
Prediction of Elbow Angle from Shoulder Angles during Three-Dimensional Reaching

Kaliki RK, Davoodi R, Loeb GE

Dept. of Biomedical Engineering, Alfred E. Mann Institute for Biomedical Engineering, University of Southern California, 1042 Downey Way, DRB Building, Suite 101, Los Angeles, CA 90089-1112, <http://ami.usc.edu/>

Abstract

C5/C6 tetraplegic patients may be able to use voluntary shoulder motion as command signals for functional electrical stimulation (FES). We propose that natural joint synergies between the proximal and distal upper limb joints utilized 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 joint. In this study we examined the ability of artificial neural networks to fit these synergies from data recorded during reaching in 3D 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 have the ability to fully move the shoulder but have limited or no control of movement at and below the elbow. The restoration of any functionality to these patients has been the paramount goal for many researchers. 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]. The primary obstacle in using FES for the restoration of reach and grasp is obtaining a reliable control signal from quadriplegic patients.

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 since the source muscles are typically unrelated to those involved in natural reaching and grasping.

Other investigators have begun to look in depth at pre-existing relationships between joint angles during reaching as a possible command source for an FES controller. Joint kinematic relationships between the shoulder and elbow joints have been shown to be stable and reproducible within and across subject trials [3]. Due to the existence of these joint "synergies" between the shoulder and elbow Popovic et al. hypothesized that the 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 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. This type of system would be too cumbersome for patients to use during daily use.

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 with more distally located target reaching data was able to accurately predict 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.

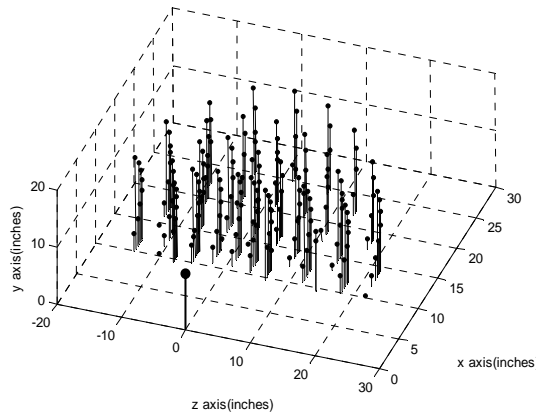


Figure 1. The 3D target locations with respect to the shoulder center of rotation.

2.2 Data Acquisition

A Flock of Birds® (Ascension Technologies Corp., Burlington, VA) motion capturing system was used to record the subject's joint angles during experimentation with a sample frequency of 100 Hz. Each Flock of Birds® sensor measured position and orientation (measured in rotation matrices) with respect to the base transmitter.

Clinically meaningful Euler angles were derived from the recorded rotation matrices. The calculated shoulder joint angles were shoulder abduction/adduction (S_{ABAD}), shoulder flexion/extension (S_{FE}), and shoulder internal external rotation (S_{IER}). The other recorded angles were sternoclavicular depression/elevation (SC_{DE}), sternoclavicular protraction/retraction (SC_{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 filtered offline with a 3 Hz third order Butterworth low-pass filter. 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 10° 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.

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.

The first set of I/Os examined the ability of the three rotational joint angles at the shoulder joint (S_{FE} , S_{IER} , and S_{ABAD}) to predict the elbow angle (E_{FE}) during reaches in 3D (ANN1). The next set of I/Os incorporated shoulder translation movements (SC_{DE} and SC_{PR}) as inputs in addition to S_{FE} , S_{IER} , and S_{ABAD} and evaluated whether these additional inputs improved predictability of the E_{FE} (ANN2). The third and final set of I/Os used the same input, the five degrees-of-freedom at the shoulder, as the previous set but added the forearm pronation/supination (F_{PS}) in addition to E_{FE} as the outputs of the ANNs (ANN3). This set of I/Os was created to examine the potential to predict F_{PS} for further study and whether predictive performance significantly degraded for prediction of the E_{FE} .

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

Name	Output	Set	R^2	RMS
ANN1	E_{FE}	Train	0.8077	0.6735
		Test	0.7515	0.7657
		Valid	0.7751	0.7229
ANN2	E_{FE}	Train	0.8909	0.5076
		Test	0.8688	0.5568
		Valid	0.8677	0.5748
ANN3	E_{FE}	Train	0.6993	0.8738
		Test	0.6046	0.8085
		Valid	0.7068	0.863
	F_{PS}	Train	0.9199	0.2794
		Test	0.7874	0.4389
		Valid	0.8821	0.3343

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 original model of 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}). It seems that these translational movements better allow the ANN identify reaches in 3D. Furthermore, adding an additional output (F_{PS}) did not greatly degrade the ANN's ability to predict the outputs. This result is a clear indication that further studies need to be made to determine whether F_{PS} angle can be predicted from the shoulder posture for targets of various orientations.

References

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