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Electrocorticogram as the Basis for a Direct Brain Interface: Opportunities for Improved Detection Accuracy

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Abstract- **A direct brain interface (DBI) based on the detection of event-related potentials (ERPs) in human electrocorticogram (ECoG) is under development. Accurate detection has been demonstrated with this approach (near 100% on a few channels) using a single-channel cross-correlation template matching (CCTM) method. Several opportunities for improved detection accuracy have been identified. Detection using a multiple-channel CCTM method and a variety of detection methods that take advantage of the simultaneous occurrence of ERPs and event-related desynchronization/synchronization (ERD/ERS) have been demonstrated to offer potential for improved detection accuracy.**

***Keywords* - Direct brain interface (DBI), brain-computer interface (BCI), electrocorticogram (ECoG), event-related potential (ERP), event-related desynchronization (ERS), event-related synchronization (ERD)**

I. INTRODUCTION

A direct brain interface (DBI) is a human-computer interface that accepts commands directly from the brain without requiring physical movement. The University of Michigan Direct Brain Interface (UM-DBI) project seeks to detect voluntarily produced patterns of electrocortical activity (ECoG) related to actual or imagined movements in humans as the basis for a DBI. ECoG provides better temporal and spatial resolution than electroencephalogram (EEG) and is less vulnerable to movement or muscle artifact. Most research to date has utilized off-line processing, therefore movement-related activity (instead of preferred motor imagery) was chosen so that movement onset (the trigger point) could be determined from muscle activity or another similar indicator and used to determine detection accuracy.

Research subjects were patients in one of two epilepsy surgery programs who had subdural macro electrodes implanted for clinical purposes unrelated to the research objectives. The electrodes were 4 mm in diameter and arranged in grids or strips at distances of 1 cm center-to-center. Subjects had between 15 and 126 subdural electrodes implanted.

Subjects performed simple voluntary movements in a self-paced (non-prompted) manner with at least 4 seconds separating each repetition of the movement. Movements were performed without feedback or feedback training. Each dataset contains ECoG channels from multiple recording electrodes during approximately 50 repetitions of the same action. An ECoG database of 211 datasets from 34 subjects has been compiled. For all experiments, the first half of each dataset was used as the training data while the second half was reserved for use as test data.

The established detection method used by the UM-DBI project is a single-channel cross-correlation template matching (CCTM) method [1]. Triggered averaging of the ECoG from the first half of a dataset is used to create templates of the ECoG corresponding to the action. Templates are 6 seconds in length and start 3 seconds before the trigger. A template showing a distinct event-related potential (ERP) is then selected and cross-correlation is performed with the ECoG from the second half of the dataset (the test data). Detections are defined when the cross-correlation value exceeds an experimentally determined threshold. Valid detections (hits) are defined to be within 1 second before and 0.25 seconds after a trigger point. Any detections outside this time interval are considered false positives. Detection accuracy is quantified by a hit percentage, which is the percentage of trigger points in the test data that were detected, and a false positive percentage, which is the percentage of the detections that are false positives. The difference between the hit percentage and the false positive percentage (the HF-difference) is used to compare detection results. Fig. 1 shows the distribution of channels with HF-differences greater than 50 using an offline single-channel CCTM approach. Note that these results are for trials with no feedback training.

Single-channel CCTM detection has been shown to be accurate for many subjects even when electrode location is not specifically chosen for purposes of a DBI. There are,

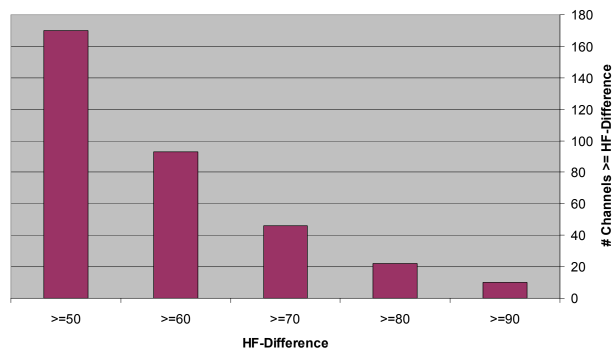

Fig. 1. ECoG channels above each HF-differences threshold for the single-channel CCTM method.

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however, many possibilities for improved detection accuracy offered by the ECoG data that may: increase the number of subjects for whom accurate detection is possible, improve the accuracy of detection for a particular subject, or increase the number of independent control channels available for a particular subject. Methods to produce improved detection accuracy are the focus of this paper.

II. Methodology

A. Multiple-Channel CCTM Detection

Multiple electrodes may show evidence of an ERP related to a particular action that can potentially be integrated into the CCTM detection scheme for improved accuracy. This information is picked up either from the same region of the brain by adjacent electrodes or from various regions of the brain that are simultaneously involved in production or imagination of the movement.

A simple multiple-channel CCTM method was designed to demonstrate the potential for improved accuracy. In this method, cross-correlation between an ERP template and the test ECoG is performed for multiple electrode channels. The channel correlograms are then averaged and an experimentally determined threshold applied to the result as if it was the correlogram from a single channel [2]. Fifty-one datasets from 14 subjects contained at least 3 ECoG channels with HF-differences greater than 30 (a total of 399 ECoG channels). All possible 3 channel combinations within each dataset (a total of 13274 combinations) were analyzed.

B. ERD/ERS Concurrence

ERPs and event-related desynchronization/synchronization (ERD/ERS) are ECoG features that may be produced by the same voluntary action or motor imagery, but are assumed to be different responses of cortical neural-networks to the action. An ERP is a phase- and time-locked response, while ERD/ERS is time- but not phase-locked [3]. The CCTM detection method relies solely on ERPs, while other detection methods, developed using EEG have relied solely on the ERD/ERS [4].

ERP localization can be visualized using topographically arranged plots of trigger averaged templates (Fig. 2). ERD/ERS can similarly be visualized using ERD maps [5] (Fig. 3). Visual comparison of ERPs and ERD/ERS in 26 datasets from 7 subjects was performed. Of the 17 datasets that showed obvious ERD/ERS patterns, all had visible ERPs on the same electrodes and 12 had ERPs that could be detected with HF-differences greater than 50. Prominent ERD/ERS patterns were not found for 7 datasets with ERPs that could be detected with HF-differences above 50, although 4 of those datasets did show minimal ERD/ERS patterns overlapping the location of the ERPs. Two datasets showed neither ERPs nor ERD/ERS.

These numbers demonstrate that the ERP and ERD/ERS commonly occur together, although as seen in Fig. 2 and Fig. 3, prominent ERD/ERS is often more widespread than prominent ERP averages. Both the ERP and the ERD/ERS effects can be produced from real or imagined movement [3] and thus a detection method sensitive to both these effects is hypothesized to produce improved detection. Three methods based on a combined detection of these two ECoG features were investigated for improved detection accuracy.

C. Quadratic Model

With a quadratic model the task of detection is viewed as the general binary problem of detecting one of two signals in additive noise.

$$\begin{aligned} H_0 &: \underline{x} = \underline{s}_0 + \underline{n}_0 \\ H_1 &: \underline{x} = \underline{s}_1 + \underline{n}_1 \end{aligned} \tag{1}$$

Where $\underline{x}$ is the observed ECoG, $\underline{s}_1$ and $\underline{s}_0$ are the signal means when the action is and is not occurring and $\underline{n}_1$ and $\underline{n}_0$ are the additive noise when the event is and is not occurring. In this case, we assume that $\underline{n}$ is Gaussian with zero mean and covariance $\mathbf{K}$ and that there is no signal when the event is not occurring, i.e. $\underline{s}_0 = 0$. The most powerful test, using the Neyman Pearson Lemma [6], is then

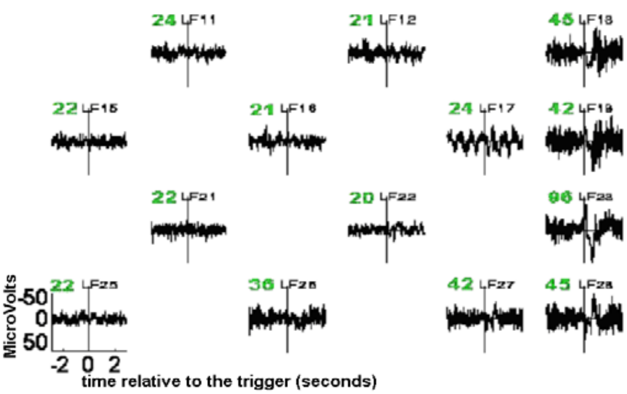

Fig. 2. Averaged ECoG templates over sensorimotor cortex for a subject performing finger extension showing ERPs on the right side of the electrode grid. Each template is labeled with the HF-difference and electrode name.

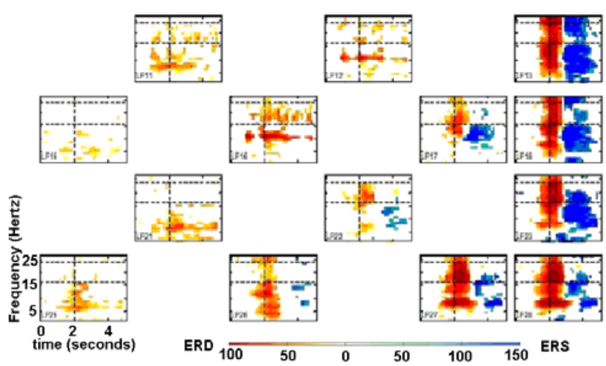

Fig. 3. Averaged ERD/ERS maps for the electrodes shown in Fig. 2. showing ERD/ERS on the right side of the electrode grid.

$$\Lambda(\underline{x}) = \underline{x}^T \left(K_0^{-1} - K_1^{-1}\right)\underline{x} + \underline{s}_1^T K_1^{-1} \underline{x} \underset{H_0}{\overset{H_1}{\gtrless}} \eta \quad (2)$$

where the threshold η is set to achieve the maximum HF-difference. This test has a benefit over the CCTM linear detector in that it assumes a model that can account for both the presence of an ERP, represented here by $\underline{s}_1$, as well as a change in the background activity such as ERD and ERS. Detection based on the quadratic model was performed on 9869 channels in 177 datasets from 25 subjects.

D. Adaptive Autoregressive Analysis

Adaptive autoregressive (AAR) modeling has been successfully applied to identifying ERD/ERS in EEG [7] and ECoG [8]. Further modifications are necessary to apply AAR modeling to ERP data, however. The classic AAR model assumes a constant (zero) mean, an assumption that does not hold for ERP data.

An ARR-model with non-zero mean, μ, can be written as

$$y_k = m + a_1 y_{k-1} + a_2 y_{k-2} + \ldots + a_p y_{k-p} + x_k \quad (3)$$

where $[a_1(t), \ldots, a_p(t)]$ are the AAR parameters, y is the observed ECoG signal and x_k is a white noise process with variance σ_x^2 and

$$m = (1 - \Sigma a_i)\, \mu \quad (4)$$

This m-term can be adaptively estimated along with the traditional AAR parameters $[a_1(t), \ldots, a_p(t)]$, to form the AAR+M parameters $[m(t), a_1(t), \ldots, a_p(t)]$ used for further processing. The additional m-term is intended to take into account the ERP phenomenon of the ECoG data.

Next, the AAR features are reduced into one component using MDA and LDA with the action and no-action brain states defined by time segments with a maximum Mahalanobis distance [9]. From this method, we can derive the sample-based accuracy, ACC% (i.e. percentage of correctly classified samples).

E. Wavelet and Genetic Algorithm Analysis

Wavelet packet analysis can be used to decompose the ECoG signal into wavelet components of specific frequency bands. These components have optimal resolution in the time and frequency domain and are therefore suitable to describe both ERD/ERS and ERP activity. Fifteen components occurring in frequency ranges where ERD/ERS and ERP are expected as well as 3 additional components from a lower frequency range where ERP activity existed were extracted to form a subset of 18 components. Genetic algorithms were employed to find the best linear transformation to reduce the dimensionality to one and to simultaneously maximize the HF-difference. Analysis was performed on 209 channels in 22 datasets from 7 subjects [10].

III. Results

A. Multiple-Channel Detection

The multiple-channel CCTM method produced a dramatic increase in the best detection accuracy for many datasets. Of the 51 datasets, the multiple-channel CCTM produced improved detection in 44, unchanged detection in 1 and reduced detection in 6, when compared to the best single-channel detection for that dataset. The average increase in the HF-difference was 11 ± 9 and the average decrease was 9 ± 5. Fig. 4 shows results from the best 3-channel combination for the top (based on single-channel CCTM) 40 datasets.

B. Quadratic Model

HF-differences greater than 90% for 12 of 177 subject/task combinations were achieved using detection based on the quadratic model. Perfect detection (i.e. HF-difference = 100%) was achieved for 2 datasets. Of the 9869 channels studied, 17 exhibited HF-differences of 90% and higher (Fig. 5).

C. Adaptive Autoregressive Analysis

HF-differences for a comprehensive comparison between the AAR analysis and the CCTM method are not yet available; however, AAC%'s as high as 99.6 have been found [8].

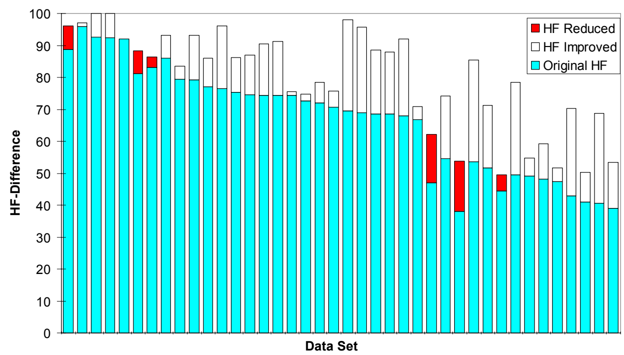

Fig. 4. Best HF-difference for each dataset using multiple-channel CCTM detection method. The 40 best datasets by original HF-difference are shown.

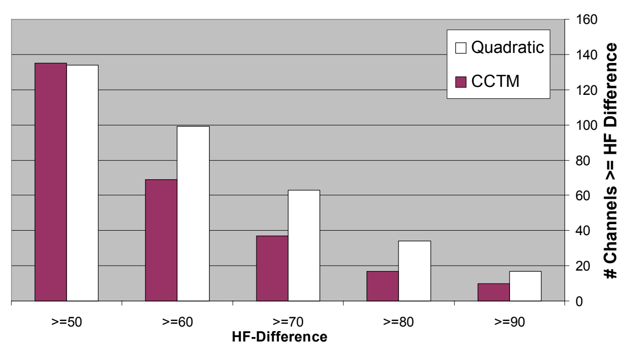

Fig. 5: ECoG channels above each HF-differences threshold for the CCTM (dark) and quadratic (light) methods.

D. Wavelet and Genetic Algorithm Analysis

The wavelet based analysis produced HF-differences greater than 90% for 9 of 22 datasets. Perfect detection (i.e. HF-difference = 100%) was achieved for 6 datasets. Of the 209 channels studied, 23 exhibited HF-differences of 90% and higher [10] (Fig. 6).

IV. Discussion

Multiple-channel CCTM, quadratic, and wavelet based detection have all been shown to improve detection over the established single-channel CCTM detection method while the AAR method also shows promise. Selection of the optimal channel combination is the biggest challenge for multiple-channel CCTM detection. To be practical for on-line experimental use, a method of rapidly selecting channels combinations is required. The exhaustive search of all possible combinations used here is impractical due to the large number of electrodes present for some subjects.

The quadratic, AAR, and wavelet based detection methods utilize the ERP and ERD/ERS effects as part of their detection model. The incorporation of the ERD/ERS detection is assumed as the cause for the improved detection over the CCTM method that has been demonstrated. At present, quadratic detection has been tested on more data than wavelet detection. Despite this, wavelet detection has produced a larger number of channels with HF-difference greater than 90% as well as more instances of perfect detection. Optimization of the quadratic detector is still underway, however, so further improvements may be possible. Results from the AAR method are still incomplete.

Many issues must be considered in the development of a practical direct brain interface. In actual use, false positives will be far more undesirable than missed hits because of the effort required to fix the error. Further, response time must be minimized, so for the CCTM methods, it will be necessary to shorten template duration after the trigger. As increased detection accuracy becomes possible, it will also be important to evaluate the ability of each method to not only detect when an action is performed, but also to differentiate between different actions that are performed.

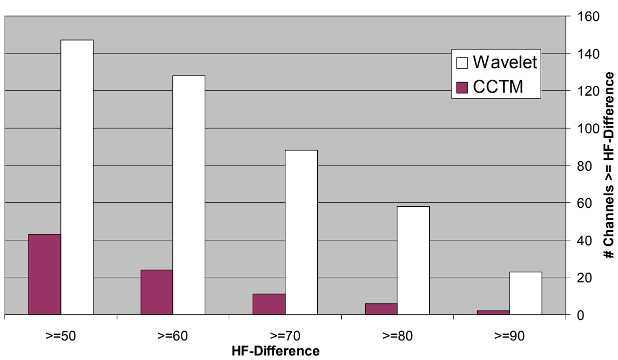

Fig. 6. ECoG channels above each HF-differences threshold for the CCTM (dark) and wavelet (light) methods.

V. Conclusion

While the single-channel CCTM method for detection of ERPs in ECoG has demonstrated sufficient detection accuracy for purposes of a DBI in a few channels, it is far from the goal of 100% accuracy for multiple channels. The results shown here make it clear that detection accuracy can be improved by a variety of approaches. In addition to improved detection accuracy from new signal processing approaches, there is also great potential for improved accuracy from feedback training [3,11]. Combination of advances from both of these areas suggests a strong potential for the development of a DBI based on detection of cognitive activity within ECoG.

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