Feasibility of EMG-based control of shoulder muscle FES in C5 SCI

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Abstract - *We investigated the potential use of EMG recordings from voluntary shoulder muscles in individuals with C5 spinal cord injury to automatically control the stimulation to paralyzed shoulder muscles in a task-appropriate manner. A musculoskeletal model of the human shoulder and elbow was used in simulation to train an artificial neural network (ANN) to automatically generate appropriate stimulation patterns for the "paralyzed" muscles based on "voluntary" muscle activations. Substantial shoulder strength was provided by adding just two muscles (pectoralis major and latissimus dorsi), and the needed activations of these "stimulated" muscles could be predicted with reasonable accuracy using just two muscles (trapezius and rhomboids) as control sources.*

Keywords: FNS, FES, shoulder, EMG, artificial neural network, musculoskeletal model

1. Introduction

Spinal cord injuries at C5-C6 typically result in paralysis of several important shoulder muscles (e.g., pectoralis major, latissimus dorsi, and serratus anterior) and result in a significant loss in their upper arm mobility [5]. In particular, these individuals have difficulty performing many activities of daily living that require manipulation ability in front of the body (horizontal flexion motions such as stabbing food with a fork), reaching above horizontal (e.g., reaching for books on a shelf), and adduction (e.g., for weight shifts). Functional neuromuscular stimulation (FNS) can be used to produce contractions in upper extremity muscles to restore some of these functions, but providing the user with control of this stimulation in a natural yet effective manner is a significant challenge. Methods used previously to control FNS for hand grasp and release rely upon the motion of another body part (contralateral shoulder or ipsilateral wrist) and are not appropriate for the shoulder because there are too many degrees of freedom for these to be controlled in a reasonably natural manner.

We have investigated the possibility of using electromyographic (EMG) signals from shoulder muscles with retained voluntary control to control the stimulation to muscles that are paralyzed. Individuals with C5 tetraplegia typically have paralysis of several important muscles (e.g., pectoralis major and latissimus dorsi),but retain at least partial voluntary control over a number of other muscles (e.g., deltoid). The basic idea of our approach is to use EMG signals from voluntary muscles to automatically detect the motion intended by the user and then to assist them through stimulated contractions to achieve this motion over a wider range, with greater force, and with better accuracy. Previous work [1] has demonstrated that the EMG signals from the muscles with voluntary control in individuals with C5 tetraplegia contain a significant amount of information about shoulder motions and indicate that it should be possible to determine where the arm is positioned (joint angles) and where it is going (velocities and accelerations). However, these methods did not indicate how to stimulate paralyzed muscles to augment the desired motions.

In this study, we used a musculoskeletal model of the human shoulder to determine the feasibility of directly predicting needed muscle stimulation patterns from the voluntary activation patterns of other, non-paralyzed muscles. Simulations performed with this model indicate that shoulder horizontal flexion and adduction can be restored in C5 tetraplegia using FNS four or fewer muscles. A simple artificial neural network was successfully trained using model-generated data to predict needed stimulation patterns for the "paralyzed" muscles from muscles that would be expected to retain voluntary control. This implies that automatic control of shoulder FNS should be possible. The methods developed here could also be applied to other shoulder motions or to other joint systems.

2. Methods

The basic approach taken in this study is illustrated in Figure 1. Figure 1(a) shows the eventual practical system whose feasibility was evaluated in the present study. EMG activities in a set of paralyzed muscles are used as inputs to an artificial neural network (ANN), which has been trained to determine task-appropriate stimulation parameters for a set of paralyzed muscles. Figure 1 (b) illustrates the approach taken here, where a

musculoskeletal model of the human shoulder [7] was modified to reflect C5 SCI and used in simulation to estimate the likely activities in voluntary muscles as well as the stimulation needed for a set of selected paralyzed muscles, thus replacing experimental procedures in real human subjects. These model-generated muscle activities were then used to develop the ANN controller.

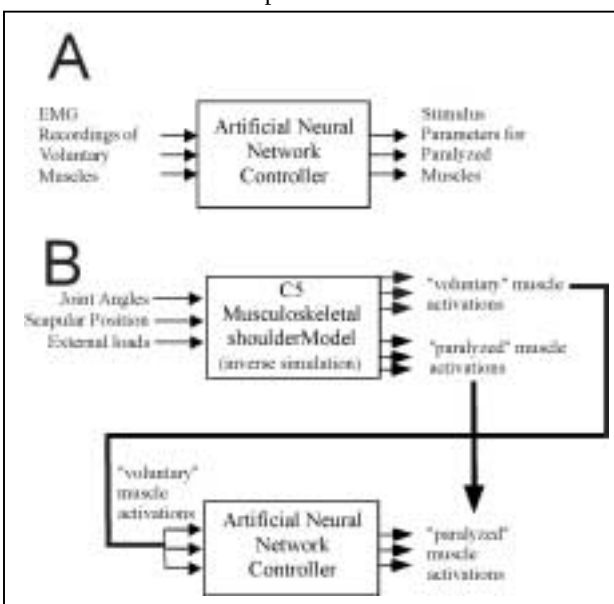

Figure 1: Model-based methods used in this study

Musculoskeletal model of the shoulder

Inverse simulations using a three-dimensional musculoskeletal model of the human shoulder and elbow [7] were used to estimate muscle activation patterns needed to maintain the arm in specified postures. The model includes descriptions of the bones of the shoulder mechanism (thorax, clavicle, humerus, and scapula) and the elbow (radius and ulna), thirty-one shoulder and elbow muscles, and three extrascapular ligaments. Each of the muscles, many of which have large attachment sites, is divided into as many as six independent elements [6]. The maximum force that can be produced by each muscle is limited by its physiological cross sectional area (PCSA), estimated for the able-bodied population by cadaver dissection [7].

The able-bodied model was modified in this study to reflect C5 tetraplegia by decreasing the maximum *voluntary* forces that could be produced by muscles with partial or total paralysis. The actual maximum voluntary forces that can be produced by the shoulder muscles in an individual with a given level of tetraplegia will vary with the details of the injury. For this study, representative maximum voluntary force values for a generic C5 individual were estimated based upon (1) the median Manual Muscle Test grades of 22 individuals with C5 tetraplegia obtained during clinical evaluations (for muscles that could be accurately evaluated) and (2) (for muscles difficult to test) the known segmental innervation of these muscles [4] and the level of spinal cord injury.

In some simulations, the effects of FNS of paralyzed muscles (coracobrachialis:Cb, pectoralis minor:PMi, serratus anterior:SA, latissimus dorsi:LD, thoracic pectoralis major:PMT, and clavicular pectoralis major:PMC) were evaluated by assuming that a completely paralyzed muscle could produce force if stimulated. In these simulations, the maximum force of each paralyzed muscle was assumed to be 50% of the same muscle in the able-bodied model. This arbitrary assumption (also made in [9]) probably represents a best-case scenario. It was also assumed that each of the several sub-elements of each "stimulated" muscle were always activated at the same relative level, simulating uniform FNS of the whole muscle.

Inverse static simulations were performed with the model to compute the set of muscle forces that minimized the sum of squared muscle stresses across all muscles while balancing various applied loads in various humeral postures. The internal kinematics of the shoulder (i.e., scapular and clavicular positions and orientations relative to the thorax) were assumed to be identical to the able-bodied results previously presented [8, 2]. Note that this would be an ideal goal to be achieved in an actual neuroprosthesis. Simulations were performed at 21 static locations throughout the workspace of the humerus (30, 60, 90, 120, and 150° of elevation in three planes: abduction (coronal), flexion (sagittal), and scapular (30° from coronal toward sagittal)). In different sets of simulations, the maximum external loads in abduction, adduction, horizontal flexion, and horizontal extension that could be sustained by the "voluntary" musculature for each posture were determined by systematically increasing the simulated load until no combination of available muscle forces could be found to balance the load.

Artificial neural network

The musculoskeletal model simulations described above produced sets of muscle activations, both "voluntary" and "stimulated", for each of the conditions tested. An artificial neural network (ANN) was trained to predict needed "stimulation" levels in the "stimulated" muscles using the activations of a small set of "voluntary" muscles. A static, two-layer ANN was used in this study, with "tansig" neurons in the hidden layer and linear neurons in the output layer. This structure was chosen because it has been shown to be capable of predicting arbitrary non-linear input/output relationships [3]. The network was trained via backpropagation using simulated muscle activations ("voluntary" ones for inputs, "stimulated" ones for outputs) from all arm positions and

external loads of 20, 40, 80, and 100 percent of the maximum sustainable load. The training procedure iterated until the sum of squared errors (SSE) between the actual variables (model-estimated "paralyzed" muscle activations) and those predicted by the neural network changed by less than 1% over 50 iterations. The network was trained for a minimum of 50 iterations to insure that the algorithm had not converged to a local minimum.

The predictive ability of the ANN was evaluated at all simulated arm positions for external loads of 60% of the maximum sustainable load in each direction for each posture (a total of 84 conditions over 21 positions). Predictive ability was quantified in two ways. First, the root-mean-squared (RMS) error between the musculoskeletal-generated activations and the ANN-predicted activations was computed. Because the activations ranged between 0 and 1, this RMS error is expressed in terms of maximum activation. Second, the forces that would be produced at the end of the humerus by the set of ANN predicted muscle activations were computed using the musculoskeletal model and compared to the forces that were originally applied in the musculoskeletal model simulations. The differences between these forces indicate the mechanical (and presumably the functional) effects of ANN-based activation prediction errors.

3. Results

The static artificial neural network (ANN) was trained as described above to predict needed activation patterns for four "stimulated" muscles (SA, Cb, LD, and PMT) using sets of two (TC and Rh)or four (TC, Rh, BiS, and Inf) "voluntary" muscles as inputs. Figure 2 illustrates the predictive ability of the ANN for each of the four stimulated muscles its primary actions. Each panel in this figure plots relative (to maximum) activation in the radial direction, while the angular direction indicates the position of the arm in elevation. The three rows of panels illustrate results for the three different planes of elevation examined. The thick black lines in each panel indicate the activation originally computed by the musculoskeletal model, the target for subsequent ANN predictions. The thin solid line in each panel indicates the activations predicted by the two-input ANN, while the dotted line indicates the activations predicted by the four-input ANN. As described above, the model is generating an external force corresponding to 60% of the maximum that can be sustained in each of the three indicated directions (horizontal flexion for the columns A and B, adduction for columns C and D, and abduction for column E). Note that the ANN predicted activations for "stimulated" muscles for force directions other than those presented here (e.g., PM activation during abduction), but the conditions included in Figure 2 required the best prediction of activation levels and were thus the most functionally relevant.

In general, the four-input ANN predicted needed muscle activations better than the two-input ANN. Activation of the SA (shown for abduction forces in Figure 2, column E) was needed in all postures at all elevation angles, and the network accurately predicted these activation levels across all arm positions and external loading. The average RMS prediction errors for the two- and four-input ANNs were 9 and 7%, respectively. The Cb (column B) was needed mostly for horizontal flexion forces in each of three elevation planes tested, with average RMS errors of 15 and 12% for two- and four-input ANNs, respectively. The PM was also important for horizontal flexion across all arm postures (column A), with some limited action required in adduction (column C) at

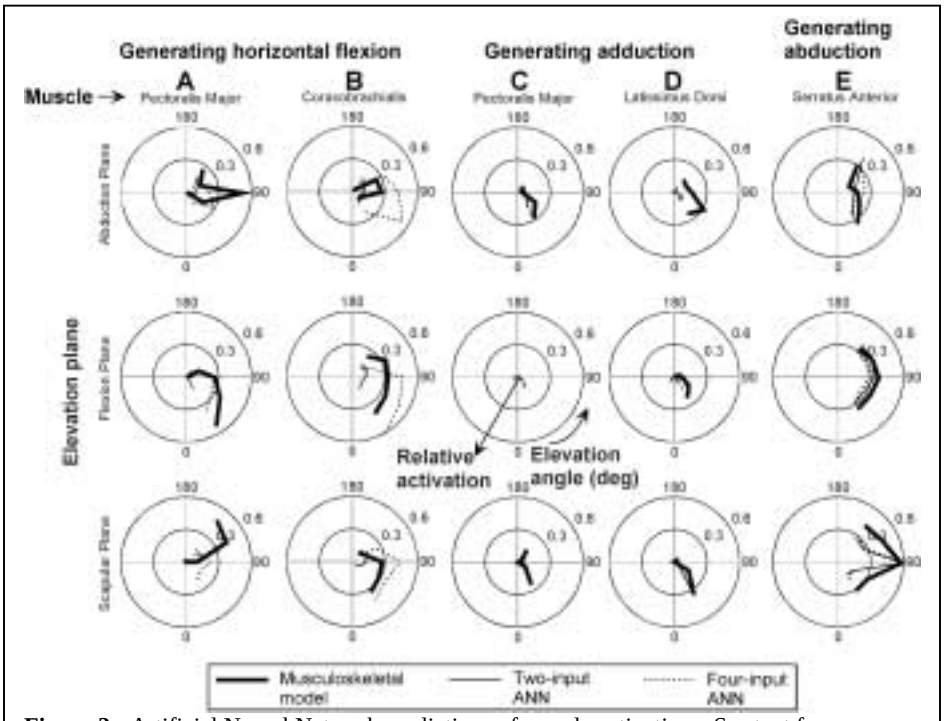

Figure 2: Artificial Neural Network predictions of muscle activations. See text for explanation of plots.

lower elevation angles. Average prediction errors for PM were 14 and 12%, respectively for the two- and four-input ANNs. The LD (column D) was primarily needed for adduction movements, and was predicted with average RMS errors of 8 and 7% for two- and four-input ANNs, respectively.

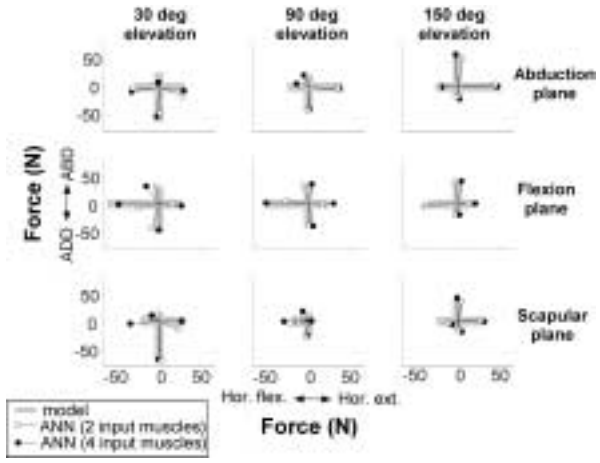

Figure 3: Force vectors predicted by ANN-predicted "stimulation" compared to desired forces.

To evaluate the mechanical impact of the ANN-based activation prediction errors on the actual moments predicted at the shoulder, the external forces at the distal end of the humerus that would result from the ANN-predicted activations were calculated for each of the various conditions (different arm postures at 60% force in four different direction). These forces were then compared to the external force originally applied in the musculoskeletal simulations. Ideally these forces would be identical. Figure 3 presents the results of these calculations for nine different arm postures (elevation angles of 30°, 90°, and 150° in the abduction, flexion, and scapular planes). In each panel, the thick gray lines indicate the musculoskeletal model-generated forces in horizontal flexion (to the left), horizontal extension (to the right), abduction (up) and adduction (down). The four open circles in each panel indicate the same forces generated using activations predicted from the two-input ANN, while the filled circles indicate the same force predictions of the four-input ANN. In almost all arm postures, both the two- and four-input ANNs accurately predicted both the magnitude and direction of the needed external forces, indicating that the modest errors in the ANN-based activation predictions would have only minor mechanical consequences.

4. Conclusions

We have examined the feasibility of automatically controlling the stimulation to paralyzed shoulder muscles in a task-appropriate manner using the activity in other shoulder muscles with retained voluntary control. A three-dimensional able-bodied musculoskeletal model of the human elbow and shoulder was modified to reflect C5 tetraplegia and used to train an artificial neural network (ANN) to determine the ability of a small number of "voluntary" muscle activations to predict the stimulation needed in "paralyzed" shoulder muscles. These simulations suggest that a maximum of four paralyzed muscles will need to be stimulated to maximize horizontal flexion and adduction forces and that two to four "voluntary" muscles will be sufficient to automatically control the stimulation to the paralyzed muscles. Although these results will have to be verified through experimental implementation, the model-based findings presented here indicate that a shoulder neuroprosthesis for horizontal flexion and adduction should be easily feasible with existing technology.

5. References

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Acknowledgment: This work was funded by the US National Institutes of Health (R29-HD32653) and by the VA Rehab. Research and Development FES Center.