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Detection of Event-Related Spectral Changes in Electrocorticograms

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Abstract
The University of Michigan Direct Brain Interface (UM-DBI) project seeks to detect voluntarily produced electrocortical activity (ECoG) related to actual or imagined movements in humans as the basis for a DBI. In past work we have used cross-correlation based template matching (CCTM) as the method for detecting event-related potentials (ERPs). That approach ignores event-related spectral changes in the ECoG signal. This paper discusses model-based signal detection methods that exploit event-related spectral changes. In particular we propose a quadratic detector based on a two-class hypothesis test with different covariances for the two classes. The covariance matrices are generated by fitting autoregressive (AR) models to training data. Preliminary results show that the quadratic detector yields more channels with good detection performance than the CCTM method, particularly when we impose constraints on detection delay.

I. Introduction

A direct brain interface accepts voluntary commands directly from the human brain without requiring physical movement and can be used to operate a computer or other assistive technology. The UM-DBI is based on detecting voluntarily generated changes in ECoG signals. The short-term goal is an interface capable of operating single-switch assistive technologies. The longer-term goal is to increase the accuracy of the interface and the number of useable control channels.
This paper discusses signal detection strategies for ECoG signals.

II. Methods

Data Collection
The data used in this project has been collected from the epilepsy surgery programs at the University of Michigan Hospital in Ann Arbor and Henry Ford Hospital in Detroit. The subjects involved were either under evaluation or undergoing surgery for alleviation of intractable epilepsy. Up to 128 subdural electrodes were implanted on the surface of the cerebral cortex of each patient to record seizure activity and map cortical function. The 4 mm diameter electrodes were oriented in grids or strips, with a center-to-center distance of 1 cm. Electrode placement was selected solely for the purpose of the epilepsy monitoring without regards for this project, and electrodes are not necessarily located on motor cortex. Each subject performed sets of approximately fifty repetitions of a simple movement. The movements were self-paced (unprompted) and spaced roughly five seconds apart. For this study, no feedback was used. The corresponding muscle activation was recorded with an EMG electrode for use as a reference. Most of the data was collected at a sampling rate of 200 Hz, with some at 400 Hz.

For simplicity, in this study we have focused on the problem of detecting event-related changes in ECoG signals recorded from a single electrode. The extension of the methods to multiple channels will be considered in future work.

Detection Algorithms
Since our ECoG data comes from unprompted events, it appears as a long record of a sampled ECoG signal. In this context, the goal of any signal detection method is to identify which portions of that signal correspond to motion events (as identified by the EMG channel triggers).

CCTM Approach
Initially, our group has used a cross-correlation based template matching (CCTM) method for signal detection. From training data, we compute an ERP template using triggered averaging of the signals from about 25 events. For test data, we cross-correlate that ERP template with the ECoG signal and compare the output to a threshold. We determine the threshold empirically from the training data so as to maximize the "HF-difference," i.e., the difference between the "hit" percentage (percentage of events that were detected within an acceptance window around each trigger) minus the percentage of "false" detections. (A classical ROC evaluation seems infeasible here due to the use of unprompted events and incompletely labeled data.)

Fig. 1 shows an example of ECoG signals from 5 events and an ERP template formed by averaging 23 events. A significant portion of the ERP template energy occurs well after the trigger (at time 0 seconds).

The CCTM approach is based implicitly on a two hypothesis test for a signal block x with the following pair of hypotheses:

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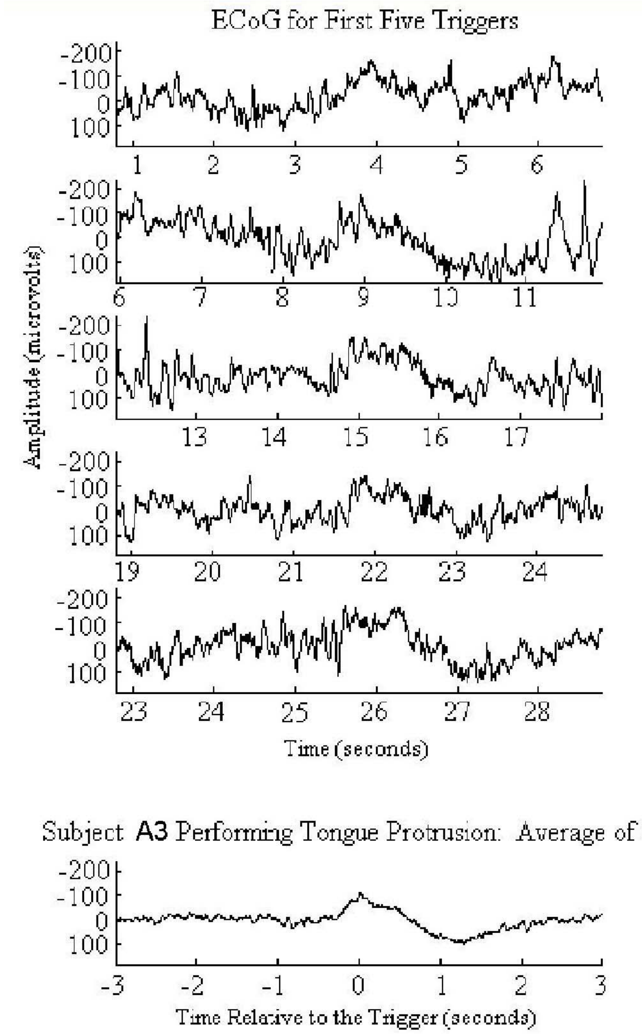

Fig. 1. Example raw data and average of 23 repetitions to create

$$H_0 : x \sim N(0, \sigma^2 I) \qquad \text{“rest”}$$
$$H_1 : x \sim N(\mu, \sigma^2 I) \qquad \text{“task/event”} \qquad (1)$$

where μ denotes the template signal vector. For this model, the Neyman-Pearson optimal detector, formed from the likelihood ratio, is the inner product $x'\mu$. When this detector is applied by sliding the signal block along the ECoG data stream, the resulting method is simply cross correlation (CCTM).

However, the “white noise” signal model (1) ignores event-related changes in the signal power. Such changes have been reported for both EEG and ECoG signals, and successful detection methods have been based on power spectrum changes [3]. Some spectral changes have even been given names, such as event-related desynchronization (ERD) and event-related synchronization (ERS) [4].

Fig. 2 shows a moving-window power spectrum computed by fitting a 6th-order AR model to about 50 events. Time “0” is

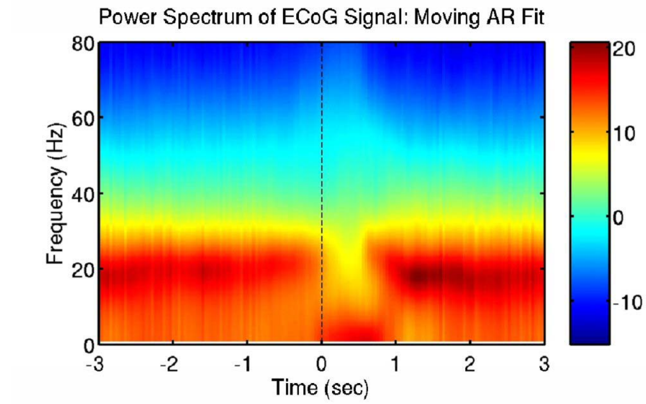

Fig. 2. Power spectrum changes near event onset

the event trigger time. The power spectrum changes significantly near event onset.

The proximity of the spectral changes to the trigger time raises the hope of reduced detection delay. These spectral changes are even more evident when we subtract a baseline power spectrum (corresponding to time -3 seconds) as shown in Fig. 3.

Such spectral changes are visible even in moving window spectra from *individual events* as shown in Fig. 4.

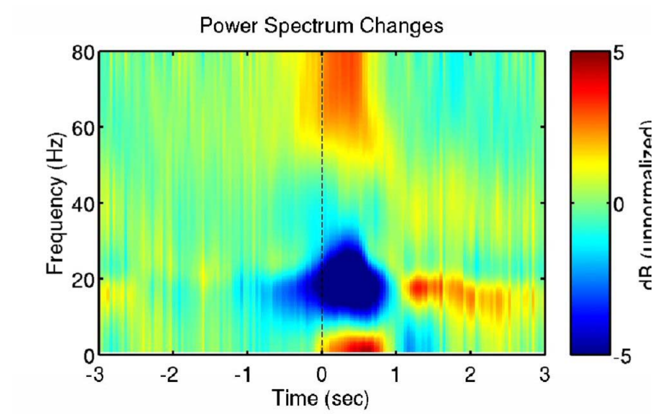

Fig. 3. Power spectrum differences relative to time -3 seconds.

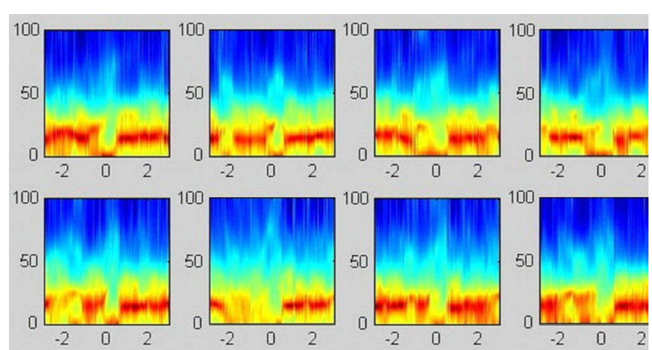

Fig. 4. Spectral changes from individual events.

Because of the prominence of such spectral changes, it is desirable to develop signal detection methods that can exploit them. A possible strategy is "feature based" methods, where one extracts signal features such as band power or other spectral parameters, and then applies a feature-based classifier such as linear discriminant analysis (LDA). Instead, here we consider a model-based approach in which we first postulate a signal model that aims to capture key signal characteristics, and then develop an "optimal" detector based on that model. (The optimality of the detector of course hinges on the accuracy of the model.)

Two-Covariance Signal Model

As an alternative to (1), we now assume the ECoG signal block x arises from one of the following two classes:

$$\begin{aligned} H_0 &: x \sim N(0, K_0) \quad \text{"rest"} \\ H_1 &: x \sim N(0, K_1) \quad \text{"task/event"} \end{aligned} \tag{2}$$

where now we ignore the ERP component μ for simplicity.

By the Neyman Pearson lemma, the most powerful test for such a detection problem is given by the likelihood ratio. Under the model (2), the likelihood ratio simplifies (to within irrelevant constants) to the following quadratic form:

$$\Lambda(x) = x' (K_0^{-1} - K_1^{-1})\, x. \tag{3}$$

The output of this quadratic detector is compared to a threshold for classification.

Training

The covariance matrices K_0 and K_1 in (2) are not known *a priori*, so one must estimate them from training data. If the length of the signal block is, say, 100 samples, corresponding to ½ seconds of ECoG data, then the covariance matrices are each 100 by 100. This would be too many parameters to estimate from limited training data. Therefore, we assume an autoregressive (AR) parametric model for the signal power spectrum. For a 6^{th}-order AR model, we must estimate 6 AR coefficients and a driving noise variance for each of the two signal states, for a total of 14 unknown parameters. An additional complication is that our ECoG data is incompletely labeled due to having unprompted events. The EMG signal triggers indicate when the event occurs, but presumably the brain is in the "task" state for some period (possibly) before and certainly after the signal trigger. We use a joint maximum-likelihood (ML) estimation procedure to estimate *both* the AR parameters and the center and width of the interval containing the "task" signal samples around each trigger from the training data. This joint labeling / training procedure requires an iterative search over the center and width parameters and repeated application of modified Yule Walker equations for finding the AR parameters.

Quadratic detector implementation

A direct implementation of the quadratic detector (3) would be inefficient due to the large matrix sizes. Fortunately, when the signals are assumed to have an AR power spectrum, one can implement (3) using simple FIR filters.

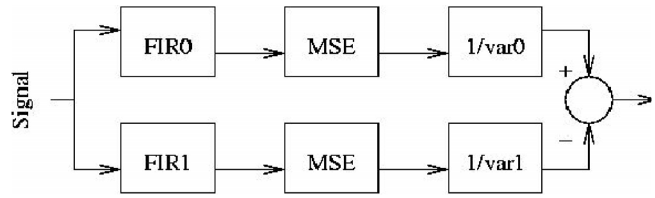

Fig. 5. Quadratic detector implementation.

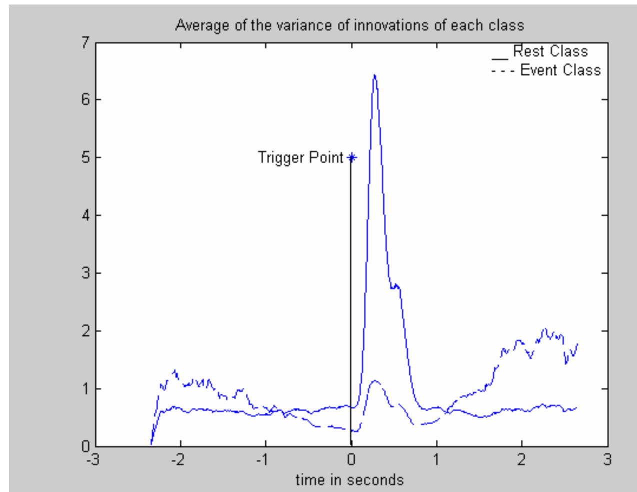

Fig. 6. Average of variance of innovations process around the trigger point

The block diagram in Fig. 5 summarizes the implementation of the quadratic detector. The ECoG signal is passed through two FIR filters, each of which come from the reciprocal of the corresponding AR model. Then a moving sum-of-squares computes the power of the innovation signal, which is normalized by the ML estimates of the driving variances. The difference operation in essence compares "which model fits better." The output signal is the test statistic that is compared to a threshold.

Fig. 6 shows how the variance of the innovations process works as a test statistic. Near the trigger point the signal spectrum becomes that of the event class, so the event class innovations variance decreases whereas the rest class innovations variance rises, leading to a large test statistic value.

III. Results

We compared the CCTM method and the quadratic detector (3) using a representative set of 20 datasets from 10 subjects, consisting of a total of 2184 channels. The results were evaluated for various detection acceptance windows, thus various delays. The length of the detection window after the trigger specifies the maximum allowed delay between the actual occurrence of an event and its detection by the algorithm. Therefore, longer detection windows correspond to

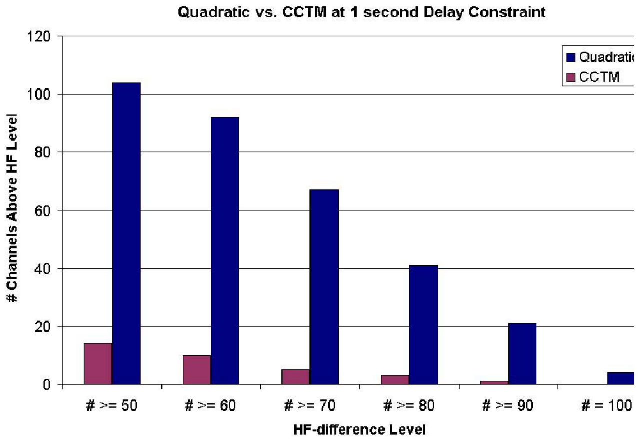

Fig. 7. Quadratic and CCTM detection performance with maximum allowed delay of 1 second.

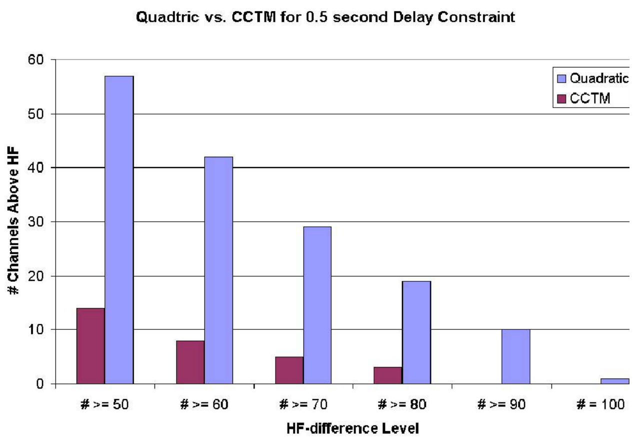

Fig. 8. Quadratic and CCTM detection performance with maximum allowed delay of 0.5 seconds.

greater detection delays. These experiments used detection windows that started 0.5 s before the trigger and ended 1s, 0.5s, 0.25s and 0s after the trigger point.

Fig. 7. compares the HF-differences of the quadratic and CCTM detectors when the delay is constrained to be at most 1s. There are many more viable channels with the quadratic method.

Fig. 8. shows the 0.5 s delay case. For this short delay, detection performance degrades considerably, yet there are still several viable channels for the quadratic detector.

For feedback studies, we would like to reduce the delay as much as possible. Fig. 9 shows that even with a 0.25 second delay there are still some viable channels for the quadratic detector.

IV. Discussion

We have described a quadratic detector for classifying ECoG signals. The quadratic detector is based on a two-covariance

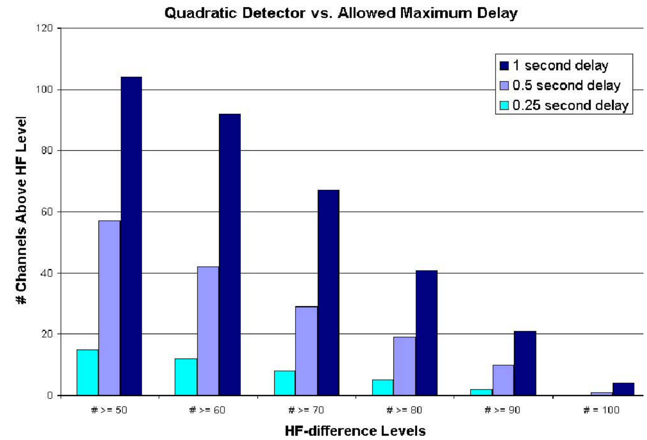

Fig. 9. Quadratic detector performance at differing maximum allowed delay.

signal model that captures event-related spectral changes in the signal. The detector has a simple implementation that is suitable for real-time use. Empirical results on real ECoG data showed that the quadratic detector offers improved detection accuracy relative to the CCTM method and can provide reduced detection delay.

We have recently implemented this approach in our real time system, and feedback studies with imagined movements are forthcoming.

There are several opportunities to improve the detection method further. Thus far we have ignored the ERP component in the quadratic detector. It can be included easily. Judging from the spectrum shown in Fig. 2 – Fig. 4 above, there are at least three distinct spectral characteristics. Separating these components rather than lumping them into just two classes may improve performance. Alternatively, time-varying models (e.g., state-space or hidden Markov methods) might better capture how the spectral properties evolve over time. Extensions to multi-channel detection are also under consideration.

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