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Reconstructing Grasping Motions from High-Frequency Local Field Potentials in Primary Motor Cortex

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Abstract

Recent developments in neural interface systems hold the promise to restore movement in people with paralysis. In search of neural signals for control of neural interface systems (NISs), previous studies have investigated primarily single and multiunit activity, as well as low frequency local field potentials (LFPs). In this paper, we investigate the information content about grasping motion of a broad band high frequency LFP (200 Hz – 400 Hz) by classifying discrete grasp aperture states and decoding continuous aperture trajectories. LFPs were recorded via 96-microelectrode arrays in the primary motor cortex (M1) of two monkeys performing free 3-D reaching and grasping towards moving objects. Our results indicate that broad band high frequency LFPs could serve as useful signals in NISs that aim at restoring motor functions such as grasp control.

I. Introduction

INTRACORTICAL recordings provide a variety of neural signals occurring at different spatial and temporal scales, such as single unit activity (SUA), multiunit activity (MUA) and low and high frequency local field potentials. The past several years have witnessed several efforts in the fields of neuroscience and neural engineering to determine the encoding mechanisms and decoding properties of these signals as well as their application in neuromotor prostheses. Previous studies have focused on the use of single unit activity (SUA), multiunit activity (MUA) and low-frequency intracortical LFPs for decoding of intended and/or executed movements [1], [2], [3], [4], [5]. However, the use of higher frequency field potentials in neural decoding has not been systematically examined.

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Recently, we investigated the potential of LFP activity in different bands, including a broad high frequency band (200 – 400 Hz, henceforth referred to as the bhfLFP), for decoding continuous 3-D reach kinematics [6]. In this paper, we examine how well discrete and continuous features of grasping motion can be reconstructed from bhfLFPs. Our results show that power in bhfLFPs carried substantial information about grasping motion and that this band can be used to classify discrete grasping motion states and decode continuous aperture kinematics trajectories with considerable accuracy. Our findings indicate that high-frequency LFPs might be a useful signal for the control of grasp actions in neural interfaces that aim at restoring motor function in people with paralysis.

II. METHODS

A. Data Acquisition and Feature Selection

Two male macaque monkeys (C and G) were trained to perform a continuous single-handed reaching and grasping task in which one of six to nine different objects attached to a string swung from above repeatedly through an arbitrary path on each trial. The monkey could grasp the same object in slightly different manners. Different trial blocks contained different objects to be grasped, such as a ball, a bead, a cube, a ring, etc. The object rotated freely. The reach workspace (25 cm × 20 cm × 25 cm) approximated the natural reaching space for a monkey. After successfully grasping the object for about one second, monkeys were rewarded with fruit juice. The grasp aperture, defined here as the distance between the distal-most joints of the thumb and the index finger, was recorded using a Vicon motion capture system (Vicon Motion System, Oxford Metrics Group, plc.) at a rate of 240 samples per second. Aperture velocity was derived from aperture through approximate time derivative calculations. Both aperture and aperture velocity data were resampled to 20 samples per second for computational convenience. 47 and 96 simultaneous LFP channels were recorded using 10 × 10 microelectrode arrays (Cyberkinetics Neurotechnology Systems, Inc., Salt Lake City) chronically and intracortically implanted in the arm region of the primary motor cortex (M1, contralateral to the hand used for the task) from monkeys C and G, respectively. Detailed descriptions of array structure and surgical implantation procedures are given in [7]. All procedures complied with protocols approved by Brown University Institutional Animal Care and Use Committee.

In this paper, we focus on bhfLFPs. We used the power as the LFP feature, which was obtained using a multitaper spectral estimation approach [8]. Both grasp kinematics data and LFP power were normalized before analyses. The normalization was done by subtracting the corresponding mean and then dividing the resulting value by the corresponding standard deviation.

B. Discrete State Classification

Discrete aperture states were determined based on aperture velocity. Aperture velocity extrema were first identified and then used to segment the data into 3 categories: (a) a grasp-opening state defined by the positive extremum and the surrounding 2 samples; (b) a grasp-closing state defined by the negative extremum and the surrounding 2 samples; a minimum spacing between two consecutive extrema was adopted to avoid overlapping; (c) an 'intermediate' state defined as the remaining samples.

We considered the following classification problems. First, we examined the classification of samples from 2 states only (grasp-opening and closing states). Quadratic Discriminant Analysis (QDA) and Logistic Regression (LGR) were applied in this case. Second, we considered the classification of samples from all 3 states. To deal with multi-class classifications (here three-class), QDA, Multinomial Logistic Regression (MLR) and

Support Vector Machine (SVM) with a Radial Basis Function kernel [9] were employed. For MLR, states were classified according to the maximal predicted probability of all of the three states. Parameters in the SVM classification were determined using a two-step grid search in the log scale as is advised in [9]. The free access library, LIBSVM, was used to perform multi-class SVM classifications [9]. Finally, we also examined the classification of 3 states based on a sequential two-step classifier that first classified every sample into extrema (i.e. opening or closing) or intermediate states. If the sample was classified as an extrema state, a second step classified the sample into opening or closing state. LGR was used in both steps.

C. Continuous Trajectory Decoding

To reconstruct continuous trajectories of grasp kinematics from bhfLFP power, we employed a Kalman filter. The Kalman filter was based on the following linear Gaussian state-space model:

$$\begin{aligned} x_k &= Ax_{k-1} + \varepsilon_k \\ P_{i,k} &= Hx_k + \eta_k \end{aligned} \quad (1)$$

where x_k is a measured (mean subtracted) kinematics state (aperture or aperture velocity in this study) and k denotes discrete time (50 ms time-steps); A is the state matrix; $\varepsilon_k \sim N(0, Q)$ is the state Gaussian noise with covariance matrix Q ; $P_{i,k}$ represents the power for the i th LFP channel in bhfLFP and is computed in a 250 ms time window preceeding the time of corresponding kinematic state; H and $\eta_k \sim N(0, W)$ are the observation matrix and observation Gaussian noise (with covariance matrix W), respectively. Further details of estimating parameters in Kalman filter and computing filter output are described in [10].

D. Performance Assessment

A 12-fold cross-validation scheme was employed in all the analyses in this study. Classification accuracy, defined as the sum of true positives (TP) and true negatives (TN) divided by the sum of numbers of both positive samples (P) and negative samples (N), was used to evaluate the performance of QDA, MLR and SVM. In the two-state aperture classification using LGR, classification accuracy was computed based on the intersection of iso-performance tangent line and the Receiver Operating Characteristics (ROC) curve [11]. For the sequential two-step classifier, since the ratio between the number of samples for opening-closing and intermediate states was very small (i.e. imbalanced classes), an alternative optimal operating point on the ROC was obtained based on True Rate (TR, not to be confounded with true positive rate) to get better classification results [12]:

$$TR = \frac{TP}{2P} + \frac{TN}{2N}. \quad (2)$$

Confusion matrices were built to test the classification accuracy of 3-state aperture states decoding results. The i, j th element in the confusion matrix counts the percentage of incidences where an actual aperture state i was classified as state j out of all actual state i incidences.

For continuous trajectory decoding, the Coefficient of Correlation (CC) and the Root Mean Square Error (RMSE) were employed to assess the reconstruction performance. The CC, defined as the maximum of the normalized Pearson correlation coefficient between the actual and decoded kinematics, was computed for a range of time lags. To reduce the

influence of outliers, we confined the aperture velocity kinematics to the 95% confidence interval of the total data when calculating RMSE values for aperture velocity decoding.

The Kalman filter incorporates prior knowledge about a kinematic variable's temporal correlation in the state matrix, so that temporal correlation alone could account for substantial decoding success even in the case of non-informative LFP features. To evaluate the dependence of decoding performance on this prior knowledge, we also estimated a chance level CC for the Kalman filter performance. To obtain the CC's chance level, we randomized the phases of fast Fourier transform of each $P_{i,k}$ sequence and then applied the inverse FFT to transform the sequence back to the time domain. This sequence shared the same autocorrelation function (power spectrum) with the original sequence, but completely differed in its time relationship to the kinematics. Trajectory reconstruction based on phase-randomized $P_{i,k}$ sequences was then performed.

E. Selection of an Optimal LFP-Channel Subset

A greedy LFP-channel selection, instead of an impractical exhaustive search, was employed to find the optimal subset for reconstructing grasping motion out of 47 (monkey C) or 96 (monkey G) channels. We also limited the maximum size of optimal subset in our search to 20 channels, although larger channel subsets could potentially achieve better performance. In the greedy selection, the best one-channel subset was chosen, then the best two-channel subset (best found one-channel included), and so forth till the best 20-channel subset. For QDA, MLR and SVM in the state classification problems, the greedy selection criterion was accuracy. For LGR, the criterion was the Area Under the ROC Curve (AUC), not to be confounded with aforementioned optimal classification accuracy which was used to make comparison among different classification methods. The sequential classifier involved the greedy selection in its first step only. For Kalman filter in continuous trajectory decoding, the CC was used as the greedy selection criterion.

III. RESULTS

The training and recording session for each monkey lasted about 45 minutes, which also included intermittent brief breaks. Monkeys tended to move the four fingers opposite the thumb in the same manner to open or close their hands, which made the aperture variable proper for capturing the variability of grasping motion. The aperture statistics (mean $\pm$ sd) for monkey C and G were 4.2 ± 1.0 cm and 4.1 ± 1.1 cm, respectively. The aperture velocity statistics for monkey C and G were 0.0 ± 4.9 cm/second and 0.0 ± 8.6 cm/second, respectively.

A. Discrete State Classification

The results of 2-state classification (grasp opening vs. grasp closing) are reported in Table I. In order to be of more practical use for prosthetic devices, a 3-state classification including intermediate state, which can be viewed as 'rest state', is desired. Table I shows the results for this case. However, direct classification of these 3 states via QDA, MNR or SVM resulted in a large fraction of closing and opening states assigned to the intermediate state. We conjecture that this misclassification resulted in part from the difficulty of clearly defining or distinguishing closing/opening states from intermediate ones in the training data used to build the classifiers. (Opening and closing states were defined by thresholding aperture velocities, which were typically noisy in our data.)

A different approach based on a sequential classifier (see Methods) provided much better performance. Two different LGR classifiers were built on training data for each step in the sequential classifier. A 12-fold cross-validation scheme was employed in both LGR

classifiers. TRs for the classifications in the first step were 75.4 for monkey C and 70.2 for monkey G. In the second step in which opening or closing movements were classified, TRs achieved 88.3 and 81.5 for monkey C and G, respectively. The confusion matrix for the overall classification result of 3-state sequential classifier is given in Table II. Correct classifications were close to 80% for closing and opening states and about 60% for the intermediate state (expected chance classification was ~ 33%).

B. Continuous Trajectory Decoding

The decoded grasp aperture and aperture velocity, based on bhfLFP power, captured most of the qualitative features of the actual trajectories (Fig. 1). CC and RMSE values of the decoding performance are summarized in Table III. In contrast, the chance level decoding (Fig. 1) showed random fluctuations which, together with much lower chance level CCs (upper limit of the 99.9% confidence intervals was about 0.2, including both aperture and aperture velocity, both monkeys), reveals that information in the bhfLFP power mainly accounted for the decoding performance, rather than prior knowledge about a kinematic variable's temporal correlation incorporated in the Kalman filter state matrix.

IV. DISCUSSION

Grasping motion control is one of several key motor functions that people with hand/arm paralysis need to restore. In this study, we have investigated how well grasping motion can be reconstructed using bhfLFP power. The results from discrete state classifications suggest the grasp states (opening, closing and intermediate state) can be recovered from bhfLFP power. People with paralysis could potentially use the bhfLFP signal to actively switch among the three grasp states. The measured aperture velocities were noisy in our training data. Nevertheless, we chose a velocity based definition for these discrete states, because aperture itself did not directly reflect the grasping motion. That was because monkeys grasped objects of different shapes and sizes. For a small object, a certain aperture value might mean 'open', while the same aperture value could mean 'closed' for a bigger object. The results from continuous trajectory decoding show an alternative for reconstructing grasping motion. Instead of switch control, the decoding performance suggests the potential application of bhfLFPs in continuous aperture control. Overall, our findings indicate that high frequency LFPs can reconstruct important features of grasping motion and potentially serve as useful neural control signals in neural interfaces that aim at restoring movement in humans with tetraplegia or other motor disorders. An important issue, which we hope to examine with further experiments, is the physiological source of the fluctuations in bhfLFP power.

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Fig. 1.

Kalman filter decoding of grasp aperture and aperture velocity based on bhfLFP power observations. Sample segments, decoded from test data, are shown for each monkey. Grasp aperture kinematics have been normalized.

TABLE I**PERFORMANCE OF STATES CLASSIFICATION**

Method	Monkey C	Monkey G
QDA (2 states)	86.4 (15)	76.5 (17)
LGR (2 states)	86.8 (20)	77.1 (20)
QDA (3 states)	79.4 (5)	70.7 (20)
MLR (3 states)	83.7 (20)	72.9 (20)
SVM (3 states)	86.0 (19)	78.1 (20)

Values outside brackets are the classification accuracy in percentage. Numbers in brackets correspond to the number of channels in the best subset yielding the classification accuracy.

TABLE II

Confusion matrix for 3-state aperture classification using sequential classifiers

Decoded	Opening	Closing	Intermediate state
Actual			
Opening n=485 n=837	76.3 67.1	8.9 16.0	14.8 16.8
Closing n=304 n=652	11.8 14.1	79.6 65.0	8.6 20.9
Int' state n=11211 n=12527	23.8 21.1	13.4 19.8	63.1 59.1

Numbers in the top and bottom row of each cell in the table correspond to values obtained from monkeys C and G, respectively. Values in the matrix are in percentage.

TABLE III**PERFORMANCE OF TRAJECTORY DECODING**

Kinematics	CC	RMSE (%)	# of channels
aperture	0.61	14.2	20
	0.63	12.5	20
aperture velocity	0.51	16.1	20
	0.42	17.9	20

Numbers in the top and bottom row of each cell in the table correspond to values obtained from monkeys C and G, respectively.