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The Effects of Training Set on Prediction of Elbow Trajectory from Shoulder Trajectory during Reaching to Targets

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Abstract - **Patients with transhumeral amputations and C5/C6 quadriplegia may be able to use voluntary shoulder motion as command signals for powered prostheses and functional electrical stimulation, respectively. Spatio-temporal synergies exist for goal oriented reaching movements between the shoulder and elbow joints in able bodied subjects. We are using a multi-layer perceptron neural network to discover and embody these synergies. Such a network could be used as a high level functional electrical stimulation (FES) controller that could predict elbow joint kinematics from the voluntary movements of the shoulder joint. Counter-intuitively, a well-chosen reduced data set for training the network resulted in better performance than use of the whole data set against which the predictions of the network were evaluated.**

I. Introduction

PATIENTS with C5/C6 level spinal cord injury retain normal control of their shoulder and elbow flexion but have no control of elbow extension, fingers, and have little or no control of their wrists. With the development of functional electrical stimulation (FES) systems, the restoration of goal oriented reaching movements through stimulation of paralyzed muscles has become a possibility, but the controller for such stimulation needs a source of command signals telling it what the user is trying to do. Similarly, patients with transhumeral amputations retain voluntary control of their shoulder but a powered prosthetic limb needs a source of command signals.

In able-bodied subjects spatio-temporal kinematic relationships exist between upper and lower arm segments during goal-oriented reaching movements [1]. A recent study by Popovic et. al modeled these synergistic relationships using neural networks to optimize radial basis functions [2]. A single reach to a training target in the workspace was used to train a neural network model whose inputs and outputs were shoulder flexion/extension acceleration and elbow flexion/extension acceleration, respectively. This approach was only able to predict targets located distally from the training target but not those located laterally. For lateral targets, the patient had to manually switch to other pre-trained networks. Such a complicated system is difficult to operate by the patient to perform activities of daily life.

In this paper, we describe a multi-layer perceptron neural network used to model shoulder/elbow synergies. In order to better characterize three-dimensional movements, all three joint angles present at the shoulder joint were used as inputs to the network. We have previously demonstrated the feasibility of extracting such information from injectable neural prosthetic interfaces called BIONs [3]. Furthermore, the spatio-temporal relationships between shoulder/elbow joint angles are relatively stable and simple in shape and, therefore, easier to model as compared to joint acceleration relationships. Also, using data from numerous reaches to different targets in a workspace should better train a network than a training set consisting of a single reach. The selection of the reaches used for training data is not arbitrary and requires a deeper understanding of how the kinematic relationships between elbow and shoulder change over a given workspace.

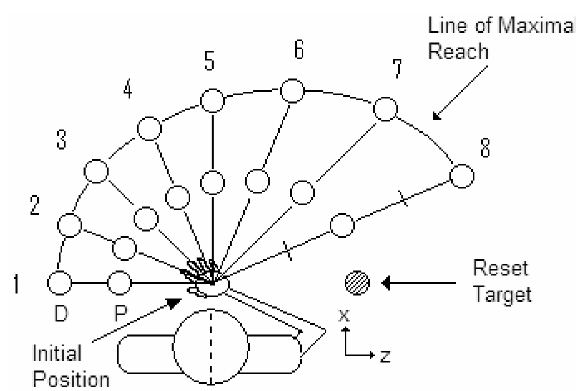

Fig. 1: Experimental work space. Two sets of 8 targets: proximal (P) and distal (D). Initial position is located along the body midline. The x- and z-axes were in the plane of the targets while the y-axis was perpendicular.

II. Methods

A. Experimental Setup

An experimental workspace was designed such that hand position is kept in a horizontal plane during a reach. Sixteen targets were placed in two concentric arcs on a pegboard as shown in Fig. 1. The distal target set was placed at the maximal reach of a subject while the proximal target set was placed at the midpoint between the maximal reach and the initial position. In each set, eight targets were spaced 22.5°

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apart from each other.

A Plexiglas® cover was placed over the workspace to allow the subject to see the targets while keeping their hand in the x-z horizontal plane during reaching. This helped reduce errors due to variance in movement in the y-direction. Subjects were seated in an armless, high back chair and an elastic restraint was placed underneath the subject's arms and around their torsos. The restraints helped limit trunk movements during the experiment. The experimental workspace was moved in and placed at a height just below the subject's elbow while held at 90° with respect to the body's longitudinal axis. The workspace's initial position was placed along the body's midline indicated by the location of the navel.

During normal unconstrained reaching trials we found there to be some drift in the initial position. This change in initial position appears to be a function of the previous motion of the arm (Fig. 2a). To reduce this variance, a reset position was used to which the subject would reach prior to every target reach. This method reduced the variance in initial position as shown in Fig. 2b.

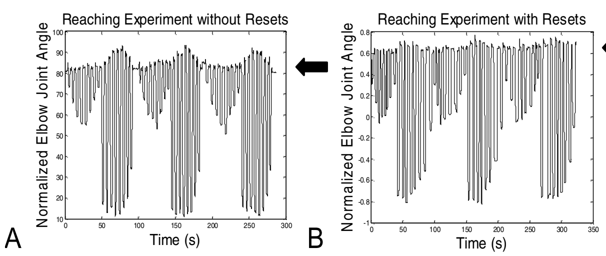

Fig. 2: Variance in initial position. Initial position is indicated by the black arrow. A. Three trials of reaches from 1P-8P and 8D-1D. B. Three sets of reaches with the use of a reset. The reaches to the reset have been removed.

Once in position, subjects were asked to reach at a natural pace from the initial position to the reset, return to the initial position, reach to the target position, then pause at the target for three seconds, and finally return back to the initial position. A subject was asked to reach in a sequence from 1P to 8P and then 8D to 1D. Each subject was asked to repeat each trial three times in succession. At this time we are using data from one subject to train and test a neural network.

B. *Data Acquisition and Pre-processing*

A Flock of Birds magnetic motion tracking system (Ascention Technology Corp., USA) was used to record the shoulder and elbow joint movements at a sampling rate of 100 Hz. Magnetic sensors were attached to the clavicle, humerus, and ulna segments. Each sensor measures the position of the attachment point and the orientation of the segment as a nine-element rotation matrix. Euler coordinate transformations were used to calculate clinically meaningful joint angles from the rotation matrices. The calculated shoulder joint angles were shoulder abduction/adduction (SABAD), the angles about the original x-axis, shoulder flexion/extension (SFE), the angle about the transformed z-axis, and internal external rotation (SIER), the angle about the transformed y-axis. The other recorded angle was elbow flexion/extension (EFE).

The recorded data was filtered offline at 3 Hz cutoff frequency using a third order Butterworth low-pass filter. The use of this filter was justified to remove 4 Hz noise present in the recorded motion data. This noise, though not related to the reaching motions, originated from our motion tracking system as evidenced by the presence of the noise when the sensors were removed from the subject. The filter had no discernible effect on the recorded trajectories.

Lastly, the data was scaled to fit within a range of -1 to 1. The scaling factor was based on the minimum and maximum of the joint angles measured during the entire experiment.

C. *Neural Network Training*

The selection of data used to train these networks is not arbitrary. A deeper understanding of how these synergy relationships change across a workspace is required to properly select reaching data with which to train a neural network. As the subject moved to different areas of the workspace, the shape and orientation of the shoulder/elbow angle varied greatly (Fig. 3A). In certain areas of the workspace, target reaches exhibited similar spatio-temporal synergy relationships. An example of the similarly shaped synergies is shown in Fig. 3B.

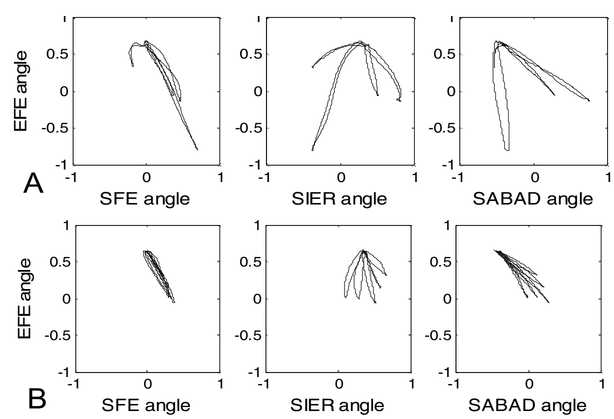

Fig. 3: **A**. Shoulder/elbow joint synergies of reaches 3P, 8P, 6D, 1D. **B**. Shoulder/elbow joint synergies of target reaches 1 - 5P.

Networks trained on single target reaches were used first to determine the extent of the relationships between reaches. A network trained on a single target reach should be able to predict reaches to targets that have similar spatio-temporal relationship. We utilized this similarity between targets as a basis for selecting targets in our training set.

First, networks were trained using only a single reach from the workspace. These networks were then tested using the validation set to see how well they were able to generalize other target reaches in the workspace. The target reach that was used to train a network that was able to estimate the most reaches accurately was combined with reaching data to targets for which the network wasn't able to predict accurately. For example, if a network trained on a reach to 3P was able to estimate the reaches to targets 2P, 4P, and 5P reasonably well but performed worst on estimating reaches to target 1P, then the reach to 3P was combined with the reach to 1P in another training set. A network was then trained with this training set and its performance on the entire set of reaches was evaluated. This process was continued iteratively until a set of target reaches was found that was best able to predict reaches in the entire workspace. For this horizontal workspace this set included reaches to targets 3P, 7P, 8P, 1D, 3D, 5D, and 8D (Fig. 4).

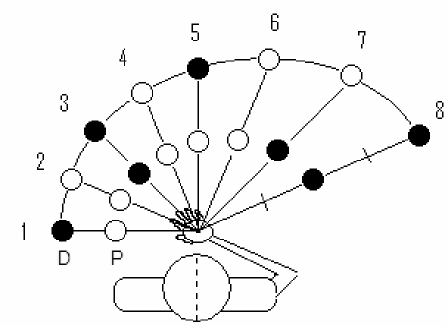

Fig. 5: Selected minimized training set. Darkened circles indicate the target reaches that were used in the minimized training set. This set included 7 target reaches: 3P, 7P, 8P, 1D, 3D, 5D, and 8D.

The angular positions of SFE, SIER, and SABAD were used as inputs to a multilayer perceptron (MLP) neural network created in NeuralWorks Predict® (NeuralWare) while EFE was designated as the output. This software employed a backpropagation algorithm to tune the weights of the MLP to minimize the error between the model predictions and the recorded data. In addition, hidden units with hyperbolic tangent (tanh) activation functions in a single hidden layer were added incrementally to improve the performance of the network. The output hidden units had logistic sigmoid activation functions. To prevent overfitting, a test set of data independent of the training set was used. The training data was partitioned such that 70% of the data was used for training while the other 30% was used as a testing set. During training the network's performance on the test set was evaluated. If the network's performance on the test set decreased then the training was stopped. After training on the minimized set, the network created a network with 12 hidden units.

After a network was trained, the network's performance was then evaluated on an independent validation set of data from the same subject. This set included targets 1-8P and 1D–8D. The elbow angle output of the model was plotted against the originally recorded elbow angle. For a given target, the difference between the model's final reached angle (corresponding to the middle of the troughs in the angle vs. time plot) and the actual reached angle was measured. Additionally, the mean squared error (MSE) of the network's performance on the validation set was recorded.

III. Results

The performance of the network trained with a minimized set of reaches on the proximal targets of the validation data set is shown in Fig. 5. The performance on the distal validation data is shown in Fig. 6. Also, a network trained using all 16 targets was used for comparison.

The final angle errors, average final angle errors, and mean squared errors are tabulated in table 1 for both networks. The network trained with all 16 targets had an average difference in final angle of 2.3° and a MSE of 8.3 while the network trained with the minimized set of data had an average difference in final angle of 1.9° and a MSE of 7.2.

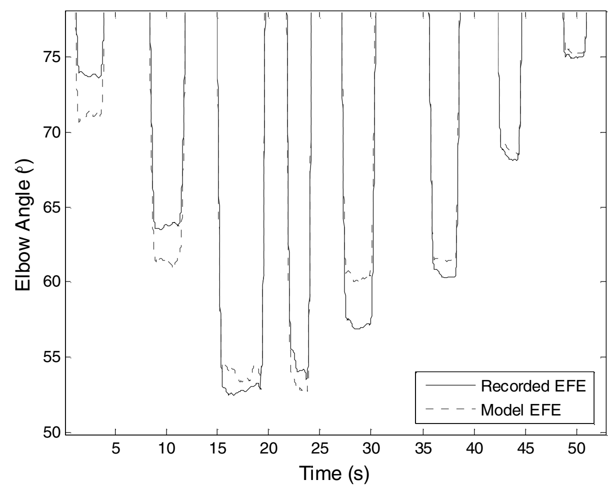

Fig. 5: The output of a network trained on minimized set evaluated on proximal reaches of validation set. From left to right: reaches to target 1P to 8P.

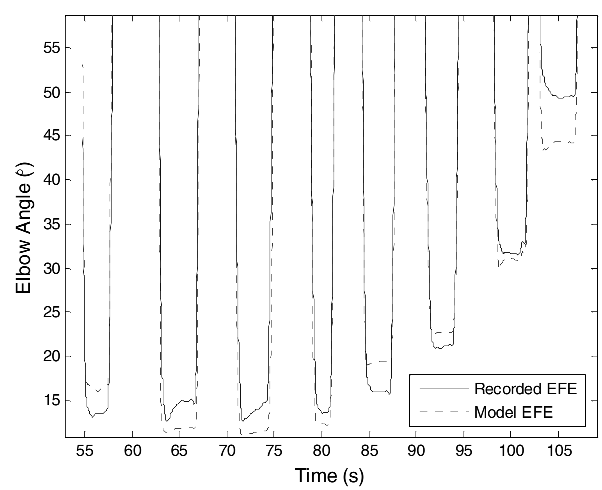

Fig. 6. The output of a network trained on the minimized set evaluated on distal reaches of validation set. From left to right: reaches to target 8D-1D

TABLE 1
TABULATED FINAL ANGLE ERRORS

Target Reach	Complete Set	Minimized Set
1P	4.2563	2.4531
2P	1.8253	2.3252
3P	2.7673	1.5277
4P	0.8832	1.1838
5P	0.9817	3.0598
6P	1.4303	1.1031
7P	3.5355	0.6118
8P	1.6869	0.3984
8D	1.1026	2.8550
7D	0.6408	1.5636
6D	0.8357	1.7989
5D	1.6007	1.2286
4D	1.2472	3.490
3D	2.4803	1.5770
2D	1.2288	0.5255
1D	9.5187	5.1069
Avg. Angle Error	2.2513	1.9256
MSE	8.2939	7.1658

IV. DISCUSSION

From the results above it is clear that using a reduced set of training data improves the performance of a neural network. Counter-intuitively, the network trained on a large set of data was less able to predict EFE over the entire set of recorded reaches. This is probably due to the fact that certain synergies are over-represented in the data set. These synergies would be weighted too highly in the training set and therefore degrade performance for reaches with less common synergies.

Although the variability in the initial positions was reduced with the use of a reset, there was still a significant variability in the joint angles prior to certain reaches. If the variances are due to the previous movement of the arm, it may be possible to train a network on a set of data that contains reaches to a target that have a large variance in initial position based on the previous target that was reached. If a workspace contains 16 targets then there should be 16 different initial positions for a given reach. This way a network may be able to predict reaches to targets in a random order better.

This work is currently in progress; there are still many obstacles to overcome before such a model becomes viable as a high level FES controller for a neuroprosthetic system. Reaches to targets in three dimensions need to be analyzed and a training set for this 3-D workspace would have to be created using methods similar to those employed here. One important lesson derived from this preliminary research is that it will be important to consider the full range of tasks to be supported and then to reduce and optimize the training set based on patterns of synergies within that large space, rather than working with arbitrarily simplified tasks such as the 2D movements studied to date.

We plan to deploy these networks in FES control systems to predict the movement of the paralyzed joint from the movement of the joints still under voluntary control. This will put the control of the paralyzed limb under the full voluntary control of the patient. In order to determine whether these predictive algorithms are actually stable and useful as a basis for real-time control, we are testing them in a virtual reality environment where a patient can train to operate a simulation of their arm as moved by FES [4] and visualized using stereogoggles.

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