subjects, despite the fact the ANN-based model was group-trained. For individually trained ANNs (i.e., one ANN for each subject), we found that their prediction performances were at least as high as the group-trained results. As all individually trained results exhibited very similar performance, we show one of them in Figure 6.

4. Discussion

This study developed an ANN-based technique and investigated its feasibility to predict end-point limb motions via intrinsic neuromuscular activity feedback from people with interrupted spinal cord. Our experimental results confirmed our hypothesis that the proposed technique can achieve a highly accurate prediction (e.g., R-values of 0.92 – 0.97, ANN(tansig+tansig) for single composition of data sets). This high prediction accuracy may be due to the fact that we are mainly focusing on predicting end-point gait parameters. Indeed, researchers have proposed adopting end-point prediction as a faster and more accurate strategy for brain-

computer interfaces (Santhanam et al., 2006). The benefits of higher speed and accuracy are important features for implementing real-time feedback control for neuroprostheses.

The motivations of using the neuromuscular activity as an intrinsic feedback are as follows: 1) neuromuscular activity is one of the best indicators used by the central nervous system (CNS) to control movement (Gottlieb, 1993); 2) neuromuscular activity is a good reflection of one's spinal cord impairment, which can be different among individuals (Dietz and Muller, 2004); 3) while closed-loop control with visual feedback may be promising for upper-limb neuroprostheses, it is less feasible for lower-limb neuroprostheses, as it will interfere (e.g., frequent heads down) with one maintaining a stable head positioning (Bril and Ledebt, 1998; Cattaneo et al., 2005), which is essential for walking.

Our results confirmed the hypothesis that ANN-based technique can “learn” to predict end-point motions from neuromuscular activity by recognizing their complex, non-linear relationship. Indeed, we found that ANN-based prediction schemes can consistently outperform regression-based techniques with considerably better (e.g., up to 80% improvement) accuracies. This significantly improved prediction power of ANN-based techniques over the traditional regression-based techniques (as measured in terms of their R-values) can be translated into highly accurate end-point locomotion prediction. Similar successes for ANN-based prediction can also be observed in other problem domains, such as 1) EMG-to-kinematics mapping (Cheron et al., 2003; Cheron et al., 2007); 2) cortical responses to auditory spatial perception (Xu et al., 1999); 3) cortical neurons in primates-to-hand trajectory mapping (Wessberg et al., 2000); 4) learning behavior prediction (Laubach et al., 2000); 5) neuromuscular activity generation (Prentice et al., 1998).

In contrast to prior studies which suggest that the performance of ANN will monotonically increase with increased number of hidden neurons (Hahn, 2007), our results, as seen in Figure 4, indicate there exists a point of diminishing return (PDR); when exceeded, the performance of ANN will gradually decrease. Upon a careful examination of our results, we believe the reason for this PDR is due to data overfitting. The exact location of this PDR can vary depending on the input data and other ANN network parameters. In our study, this point occurs at around 30 hidden neurons.

In conclusion, our findings suggest that: (a) intrinsic neuromuscular information recorded through EMG sensors can successfully predict extrinsic end-point locomotion, such as walking speed and stride length, by applying the proposed ANN-based technique for people with SB; (b) the proposed ANN-based technique can outperform traditional robust regression with 80% more accuracy for predicting altered locomotion due to the interrupted spinal cord; (c) ANN-based technique with neuromuscular activity as intrinsic feedback to obtain accurate end-point limb movements could form the basis of neural prosthesis interface for allowing people with SB and other paralyzed individuals to independently control voluntary movements using prosthetic limbs. Looking ahead, we will develop a self-organizing and adaptive controller using low-power, high-performance hardware-software co-design techniques (Cheng and Tyson, 2005; 2006; Cheng, 2007; 2008; Jin and Cheng, 2008) for neuroprostheses to enhance independent movement for people with disability.

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Figure 1.

System overview of the proposed closed-loop feedback control neural prosthesis. The Artificial Neural Network-based (ANN-based) engine will use the intrinsic neuromuscular activity of an individual with impaired spinal cord to estimate the corresponding extrinsic end-point gait parameters. A Self-Organizing and Adaptive Control chip (future work) can compare the estimated impaired gait with preferred normal gait to determine appropriate parameters of neural prosthesis (e.g., amplitude and frequency of electrical stimulation) that are necessary to achieve the intended locomotion behavior.

Figure 2.

We attached markers (2.5 cm diameter) to the lateral surface on each side of the body at 8 locations: temporomandibular joint, shoulder, elbow, greater trochanter, femoral condyle, mid-shank, heel, third metatarsophalangeal joint. The reference EMG electrode was placed at the L4 spinous process. Figure 2a. A stick figure generated by collected marker data. Figure 2b. One participant example with markers and EMG electrodes.

Figure 3.

Workflow of the proposed Artificial Neural Network (ANN)-based technique. It includes three layers: input (neuromuscular activity), hidden, and output (end-point gait parameters) layers. The inputs to the ANN are the intrinsic neuromuscular activity. Following the inputs are the hidden and the output layers, where the hyperbolic tangent sigmoid activation function (“tansig”) and the simple linear activation function (“purelin”) are used, respectively. Before the ANN-based model can be deployed, it must be trained so that it can learn to recognize the inherent characteristics and complex correlation from the input neuromuscular activity of the target individuals. To start training process, the network weights and biases are initialized randomly. Training the network to produce a desired output vector when presented with an input vector typically involves systematically changing the weights and biases of all neurons until the network produces the desired output within a given error threshold. This tuning process is repeated over the entire training set. Thus, training of an ANN can be simplified to a minimization process of the error measure over the entire training set during a finite number of training cycles.

(a)

(b)

Figure 4.

Exploring the design space of ANN hidden layer by measuring the accuracy of ANN as a function of the number of hidden neurons. The optimal range for the number of hidden neurons has the highest corresponding R-values. R-values increased substantially as hidden neurons increased from 5 to 15; from 15 to 30, R-values increased more gradually; when exceeding 30 neurons, R-values started to gradually decrease with additional hidden neurons.

Figure 5.

Comparison of end-point locomotion predicted by ANN-based model and the actual end-point locomotion for all 12 subjects: the dashed lines delineate the data of one subject from another.

Figure 6. Comparison of end-point locomotion predicted by ANN-based model and the actual end-point locomotion for single subject using the leave-one-out cross validation method.

Table 1

Comparing fitting performance among 2 ANN-based and 2 statistical regression-based prediction schemes for single composition and 500 compositions of data sets in both training and testing phases

	Training Set		Testing Set	
	R-value of 500 Compositions	R-value of 1 Composition	R-value of 500 Compositions	R-value of 1 Composition
ANN(tansig+purelin)	0.9047	0.9595	0.7090	0.8501
ANN(tansig+tansig)	0.8712	0.9721	0.6742	0.9178
Linear Regression	0.6601	0.6264	0.5385	0.6516
Robust Regression	0.6407	0.5566	0.5284	0.5116