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Detection and Classification of Multiple Finger Movements Using a Chronically Implanted Utah Electrode Array

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***Abstract*—The ability to detect and classify individual and combined finger movements from neural data is rapidly advancing. The work that has been done has demonstrated the feasibility of decoding finger movements from acutely recorded neurons. There is a need for a recording model that meets the chronic requirements of a neuroprosthetic application and to address this need we have developed an algorithm that can detect and classify individual and combined finger movements using neuronal data acquired from a chronically implanted Utah Electrode Array (UEA). The algorithm utilized the firing rates of individual neurons and performed with an average sensitivity and an average specificity that were both greater than 92% across all movement types. These results lend further support that a chronically implanted UEA is suitable for acquiring and decoding neuronal data and also demonstrate a decoding method that can detect and classify finger movements without any *a priori* knowledge of the data, task, or behavior.**

***Index Terms*—Arrays, decoding, microelectrodes, neural engineering, neural prosthesis**

I. Introduction

NEURONAL populations have proven effective in decoding both sensory input and motor output because multiple neurons fire in response to a single variable [1, 2]. Consequently, the ability to decode neuronal population signals in real time is leading to neuroprosthetics that are directly controlled by these signals [3-5]. Extensive progress has been made in decoding reach and simple grasp movements of non-human primates (NHPs). However, only a few studies have decoded individual finger movements [6-9]. This work has demonstrated the feasibility of decoding finger movements using acutely recorded individual neurons. As the work done utilized neurons recorded individually and sequentially, the need still exists for a model that relies on a chronically implanted microelectrode array.

To address this need, we set out to create an algorithm that could reliably perform on data obtained during individual and combined finger movements using a chronically implanted Utah Electrode Array (UEA). The algorithm requires no *a priori* knowledge of the data, task or behavior. Continuous data sets that included a no-movement state and up to eight movement types were decoded using the algorithm. The average sensitivity and specificity results were >92% across all movement types. This ability to decode finger movements using continuously recorded action potentials from a chronically implanted microelectrode array demonstrates a viable method for neuroprosthetic hand applications.

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II. Methods

A. Approvals

Approval for the animal use protocol in this study was obtained from the local Institutional Animal Care and Use Committee (IACUC). All procedures conformed to National Institutes of Health (NIH) standards for animal care.

B. Experimental Apparatus

A male macaque monkey was trained to perform flexions, extensions, and combined flexions of the thumb, index finger, and middle finger when cued. Extensions and flexions were recorded using a manipulandum that had separate microswitches for flexion and extension for the thumb, index finger, and middle finger.

Neural data was recorded from an implanted Utah Electrode Array (UEA) that had 96 functional electrodes located at the tips of 1 mm shanks. The neural data, microswitch closures, markers, and task parameters were recorded using a Cerebus data acquisition system (Blackrock Microsystems, Salt Lake City, UT). Thirteen sessions were recorded over the course of 35 days that ranged from 13 days to 48 days post-implantation.

C. UEA Implantation

A UEA was implanted in the hand region of the primary motor cortex (M1) contralateral to the monkey's trained hand (Fig. 1). The M1 region was located using anatomical landmarks and stereotaxic coordinates.

D. Spike Sorting

A threshold of -70 microvolts was applied to the neural recordings in order to identify action potentials from isolated neurons. This data was then sorted using a principle components analysis algorithm. These sorted spikes were then visually evaluated to correct for any obvious algorithm deficiencies or over-sorting issues.

E. Analysis

The instantaneous firing rate was calculated by taking the reciprocal of the inter-spike interval. A low-pass filter was applied that eliminated any instantaneous firing rates that exceeded 100 Hz in order to correct for erroneous sorting. The instantaneous firing rates were then smoothed using a moving window with a window size of 200 ms and a step size of 40 ms. All analyses and computations were done using custom MATLAB scripts.

F. Training and Decoding

Training—Find tuned neurons and their optimal thresholds

The decoder was trained using a portion of the total trials for each movement type from a given session. The monkey did not perform every possible movement type each session; therefore, a minimum of 15 trials for a given movement type had to occur in a given session for the decoder to be trained on that movement type. If the minimum number of total trials was met, forty-five percent of the total trials were used for training. An maximum of 35 trials were used for training to maximize the number of trials decoded by the algorithm. Some sessions included periods of inactivity that were more than 20 seconds in duration; in these cases, forty percent of the inactive period(s) was(were) included in the training.

A receiver operating characteristic (ROC) curve was generated to determine which neurons demonstrated a change in firing rate just prior to movement. An ROC curve was generated by stepping through trial firing rate thresholds for each movement type with every neuron. To generate a single point on an ROC curve, a trial threshold within a range from 0 to 100 Hz was set for that neuron's instantaneous firing rate. The instantaneous firing rate of the neuron was then stepped through using a time window of 400 ms and a step-size of 40 ms for the duration of the training portion of the session. If, within the window, the smoothed instantaneous firing rate surpassed the set threshold, the result of that window was detection. Simultaneously, if a microswitch closure for the movement type of interest occurred within the window, then the result was movement. Based on the detection and movement results for each window, true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) were determined (Table I). From the true positives, false positives, true negatives, and false negatives the true positive rate (TPR) was calculated using equation (1) and the false positive rate (FPR) was calculated using equation (2). Statistically, the TPR is equivalent to sensitivity and the FPR is 1 – specificity. The TPR and FPR were calculated for each trial threshold as the process was repeated through the range of trial thresholds. An ROC curve for the specified movement type and neuron was then generated point by point by plotting the TPR against the FPR for each trial threshold.

After an ROC curve was generated for each movement type with every neuron, the area under the curve (AUC) was used to rank the neurons. The neurons were ranked by movement type in descending order with the largest AUC indicating the most tuned neuron for that movement type.

The optimal threshold for each neuron for a given movement type was found by subtracting the FPRs from the TPRs. The threshold associated with the largest difference was chosen as the optimal threshold for that neuron.

Training—Find the optimal number of neurons

The neurons with the largest AUCs were then used in a majority vote on the training data to determine the optimal number of neurons to use in the algorithm. To find the optimal number of neurons for the decoder, combinations of the neurons with an AUC greater than 0.70 were used. A minimum of three neurons were used with the maximum number being the number of neurons that had an AUC

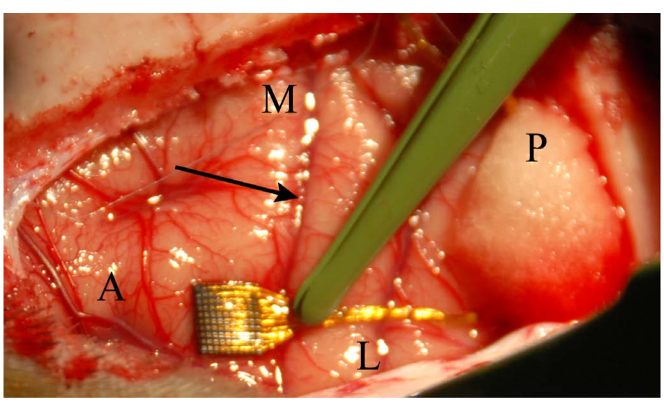

Fig. 1 A Utah Electrode Array (UEA) was implanted in the M1 region of the motor cortex. The central sulcus is marked by an arrow. The letters A, P, M, and L refer to anterior, posterior, medial, and lateral respectively.

TABLE I
DETERMINING THE OUTCOME OF EACH WINDOW

	Movement Microswitch closure occurred within the window.	**No Movement** Microswitch closure did not occur within the window.
Detection Instantaneous firing rate rose above threshold within the window	True Positive (TP)	False Positive (FP)
No Detection Instantaneous firing rate did not rise above threshold within the window	False Negative (FN)	True Negative (TN)

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad (1)$$

$$\mathrm{FPR} = \frac{\mathrm{FP}}{\mathrm{FP}+\mathrm{TN}} \quad (2)$$

greater than 0.70. The data was moved through in a similar fashion as before, using a 400 ms window and a 40 ms step-size. For each window, if the majority (>50%) of the neurons being used had their smoothed instantaneous firing rate rise above their respective optimal thresholds, then that window was counted as a detection. The algorithm recognized that a movement occurred if a microswitch closure for the movement type being evaluated occurred within the window. Based on the combination of detection and movement for each window, true and false positives and true and false negatives were determined (Table I). The group of neurons that yielded the largest TPR and the smallest FPR was considered the optimal group of neurons for that movement type and was used in the algorithm.

Decoding

The algorithm was tested on novel data and did not use any *a priori* knowledge of the data, task, or behavior. Each session included a given number of trials upon which to test the algorithm; the number of decoded trials ranged from 10 to 147 trials for each movement type performed in the session with an average of 34.8 ± 21.9 trials.

The optimal groups of neurons for each movement type, as determined by the training, were used in a majority vote method on the testing data. The testing data was moved through in time steps in a similar fashion as the training data, using a 400 ms window and a 40 ms step-size. For each window, if the majority of the neurons being used had their smoothed instantaneous firing rate rise above their respective thresholds, then that window was counted as a detection. If a microswitch closure occurred within the window for the movement type being evaluated, then the result was counted as a movement. Movement events were tracked in order to verify the accuracy of the algorithm. Based on the combination of detection and movement for each window, true and false positives and true and false negatives were determined (Table I). The TPR, or sensitivity, and FPR, or 1 – specificity, were each computed to measure the accuracy of the algorithm. This training and testing process was repeated for each of the thirteen sessions.

III. Results

A. Neurons Demonstrate Robust, Differential Firing Rates for Each Movement Type

Initial observations of the neuronal firing rate revealed that a change in the firing rate correlated with movement events. The change was typically an increase in firing rate (Fig. 2), although some neurons show a decrease in firing rate that is correlated with movement events. In both the rasters and the peristimulus time histograms (PSTHs), the movement event was aligned at time zero.

B. ROC Curves Used to Identify Task-Related Neurons

The ROC curves were constructed using the true positive rates (TPRs) and false positive rates (FPRs) from each of the trial thresholds. The area under the curve (AUC) was found to be larger for neurons that exhibited a distinct increase in firing rate just prior to movement. The differentiability between the AUC for each movement type for each neuron allowed for the training to identify the task-related neurons for each movement type (Fig. 3).

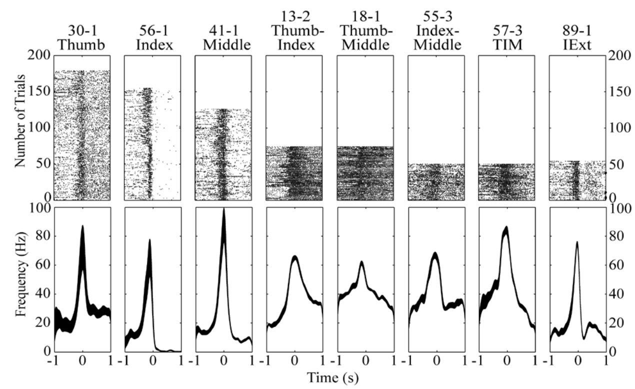

Fig. 2 PSTHs and rasters for eight different neurons with the data aligned on movement, i.e. switch closure, at zero seconds. The rasters exhibit a band of activity that begins just before zero seconds. PSTHs demonstrate a distinct increase in firing rate just prior to each movement type. All movements are flexions except for IExt (30-1 signifies Electrode 30 Unit 1 and so forth, TIM = Thumb-Index-Middle, and IExt = Index Extension).

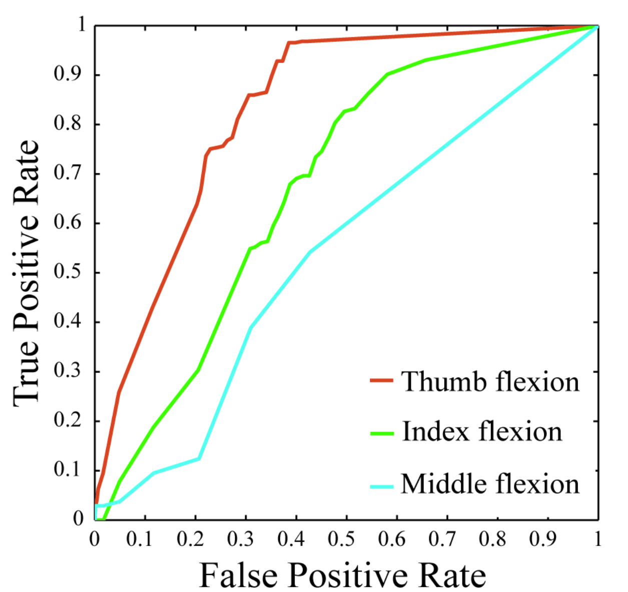

Fig. 3 Three ROC curves for a single neuron. The areas under the curves were used to determine which neurons were task-related and also determined the preferred movement type of each neuron. The neuron shown was sufficiently tuned for thumb flexions to be used by the decoder.

C. Algorithm Performance is Highly Accurate

The algorithm performed over a continuous, novel dataset with the median TPR, or sensitivity, being above 91% for each movement type except thumb-middle flexion, which had a median value of 88%. Furthermore, the median FPR values were less than 10% for each movement type (Fig. 4). As specificity is 1 – FPR, this indicates median specificity values were greater than 90% for each movement type. Results that were beyond ±2.7σ were considered outliers. Disregarding the outliers, the decoder performed across all movement types with an average sensitivity of 92.2 ± 2.5% and an average specificity of 92.6 ± 1.3%

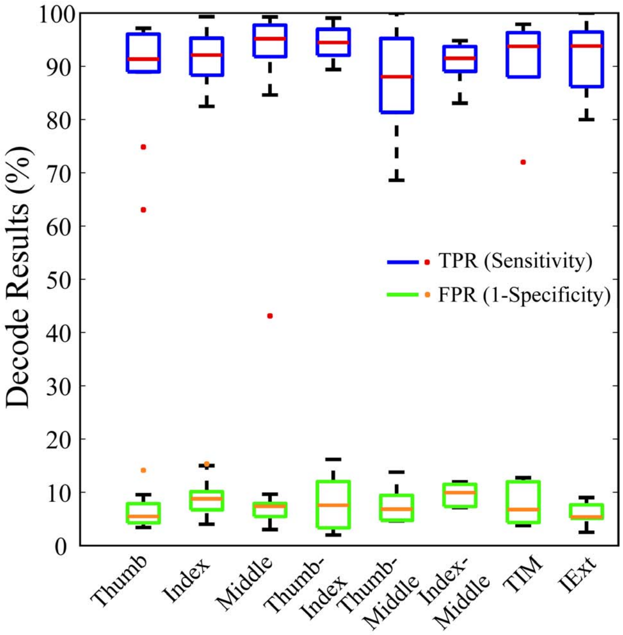

Fig. 4 Decode accuracy denoted by a high true positive rate (TPR) and a low false positive rate (FPR) for each movement type. The TPR is equal to sensitivity, and the FPR is equal to 1 – specificity. The distribution of the decode results for each of the sessions across each movement type is shown. Data beyond ±2.7σ are considered outliers; outliers are marked as dots. All movements are flexions except for IExt (TIM = Thumb-Index-Middle, IExt = Index Extension).

IV. Discussion

A. Utilization of Neurons near the Gyral Surface

Neuronal recording and consequent decoding success has previously been obtained by recording neurons within the central sulcus that are up to 7mm deep to the cortical surface, demonstrating that many grasp related neurons are located deep in the central sulcus [9]. Our results show that task-related neurons associated with finger movements are also near the gyral surface in the M1 region of the motor cortex and can be recorded using a UEA of 1mm shank length. These results demonstrate that a chronically implanted array on the gyral surface records a sufficient number of task-related neurons to accurately decode individuated finger movements.

B. Implications for Neuroprosthetics

The differentiability of the individual neuronal firing rates allowed for decoding very fine finger movements. Work done on decoding arm movements has shown that individual neurons have variable firing rates based on the direction of the movement, with each task-related neuron in the motor cortex having a preferred direction [2]. Similarly, individual neurons decoded in this study demonstrate variable response to various individual and combined finger movements, with many neurons exhibiting a preferred finger movement type. The training of the algorithm is able to identify the preferred neurons for each movement type, which would customize the algorithm for variations within each patient. The performance of the algorithm included an overall average of greater than 92% not only for sensitivity (TPR) but also for specificity (1-FPR) despite long periods of no movement. Having both a high sensitivity and a high specificity would be important in a neuroprosthetic application, as the no movement state is just as important as the movement states.

The results indicate that this method of acquiring neuronal data using a chronically implanted UEA and then detecting and classifying finger movements with this algorithm yields high specificities and sensitivities for finger movements. In addition to research directed at developing arm and hand neuroprosthetics, this technique may also be useful in other areas of neural engineering.

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