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Neural Correlates of error processing during grasping with invasive brain-machine interfaces*

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***Abstract*— Brain-machine interfaces (BMIs) may generate more errors than those encountered during normal motor control. Thus, they provide an opportunity to investigate neural correlates of error processing. Characterizing neural correlates of error processing may, in turn, provide a tool for on-line correction of the errors that are made by the interface. We investigated neural correlates of error processing during BMI experiments in which monkeys controlled an animated hand on the screen to touch a ball by moving their own fingers. Short movement segments that were consistently toward or away from the target were labeled accordingly and used to train a classifier to differentiate between correct and erroneous movements based on the neural activity. The results indicate that despite the limited number of labeled segments and active neurons in the studied data, the classifier achieved a classification rate of 68% on testing. The full receiver operating curve (ROC) has been estimated and indicates that even when the false alarm is restricted to 5%, the classifier can detect 36% of the erroneous movements. Better results are expected when using more data, especially as more challenging grasping tasks are performed. Such a classifier could be used to improve the performance of BMIs by detecting and correcting erroneous movements.**

I. Introduction

Despite recent advances in adaptive BMI filters and in particular the 'recalibrated feedback intention-trained Kalman Filter' (ReFIT-KF) [4][3], invasive BMIs are still prone to errors [4][2], especially as more challenging motor tasks, like those involving finger movements, are attempted. Invasive BMIs rely on the correlation between neural activity and movement kinematics. However, many characteristics of neural activity, including the apparent preferred direction, change after switching to brain control [7].

Interestingly, it was demonstrated that the modulations in neural activity recorded during BMI experiments increase after switching to brain control [11] and that this can be attributed to increasing process noise due to imperfections in the BMI filter [1]. Whether and how the increasing neural modulations encode information about the error are still open issues.

In typical closed-loop BMI applications, the errors made by the BMI evoke error-processing in the user's brain. Investigating neural correlates of error-processing is important both for understanding motor learning and for improving BMIs. In particular, on-line detection of neural correlates of error processing would facilitate on-line correction of erroneous movements made by the BMI decoder, even without knowing the movement intention [8][9]. Furthermore, depending on the information that could be extracted from those error-correlates, they could also provide either an error-signal or at least a reinforcement-signal for adapting the BMI decoder.

II. Methods

A. Experimental Methods

BMI experiments were conducted at the Cortical Neural Prosthetics Laboratory with nonhuman primates (NHP) using Utah arrays implanted in primary motor cortex [5][6][10].

Two rhesus macaques were trained to acquire targets by flexing and extending their fingers. A bend sensor taped to their fingers directly controlled the flexion of an animated hand (hand control) in a virtual environment in which the targets appeared.

During some sections of the experiment, the firing rates of neurons were used to control the animated hand rather than the bend sensor (brain control). Decoding was performed every 50msec.

During both hand control and brain control sessions, animals made corrective movements on the majority of trials and outright mistakes on ~15% of trials. Thus, these datasets provide a rich database for analyzing how single unit activity in primary motor cortex relates to error processing associated with movement corrections and mistakes.

B. Analysis Methods

A dataset of 20.82 minutes, recorded during a single session with both hand and brain control sections, has been analyzed.

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The dataset includes the spike times recorded by each of 96 electrodes, the angle of the fingers measured by the bend-sensor, and the decoded finger angle, with 1ms resolution.

For classification, the number of spikes from each electrode was counted in 100ms bins. A moving window of N bins was used to generate overlapping movement segments. Segments were labeled as "toward" or "away" if the velocity in each of the N bins was toward or away from the target, as shown in Figure 1 for N=3, and were unlabeled otherwise. Figure 2 depicts the decoded finger position and target location during a 30sec section of brain control. The corresponding labels of toward and away segments are marked by yellow and purple pluses, respectively, at the top.

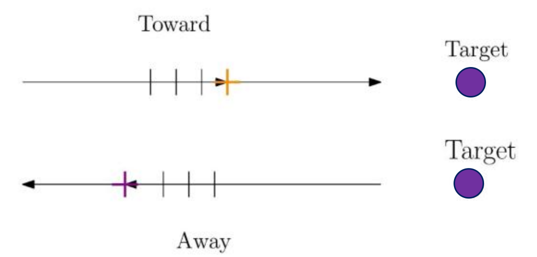

Figure 1: *Grouping of binned neural activity to segments of N=3 bins (of 100ms each). Segments in which the movement was consistently toward or away from the target were labeled accordingly, and marked by a yellow or purple plus at their end, respectively, while others were not labeled.*

The number of toward and away segments during hand and brain control sections of the experiment are indicated in Table I. The grasping movement, whether flexion or extension, is also noted. Thus, there are a total of four label/grasp sub-groups: toward/flexion, toward/extension, away/flexion, and away/extension.

TABLE I. NUMBER OF SEGMENTS IN THE DATASET AND, IN PARENTHESIS, THE NUMBER OF EXAMPLES SELECTED FOR BOTH TRAINING AND TESTING OF EACH CLASSIFER

	# movement segments	
Label	***Away***	***Toward***
Grasp Movement	Hand control	
Flexion	195 (35)	510 (35)
Extension	35 (35)	496 (35)
	Brain Control	
Flexion	138 (112)	170 (112)
Extension	112 (112)	353 (112)
	Combined	
Flexion	333 (147)	680 (147)
Extension	147 (147)	849 (147)

C. Classification Methods

In order to investigate whether the neural activity encodes information related to errors, we evaluated the ability to classify toward (correct) versus away (erroneous) segments from the recorded neural activity. Specifically, the input to the classifier was the number of spikes for each of the $M=96$ electrodes in the N bins composing each segment. The desired output was either +1 or -1 for segments away or toward the target, respectively.

As apparent from Tables I, there is a small correlation between the type of movement (flexion versus extension) and the direction of the movement with respect to the target (toward versus away). In particular, during brain control, and in the combined dataset, a higher percentage of segments toward the target are extension rather than flexion, while a higher percentage of segments away from the target are flexion rather than extension. To avoid classifying toward versus away segments based on features related to flexion versus extension, classification was evaluated on the same number of examples of each of the four sub-groups, as detailed in Table I (in parentheses).

It is noted that the prior probabilities in the examples used for classification are the same for both toward and away classes, while the prior probabilities during brain control are about 2/3 and 1/3, respectively (Table I). The prior probabilities affect only the threshold, which should also account for the “cost” associated with each classification error. For completeness, we evaluated also the case in which the ratio between the prior probabilities was 2:1 (twice as many segments toward the target compared to segments away from the target, but still the same number of flexion and extension from each label). While the optimal performance in that case was similar to the case in which the priors were the same, the performance with false alarm of 5%, detailed below, was worse.

Step-wise linear discriminate analysis (SWLDA) was applied for classification. SWLDA automatically selects the best features for the classification by evaluating the merit of adding or deleting different features at each step. Classification is based on the output of the LDA: An input that generates an output that is larger or smaller than the threshold is classified as +1 or -1, respectively. SWLDA uses a default threshold of zero.

Results are based on 10-fold cross validation. The indicated number of examples (Table I, in parentheses) was selected randomly from those sub-groups in which there were more segments in the dataset (e.g., both toward and away examples of flexion in hand control). Each classifier was trained on 70% of all the examples and tested on the remaining 30%.

III. RESULTS

Figure 3 and Table II describe the performance of classifiers that were trained on movement segments of N=3 bins. In that case, the total number of input features is 288 ($M=96$ electrodes * $N=3$ bins). The upper part of Table II indicates that on average, SWLDA maintained about 29 features for optimal classification.

The left panel of Figure 3 depicts the normalized histogram of the output of all ten classifiers on testing examples for movement segments that were labeled as away (purple) and toward (yellow) the target, respectively. The normalized histograms provide scaled estimates for the class conditioned probability density functions. Optimal performance is achieved with a threshold of zero. Testing performance, averaged over the 10 folds, is reported in the lower part of Table II.

TABLE II. TESTING PERORMANCE

		Training	
	Comment	***Mean***	***Std***
# Features	Selected by SWLDA out of a total of 288 (*M***N*=96*3) features.	29.1	3.6
	Definition	**Testing performance**	
Accuracy	(TP+TN)/ (P + N)	0.685	0.04
Sensitivity	TPR =TP/P = 1- FNR	0.701	0.037
Specificity	TNR= TN/N = 1-FPR	0.683	0.064

SWLDA = Stepwise linear Discriminant Analysis, P = Positive (away); N= Negative (toward), TP = true positive, TN = True negative, TPR = True positive rate, FNR = False negative rate, TNR = True negative rate, FPR = False positive rate. See text.

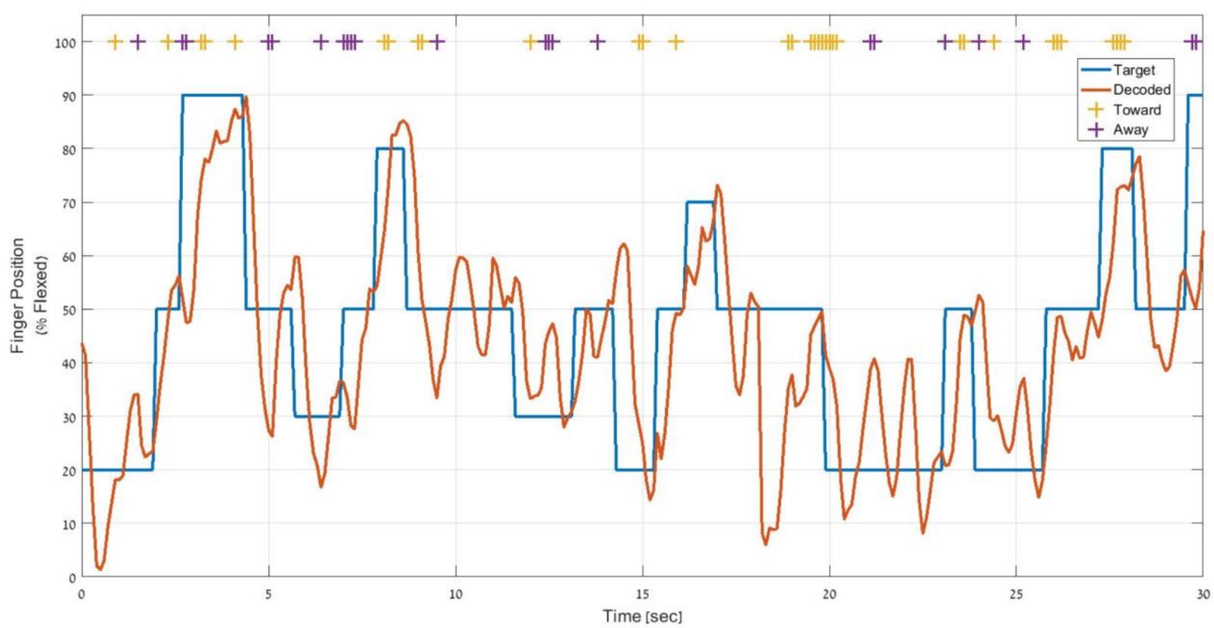

Figure 2. *A 30 sec section of behavioral data during brain control. Decoded finger flexion (orange) with the corresponding position of the target (blue). Segments of N=3 bins (bin-width of 100ms) with consistent movement toward or away from the target are labeled accordingly, as marked by yellow and purple pluses at the top (see Figure 1).*

Classification depends on the selected threshold. The classification performance for different thresholds is presented by the receiver operating curve (ROC) in the right panel of Figure 3. The ROC describes the tradeoff between true positive rate (TPR, i.e., the rate at which segments away from the target are correctly classified as such) versus false positive rate (FPR, i.e., the rate at which segments toward the target are mistakenly classified as away from the target). Optimal performance, achieved with zero threshold, is marked by a blue circle.

It is common practice to limit FPR, also known as false alarm (FA), to 5%. This can be accomplished by selecting the threshold corresponding to the red star in the right panel of Figure 3. At that point, TPR=~0.36, suggesting that away segments will be correctly identified at that rate.

IV. CONCLUSIONS

Our analysis demonstrates that incorrect movement segments, i.e., movement segments away from the target, can be distinguished from correct movements based on the neural activity in M1 during experiments with invasive BMIs. Scientifically, this suggests that the neural activity encodes information related to error processing. Technically, it indicates that the performance of BMIs could be improved by applying a proper classifier to detect incorrect movement segments. Further investigation and validation on a larger data set is needed to establish those results, and provide better estimates of the performance.

Rough estimate suggests that by correcting movement segments classified as erroneous the performance of the BMI can be improved by over 5%. Higher improvement may be achieved in more challenging tasks. However, actual experiments have to be conducted to obtain a reliable estimate. We also developed initial classifiers that distinguish between correct and erroneous movement changes made by the BMI, based on the neural activity in *N* bins before the change. Preliminary analysis indicates that the accuracy of that classifier is ~75%. However, further analysis is required to assess the redundancy between that classifier and the one reported here, and how they may be combined.

In summary, this work provides initial evidence for neural correlates of error processing and suggests that they can be detected to improve the performance of BMIs.

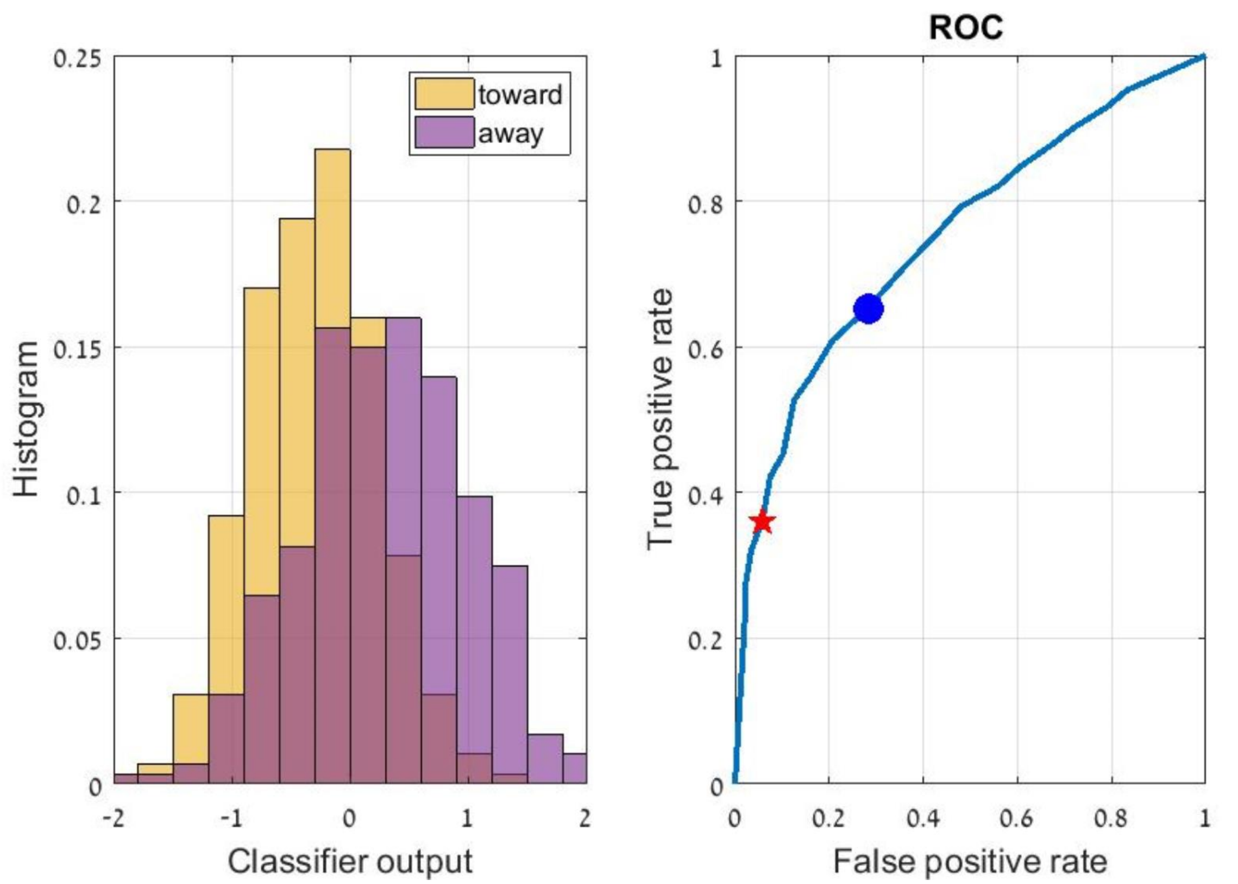

Figure 3. *Classifier performance during testing in all 10-folds, after training to classify toward and away movement segments as -1 and +1, respectively. Left: Normalized histogram of the output from the classifier during testing of toward (yellow) and away (purple) movement segments. Right: Receiver operating curve (ROC) describing the trade-off between true positive rate (TPR, i.e., the rate at which segments away from the target are correctly classified as such) and false positive rate (FPR, i.e., the rate at which segments toward the target are mistakenly classified as away from the target). Blue circle corresponds to optimal performance with zero threshold. Red star corresponds to 5% FPR (also known as false alarm).*

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