An Artificial Neural Network Approach to Cortical Control for FES Motor Systems

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Abstract

This project has three specific aims. First, demonstrate the practicality of using an Artificial Neural Network based approach to correlate cortical signals with actual and imagined arm movements. Second, predict features of motion from cortical signals, and third, to quantify the information content and information transfer rate of cortical signals after application of a variety of signal processing techniques. This work presents progress toward these aims.

1. INTRODUCTION

Neuroprosthetics employing Functional Electrical Stimulation (FES) have grown to become an accepted therapy and treatment for certain individuals with severe neurological impairment. Several examples have shown that this technology can restore effective function in the upper and lower extremity. However, to expand the populations of these individuals who may be able to benefit from this technology, improved ways for the subject to command FES-generated movements are needed. Current technology focuses on using retained motor function, through movement of unaffected joints or EMG recordings from nonparalyzed muscle activity. This limits application to individuals with some remaining function and excludes those with severe stroke, amyotrophic lateral sclerosis, or high-level spinal cord injury. Therefore, much recent effort has been focused on recording subdural electroencephalographic signals, called electrocorticogram (ECoG), as a command source. These signals have the benefit of dynamic control over several degrees of freedom. In this study, we are examining the feasibility of using arrays of subdural recording electrodes to acquire useable neuroprosthesis command signals from the cortex.

2. METHODS

2.1 Motion Data Collection

The position of the arm is determined using the Fastrak electromagnetic motion tracking system by Polhemus, Inc. Three sensors are used to determine the position of the arm relative to the torso. The first sensor is securely taped to the sternum, the second is strapped to the dorsal aspect of the upper arm close to the elbow, and the third sensor is strapped to the forearm over the dorsal aspect of the wrist. The two arm sensors are held in place by tight Velcro straps. Using a stylus, bony landmarks are identified relative to the appropriate sensors according to Table I.

Features of the arm motion are extracted from these bony landmarks, including endpoint position, velocity, acceleration, and joint angles. The joint angles are determined using the protocol determined by the International Shoulder Group [1].

Each subject undertook a series of arm movements that included center-out tasks, reaching movements and simulated activities related to feeding.

Calibration of the workspace to compensate for electromagnetic distortion was accomplished

TABLE I
RELEVANT SENSORS FOR BONY LANDMARKS

Bony Landmark	Referenced Sensor
Iliac Crest	Sternum
Ipsilateral Acromion	Sternum
Contralateral Acromion	Sternum
Medial Epichondyle	Upper Arm
Lateral Epichondyle	Upper Arm
Unlar Styloid	Lower Arm
Radial Styloid	Lower Arm

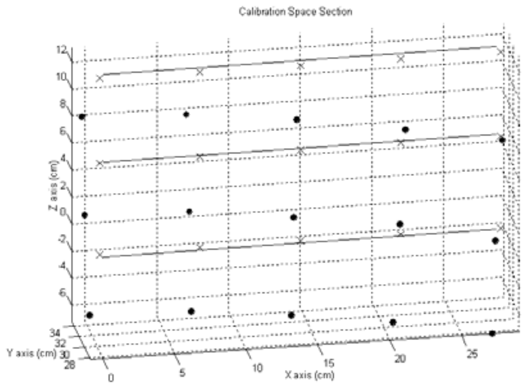

Fig 1. A section of the calibration space. Dark lines indicate the ideal calibration and measured points. Dots are points calculated by the fastrak, and X's are points after calibration.

using a polynomial regression, similar to [2]. Known points in the workspace are marked using an orthogonal 3-D 5 x 5 x 3 grid, and then using the stylus to mark the same positions as measured by the Fastrak. The error at each point is calculated, and a polynomial regression is performed in the x-, y-, and z-directions to predict and account for the errors between the measured points.

2.2. ECoG Data Collection

Electroencephalographic signals are recorded at the Epilepsy Monitoring Unit at the Cleveland Clinic Foundation in Cleveland, OH. Electrode location is determined by clinical necessity only. Signals are recorded from as many as 256 individual subdural channels, although the typical number of channels is128. Ideally, subjects have electrodes over motor areas in the cortex, although this is not an exclusion criterion, as information recorded in other areas may contain useful information as well.

2.3. Signal Processing

The motion data is used as recorded, after compensating for electromagnetic distortion. These data, recorded at about 12Hz, are resampled to 200Hz in order to match the sampling frequency of the recorded ECoG signal.

Several features of the ECoG data were examined. First, a spatial Laplacian filter was applied to each electrode of interest [3], and then each of the following techniques was applied to every channel, and the result is used as the input to the ANN: Windowed Variance is the variance of the signal over the preceding second. Median Power is the frequency at which half of the spectral power is above, and one half below, calculated over the preceding second. Moving estimates of power in frequency bands known to have correlation to movement were calculated. Finally, a 4th order autoregressive model of the data was fit to each channel. The model uses a "forgetting factor" algorithm, and thus the model parameters contain dynamic spectral information for a preceding period of time, determined by the forgetting factor coefficient (λ).

2.4. Artificial Neural Networks

A time-delayed, feed-forward, backpropagating artificial neural network was implemented in the MATLAB environment. The network used linear neurons as input and output layers, and contained one hidden layer of sigmoidal neurons. Inputs to the network were the results of one of the signal processing techniques described above. Outputs of the network used during training were features of the arm movements. The data were broken into training (60% of total), testing (25%), and validation sets, and a validation stop was implemented in the training process.

3. RESULTS

In figure 1, the accuracy of the calibration of the motion tracking system is demonstrated. During the calibration, a 5 x 5 x 3 grid of points is gathered; only one of the five X-Z planes is shown for clarity. The straight dark lines indicate the exact measured positions. Points marked by a solid dot represent the pre-calibration points calculated by the Fastrak system, and points marked by an X represent the same points after the error correction has been applied. Note the reduction in systematic error between the original, pre-calibration points and the final, calibrated points. Repeated calibrations at the conclusion of the trials demonstrate that the single calibration before

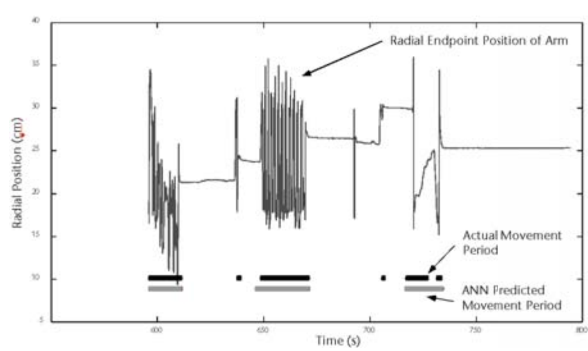

Fig 1. ANN Prediction of Motion. The network predicts the presence of motion, as demonstrated by the light-colored bars, which match the obvious periods of motion.

gathering data is sufficient. Mean Squared Error is typically reduced to less than 10% of the original, and is around 0.5cm. Figure 2 shows the results of network training on a single reaching type movement. The network input was the power in the 8-12 Hz range, which has been shown to be highly correlated to movement [4],[5]. The output used for training and prediction was 3-D endpoint location. These data are the training set only, which show the high correlation that can be discerned by the ANN algorithm.

The predictive capability of the ANN is shown in Figure 3. Here, the network was presented with a series of novel, pre-processed ECoG data as inputs and a binary target signal, where a target value of "1" signified motion, and a "0" signified rest. The network accurately predicted the presence of nonstereotypical movement with a variety of speeds and directions.

4. DISCUSSION AND CONCLUSIONS

The clinical environment is not conducive to recording the electromagnetic signals used by the Fastrak system. However, through the use of careful calibration of a small workspace, the distortion present in this setting can be overcome.

Figure 1 demonstrates the accuracy of the polynomial approach in this case, where the distortion is of low spatial frequency relative to the workspace volume. This type of calibration is fast and highly accurate, lending itself well to this situation. The error is typically reduced to around 0.5cm, which, especially because it is stable over the length of the trial, is ample.

In Figure 2, the correlation between the recorded endpoint position and that predicted by the ANN is evident. Although significant noise around the mean is noticeable, this high-frequency component is not useful information, and can be filtered to produce a smooth correlation. These data represent the first step toward prediction of movement features from ECoG signals. In this case only a single feature, the power in the 8-12 Hz μ frequency band, is used as input. It is anticipated that several features of the ECoG signal will be necessary for improving generalization, and ultimately for prediction.

A simple prediction task is represented in Figure 3. Here, the network is able to predict the presence of movement. The movements shown are not repeated, averaged, or cue-based. Although population vectors from single unit recordings have been shown to be excellent predictors of endpoint location [6], it is increasingly evident that local field potentials from cortical or scalp surface recordings can provide additional useful information [7], in addition to providing a useful bridging step in the development of cortically controlled FES systems.

References

[1] Veeger, F. Van Der Helm, E. Chadwick, and D. Magermans, "Toward standardized procedures for recording and describing 3-D shoulder movements," Behav. Res. Methods Instrum. Comput, vol. 35, pp. 440-446, 2003.

[2] C. G. Meskers, H. Fraterman, F. C. van der Helm, H. M. Vermeulen, and P. M. Rozing, "Calibration of the "Flock of Birds" electromagnetic tracking device and its application in shoulder motion studies," Journal of Biomechanics, vol. 32, pp. 629-33, 1999.

[3] F. Babiloni, F. Cincotti, L. Lazzarini, J. Millan, J. Mourino, M. Varsta, J. Heikkonen, L. Bianchi, and M. G. Marciani, "Linear classification of low-resolution EEG patterns produced by imagined hand movements," IEEE Transactions on Rehabilitation Engineering, vol. 8, pp. 186-8, 2000.

[4] C. Toro, C. Cox, G. Friehs, C. Ojakangas, R. Maxwell, J. R. Gates, R. J. Gumnit, and T. J. Ebner, "8-12 Hz rhythmic oscillations in human motor cortex during two-dimensional arm movements: evidence for representation of kinematic parameters," Electroencephalography & Clinical Neurophysiology, vol. 93, pp. 390-403, 1994.

[5] J. R. Wolpaw and D. J. McFarland, "Multichannel EEG-based brain-computer communication," Electroencephalography & Clinical Neurophysiology, vol. 90, pp. 444-9, 1994.

[6] D. Taylor and S. AB, "Direct 3D Control of an Upper Limb Neural Prosthesis Using Motor Cortex Cells Trained in a Brain-Controlled Virtual Movement Task," presented at Society for Neuroscience, San Diego, 2001.

[7] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, "Brain-computer interfaces for communication and control.," Clinical Neurophysiology : Official Journal of the International Federation of Clinical Neurophysiology, vol. 113, pp. 767-91, 2002.

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