# **Three Cases of Feature Correlation in an Electrocorticographic BCI**

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Abstract—Three human subjects participated in a closedloop brain computer interface cursor control experiment mediated by implanted subdural electrocorticographic arrays. The paradigm consisted of several stages: baseline recording, hand and tongue motor tasks as the basis for feature selection, two closed-loop one-dimensional feedback experiments with each of these features, and a two-dimensional feedback experiment using both of the features simultaneously. The two selected features were simple channel and frequency band combinations associated with change during hand and tongue movement. Inter-feature correlation and cross-correlation between features during different epochs of each task were quantified for each stage of the experiment. Our anecdotal, three subject, result suggests that while high correlation between horizontal and vertical control signal can initially preclude successful two-dimensional cursor control, a feedback-based learning strategy can be successfully employed by the subject to overcome this limitation and progressively decorrelate these control signals.

## I. INTRODUCTION

**COMPUTER** interfaces (BCI) explore Brethodologies for interaction by means of brain signals alone. BCIs designed for humans have used noninvasive scalp measurements known as electroencephalography (EEG), and signals recorded by implanted electrodes on the surface of the brain via a process known as electrocorticography (ECoG). Using the BCI2000 program [1], some current BCI systems have achieved 1-dimensional (1-D) and 2-dimensional (2-D) control of a cursor with the use of EEG signals [2, 3], and similar 1-D and 2-D control with ECoG signals [4-6]. In each of these experiments, initial motor tasks identify channel locations and spectral band power features that are reliably modulated by the subject. Each of these features can then be used to control an independent degree of freedom, e.g., the horizontal or vertical axis of the cursor on a computer screen.

The features selected in this manner (e.g., features that correlate well with movement or imagined movement of the hand or tongue) may also be correlated with each other, rendering them unsuitable for direct control of independent

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# Task Sequence

Figure 1: This figure illustrates the closed loop cursor to target task. The top-left window shows the four potential target locations with the cursor starting position in the middle. The top-right windows on the right show two example cursor trajectories for a target #4 trial. The upper correctly hits the proper target, while the lower errs by hitting target #1. The lower images show the task sequence, with the yellow color reward for a correct trial.

degrees of freedom. In the EEG studies, careful alternation of control with each individual feature alone, in combination with continual re-adaptation of these features, allows decorrelation of features over time [7]. However, for ECoG signals, this mechanism is impractical for two reasons: (a) the subject population has implanted electrodes for a very short period of time (2-7 days, with EEG patients participating over a course of months [7]), and (b) each individual feature is very quickly controlled.

In this paper, we characterize the properties of two control

TABLE	1
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SUBJECT INFORMATION						
Subj	Age	Sex	Hand	Cognitive Array Location (number Capacity of electrodes)		Seizure Focus
1	18	F	R	Normal	Left Frontal Grid and Frontal Strip (72)	Left Frontal
2	48	М	R	Borderline (IQ - 82)	Right Temporal- Parietal-Occipital Grid (64)	Right Temporal- Occipital
3	19	М	R	Borderline (IQ - 82)	Bilateral Frontal and Temporal Strips (26)	Right Temporal and Insular

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signals during each stage of an experimental protocol: a preliminary fixation phase, motor tasks, two isolated 1-D feedback tasks using each feature, and a 2-D feedback task using both features. The relationship of each feature with the task is examined using the cross-correlation of the feature with the task, and the relationship between the two features is examined by calculating their correlation during different periods in each task. This study connects the observed correlations with the subsequently observed performance during closed-loop control, as well as with the absence and presence of simultaneous feedback.

Our results from three subjects performing closed-loop cursor control demonstrate that. (1) when the chosen features are sufficiently uncorrelated, the subject is able to achieve 2-D control as expected, (2) when the features are correlated, 2-D control can be difficult for some subjects but may eventually be achieved through feedback-based learning.

#### **II. METHODS**

The experimental methods used rely on the BCI2000 program. The reader may find it useful to examine existing papers [4, 5]. Subjects: All three subjects who participated in this study were neurosurgical patients with intractable epilepsy who underwent temporary placement of intracranial subdural electrode arrays to localize seizure foci prior to surgical resection of the epileptic focus. *Electrode Arrays:* Patients underwent craniotomy for electrode placement and were typically studied 4-6 days after placement to allow for recovery from the original surgery. The platinum electrode arrays<sup>1</sup> were linear strips or 8x8 electrode arrays, with 1 cm inter-electrode distance, embedded in silastic with 2.3mm diameter exposed (of a 4mm diameter electrode). The signals were recorded at 1000Hz (band-pass filtered from 0.15-200 Hz) with Neuroscan Synamps2 amplifiers<sup>2</sup>. Tasks: All cues and feedback were delivered visually in a 10cm by 10cm presentation window at a distance of 75 -100 cm from the subject using the BCI2000 program. All experiments were conducted at the bedside in each subject's hospital room. Baseline Fixation Task: The subject was instructed to fixate on a point in the hospital room 5m directly in front of the subject for 4-6 minutes. Motor Tasks: Patients performed simple, repetitive motor tasks of hand or tongue movement in an interval-based fashion. Three-second visual cues for hand and tongue movement were randomly interleaved and separated by three-second rest intervals. There were 30 cue periods for each movement (59 rest intervals.) Features identified from these experiments were used to derive control signals for closed-loop cursor control (Table 2). Online Feedback Tasks: Specific channel-frequency combinations were identified from the motor tasks. Linear combinations of the signal power at these channels and frequencies produced control signals that drove vertical

(tongue movement feature) or horizontal (hand movement feature) cursor movement [4, 5]. The direction and speed of the cursor movement along each axis was calculated each 40ms. The ratio of the power in the relevant feature over the preceding 280ms to an intermediate power range between movement and rest, in that signal, drove cursor movement [1]. Tongue movement was always coupled to upward cursor movement, and hand movement was coupled to cursor movement in the direction of the hand being moved.

In the one-dimensional closed-loop tasks (1-D BCI), targets appeared randomly in one of two locations: top or bottom with tongue feature control and left or right with hand feature control. The cursor was constrained to move in a line along the relevant direction only, as governed by the relevant feature. The two-dimensional feedback tasks (2-D BCI), combined vertical and horizontal control.

Individual target trials were terminated when the cursor hit any target or at a designated timeout duration (7200ms). A 1s reward duration was given at trial termination, and a 1s rest between reward duration

TABLE 2								
FEATURES AND TASK PERFORMANCE								
Patient	Modality	Freq(Hz)	Electrode Location	1D BCI Accuracy	1D Learning (min)	2D BCI Accuracy	2D Learning (Min)	
1	Hand	79-85	-44,-14,56	100%	2	Q /10/	18	
	Tongue	79-87	-60, -3, 30	97%	8	0470		
2	Hand	77-83	54, -29, 49	85%	0	6.40/	0	
	Tongue	29-35	63, -1, 17	76%	20	0470		
3	Hand	97-103	-42, -14, 55	98%	0	06%	4	
	Tongue	77-83	-25, 21, -28	98%	22	7070		

Analysis: Spectral Calculation: All spectral coefficient power calculations, both online and offline, were made using the maximum entropy method (also called the all-poles method, [12]). Coefficients were calculated every 2Hz, at even frequencies, and frequency ranges in features reflect summation of power in contained consecutive coefficients (i.e. 79-85 corresponds to the sum of the power at 80, 82, and 84 Hz.) Task-related Cross-correlation: The measure used to determine the relevance of a feature with the task was the square of the correlation coefficient  $(R^2)$  of the feature between different states. This measure may be interpreted as the amount of variance in a joint distribution that may be accounted for by the difference in means of the component distributions. For the motor tasks, the power of each feature during each cue period was calculated. Distributions from different cue types were compared using the  $R^2$  metric to determine how relevant each feature was in discriminating states in the task. For the online experiments, mean power during each target presentation - including reward duration - was calculated (the mean power is necessary because target trial duration varies), and these values were used to calculate R<sup>2</sup> values. These measures are

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all shown in Table 3. *Inter-feature Correlation:* The standard correlation (r) between the time series of the two control signals was measured in each of the tasks, and also during behavior-specific epochs of the data. These correlations are shown in table 4. *Mapping:* The maps in figures 2-4 were created by linear superposition of spherical Gaussian kernels centered at the location of each electrode, and interpolated activations are calculated at each point in a template brain. Kernels had width 5 mm (variance 25 mm) and were scaled by an  $R^2$  at each electrode for the frequency band of the relevant feature. Electrode positions, in Talairach standardized coordinates [10], were calculated using anterior-posterior and lateral skull x-rays [11], and are shown in each map with white dots.

TABLE 3

R <sup>2</sup> VALUES FOR THE DIFFERENT TASKS (FEATURE-TASK RELEVANCE)						
Squared Cross- Correlation Values	Patient 1		Patient 2		Patient 3	
	Hand	Tongue	Hand	Tongue	Hand	Tongue
contraction values	Feature	Feature	Feature	Feature	Feature	Feature
Screening: rest cue vs. tongue cue	0.06	0.58	0.03	0.45	0.002	0.30
Screening: hand cue vs. rest cue	0.76	0.004	0.19	0.03	0.73	0.06
Screening: hand cue vs. tongue cue	0.85	0.57	0.22	0.61	0.82	0.06
Hand feedback task: vertical targets	0.74	0.0001	0.17	0.28	0.79	0.39
Tongue feedback task: horizontal targets	0.02	0.66	0.4	0.54	0.41	0.60
Dual feature feedback task: vertical targets	0.06	0.33	0.01	0.09	0.60	0.85
Dual feature feedback task: horizontal	0.74	0.12	0.05	0.08	0.95	0.89



Figure 2: Four consecutive runs of tongue movement- (A) and word imagery- (B) based 1-D BCI, for subject 1. The frequency band displayed for both is 79-87Hz. The feature used for feedback in (A) is the electrode at  $\{-60, -3, 30\}$  in Talairach coordinates (the electrode in the middle of the dark red on the top far right plot) with the frequency band 79-87Hz. The runs in (A) were the first feedback experiments of any kind with this subject. The feature used for (B) was the sum of the feature from (A) and one at  $\{-53, 8, 38\}$  with the frequency band 89-95Hz. The subject had not used this action (speech or imagined speech) for any feedback runs prior to those shown in (B). Target accuracy percentages are indicated below each map.

### III. RESULTS AND DISCUSSION

As shown in Table 2, the frequency ranges used for control varied from 29-103 Hz, although the majority of feature ranges were chosen in the Chi frequency range (75-150Hz [13]). Except for patient 3's tongue feature, which

was temporal and extra-rolandic, the feature locations corresponded to classic hand and tongue homuncular positions. Subjects 1 and 3 obtained superb control in both 1-D tasks (97-100% target accuracy), while subject 2 had more difficulty with the vertical 1-D task (76%, above 50% chance). Subjects 1 and 3 were subsequently able to gain significant control in the 2-D BCI task. Learning, defined in Table 2, is the time before the reported accuracy.

## A. Subject 1: Ideal Features and Straightforward Success

Subject 1 had coverage and feature separability such that the two control signals met optimal conditions for online control. Although the signals were correlated with each other (Table 4), the cross-correlations for each feature during the motor tasks were good (Table 3): each signal could resolve its own cue type with respect to rest, but not the other active cue type with respect to rest, and could resolve the

TABLE 4 Inter-Feature Correlation (Italics indicate "Active" Epochs)

(ITALICS INDICATE ACTIVE EPOCHS)						
Correlation betw	veen features	Patient 1	Patient 2	Patient 3		
Fixation task		0.04	0.46	-0.05		
	Hand	0.12	-0.08	0.05		
Screening Task	tongue	0.19	0.26	0.06		
	Rest	0.21	0.11	0.03		
Hand feedback	target 2	0.04	-0.16	0.13		
task:	target 4	0.00	-0.1	0.16		
(Horizontal)	Rest	0.07	-0.07	0.1		
Taurent faaillaala	target 1	0.00	0.35	0.56		
task: (Targets)	target 3	0.14	-0.07	0.23		
	Rest	0.06	-0.04	0.2		
	target 1	0.00	-0.04	0.47		
Dual facture	target 2	0.18	0.26	0.1		
feedback task:	target 3	0.2	0	0.6		
	target 4	0.00	0.09	0.66		
	Rest	0.34	-0.07	-0.02		

difference between its own cue type and the other active cue type.

During all aspects of the horizontal 1-D BCI, the two features showed very low correlation; less than during the vertical 1-D BCI, where the two features were moderately correlated during passive feedback durations. Both features were able to resolve the appropriate task. In the 2-D task, Subject 1's hand feature was able to selectively isolate the horizontal aspects of the task, and was correlated with the tongue feature during the trials where the target was in one of the two passive directions. The tongue feature was less able to resolve the task, but the combined effect of the two features demonstrated control. The focal, localized, nature of these features across the task is illustrated in Figure 3. Figure 2a demonstrates the tongue feature learning in subject 1 during the vertical 1-D BCI training period, and Figure 2b shows how this learning process is similar for speech imagery as a control mechanism (imagine saying the word "move").

#### B. Subject 2: Inseparable Features

Subject 2 had inseparable tongue and hand features. If the chosen features had been examined for correlation during

the fixation task (Table 3) once they had been chosen by cross-correlation values in the motor tasks, different features could have been chosen prior to feedback experimentation. In the 1-D feedback tasks, the tongue feature resolved both horizontal and vertical better than the hand feature. The 2-D task shown was the first run, neither direction was resolved with either The middle column of Figure 3 for subject 2 shows sparse, disorganized cortical modulation.

# C. Subject 3: Brute-force Feedback Success

Subject 3 had an array of strip electrodes, providing only sparse rolandic area coverage. One feature spanned the central sulcus in hand area, and provided a clear feature which was able to selectively resolve hand cues from null and tongue cues. The feature chosen from tongue was an extra-rolandic temporal electrode – an atypical control electrode selection – which showed a reasonable  $R^2$  for tongue cues with respect to rest cues. After extensive feedback, the patient was able to modulate the frequency band associated with the chosen tongue feature in his entire left hemisphere. Although both features were correlated with each other, during both active and passive durations they were even more highly correlated with the appropriate task, and he was able to learn to coordinate this in a brute-force approach for successful task performance. This is illustrated



Figure 3: Task-Related Cross Correlation. Activation maps illustrating the spatial distribution in the indicated frequency range for the screening task, each of the two 1-D BCI tasks, and the 2-D BCI task for each of the three patients. The colored bar indicates the scale of  $R^2$ values, ranging from 0 (dark blue) to 1 (dark red).

in the bottom third of Figure 3: the 1-D BCI task based upon the tongue feature shows activation across his entire array, and both features show activation across the entire array for the 2-D BCI task.

# IV. CONCLUSIONS

Subject 1 demonstrated that biologically straightforward, independent, signals which correlate well with tasks can produce successful 2-D feedback control; subject 2 demonstrated that signals that are correlated with each other are difficult to control; and subject 3 demonstrated that the cortex can be modulated in response to feedback to progressively decorrelate control signals. This suggests that simple location/frequency band feature coupling to cursor control is sufficient to gain closed loop, 2-D, cursor control in some individuals. Future iterations of this technology, using more sophisticated approaches, will make use of these somatotopically distinct yet highly correlated features.

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