Dimensionality reduction for EMG prediction of upper-limb activity from LFP recordings in primates

Research proposal for MSc by Research Thesis
DTC Neuroinformatics and Computational Neuroscience

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Abstract

Neural prosthetic systems aim to assist patients suffering from sensory, motor and other disabilities by translating neural brain activity into control signals for assistive devices, such as computers and robotics prostheses, or by restoring muscle contraction through functional electrical stimulation (FES). In a neuro-motor prosthetic device, the prediction of intended muscle electrical activity is required for effective FES. It has been already known that upper-limb electromyogram (EMG) signals in primates can be accurately predicted by decoding the spike activity of single and multi-units in the primary motor cortex (M1). Recent work now suggests that EMG signals can also be decoded by local field potential (LFP) recordings in M1. In such decoding schemes, the number of input variables is usually very large and no systematic way of performing effective variable selection has yet been suggested. The proposed research project will investigate the potential benefit of using dimensionality reduction and sparse variable selection techniques for predicting upper-limb EMG activity, based on recorded LFP signals in the M1 and ventral premotor cortex (PMv) of primates. The study will use already existing datasets coming from two freely-behaving animals. Prediction accuracy with different techniques will be evaluated, and compared to results reported in the literature.

I. Introduction

Electrical activity in the primary motor cortex (M1) has been found to correlate with both kinematic (e.g. position and velocity) [1], and kinetic (e.g. force) [2] aspects of movement. These findings have led to the inspiration and development of brain-machine interfaces (BMIs), which by recording activity from motor cortical areas allow users to move a computer cursor [3, 4, 5] or a robotic limb [6]. In some cases, muscle contraction of temporarily paralysed animals [7] or patients with tetraplegia [8] has been achieved through functional electrical stimulation (FES), and found to be effective in allowing subjects to regain control of basic hand movements. Worldwide, thousands of people suffering from spinal cord injury (SCI), brainstem strokes or other disorders, would potentially benefit from neuro-motor prosthetic devices [5].

The operation of a neuro-motor prosthesis (NMP) can be divided into four major components; signal acquisition, signal/information processing, neural decoding and control signal generation for artificial limb movement [9]. Most studies [5, 10, 7, 11, 12], have used multielectrode arrays to record single and multi-unit spike activity, which was then used as the source signal for decoding intended hand movements. Motion-related spike activity has been found to be present in the M1 even after three years of SCI [5]. For effective FES, an accurate mechanism for prediction of electromyogram (EMG) signals is needed, and many methods spanning from linear [4], Wiener cascade models [12] and Kalman filters [13, 14, 11] have been proposed in the literature.

Recently, it has been found [15, 16] that local field potential (LFP) recordings can also be used to decode upper limb activity in primates. In these studies it was shown that position and velocity decoding, as well as EMG prediction, can be achieved from LFP signals with accuracy nearly as high as with spike signals. The advantages of using LFP signals instead of spike activity signals, as source signals for

BMIs are numerous; firstly, the bandwidth is significantly lower (sampling rate at 1 kHz instead of 30 kHz for spike signals), which translates into lower power requirements for the processor of the BMI. Secondly, single-unit activity is difficult to record for a long time after the implantation. Another study has also shown that EMG prediction can be achieved by using electrocorticography (ECoG) signals [17], which are measured with electrodes placed on the surface of the brain, thus constituting a less invasive candidate for BMIs source signals.

II. Motivation

The proposed study will focus on upper-limb EMG activity prediction in primates, by using LFP signals recorded in the animals' M1 and ventral premotor cortex (PMv).

The first novelty of the study is that recordings come from freely-behaving animals, in comparison with most studies in the literature, which investigate EMG prediction during center-out reaching tasks. Hence, we will seek to investigate whether decoding is also possible during free behaviour, or whether it is limited only to repetitive tasks.

The second novelty will consist in applying dimensionality reduction techniques for predicting EMG signals. LFP signals are usually highly-correlated, and it has also been shown that some LFP frequency bands are more correlated to EMG activity than others [15, 18]. Furthermore, decoding EMG activity from LFP recordings usually involves extracting a very large number of features. In order to deal with this curse of dimensionality, two different techniques have been proposed in the literature. In [15], the 150 features which were most strongly correlated with the EMG signals were selected, by computing the absolute values of the Pearson-r correlation coefficients. In [17], where EMG activity was predicted by using ECoG signals, a sparse linear regression (SLiR) algorithm based on a variational bayes (VB) method [19] was used. Other methods, such as neuron dropping [12], and a variational Bayesian least squares (VBLS) approach [20] have been used in paradigms where EMG activity is predicted by using spike trains (rate coding) from neurons in M1.

Our objective will be to use dimensionality reduction techniques to perform effective sparse variable selection, and subsequently test EMG prediction accuracy based on the selected variables.

III. Datasets

The available datasets come from recordings from two freely-behaving animals. During the recordings, the animals were offered food in a peg-board that had holes of 1-cm diameter. The behavioural task comprised reaching the board, picking up the food and putting it into the animals' mouth. The duration of the two recording sessions is 15.26 and 5.79 min, respectively. The datasets comprise recordings from:

- Spike activity of 56 single units in the M1 (44/56) and the PMv (12/56)
- 56 LFP channels in the same areas
- 9 EMG signals from the following muscles (see Fig. 1): extensor carpi radialis (ECR), flexor carpi ulnaris (FCU), biceps (Bi), extensor carpi ulnaris (ECU), flexor carpi radialis (FCR), triceps (Tri), first dorsal interosseous (1DI), flexor digitorum superficialis (FDS), flexor digitorum profundus (FDP)

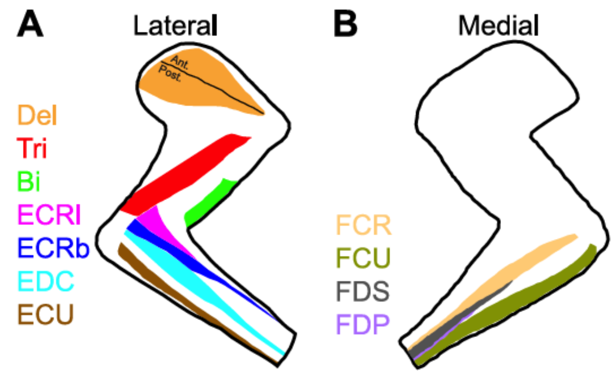

Figure 1: Schematic of recorded limb muscle locations. Both medial (**A**) and lateral (**B**) views are shown. Adapted from [15].

Fig. 2 shows an example of the raw data containing the spike activity of 10 units in M1, two LFP channels and two EMG signals. The duration of the shown excerpt is 6 s.

IV. Methods

4.1 Signal processing

For the EMGs, the signals envelopes will be extracted and used for the decoding process. Thus, the signals will be high-pass filtered at 50 Hz, full-wave rectified, low-pass filtered at 5 Hz and finally downsampled to 20 Hz. All filters will be applied forward and backward in time, to avoid phase delays [15].

For each LFP signal, six spectral features will be used: the local motor potential (LMP), which is a sliding window average of the raw LFP, and the power in five frequency bands (0-4, 7-20, 70-115, 130-200, and 200-300 Hz). The power in each band will be computed by applying a Hanning window and the fast fourier transform (FFT) . All features will be computed in 256-point windows, with 206-point overlaps.

4.2 Model fitting

For fitting EMG envelopes to LFP signals, we will explore the potential benefit of using a variety of methods, which include but are not limited to:

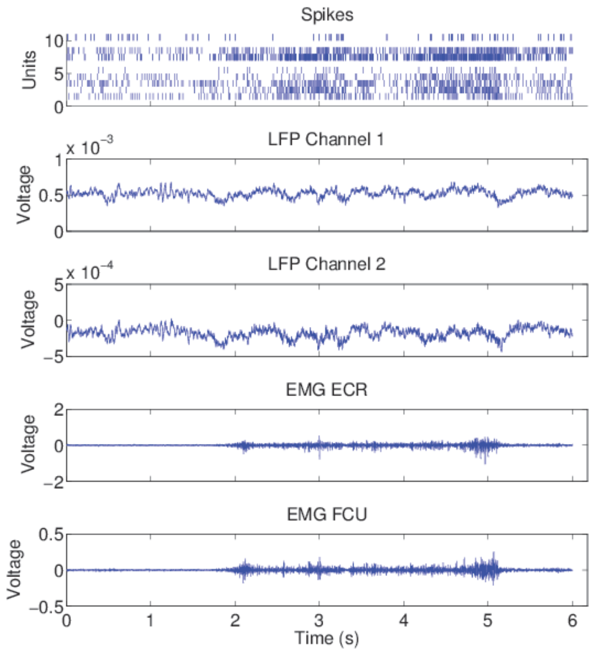

Figure 2: Raw data. The spike activity of 10 single-units is shown, along with two LFP channels and the EMG signals from ECR and FCU muscles.

- the least absolute shrinkage and selection operator (LASSO) technique [21] is a method for linear regression which results in sparse interpretable models, by shrinking certain regression coefficients exactly to zero. The shrinkage effect of the method arises naturally from using a penalty for the L_1 norm of the coefficient vector. One drawback of the algorithm is that the regularization parameter needs to be set manually.
- the elastic net [22] is an extension of the LASSO which, by introducing an additional penalty on the L^2 norm, encourages a group effect of the variables, in a way that correlated variables tend to be in or out of the model together.
- the online VB method [19] uses a Bayesian approach to perform model selection. The free energy is defined for a trial distribution, and it can be shown that its maximisation gives the true posterior distribution.
- the VBLS is also a Bayesian approach to linear regression, which by performing automatic relevance detection (ARD) of the input variables, excludes the ones that are irrelevant to the data, resulting thus in sparse representations.

Tools that will be potentially used include the SpaSM (Sparse statistical modelling toolbox for MATLAB®) [23] and the VBSR (Variational Bayesian Sparse Regression) [24] and Variational Bayesian Least Squares [25] toolboxes for MATLAB®.

V. Evaluation of performance

The EMG prediction accuracy (similarity between actual and predicted EMG activity) can be evaluated by using various measures, such as:

- the proportion of the variance accounted for (VAF), which is a similar measure to the coefficient of determination (R^2), and is defined as follows:

$$VAF = 1 - \frac{\sum_{j=1}^{M} \left(p_j - \hat{p}_j\right)^2}{\sum_{j=1}^{M} \left(p_j - \bar{p}\right)^2} \tag{1}$$

- the coefficient of correlation (CC), given by:

$$CC = \frac{\sum_{j=1}^{M} \left(p_j - \bar{p}\right)\left(\hat{p}_j - \bar{\hat{p}}\right)}{\sqrt{\sum_{j=1}^{M} \left(p_j - \bar{p}\right)^2}\sqrt{\sum_{j=1}^{M} \left(\hat{p}_j - \bar{\hat{p}}\right)}} \tag{2}$$

- the normalised root-mean-square error (nRMSE), defined as:

$$nRMSE = \sqrt{\frac{\sum_{j=1}^{M} \left(p_j - \hat{p}_j\right)^2}{n}} \Big/ \left(p_{max} - p_{min}\right) \tag{3}$$

where M is the number of samples of a dataset, p_j and $\hat{p}_j$ are the actual and predicted values of the EMG signal for the jth sample, $\bar{p}$ and $\bar{\hat{p}}$ denote the mean values of the actual and predicted signals within the dataset, and p_{max} and p_{min} are the maximum and minimum values, respectively, of the actual signal.

Our results will be compared to [15], where a decoding technique based on a Wiener cascade model was used, and variable selection was performed by choosing the 150 features which were more strongly correlated with the EMG signals.

VI. Roles of supervisors

Each of the two supervisors has their own field of expertise. Dr. Kianoush Nazarpour has a long experience in signal processing research for BMIs for motor rehabilitation, and currently holds a position of senior algorithm engineer at Touch Bionics, Livingston, UK. He also holds a position of visiting researcher at the Motor Control Group, Institute of Neuroscience, University of Newcastle. He will serve as the principal supervisor of the project and will provide guidance, as well as the datasets used for the analyses. Prof. Sethu Vijayakumar holds the position of Professor of Robotics and Director of the Institute for Perception, Action and Behavior (IPAB) at the School of Informatics,

May 2013	Literature review Background reading on EMG prediction from LFP recordings Background reading on dimensionality reduction and sparse variable selection techniques Earn familiarity with available datasets
June 2013	Replication of results in [15] EMG prediction with LASSO EMG prediction with elastic-net
July 2013	EMG prediction with online VB EMG prediction with VBLS Analysis of results and comparison to [15]
August 2013	Thesis write-up

Table 1: Timeline of the proposed research project

	Quantity	Price (£)
16-25 Railcard	1	28
Return tickets from Edinburgh to Livingston	13	13 X 5.5 = 71.5
Total		99.5

Table 2: Budget of the proposed research project

University of Edinburgh, UK. He will be serving as the internal supervisor. The student is planning to have weekly meetings with the principal supervisor in Livingston, and with the internal supervisor in Edinburgh.

VII. Timeline

A detailed timeline of the proposed research project is given in Table 1.

VIII. Budget

The student will need to travel weekly to Livingston to hold meetings with the principal supervisor. The travel expenses are not expected to exceed £100 in total, and a detailed description is given in Table 2.

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