BCI Competition 2003—Data Set Ia: Combining Gamma-Band Power With Slow Cortical Potentials to Improve Single-Trial Classification of Electroencephalographic Signals

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***Abstract*—In one type of brain-computer interface (BCI), users self-modulate brain activity as detected by electroencephalography (EEG). To infer user intent, EEG signals are classified by algorithms which typically use only one of the several types of information available in these signals. One such BCI uses slow cortical potential (SCP) measures to classify single trials. We complemented these measures with estimates of high-frequency (gamma-band) activity, which has been associated with attentional and intentional states. Using a simple linear classifier, we obtained significantly greater classification accuracy using both types of information from the same recording epochs compared to using SCPs alone.**

***Index Terms*—Multitaper, spectral analysis.**

I. Introduction

THE ability of trained subjects to control the amplitudes of their own electroencephalographic (EEG) rhythms was first reported four decades ago [1], [2]. Since then, it has been widely hypothesized that EEG signals could form the basis of a brain–computer interface (BCI) in order to provide an alternative channel for communication or prosthetic control in severely paralyzed patients. In an EEG-based BCI, electrical signals recorded from the subject's scalp are analyzed in real time to determine the state of the subject's brain. The results of that analysis are usually fed back to the subject by a visual display so that he/she can learn which forms of mentation produce a discriminable EEG signal.

A number of systems have been developed which allow trained subjects to communicate effectively via BCIs (albeit slowly—current systems have achieved information transfer rates of up to about 20 bits per minute in healthy subjects). In several of these [3]–[5], the subject learns to modulate the amplitude of mu (8–12 Hz) or high-beta (18–26 Hz) rhythms on the scalp just above the motor cortex. Other systems use the P300 event-related potential [6], [7] or slow cortical potentials (SCPs) [8], [9] as the BCI control signal.

These BCIs each use a single type of the information present in the signal to assess the state of the subject's brain: frequency-domain information as with mu- and/or beta-rhythm amplitude, time-domain waveforms such as the P300, or dc potentials in the form of SCPs. While the use of multiple-type classifiers within a single BCI has been suggested (frequency-domain as the primary signal carrier, plus waveform for error detection) [10], no previous BCI has used multiple information types of the signal to classify mental state. Here, we describe a case in which combining SCPs with frequency information in one classifier significantly improves its performance.

Most frequency-based BCIs have focused on the mu and/or beta rhythms. Oscillations at higher frequencies (gamma-band, variably defined as >24–30 Hz) in the human brain have been widely associated with integrative functions and awareness [11]–[15]. Motor actions that attenuate the amplitude of the mu rhythm are simultaneously associated with increases in gamma amplitudes [16]. These findings suggest that local gamma synchrony may be related to a variety of controllable mental states, indicating its possible utility in BCIs.

In order to stimulate improvements in the signal-processing component of BCIs, "BCI Competition 2003" [17] was recently held, in which several data sets were made publicly available for analysis by research groups worldwide. Using the principles described above and the algorithms described below, our system produced the highest rate of correct classification among the 15 groups who submitted entries for the data set pertaining to SCPs in a healthy human subject.

II. Methods

A. Data Acquisition and Task

All data were acquired from a single healthy subject at the University of Tuebingen, Germany, as described in [17]. Six EEG electrodes were all referenced to the vertex electrode $\mathrm{C_z}$ (International 10–20 system) as follows: channels 1 and 2, left and right mastoids; channels 3–6, anterior (ch. 3, 5) or posterior

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(ch. 4, 6) to position C_3 (ch. 3, 4) or C_4 (ch. 5, 6). These six EEG voltages were sampled at 256 Hz.

Trials consisted of three phases: a 1-s rest phase, a 1.5-s cue-presentation phase, and a 3.5-s feedback phase. At the beginning of the 1.5-s cue-presentation phase, a visual target indicator appeared either at the top ("cueN" trials, instructing the subject to strive for cortical Negativity, defined below) or bottom ("cueP" trials, cortical Positivity) of the screen. The target remained visible during the subsequent 3.5-s feedback phase, during which a cursor appeared, whose vertical position indicated the current level of cortical negativity being generated by the subject.

Cortical negativity was defined as the running average of the voltages on the two mastoid electrodes (channels 1 and 2) over the past 0.5 s, relative to the cue-presentation phase. Because these electrodes are referenced to C_z, positive values correspond to cortical negativity. Phenomenologically, cortical negativity is a form of SCP which has been associated with a wide range of behavioral states pertaining to alertness, anticipation, and preparation (see [18] for review).

The trials were separated into a training set (268 trials) and a test set (293 trials), both of which contained EEG data from only the feedback phase of each trial. The cue labels (class "cueN" or "cueP") for the training set were used to tune the parameters of the classification algorithm, whose performance was subsequently assessed on the test set.

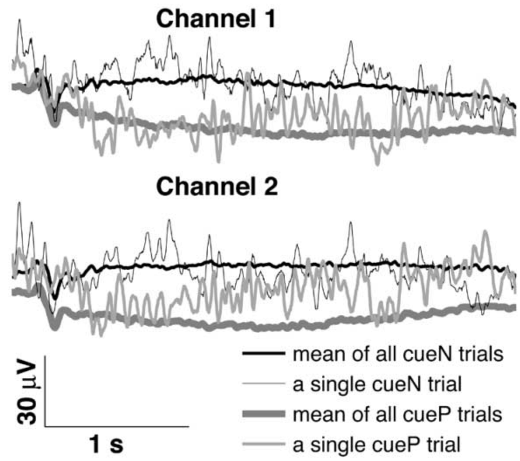

Fig. 1. Slow cortical potential measurements, training set.

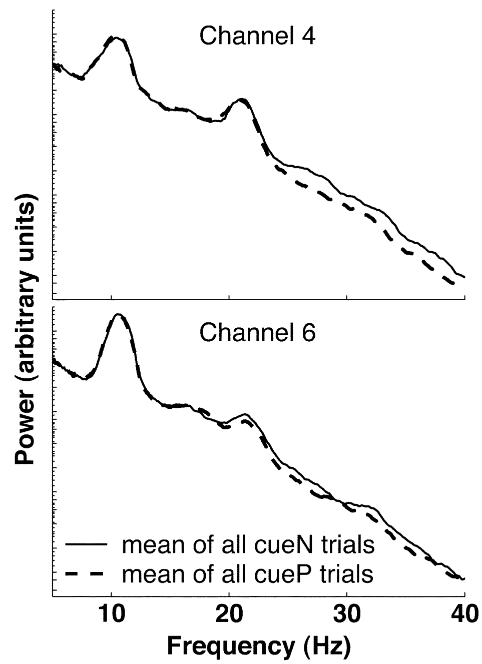

Fig. 2. Multitaper spectral power estimates, training set.

B. Analytic Methods

1) Approach: We used MATLAB (release 13) for analysis. In order to identify features of the data which could discriminate between the two cue classes for each trial, we separated the training set into cueN trials and cueP trials. For each EEG channel, we plotted the time-domain and frequency-domain averages across trials for each class. From these plots, a set of candidate features was identified for separating the two classes. The feature set was then screened for statistical significance between the two classes and for those features which were able to predict cue labels most accurately, using the classification algorithm described in Section IV. This screening identified the four features of the data set that were ultimately used in our classification algorithm, two in the time domain and two in the frequency domain.

2) SCP Analysis: Time-domain features of the SCPs for channels 1 and 2 are illustrated in Fig. 1. The mean traces of the 3.5-s feedback phase reveal an initial transient which is probably due to the onset of the feedback stimulus. After this transient, there is a 20–30 mV difference between the cue class means ($p < 0.0001$ for both channels) throughout the rest of the trial. Cue-class differences were minimal in the time-domain for the other four channels. The single-trial traces illustrate the drift and "noise" of the SCP measurement; intertrial variability across the entire data set can be seen in Fig. 3. We extracted two features from each trial (one from each of channels 1 and 2) for use in the classification algorithm by averaging the SCP voltage from 0.5 to 3.5 s after the beginning of the feedback phase.

3) Frequency-Domain Analysis: One of the most commonly used techniques for estimating the spectral power of signals is the Welch method, which consists of averaging the power spectra produced by sliding-windowed fast Fourier transforms (FFTs) across the duration of the trial. Our implementation of the Welch method used a Hamming window of width 1 s.

To assess the effect of spectral-estimation methods on the results, we also estimated the power spectra using the Thomson multitaper method [19], [20], using six prolate spheroidal tapers. Proponents of multitaper methods argue that they are able to treat averaging in a more principled way than other nonparametric methods. The use of this method has been widely adopted by geophysicists and has been used effectively in neuroscience [21].

Average multitaper-estimated spectra for the training-set data in channels 4 and 6 are plotted in Fig. 2 (cue-class differences were minimal in the frequency-domain for the other four channels). Spectral power below 24 Hz (which includes the mu band

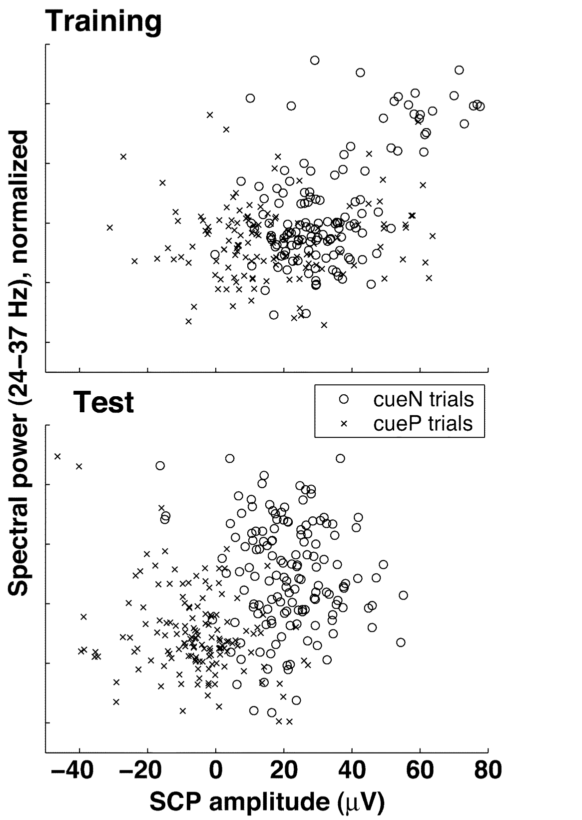

Fig. 3. Gamma-band power in channel 4 versus SCP amplitude in channel 1.

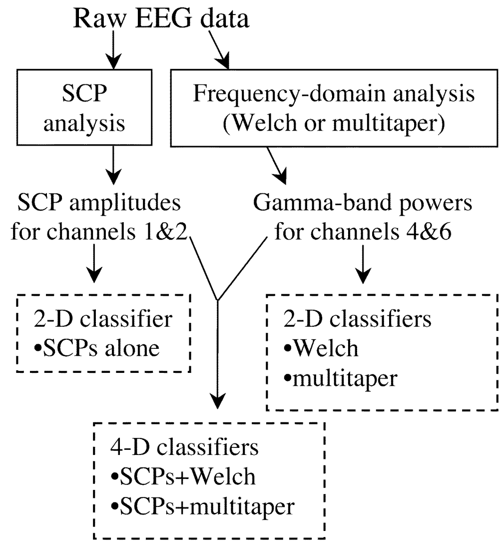

Fig. 4. Data flow for construction of the five classifiers. (marked with •).

TABLE I
CLASSIFICATION PERFORMANCE

FEATURE (S)	TRAINING SET (% CORRECT)	TEST SET (% CORRECT)
SCP	70.9	82.6
Gamma (Welch)	62.3	72.4
Gamma (multitaper)	64.9	73.4
SCP + Welch	80.2	85.3
SCP + multitaper	81.3	88.7

commonly used in BCIs) was not significantly different between the two cue classes. In the band 24–37 Hz, however, mean power was greater for cueN trials ($p < 0.0001$ for both channels) than for cueP trials.

For each 0.125-Hz-wide subband, we took the log of the power and then rescaled across all trials (independent of cue class) to obtain mean 0 and standard deviation 1. Taking the mean of this normalized quantity across the subbands from 24–37 Hz provided two more dimensions for classification, one each for channels 4 and 6.

4) Classification: Each trial was thus represented by four values (the two SCP means and the two gamma-band powers), defining a four-dimensional (4-D) feature space in which each trial is represented by one point. Two of the four dimensions (SCP mean for channel 1 and normalized gamma-band power for channel 4) are plotted in Fig. 3. From these plots, the inter-class differences and trial-to-trial variance can be appreciated.

We separated trials in the 4-D feature space into the two cue classes using a linear discriminant classifier, in which a normal density distribution is fit to each cue class, with class means and pooled covariance estimated from the training set. The class of a test trial was then predicted based on which distribution had higher density at the corresponding point in the feature space.

As outlined in the flowchart of Fig. 4, the relative contributions of the SCP features, frequency-domain features, and spectral-estimation methods were assessed by generating five distinct classifiers, each trained on a different subset of the data.

Performance of the algorithm on the training set was estimated using a leave-one-out jackknifing method. Test-set performance was assessed after the true labels were announced at the end of the competition.

III. RESULTS

The performance of the classification algorithm using various subsets of the data is listed in Table I. Using SCP information alone, the correct label was obtained on 70.9% of the training set trials, 82.6% on the test set. This improvement may be due to a subject-training effect, since the test data were taken later in the recording sessions than the training data (from Fig. 3 it can be seen that the overlap of classes is decreased in the test set, compared with the training set).

Gamma-band power alone, computed with either the Welch or multitaper method, was predictive at a rate much better than chance ($p < 0.001$, sign test). Multitaper spectral estimates outperformed the Welch periodogram estimates in both data sets, but this trend did not reach statistical significance (T-test, $n = 268$ for the training set, $n = 293$ for the test set).

Using gamma-band power in combination with the SCP measures produced the best result of all, significantly better than using SCP alone (T-test, $p < 0.001$ for Welch and multitaper in the training set, $p < 0.02$ for multitaper in the test set, $p < 0.10$ (marginally significant) for Welch in the test set).

An additional observation, illustrated in Fig. 3, was the correlation between the SCPs and gamma-band power, which was stronger for the training set $(\mathrm{r} = 0.48, \mathrm{p} < 0.0001)$ than for the test set $(\mathrm{r} = 0.25, \mathrm{p} < 0.0001)$.

IV. Discussion

We have demonstrated the value of using multiple types of information for single-trial EEG classification in one subject. This finding should motivate further exploration of multimodal classification approaches.

Gamma-band power, because of its correlation with high-level mental states, seemed promising as a potential control signal for BCIs. We initially hypothesized that it could be useful as we entered BCI Competition 2003, despite its lack of representation in existing BCIs. Because most frequency-based BCIs are based on the mu and beta bands, we were surprised that most of the useful frequency information for classification in this data set in fact turned out to be in the gamma range, with essentially none below 24 Hz. Incorporating gamma-band activity and multimodal information into the feedback signal of a BCI can be accomplished in real time on modern computers and may provide the user with a broader set of "mental handles" to grasp as they are learning to control the interface.

The discriminant analysis used presently is limited by its linearity. More elaborate classifiers such as support vector machines, while computationally more costly, may yield further improvements in performance.

A long-term goal of BCI research is to develop systems which enable the user to control multiple simultaneous degrees of freedom by self-modulating independent brain signals. Progress toward this goal has been made in two dimensions using multiple frequency-domain features [22] and neural networks [23]. Introducing additional interface dimensions, however, tends to degrade the accuracy of control over each one. The exploration of multimodal approaches, in addition to improving classification accuracy within each control dimension as in the present report, may also help to identify independently controllable channels for future BCIs.

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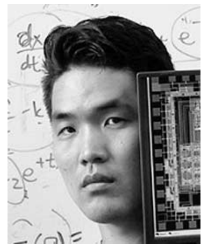

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