Pilot Study for Grip Force Prediction Using Neural Signals from Different Brain Regions

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Abstract- The design of brain machine interfaces (BMI) has been improving over the past decade. Such improvements have led to advanced capability in terms of restoring the functionality of a paralyzed/amputated limb and producing fine controlled movements of a robotic arm and hand. However, there is still more to be invested towards producing advanced BMI features such as producing appropriate forces when gripping and carrying an object using an artificial limb. This feature requires direct supervision and control from the brain to produce accurate results. Toward this goal, this work investigates the processing of neural signals from four brain regions in a nonhuman primate to predict maximum grip force. The signals received from each of the primary motor (M1) cortex, primary somatosensory (S1) cortex, dorsal premotor (PmD) cortex, and ventral premotor (PmV) cortex are used to build regression models to predict the applied maximum grip force. Comparisons of model prediction results are presented. The relative prediction accuracy from all brain regions would assist in further investigation to build robust approaches for controlling the force values. The brain regions and their interactions could eventually be summed in a weighted manner to complete the targeted approach.

I. Introduction

Neuroscientists have long been developing tools to advance the design, performance, and capabilities of brain machine interface (BMI) [1-4]. The common functionalities of BMIs include, but are not limited to, directing artificial limb motions, controlling robotic arms, and assisting in the proper interaction of paralyzed or handicapped people with their axillary devices. Toward the improvement of one significant piece of BMI design, this work investigates the prediction of the grip force applied by the hand from the brain's neural signals. Machine learning techniques were used to predict the maximum grip force generated by a nonhuman primate. This study will eventually be used as the basic structure for a more thorough investigation of grip force prediction.

Investigating advanced BMI features like producing appropriate forces when gripping and carrying an object using an artificial limb requires a combination of the proper tools. The main tools in this case involve the use of signals from brain regions best suited to picking up the force generation orders, as well as the machine learning techniques that are able to extract the correct hidden patterns when predicting complex systems. While researchers have investigated grip force simulation and decoding at the level of specific brain regions [5-7] in the past, this work provides a comprehensive comparison of grip force prediction performance using four different brain regions recorded in parallel. The signals received from each of the primary motor (M1) cortex, primary somatosensory (S1) cortex, dorsal premotor (PmD) cortex, and ventral premotor (PmV) cortex were used to build regression models to predict the applied maximum grip force. In addition, two different predictive approaches were used to build regression models for all the regions.

II. Methods

Data used to train these models was collected from one bonnet macaque (*Macaca radiata*) using four chronic 96-channel platinum microelectrode arrays (10 x 10 array separated by ~400 μm, 1.5 mm electrode length in M1, PmD, and PmV, and 1.0 mm length in S1, Blackrock Microsystems). These four arrays record single unit activity from the four brain regions (M1, S1, PmD, and PmV). The animal was trained to perform a grip force match to sample task, which required the animal to match and hold its applied grip force to a designated level to receive a juice reward. Following successful training, the animal was implanted in the brain regions of interest [1]. Using the signals recorded from M1, S1, PmD, and PmV, regression models were built to compare the decoding accuracy of grip force from each area. First, extensive data preprocessing is performed by pinning the neural signals to extract the input features, and perform dimensionality reduction on these signals to reduce the number of inputs in the built model. The preprocessing steps also include matching the times of the extracted neural signals and that when the macaque applies the grip force. Then, a linear regression [8, 9] approach and a linear Bayesian-Ridge [8, 10] regression approach were both used and compared in simulating the neural ensemble data to predict the maximum grip force applied by the macaque.

III. Results

All data used in the training of these models was taken from trials successfully completed by the animal, 93 trials in total. Data was divided into groups of 70% and 30% for training and testing the models, respectively. Cross validation was performed to provide more generalized statistical results for the prediction models.

These models aim to predict the maximum grip force applied by the macaque. The peristimulus time histograms (PSTHs) of the neural data collected from the four regions were used as the input for the prediction models. The PSTHs of each region were derived from the recordings of multiple neurons. The histograms were formed with 10 bins in a window between negative 0.5s to positive 0.5s centered at the time when maximum force was generated during a given trial. Before being fed into the model, the PSTH data were preprocessed by the dimensionality reduction method of principal component analysis (with ten components). The dimensionality reduction step essentially involves including only the significant components of the neural signals (i.e., the important neurons), and eliminates those that might act as noise (i.e., the less significant neurons) to the main neural patterns changes associated with the applied grip force. Then, the processed data for each brain region was used to generate the predictive models. The test results for linear and Bayesian-ridge models are summarized in Table I.

TABLE I
MAXIMUM GRIP FORCE PREDICTION RESULTS FOR TWO REGRESSION MODELS USING NEURAL DATA OF FOUR BRAIN REGIONS.

Brain region		**M1**	**S1**	**PmD**	**PmV**
Linear Model	**MAE**	43	57	65	48
	R-score	0.45	0.1	-0.05	0.53
Bayesian-Ridge Model	**MAE**	46	57	62	49
	R-score	0.42	0.04	0.03	0.47

The results in Table I show that for the mean absolute error (MAE) and R-squared scores (i.e., coefficient of determinant), the best performance of the models is obtained when using M1 and PmV data to predict grip force, while data from PmD produces the worst performance. The most apparent difference in the results is for the R scores, which are significantly higher for PmV and M1 compared to those generated from S1 and PmD. In summary, although this work is preliminary and the presented results do not provide substantial difference between both models, the linear model in this work produces the highest R score (0.53) when using data collected from PmV. Further investigation on larger samples need to be done before reaching any concise conclusions regarding the best model to be used when simulating the maximum force prediction task.

IV. Discussion

This pilot study investigates prediction of grip force using machine learning techniques. The results show that even with a very small training size of just 65 trials, an acceptable level of accuracy can be achieved from some brain regions, specifically M1 and PmV. The MAE of 43 achieved from the linear model when using data from M1 represents approximately 13% of the mean maximum force applied during a trial (324 N). Moreover, given the trials size the reported R-scores in M1 and PmV regions are acceptable and can be the fundamental layout in the next stage of this study. Future work will also consider having more training cases for further prediction capability. In addition, other predictive modeling techniques can be used and compared against the currently used models. Combining the neural data from multiple brain regions could also have some impact on the prediction accuracy. We are currently working toward providing more comprehensive answers regarding the brain regions that control the gripping task orders, as well as improving the performance of the prediction models.

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