Prediction of Distal Arm Posture from Shoulder Posture during Three-Dimensional Reaching

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Abstract
C5/C6 tetraplegic patients may be able to use voluntary shoulder motion as command signals for ipsilateral functional electrical stimulation (FES). We propose that natural synergies between the proximal and distal limb trajectories during goal oriented reaching can be used as a foundation for a high level FES controller that could predict distal joint kinematics from the voluntary movements of the shoulder. In this study we examined the ability of artificial neural networks to identify these synergies from data recorded during 3D reaching in a large extrapersonal space. Furthermore, we examined how the inclusion of additional inputs and outputs affected neural network performance.

1 Introduction
Patients with tetraplegia, characterized by the paralysis of all four limbs, are very limited in their abilities to perform many activities of daily living. Most tetraplegics have injuries at the C5/C6 level. These patients typically retain substantial voluntary control of shoulder movement but have limited or no control at and below the elbow. The restoration of reaching and grasping is arguably one of the most important priorities for these patients. With the development of functional electrical stimulation (FES) devices such as the BION, the restoration of upper-limb functionality through reanimation of paralyzed muscles has become a possibility [1]. Obtaining reliable command signals remains a substantial obstacle, however.

Recently, myoelectric control has been coupled with FES to restore some functionality to the C5/C6 patients [2]. This system has been a great improvement in patients’ ability to carry out many activities of daily living, yet the use of myoelectric control is fairly awkward and unnatural. Experience with myoelectric prostheses has shown that subjects have difficulty producing finely graded levels of muscle activation in the absence of proprioceptive feedback, and they find it difficult to learn unnatural patterns to control joints unrelated to the original function of the muscles still under voluntary control.

Other investigators have begun to look at pre-existing relationships between joint angles during reaching as a possible command source for an FES controller. Synergistic kinematic relationships between the shoulder and elbow joints have been shown to be stable and reproducible within and across trials and subjects [3]. Popovic et al. hypothesized that shoulder flexion/extension could be used as an accurate predictor of elbow flexion/extension during reaching movements [4]. To extract these synergies, radial basis function artificial neural networks (RBF ANNs) were trained with joint accelerations during single reaches to targets in a 2D plane. They found that trained RBF ANNs were able to predict elbow angle for reaches distal to the initial trained target but not laterally to the trained target. To reach to targets located lateral to the initial position, subjects would need to manually switch between networks trained in different sectors of extrapersonal space. This type of system seems likely to be cumbersome for use during activities of daily living.

In our own study we extended the previous model by adding the additional degrees of rotation at the shoulder to the inputs and by using the more stable joint angle data instead of joint accelerations [5]. We also iteratively added target reaching information to the training set as opposed to training with data from one target reach. We found that a multi-layer perceptron artificial neural network trained primarily on data from the more distally located target was able to predict accurately the elbow angle during reaching to all targets across a 2D workspace. In this paper we extended the workspace to include targets located in 3D.
2 Methods

We constructed a large robotic gantry (Parker Hannifin, Co.) to automate the presentation of targets in 3D workspace of the arm. The computer controlled gantry was able to reach anywhere within a 2m x 1m x 1m workspace. Subjects were instructed to reach and grasp a cylindrical, vertically oriented handle on the working end of the gantry arm. Prior to experimentation target locations were tailored to the subject’s physical measurements (Fig. 1). In this study, the subject’s workspace included 186 target locations.

![Figure 1. The 3D target locations with respect to the shoulder center of rotation.](image)

2.2 Data Acquisition

A Flock of Birds® (Ascension Technologies Corp., Burlington, VA) motion capture system was used to record the subject’s joint angles at 100 samples/s. Each sensor measured position and orientation (as rotation matrices) with respect to the base transmitter.

Clinically meaningful Euler angles were derived from the shoulder rotation matrices, including abduction/adduction (S_{ABAD}), flexion/extension (S_{FE}), and internal external rotation (S_{IER}). The other recorded angles were sternoclavicular depression/elevation (S_{DE}), sternoclavicular protraction/retraction (S_{PR}), elbow flexion/extension (E_{FE}) and forearm pronation/supination (F_{PS}).

Once the subject was secured in the chair, targets from the predetermined reaching space were pseudo-randomly presented to the subject. The subject was told to move to each target and grasp the handle at a comfortable, self-determined pace. After reaching and grasping the target the subject was instructed to move back to the initial position and remain there until cued to reach the next target. The experiment continued until all the target locations were reached.

2.3. Data Preprocessing and Partitioning

After experimentation the data was low-pass filtered offline to remove 4Hz noise present in the sensors. The data were then normalized by subtracting the mean from each channel and dividing by the standard deviation. Finally, data recorded during the resting periods between target reaches were removed in order to limit the contribution of the initial posture to the training of the neural network.

Prior to data partitioning, target reaches that contained “weak” synergies were removed. These weak synergies included reaches in which the elbow angle while grasping the target handle was less than 10º different from the initial elbow angle. Shoulder motion accounted for most of the movement to these targets, so they were not useful for predicting elbow angle output. After we removed these target reaches, the data set included 146 target reaches.

From the remaining data, 80% was randomly sampled and set aside as the training data set. The training set was used during offline training of the neural networks. The remaining data in the primary working set were set aside as the validation set. The validation set was used as novel data with which to test the neural network after neural network training was complete. Because the entire set included only one reach to each target, the validation set necessarily reflected the ability of the ANN to interpolate from the training set.

2.4. Neural Network Training

Three-layer perceptron ANNs were created in NeuralWorks Predict® (NeuralWare). This software employed an adaptive gradient back-propagation algorithm to tune the weights and biases of the ANN to maximize the correlation between the model predictions and the recorded data. To improve the ANNs ability to generalize and to prevent overfitting, the program employed a method of “early stopping,” which stopped training of the neural network if the neural network’s performance on novel, test data (randomly selected from the training set) no longer improved.

The hidden layer contained units with hyperbolic tangent activation functions. The output units were logistic sigmoid activation functions. Hidden layer size was determined...
through a cascade learning algorithm developed by Fahlman and Lebiere [10]. This algorithm adds hidden units incrementally to the hidden layer until performance on the test data is no longer improved.

ANNs were constructed with three different input/output (I/O) relationships to examine the efficacy of different inputs and whether the addition of multiple distal angle outputs significantly degraded ANN performance:

**ANN1** predicted elbow angle ($E_{FE}$) from the three rotational joint angles at the shoulder joint ($S_{FE}$, $S_{IER}$, and $S_{ABAD}$)

**ANN2** added shoulder translation movements ($SC_{DE}$ and $SC_{PR}$) as inputs in addition to $S_{FE}$, $S_{IER}$, and $S_{ABAD}$ to predict $E_{FE}$.

**ANN3** used all five DOFs at the shoulder to predict $E_{FE}$ plus forearm pronation/supination ($F_{PS}$). This set of I/Os was created to determine whether adding new outputs tended to degrade the original predictions.

The coefficient of determination ($R^2$) between the predicted output and recorded output was measured for all the ANNs. Any $R^2$ value above 0.7 was considered a strong correlation. Additionally, the root mean squared error (RMS) between the predicted and recorded outputs was measured. Because the data were normalized by the standard deviation prior to training, the error is unitless.

### TABLE 1
Performance of ANNs on different data sets

<table>
<thead>
<tr>
<th>Name</th>
<th>Output</th>
<th>Set</th>
<th>$R^2$</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ANN1</strong></td>
<td>$E_{FE}$</td>
<td>Train</td>
<td>0.8077</td>
<td>0.6735</td>
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<td></td>
<td></td>
<td>Test</td>
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<td></td>
<td>Valid</td>
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<tr>
<td><strong>ANN2</strong></td>
<td>$E_{FE}$</td>
<td>Train</td>
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<td></td>
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<td></td>
<td>Valid</td>
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<tr>
<td><strong>ANN3</strong></td>
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<td>$F_{PS}$</td>
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<td>0.8821</td>
<td>0.3343</td>
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</table>

### 3 Results

The performance criteria ($R^2$ and the RMS values) were tabulated (Table 1) for each of the ANNs on the training, test, and validation sets. All three ANNs performed well on the validation set ($R^2 > 0.7$). The prediction of $E_{FE}$ was highest (lowest RMS and highest $R^2$) for the network trained with all five degrees of freedom at the shoulder predicting the elbow angle (ANN2). In addition, ANN3 was able to accurately predict $F_{PS}$ ($R^2 = 0.88$ and RMS = 0.33).

### 4 Discussion and Conclusions

From the results above it is clear that our earlier result using the three rotational shoulder angles to predict elbow angle can be extended to reaching in 3D. The prediction of elbow angle was improved by the addition of shoulder translation movements ($SC_{DE}$ and $SC_{PR}$). Furthermore, adding an additional output ($F_{PS}$) did not greatly degrade the ANN’s ability to predict the outputs. Further studies are needed to determine whether $F_{PS}$ angle can be predicted from shoulder posture for targets in various orientations. Experiments are underway in which previously trained ANNs are used to control an animation of an arm performing reaching tasks in a virtual environment. This is important to assess the ability of subjects to use shoulder posture as a real-time command signal for FES and prosthetic limbs.

### References


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